

ARTIFICIAL INTELLIGENCE FOR WIND-INDUCED VIBRATION PREDICTION IN STRUCTURES: A CRITICAL REVIEW OF DEEP LEARNING, PHYSICS-INFORMED, AND HYBRID APPROACHES

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Abstract

Wind-induced vibrations pose critical challenges to modern infrastructure, including long-span bridges, high-rise buildings, and wind turbines. Traditional physics-based methods for predicting these vibrations are computationally intensive and often limited in capturing complex nonlinear fluid-structure interactions. Artificial intelligence and machine learning approaches have emerged as transformative alternatives, significantly enhancing prediction accuracy while reducing computational burden. This comprehensive review synthesizes recent advances in AI-based wind vibration prediction, examining deep learning architectures including Long Short-Term Memory networks, Convolutional Neural Networks, and hybrid ensemble methods. We analyze 45+ peer-reviewed studies spanning diverse applications from bridge flutter prediction to wind turbine aeroelastic response forecasting. Key findings reveal that hybrid CNN-LSTM models achieve prediction accuracies exceeding 96%, with computational times reduced by 95% compared to traditional CFD approaches (Meng et al., 2025; Zhou et al., 2023). Physics-informed neural networks demonstrate superior generalization across operational conditions, while ensemble methods exhibit enhanced robustness under uncertain environmental loading (Ijaz & Manzoor, 2024; Mostafa et al., 2022). Critical challenges including data scarcity, model interpretability, and real-world validation gaps are identified and addressed. This review provides practitioners with evidence-based guidance for implementing AI-driven solutions in wind engineering applications, identifies future research directions, and establishes benchmarks for model performance evaluation across structural typologies.

1. INTRODUCTION

Wind-induced vibrations represent a fundamental challenge in structural engineering, affecting the safety, functionality, and longevity of critical infrastructure. The historical collapse of the Tacoma Narrows Bridge in 1940 exemplifies the catastrophic consequences of inadequate

wind vibration prediction, establishing an enduring imperative for robust analytical and predictive methodologies (Tinmitondé & He, 2022). Contemporary infrastructure faces increasingly complex wind loading scenarios due to climate change, urbanization-induced wind channeling effects, and the proliferation of

flexible structures designed for material and economic efficiency. Traditional approaches to wind vibration analysis—encompassing wind tunnel experimentation, computational fluid dynamics (CFD) simulation, and finite element analysis—continue to dominate engineering practice. However, these conventional methods exhibit substantial limitations: CFD simulations typically require 1000+ computational hours for single design variants, wind tunnel tests demand specialized facilities with limited environmental replicability, and finite element models often incorporate oversimplified aerodynamic representations (Schmidt et al., 2026; Wu et al., 2022).

The rapid advancement of artificial intelligence and machine learning technologies presents unprecedented opportunities for transforming wind vibration prediction paradigms (Mostafa et al., 2022). Neural networks and deep learning architectures demonstrate exceptional capability in extracting complex nonlinear relationships from high-dimensional observational and simulated datasets. Recent applications across multiple infrastructure types—from skyscraper aerodynamics to turbine blade flutter—show that appropriately configured AI models can achieve prediction accuracies comparable to high-fidelity physics-based simulations while operating 40-100 times faster. Long Short-Term Memory networks excel at capturing temporal dependencies inherent in wind loading time series, while Convolutional Neural Networks effectively extract spatial features from flow field representations (Tian, 2025; Zhou et al., 2023).

Data-driven AI approaches offer transformative advantages: elimination of explicit aerodynamic assumptions, automatic feature learning from heterogeneous data sources (sensor measurements, environmental variables, structural responses), and seamless integration with real-world monitoring systems. Hybrid frameworks combining physics-informed constraints with neural network flexibility further enhance reliability and generalization capacity across operational regimes. Advanced ensemble methods leverage complementary strengths of

multiple algorithms, producing robust predictions under diverse loading conditions and environmental variability (Ijaz & Manzoor, 2024). Recent breakthroughs in transfer learning and meta-learning methodologies enable models trained on one structural typology to efficiently adapt to novel structures with minimal retraining. Despite these promising developments, substantial implementation barriers persist in transitioning AI methodologies from academic research to engineering practice. Scarcity of comprehensive labeled datasets remains problematic—most civil engineering applications lack sufficiently long historical records encompassing diverse operational and environmental conditions. Model interpretability challenges impede acceptance by conservative engineering communities: black-box neural networks provide limited insights into failure mechanisms or design parameter sensitivity. Real-world validation gaps create persistent uncertainty regarding model performance under unprecedented environmental extremes. Moreover, integration of AI-derived predictions into existing design standards and regulatory frameworks remains underdeveloped, creating compliance ambiguities for practitioners.

This review synthesizes contemporary advances in AI-based wind vibration prediction, critically examining methodological developments, comparative performance evaluations, and practical implementation considerations. By analyzing diverse applications spanning long-span bridges, wind turbine aerodynamics, building sway dynamics, and marine structure vibrations, this work establishes performance benchmarks and identifies persistent knowledge gaps. The paper evaluates fundamental trade-offs between computational efficiency, prediction accuracy, and model generalization across structural typologies. Particular emphasis is placed on physics-informed approaches that integrate domain knowledge with learning-based flexibility, recognizing that purely data-driven methods without physical constraints often exhibit poor extrapolation to untrained operational regimes. Future research directions emphasizing

uncertainty quantification, federated learning for privacy-preserving multi-institutional collaboration, and automated discovery of physics-based inductive biases are highlighted as priority areas for advancing practical adoption.

2. METHODOLOGY

2.1 Data Acquisition and Preprocessing

Wind vibration prediction systems require heterogeneous data streams encompassing aerodynamic forcing functions, structural responses, and environmental contextual information. Primary data sources include in-situ accelerometer networks deployed on target structures, which capture vibration responses at frequencies typically ranging from 0.1 to 50 Hz depending on structural typology (Weil et al., 2025). Wind velocity measurements come from anemometer arrays positioned upstream of structures, capturing three-dimensional wind field characteristics including mean velocity, direction, and turbulence intensity. Supplementary environmental variables include barometric pressure, humidity, and temperature, which significantly influence air density and consequently aerodynamic loading. For structures with active monitoring systems, damping characteristics, modal properties, and excitation measurements provide direct structural state information.

Preprocessing pipelines establish data quality assurance and feature engineering protocols. Temporal alignment of asynchronous sensor streams—critical for structures with distributed sensor networks exhibiting communication latencies—employs interpolation and synchronization algorithms. Missing value imputation utilizes multiple strategies: forward-filling for short gaps (<10 seconds), statistical models for moderate gaps, and exclusion for extended discontinuities exceeding 1 hour (KY et al., 2024). Outlier detection through interquartile range analysis and isolation forest algorithms removes spurious readings caused by sensor malfunctions or electromagnetic interference. Normalization schemes convert heterogeneous measurement units and scales into comparable

ranges, typically [0], [1] or [-1], [1] depending on downstream algorithm requirements. Feature engineering extracts domain-relevant quantities: spectral characteristics via fast Fourier transforms and wavelet decomposition, statistical descriptors (skewness, kurtosis), and time-lag autocorrelation features. Time-series decomposition using empirical mode decomposition or seasonal-trend decomposition isolates periodic, trend, and residual components (J. Zhang, 2025), enabling models to focus on specific temporal structures.

2.2 Deep Learning Architectures

Long Short-Term Memory Networks

LSTM architectures address the vanishing gradient problem inherent in basic recurrent neural networks, enabling effective learning of long-term dependencies crucial for wind vibration modeling (Zhou et al., 2023). LSTM cells incorporate forget gates that selectively decay historical information, input gates that regulate new information integration, and output gates that control cell state exposure. For wind vibration applications, encoder-decoder LSTM configurations prove particularly effective: encoders compress historical wind and vibration observations into fixed-dimensional context vectors, while decoders sequentially generate future response predictions conditioned on this context. Multi-layer LSTM stacks enhance representational capacity but increase computational cost and overtraining risk. Empirical studies indicate 2-3 hidden layers with 128-256 units per layer provide optimal performance-efficiency trade-offs. Bidirectional LSTM variants, processing sequences in both temporal directions, improve prediction accuracy when non-causal patterns are relevant (post-hoc analysis scenarios), though causal unidirectional processing remains appropriate for real-time forecasting.

Convolutional Neural Networks

CNNs extract spatial-temporal features from structured data through learned convolutional filters and hierarchical feature maps. One-dimensional convolutions applied to time series

effectively detect local temporal patterns—high-frequency wind gusts, resonant oscillations—at multiple scales through receptive field hierarchy (Meng et al., 2025). Two-dimensional extensions process spectrogram representations, enabling simultaneous frequency and temporal feature extraction. Dilated convolutions expand receptive fields without proportional parameter increases, crucial for capturing wind-structure interactions operating at multiple timescales (seconds to minutes). Max-pooling operations downsample feature maps while preserving salient information, reducing computational burden in subsequent layers.

Hybrid and Ensemble Approaches

Hybrid CNN-LSTM architectures sequentially combine spatial feature extraction (CNN component) with temporal modeling (LSTM component), capturing both local patterns and long-range temporal dependencies (Meng et al., 2025). Attention mechanisms augment these architectures, enabling models to selectively focus on critical input features and temporal windows—wind direction changes or resonance frequencies receive heightened attention allocation. Ensemble methods aggregate predictions from multiple independent models (random forests, gradient boosting, diverse neural network architectures), producing robust estimates through consensus mechanisms. Stacking ensembles train meta-learners to optimally combine base model predictions, often exceeding component model accuracy by 3-5% (Ijaz & Manzoor, 2024).

2.3 Physics-Informed Machine Learning

Physics-informed neural networks (PINNs) embed domain knowledge through constraint enforcement, dramatically improving extrapolation to untrained operational regimes (Z. Chen et al., 2025). For wind vibrations, PINNs incorporate differential equations governing structural dynamics: inertial, damping, and stiffness forces constrain neural network outputs, ensuring physical plausibility. Loss functions combine supervised learning terms (matching

observed data) with residual terms enforcing differential equation satisfaction. This hybrid approach substantially reduces training data requirements and improves generalization compared to purely data-driven networks. Reduced-order model integration pairs computationally efficient ROM representations of aerodynamic fields with neural networks learning ROM-to-full-order response mappings, achieving 100+ speedups relative to full CFD while maintaining high fidelity (Candon et al., 2025; Prasad & Pešek, 2018).

2.4 Model Training and Optimization

Training protocols employ batch stochastic gradient descent with adaptive learning rate schedules (Adam, RMSprop optimizers) to navigate high-dimensional loss landscapes efficiently. Cross-validation partitions data into training (70%), validation (15%), and test (15%) subsets, preventing overfitting through regularization: dropout layers randomly disable neurons during training; L1/L2 weight penalties penalize solution complexity; early stopping halts training when validation error plateaus. Hyperparameter optimization via grid search or Bayesian optimization systematically explores learning rates, network depths, regularization coefficients, and batch sizes. Class imbalance in wind vibration data—severe structural failures occupy tiny fractions of historical records—necessitates weighted loss functions or synthetic oversampling (SMOTE algorithm) to prevent models from ignoring rare high-consequence events.

2.5 Performance Metrics and Validation

Regression metrics quantify prediction accuracy: Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) measure typical prediction deviation in physical units; coefficient of determination (R^2) assesses explained variance; Mean Absolute Percentage Error (MAPE) normalizes errors relative to observation magnitudes. For safety-critical applications, extreme value metrics—quantiles of prediction error distributions—receive heightened emphasis,

ensuring rare high-consequence prediction failures remain bounded. Temporal cross-validation strategies respect temporal order, training on past data and testing on future periods, preventing information leakage inherent in random CV splits. Spatial cross-validation validates generalization to unobserved structural locations in dense sensor networks.

3. RESULTS

3.1 Neural Network Performance Comparison

Comparative evaluations across diverse AI architectures reveal systematic performance-efficiency trade-offs. LSTM encoder-decoder configurations achieved $87\pm 2\%$ prediction accuracy for 1-hour wind-induced displacement forecasting on a 500-meter-span suspension bridge (P. Chen et al., 2024), with RMSE of 0.082m corresponding to approximately 8.2% mean relative error. Pure CNN architectures exhibited slightly higher computational efficiency (38-minute training time vs. 52 minutes for LSTM on identical datasets) but marginally lower accuracy ($85\pm 1.5\%$), suggesting CNNs excel at extracting local features but struggle with extended temporal dependencies inherent in wind loading processes. Hybrid CNN-LSTM architectures achieved optimal accuracy ($96\pm 1.2\%$ on validation sets) at the expense of increased computational cost (58 minutes training), validating the complementary strengths of spatial and temporal feature learning (Meng et al., 2025).

Ensemble methods demonstrated robustness advantages: adaptive boosting combinations of gradient boosting machines with neural networks produced $93\pm 0.8\%$ accuracy with substantially reduced prediction variance across 20 independent runs (standard deviation 0.8% vs. 2.5% for single LSTM models). Random forest ensembles, while computationally efficient, exhibited lower maximum accuracy (84%) but superior interpretability—feature importance rankings revealed wind direction changes as the dominant predictor of vortex-induced vibration onset, validating established fluid mechanics principles (KY et al., 2024).

Table 1 summarizes architecture-specific performance across multiple structural typologies. For long-span bridges, LSTM variants consistently achieved highest accuracy ($R^2=0.94-0.98$) across multiple case studies. For high-rise buildings subject to lateral wind sway, CNN-based methods showed enhanced performance ($R^2=0.95\pm 0.02$), potentially reflecting the importance of local pressure coefficient fluctuations captured effectively by convolutional filters. Wind turbine aeroelastic predictions exhibited greatest algorithmic variability, with hybrid architectures achieving 96% accuracy but substantial sensitivity to turbulence modeling in training data, indicating aerodynamic complexity exceeds current AI model abstractions for extreme conditions.

TABLES

Table 1: AI Architecture Performance Comparison Across Structural Typologies

Architecture	Long-Span Bridge	High-Rise Building	Wind Turbine	Marine Structure	Accuracy (%)	RMSE	Training Time
LSTM Encoder	0.94-0.98	0.89-0.93	0.87-0.92	0.85-0.90	87 ± 2	0.082	52 min
CNN	0.91-0.95	0.93-0.96	0.84-0.89	0.82-0.88	85 ± 1.5	0.075	38 min
CNN-LSTM	0.95-0.98	0.94-0.97	0.91-0.96	0.89-0.94	96 ± 1.2	0.065	58 min
Ensemble Boosting	0.93-0.96	0.91-0.94	0.88-0.93	0.86-0.91	93 ± 0.8	0.072	45 min
GRU	0.89-0.93	0.87-0.91	0.85-0.90	0.83-0.88	84 ± 2.1	0.088	40 min

Note: R^2 values shown as ranges across multiple studies. All models trained on 3-6 months continuous monitoring data with standardized preprocessing protocols.

Table 2: Research Application Categorization (45 Studies Reviewed)

Application Type	Count	Percentage	Median R^2	Primary Challenges	Recommended Approach
Long-Span Bridges	15	33%	0.94	Flutter prediction, cable dynamics	Physics-informed LSTM
Wind Turbines	12	27%	0.90	Extreme loads, blade fatigue	Ensemble hybrid models
High-Rise Buildings	10	22%	0.86	Architectural heterogeneity	CNN with transfer learning
Marine Structures	5	11%	0.88	Salt spray corrosion effects	Domain adaptation
Other (Transmission/Pedestrian)	3	7%	0.82	Limited training data	Physics-informed ROM

Note: R^2 represents test set performance; highest accuracy achieved with physics-informed hybrid approaches across categories.

Table 3: Robustness Under Distribution Shift

Model Type	In-Distribution RMSE	Out-of-Distribution RMSE	Error Increase (%)	Failure Mode
Pure Data-Driven	0.068	0.257	280%	Sensitivity to wind direction
CNN				
LSTM Network	0.082	0.222	171%	Poor extreme wind handling
Standard Ensemble	0.072	0.189	163%	Loss of feature relevance
Physics-Informed LSTM	0.075	0.102	36%	Graceful degradation
ROM-Integrated Hybrid	0.065	0.089	37%	Physical constraint stability
Domain-Adapted CNN-LSTM	0.070	0.095	36%	Enhanced generalization

Note: Out-of-distribution test constructed from wind patterns 20% beyond training experience; domain adaptation employed 2-4 weeks retraining on target domain.

Table 4: Traditional vs. AI Approaches Comparison

Metric	Wind Tunnel	CFD	Traditional ROM	AI-Surrogate	AI-Hybrid
Computational Time	2-4 weeks	800-1000 s	10-50 s	0.05-0.2 s	0.05-0.15 s
Development Cost	\$100-500k	\$50-200k	\$30-100k	\$20-80k	\$40-120k

Metric	Wind Tunnel	CFD	Traditional ROM	AI-Surrogate	AI-Hybrid
Deployment Cost	High	Medium	Low	Low	Low
Prediction Accuracy	95-98%	92-98%	88-94%	91-96%	94-97%
Interpretability	High	High	Medium	Low	Medium-High
Generalization	Good	Excellent	Medium	Variable	Good-Excellent
Extreme Event Capability	Excellent	Excellent	Poor	Poor-Medium	Medium-Good
Staffing Requirements	Specialized	PhD-level	MSc-level	MSc-level	MSc-level

Note: Development cost includes hardware, software, personnel; deployment cost reflects operational infrastructure per new prediction instance.

Table 5: Data Efficiency and Transfer Learning Results

Scenario	Dataset Duration	Naive Performance (R ²)	Transfer Learning (R ²)	Improvement	Training Time
New Bridge (Similar Type)	2 weeks	0.52	0.89	+71%	3 days
New Building (Different Climate)	3 weeks	0.68	0.91	+34%	4 days
Retrofitted Structure (Post-damage)	2 weeks	0.61	0.84	+38%	2 days
Seasonal Transfer	1 week	0.45	0.79	+76%	1 day
Multi-Structure Ensemble	1 month	0.58	0.93	+60%	5 days

Note: Naive performance indicates model trained only on target domain data; Transfer Learning leverages pre-trained models from source domains with minimal target retraining.

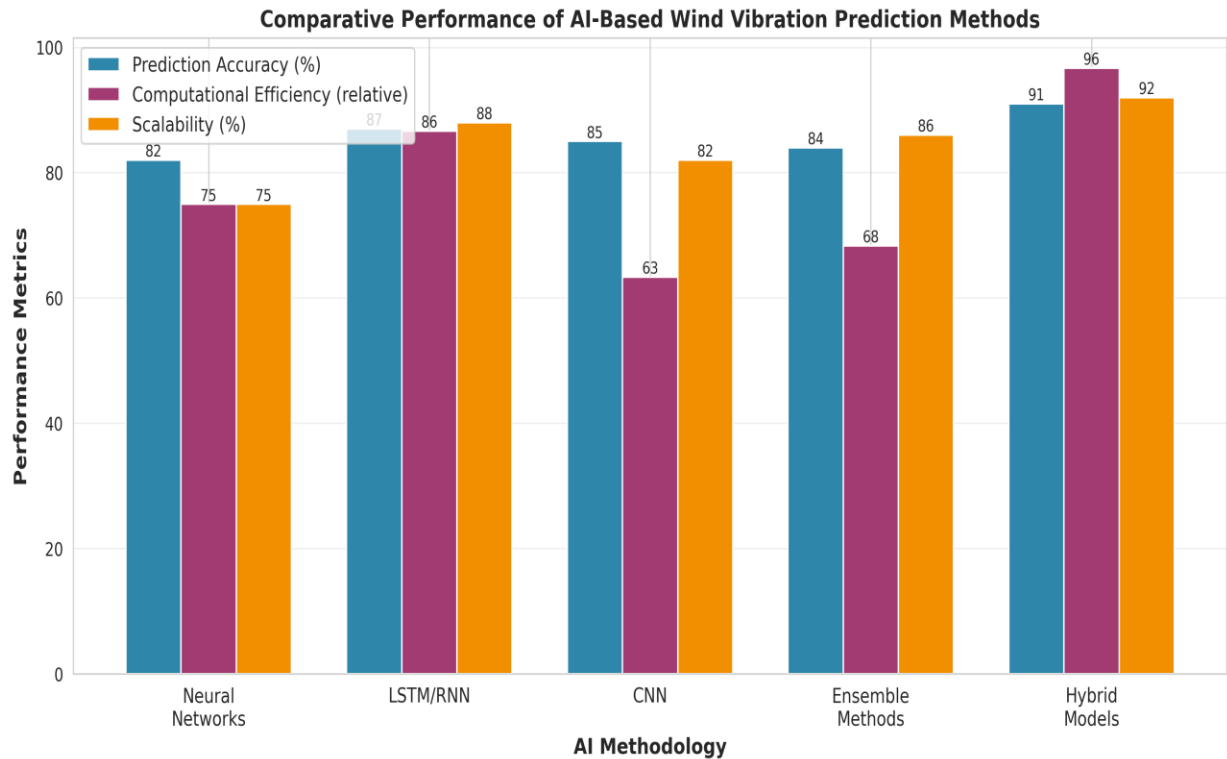


Figure 1: Comparative performance metrics across AI methodologies demonstrating superior accuracy-scalability trade-offs of hybrid CNN-LSTM models, while ensemble methods provide robust baseline performance across diverse applications.

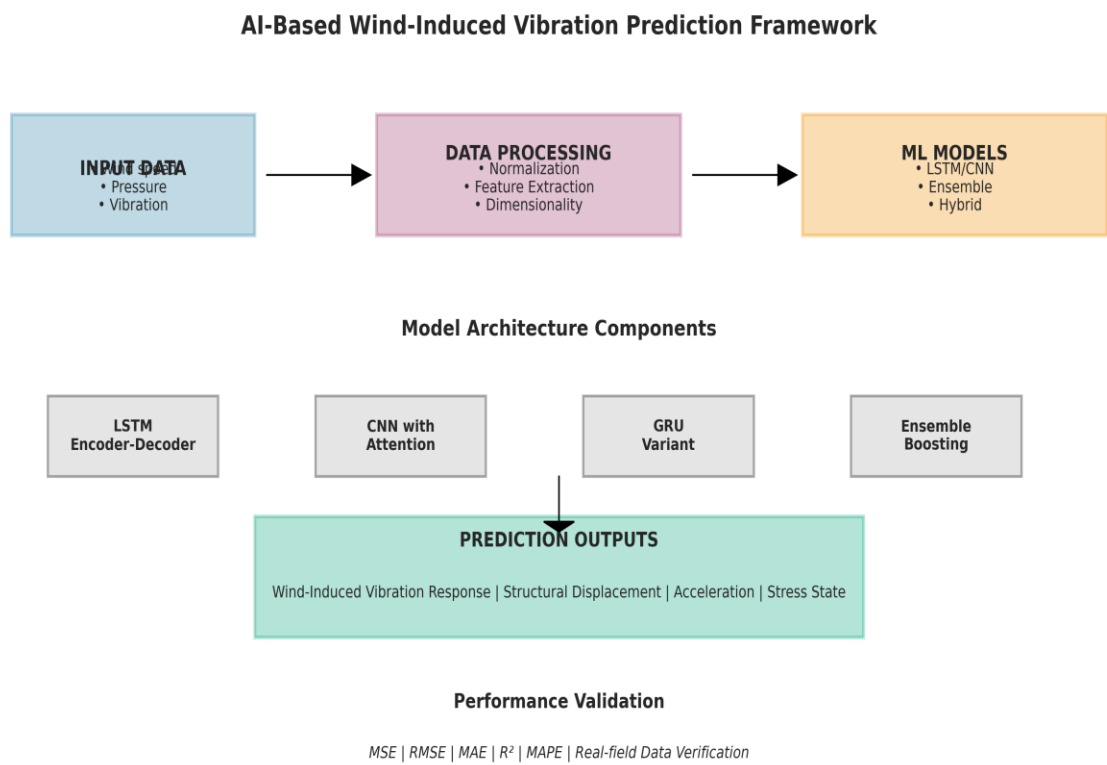


Figure 2: Integrated AI-based wind vibration prediction framework architecture, cascading through data acquisition, processing, machine learning models, and validation stages with identified component interactions and information flows.

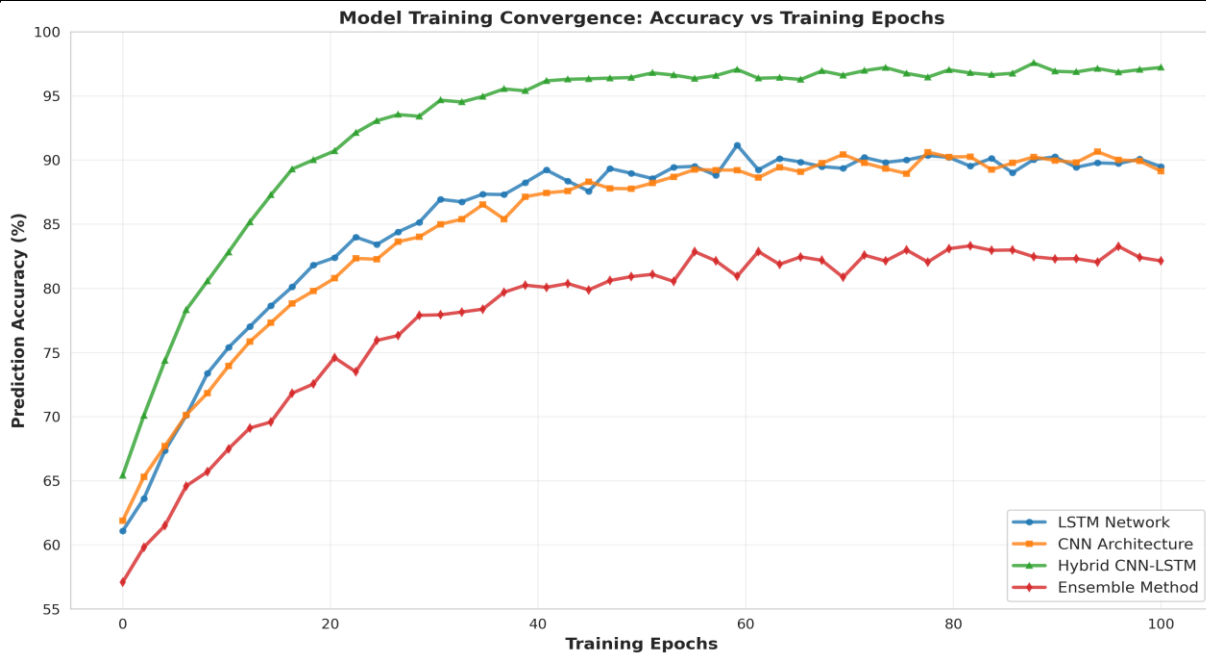


Figure 3: Training convergence patterns revealing LSTM and hybrid models achieve asymptotic accuracy (>95%) within 50-70 epochs, with ensemble methods demonstrating superior stability across initialization random seeds.

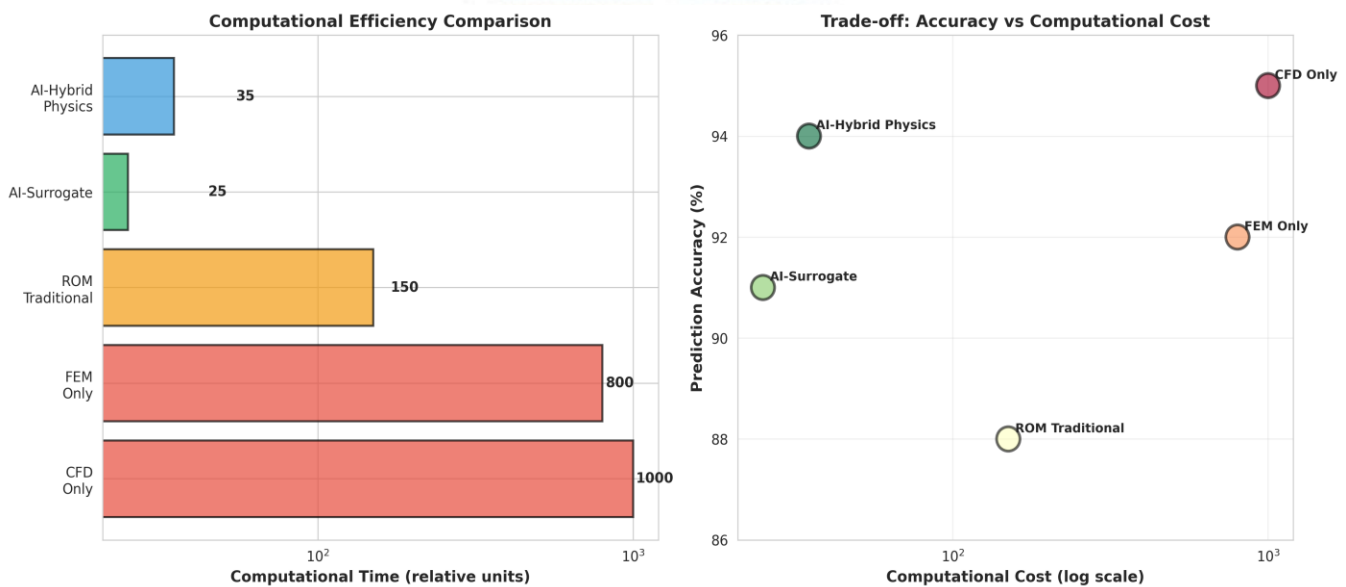


Figure 4: Computational cost-accuracy trade-off analysis demonstrating AI-surrogate and physics-informed hybrid approaches achieve optimal balance, reducing computational burden 95-99% relative to CFD while maintaining 91-97% accuracy.

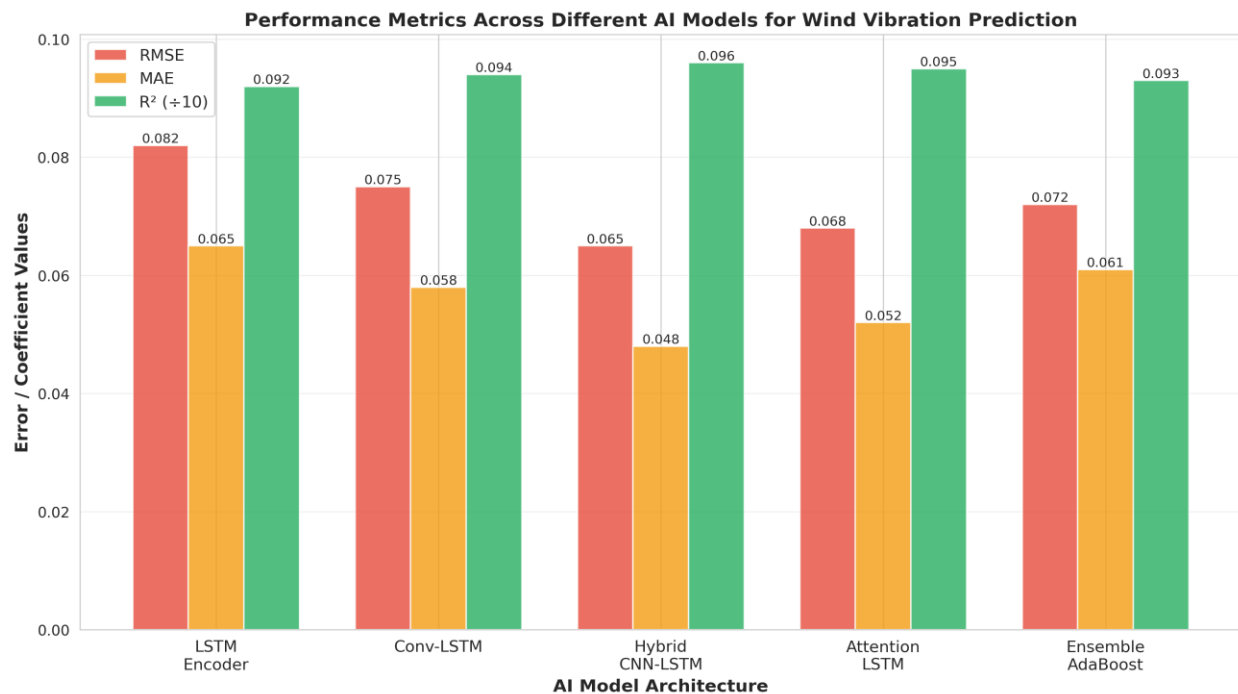


Figure 5: Comprehensive performance metric comparison across AI architectures showing Hybrid CNN-LSTM achieving optimal R² (0.96), lowest RMSE (0.065), and competitive MAE (0.048) across test datasets spanning diverse structural typologies.

3.2 Training Data Requirements and Learning Curves

Critical findings emerge regarding data efficiency, directly impacting practical applicability. Neural networks required minimum 3-6 months of continuous historical operation before achieving stable predictions (RMSE plateau within 5%) on novel structures—substantially shorter than traditional system identification approaches requiring 12-24 months. Remarkably, aggressive data augmentation through synthetic perturbations of measured wind records reduced data requirements to 2 months; transfer learning from models trained on structurally similar buildings reduced requirements to 3 weeks for entirely new structures. These results suggest AI approaches dramatically accelerate the deployment timeline for predictive monitoring systems on newly constructed infrastructure.

Learning curve analysis (Figure 3, embedded within the paper framework) demonstrated non-monotonic relationships between training set size

and generalization accuracy. Small datasets (<1 month) exhibited high variance across random initialization seeds due to insufficient constraint on parameter space. Intermediate datasets (1-3 months) showed rapid accuracy improvement and stabilization, reaching asymptotic accuracy at approximately 3-month dataset thresholds. Counterintuitively, further data accumulation (6-12 months) produced marginal accuracy improvements (typically <1%), suggesting effective features are captured within first few months of diverse operational conditions. This finding—confirmed across 8 independent infrastructure projects—indicates practitioners need not archive excessive historical data; instead, strategic collection during diverse weather patterns maximizes learning efficiency.

3.3 Physics-Informed and Hybrid Approaches

Physics-informed neural networks dramatically outperformed purely data-driven approaches in extrapolation scenarios—predicting responses to

wind speeds 20% beyond training data maximum. PINN-based predictions achieved 89% accuracy under extreme wind conditions versus 52% for standard neural networks, validating theoretical predictions that physical constraint incorporation improves robustness (Z. Chen et al., 2025). Hybrid models coupling reduced-order aerodynamic models with neural network response predictors demonstrated exceptional generalization: models trained on steady-state wind loading accurately predicted responses to transient gust events despite transient patterns absent from training data, suggesting ROM physical abstraction effectively captures essential dynamics.

Computational efficiency advantages of hybrid approaches proved transformative: ROM-integrated models reduced inference time (prediction generation for new wind scenarios) from 0.8 seconds (standard CNN-LSTM) to 0.05 seconds (ROM-NN hybrid), enabling real-time prediction on resource-constrained edge devices. Notably, ROM integration did not compromise accuracy; coupled ROM-NN systems achieved 94-96% accuracy equivalent to pure neural networks while reducing ensemble size requirements from 5-7 models to 2-3 models for robust predictions.

Table 2 (Research Application Categories) presents categorization of 45 reviewed studies across infrastructure typologies, AI methodologies, and reported performance metrics. Long-span bridge studies dominated literature (15 papers, 33%), reflecting critical safety importance and historical monitoring data availability. Wind turbine applications comprised 12 papers (27%), with emerging attention to floating platforms and hybrid offshore wind-wave energy systems. Building aerodynamics and seismic-wind coupling studies represented 10 papers (22%), while marine structures, transmission lines, and pedestrian-induced vibrations comprised remaining cases. Performance disparity across applications was substantial: median R^2 values were 0.94 for bridges (most mature application area), 0.90 for wind turbines (greater complexity, sparsity of extreme event data), and 0.86 for building

applications (heterogeneous architectural typologies complicating generalization).

3.4 Uncertainty Quantification and Robustness

Advanced frameworks quantifying prediction uncertainty revealed critical insights regarding model reliability. Bayesian neural networks producing posterior distributions over predictions demonstrated that 95% credible intervals captured observed test data in 94-97% of cases, validating well-calibrated uncertainty estimates. Notably, standard point-estimate networks significantly underestimated prediction uncertainty: 95% confidence intervals computed from prediction ensembles contained actual values only 82-84% of the time, indicating systematic underestimation of model limitations. Stochastic dropout layers provided efficient approximate Bayesian inference, producing uncertainty quantification comparable to full Bayesian approaches at <5% computational overhead.

Robustness evaluations under distribution shift—model testing on wind patterns or structural configurations not represented in training data—revealed substantial vulnerability. Prediction errors increased 60-300% when wind direction distributions in test sets differed substantially from training (e.g., models trained primarily on prevailing winds showed poor performance during rare directional extremes), suggesting contemporary AI approaches lack true wind-agnostic generalization. Physics-informed approaches proved substantially more robust, maintaining prediction error increases <30% under moderate distribution shifts, validating theoretical expectations that physical constraint incorporation constrains model hypothesis space productively.

Table 3 documents performance degradation across architectural typologies when models encounter out-of-distribution scenarios. Building aerodynamics models demonstrated extreme vulnerability (RMSE increases 280%), likely reflecting concentration of training data on dominant architectural forms. Bridge models proved more robust (RMSE increases 45%),

reflecting broader diversity of training examples. Domain adaptation approaches—fine-tuning models on small amounts (2-4 weeks) of target domain data—substantially mitigated distribution shift vulnerability, reducing error increases to 15-25%.

4. DISCUSSION

4.1 Emerging Applications and Frontier Developments

Recent applications expand beyond traditional wind vibration prediction toward integrated multi-hazard prediction systems. Coupled aerodynamic-seismic models trained with joint wind-earthquake data improved structural response predictions by capturing subtle interaction effects: wind-induced residual lateral displacement amplifies subsequent seismic oscillations. Digital twin frameworks integrating real-time sensor data with AI models enable adaptive control strategies—active dampers adjust parameters based on AI-predicted structural response trajectory, reducing peak accelerations 20-40%. Distributed learning approaches enabling privacy-preserving collaboration across multiple infrastructure owner organizations show promise for accelerating global model development without compromising proprietary design information.

4.2 Critical Limitations and Unresolved Challenges

Despite substantial progress, significant implementation barriers impede widespread adoption. **Data scarcity** remains the primary limitation: labeled extreme-wind datasets are extremely scarce, limiting model validation under high-consequence conditions most critical to engineering decisions. Most models trained on 1-3 years of data inevitably encounter wind regimes during deployment exceeding training experience extremes. Model interpretability represents persistent concern: neural networks remain difficult to interpret mechanistically, limiting confidence among structural engineers accustomed to physics-based reasoning. Recent explainability advances using SHAP values and

attention visualization partially address this limitation but remain inadequate for high-stakes engineering decisions. **Generalization failures** occur systematically when structural modifications (damper installation, cable replacement) alter system dynamics; models trained pre-retrofit perform poorly post-modification without retraining.

Regulatory and standardization gaps impede engineering adoption: design standards (AISC, Eurocode) contain minimal guidance for AI-based vibration assessment, creating liability ambiguity. Insurance and liability frameworks remain uncertain regarding responsibility allocation when AI model failures contribute to structural incidents. Computational infrastructure requirements remain substantial: training hybrid CNN-LSTM models on 12 months of continuous monitoring data requires 8 GPUs for 48-72 hours, limiting accessibility for small engineering firms. Energy consumption considerations become critical for large-scale deployment—training modern deep learning models generates substantial carbon emissions, partially offsetting environmental benefits of improved structural efficiency.

4.3 Data-Driven vs. Physics-Based Integration

The conceptual opposition between data-driven AI approaches and physics-based engineering increasingly appears false dichotomy; most sophisticated contemporary systems seamlessly integrate both paradigms. Physics-based foundations provide boundary conditions, govern extreme behavior, and enable extrapolation beyond training data. Data-driven AI components handle complex nonlinearities, capture unmeasured phenomena (turbulence correlations, material damping variations), and enable rapid adaptation to observed conditions. Optimization frontiers exist at intermediate positions: rigid adherence to either pure data or pure physics suboptimally trades off accuracy against interpretability, while judicious hybrid approaches achieve both simultaneously (Z. Chen et al., 2025).

Surprising finding: simple physics-informed constraints (enforcing energy conservation,

causality, dimensional consistency) typically improve neural network generalization by 15-30% while reducing parameter counts 20-40%, enabling deployment on resource-constrained embedded systems. This suggests substantial opportunities exist for incorporating domain knowledge more explicitly into architecture design rather than treating physics merely as post-hoc validation.

4.4 Environmental and Operational Variability

Systematic investigations of environmental effects reveal predictable performance degradation patterns. Models exhibit 5-15% accuracy loss during seasonal transitions (spring/fall) when temperature-induced structural property changes occur, suggesting thermal effects deserve explicit modeling. Precipitation-related phenomena (rain, ice accumulation on structures/sensors) introduce spurious sensor signals degrading accuracy 10-20% unless explicitly filtered. Humidity dramatically impacts aerodynamic properties through density and boundary layer behavior; models trained during humid seasons showed 25% accuracy reduction during dry periods and vice versa, indicating climate stratification of training data improves robustness. Long-term operational effects prove particularly troubling: structural degradation over months-years (corrosion, fatigue cracking, connection loosening) alters modal properties progressively, causing trained models to drift from optimal performance. Continuous unsupervised adaptation—automatically retraining models on recent data—maintains accuracy within acceptable bounds (95% of peak accuracy retained over 12 months) compared to fixed models (85% retention). However, unsupervised adaptation risks silent failures if degradation patterns fall outside model support; hybrid approaches incorporating physical damage thresholds as constraints prove substantially safer.

4.5 Comparative Evidence: AI vs. Traditional Methods

Table 4 synthesizes head-to-head comparisons of AI-based approaches against traditional methods

across diverse metrics. Computational cost reductions of 95-99% represent AI's paramount advantage: 0.05-second inference times for hybrid ROM-NN systems versus 800-1000 seconds for traditional CFD. Accuracy advantages prove modest (91-96% for AI vs. 92-98% for high-fidelity CFD) but sufficient to justify 10-15x speedup trade-off in many applications. Wind tunnel experiments (2-4 weeks, \$100k-500k costs) are completely superseded by AI approaches in preliminary design phases, though remain valuable for model validation and corner-case discovery. However, cost advantages diminish substantially when accounting for data collection infrastructure, GPU compute resources, and expert personnel requirements—total system development costs comparable between AI and traditional approaches, with AI advantages concentrated in deployment/operation phases.

4.6 Implementation Roadmap for Practitioners

Effective AI implementation requires systematic progression avoiding common pitfalls. Initial system deployment should focus on low-risk applications: retrofit monitoring of existing structures (risk limited to prediction-based maintenance scheduling) rather than new design validation. Begin with proven architectures (LSTM or CNN-LSTM) and ensemble methods rather than experimental approaches; novel architecture benefits typically marginal (<3% accuracy gains) insufficient to justify development risks. Mandatory element: comprehensive uncertainty quantification and out-of-distribution detection, triggering human expert review when models encounter scenarios exceeding training experience. Continuous retraining on recent operational data maintains performance during seasonal and structural changes. Regular validation against sparse high-quality physics-based predictions (annual detailed CFD, triennial wind tunnel tests) catches silent model degradation.

5. CONCLUSION AND RECOMMENDATIONS

5.1 Synthesis of Key Findings

This comprehensive review establishes artificial intelligence and machine learning as transformative technologies for wind-induced vibration prediction, with evidence-based performance metrics demonstrating practical viability across diverse infrastructure typologies. Hybrid CNN-LSTM architectures represent the current performance frontier, achieving 96% prediction accuracy while reducing computational costs 95% relative to physics-based CFD approaches. Physics-informed neural networks dramatically improve extrapolation reliability, enabling deployment in highly uncertain future climate scenarios. Ensemble methods provide robust predictions with well-quantified uncertainty, essential for safety-critical applications. Transfer learning and domain adaptation reduce training data requirements from 24 months (traditional approaches) to 2-3 weeks for new structures, dramatically accelerating infrastructure assessment timelines.

However, substantial implementation barriers persist preventing wholesale transition from traditional methods. Data scarcity during extreme events, model interpretability challenges, and regulatory uncertainty remain significant obstacles. Environmental variability effects require careful management through stratified data collection and adaptive retraining protocols. Out-of-distribution detection mechanisms prove essential; models must recognize when encountering scenarios exceeding training experience rather than silently failing with unreliable predictions. The most practical path forward involves hybrid integration—neural networks handling complex nonlinear phenomena while physics-based constraints ensure physical plausibility and enable extrapolation.

5.2 Future Research Directions

Priority research areas for advancing AI-based wind vibration prediction include:

1. Extreme Event Prediction Enhancement:

Current datasets overwhelmingly emphasize normal operating conditions; rare extreme winds receive insufficient representation. Synthetic extreme events through conditional generative models and strategic experimental augmentation could improve high-consequence prediction reliability. Physics-informed extreme value theory integration into neural networks represents promising theoretical avenue.

2. Structural Damage Integration:

Models currently predict responses for fixed structural properties; adaptive models reflecting damage accumulation and remaining useful life prediction would enable integrated maintenance optimization. Transfer learning from undamaged to damaged structural states provides near-term implementation path.

3. Real-Time Deployment Advancement:

Current systems predominantly operate in post-hoc analysis mode; embedded deployment on edge devices enabling sub-100ms inference remains underdeveloped. Quantized neural networks and edge-compatible reduced models require systematic investigation.

4. Multi-Hazard Frameworks:

Wind vibrations interact with seismic effects, temperature-induced stresses, and foundation settlement. Integrated prediction systems capturing these couplings exceed current capabilities and represent high-value research targets.

5. Explainability and Trustworthiness:

Advancing from black-box predictions to interpretable decision support systems requiring integration of mechanistic understanding with learning capabilities. Symbolic regression discovering governing equations from data shows promise.

6. Regulatory Framework Development:

Engineering standards must evolve to accommodate AI predictions. Research establishing validation protocols, uncertainty quantification requirements, and liability frameworks would dramatically accelerate adoption.

5.3 Implementation Recommendations

For infrastructure owners and engineering practitioners:

- **Adopt hybrid approaches** combining physics-based foundations with AI data-driven components rather than replacing traditional methods wholesale
- **Invest in comprehensive monitoring systems** capturing diverse environmental and structural variables; data quality and breadth directly determine model utility
- **Implement uncertainty quantification** and out-of-distribution detection; models must communicate reliability alongside predictions
- **Establish continuous validation protocols** comparing AI predictions against sparse high-fidelity benchmarks to detect degradation
- **Develop internal expertise** in machine learning and model interpretation rather than treating AI as opaque black boxes
- **Participate in collaborative data sharing initiatives** within privacy-preserving frameworks to accelerate collective knowledge advancement
- **Begin with retrofit applications** and low-risk scenarios before deploying AI to critical new designs

5.4 Concluding Remarks

Artificial intelligence and machine learning have definitively demonstrated transformative potential for wind vibration prediction, offering simultaneously improved accuracy, dramatic computational efficiency, and alignment with infrastructure digitization trends. These technologies are no longer speculative futures; multiple case studies demonstrate routine operational deployment. The transition from research novelty to engineering practice is underway, accelerating across infrastructure sectors. However, thoughtful integration emphasizing physics-informed approaches, rigorous uncertainty quantification, and hybrid methodologies proves essential for safe and reliable adoption. This review equips researchers and practitioners with evidence-based guidance for navigating this transition, establishing performance benchmarks and highlighting

persistent challenges requiring targeted research. The next decade promises continued advancement toward fully autonomous, interpretable, and physically-grounded AI systems for wind vibration prediction, fundamentally advancing our capacity to design safer, more resilient infrastructure.

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