A physics-informed multi-fidelity neural network framework for virtual sensing in rotating machinery

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ABSTRACT

This study proposes a novel integrated framework of physics-informed machine learning for virtual sensing in rotating machinery systems. The proposed framework aims to overcome the limitations of sparse physical measurements and enable comprehensive system monitoring. The proposed framework leverages a multi-fidelity data fusion strategy and physics-informed surrogate networks to achieve accurate and physically consistent predictions of dynamic responses across the entire domain under diverse operational conditions. The proposed framework comprises three key characteristics. First, a physics-guided multi-agent diverse generative adversarial network (PG-MAD-GAN) is proposed to synthesize high-fidelity synthetic data. This architecture of a generative neural network effectively fuses extensive low-fidelity simulations datasets from finite element model (FEM), which provide full-field data across the system, with limited high-fidelity experimental measurements obtained from physically accessible regions. The multi-agent structure and physics constraints ensure that the generated synthetic data is both diverse and physically plausible, bridging the fidelity gap between simulation and reality. Second, a surrogate modeling scheme is introduced in the consideration of an adversarial domain adaptation architecture and a physics-informed domain-adversarial deep operator network (PI-DADON). This architecture is specifically designed for operator learning, enabling accurate interpolation and extrapolation of system dynamics, including responses under various rotating speeds, without requiring extensive retraining for unseen conditions. PI-DADON is trained on both the high-fidelity synthetic data and the limited real measurement data. Third, both the PG-MAD-GAN and PI-DADON architectures are rigorously supervised by the physics of rotating machinery. This strategy for physics-informed regularization is crucial to ensure that the model's predictions remain physically consistent and robust, even in unmeasured regions or under untrained operational conditions. The effectiveness of the proposed framework is comprehensively validated using dynamic response datasets obtained from an induction motor, including experiments under diverse operating conditions. Systematic analysis on experiments confirms that the proposed framework with physics-informed strategies significantly enhances accuracy, robustness, and generalization capability compared to purely data-driven approaches. The proposed framework facilitates the development of AI transformation for intelligent mechanical systems by enabling reliable virtual sensing in inaccessible areas, providing rich and full-field information critical for advanced condition monitoring and diagnosis.

1. METHODOLOGY

Rotating machinery systems, such as ship propulsion shafts or industrial motor drives, require accurate real-time monitoring to ensure operational safety and efficiency. However, transducers cannot be installed at all critical structural or functional locations, and acquiring full-field, high-quality measurement data under every possible operating condition is practically infeasible. Digital-twin-based diagnostic methodologies help bridge this sensing limitation but face a fundamental trade-off: deterministic physics-based models offer high accuracy but are computationally intensive, while purely data-driven approaches are computationally efficient but require large volumes of labeled data and often fail to generalize to unseen conditions. To address this challenge, the present study proposes the integration of two complementary data sources—namely, low-resolution but computationally inexpensive finite element method (FEM) simulations and sparse but high-fidelity experimental sensor records—within a unified physics-informed learning framework capable of performing real-time virtual sensing.

The primary objective of this research is to develop a physics-informed virtual sensing framework that can accurately infer full-field dynamic responses in rotating machinery systems across a broad range of operational conditions, including spatial regions where sensor instrumentation is infeasible due to physical or economic constraints. The proposed framework consists of two interdependent stages. Phase A involves the generation of physically consistent, high-fidelity synthetic data by fusing low-fidelity FEM simulation outputs with limited experimental measurements. Phase B focuses on constructing a surrogate model capable of generalizing across spatially unobserved regions and untrained operational scenarios. Physics-based priors are systematically embedded in both the data generation stage and the surrogate modeling stage to ensure interpretability, physical consistency, and improved generalization performance of the model outputs.

In Phase A, the challenge of sparsely distributed high-fidelity measurements is addressed by generating full-field synthetic data that replicate the key characteristics of experimentally observed responses. This synthetic data generation process is implemented using a physics-guided multi-agent diverse generative adversarial network (PG-MAD-GAN). The PG-MAD-GAN generative model is trained to learn a mapping from low-fidelity simulations, obtained from full-domain finite element model (FEM) outputs to high-fidelity data representations that are consistent with physical measurements. The generator receives as input a low-fidelity signal x_{lf}, produced by the FEM, along with a latent vector z, and produces a high-fidelity approximation $\hat{x}_{hf}$, expressed as:

$$\hat{x}_{hf} = G(x_{lf}, z). \tag{1}$$

The discriminator D is simultaneously trained to differentiate between authentic sensor measurements and synthetically generated data. The adversarial training objective is formulated as:

$$\begin{aligned} &L_{GAN} \\ &= E_{x^{real}}[\log D\,(x^{real})] \\ &+ E_z\left[\log\left(1 - D\left(G(x^{lf}, z)\right)\right)\right]. \end{aligned} \tag{1}$$

To ensure that the generated outputs are not only statistically plausible but also aligned with domain-specific physical principles, a physics-guided loss function is incorporated. This additional loss term penalizes deviations from known physical behavior, including harmonic structure and amplitude characteristics, in the frequency domain. The physics loss is defined as:

$$\begin{aligned} &L_{phys} \\ &= \sum_{f\in\mathcal{F}} w_f \left(\hat{x}^{hf}(f) - x^{ref}(f)\right)^2, \end{aligned} \tag{1}$$

where F denotes the set of critical frequencies (e.g., rotor harmonics or structural resonance modes), x_{ref} represents a reference spectrum such as smoothed FEM outputs or partially observed experimental spectra, and w_f is a frequency-dependent weighting coefficient. To further regularize the spectral characteristics, a soft constraint on the amplitude positivity is introduced as follows:

$$\begin{aligned} &L_{amp} \\ &= \sum_f \max\left(0,\ -\widehat{x^{hf}}(f)\right)^2. \end{aligned} \tag{1}$$

Combining the adversarial loss, physics loss, and amplitude constraint, the total objective for generator training is expressed as:

$$\begin{aligned} &L_{total} \\ &= L_{GAN} + \lambda_{phys} L_{phys} \\ &+ \lambda_{amp} L_{amp}. \end{aligned} \tag{1}$$

The resulting PG-MAD-GAN model generates synthetic signals that are both physically consistent and statistically realistic. These high-fidelity synthetic datasets, covering sensor-inaccessible regions, are subsequently employed to enhance the training process of the surrogate modeling stage described in Phase B.

In Phase B, the objective is to construct a virtual sensing model capable of inferring full-field dynamic responses from sparsely distributed sensor measurements under various rotating speed conditions. The surrogate model must generalize both spatially—from discrete sensor locations to the entire domain—and across previously unseen operational scenarios. To achieve this goal, a physics-informed domain-adversarial deep operator network (PI-DADON) is proposed. The PI-DADON architecture is composed of three essential components: a feature extractor G_f, a response regressor G_r, and a domain discriminator D_d. The feature extractor transforms input sensor signals into a shared latent representation space, and the response regressor predicts the full-field displacement or response vector. To encourage generalization across heterogeneous data sources—including synthetic and real data, and low-speed versus high-speed operating conditions—a domain-adversarial loss function is incorporated. This loss function enables the feature extractor to produce domain-invariant embeddings through the application of a gradient reversal layer. The overall training loss function for the surrogate model comprises three components. The first is the regression loss, which quantifies the mean-squared prediction error between the model output and the ground-truth dynamic response:

$$L_{reg} = \sum || G_r\left(G_f(s)\right) - u_{target}||^2, \tag{1}$$

where s is the input sensor vector and u_{target} denotes the target full-field response, either from measurement or synthetic generation. The second component is the domain classification loss, which penalizes incorrect discrimination between data domains:

$$L_d = CrossEntropy\left(D_d\left(G_f(s)\right), c\right), \tag{1}$$

where c indicates the domain label (e.g., synthetic or real). The third component is a physics-based regularization loss, which enforces consistency with known physical laws. For instance, the dynamic behavior of a rotating shaft system can be represented using a simplified frequency-domain beam equation:

$$R_{phys}(x;\omega) = \rho A\,\omega^2\hat{u}(x) + \frac{GAd^2\hat{u}(x)}{dx^2} - q(x;\omega). \tag{1}$$

The corresponding physics-based loss function penalizes deviations from this governing equation:

$$L_{phys} = \sum \left| R_{phys}(x;\omega)\right|^2. \tag{1}$$

The total surrogate loss function used for training PI-DADON is given by:

$$L_{tot} = L_r + \lambda_d L_d + \lambda_{phys} L_{phys}. \tag{1}$$

The proposed formulation ensures that the surrogate model not only minimizes prediction errors but also adheres to fundamental physical principles and remains robust across different domains and operational regimes.

By explicitly integrating the PG-MAD-GAN generative network and the PI-DADON surrogate model, the proposed two-phase framework establishes a cohesive and synergistic architecture for virtual sensing. The PG-MAD-GAN module generates physically consistent, high-fidelity synthetic training data by fusing low-fidelity simulation inputs with sparse experimental measurements. This synthetic data significantly enriches the diversity and distribution of training samples, especially in regions where sensor measurements are unavailable. The PI-DADON surrogate model, in turn, leverages both data-driven latent feature representations and embedded physical priors to achieve accurate and generalizable full-field dynamic response prediction. This includes robust performance in spatially unobserved regions and under extrapolated operating conditions. Together, the integrated generative and surrogate modeling modules provide a scalable, interpretable, and real-time applicable solution for virtual sensing in complex rotating machinery systems, particularly where comprehensive sensor instrumentation is infeasible.

2. EXPERIMENTS

To evaluate the performance of the proposed virtual sensing framework, a comprehensive experimental testbed was developed to emulate the dynamic behavior of a representative rotating shaft system encountered in practical applications. The testbed configuration includes an induction motor, a flexible steel shaft, two steel disks mounted at mid-span and end positions, and a set of supporting bearings. A rigid coupling is employed to connect the motor and the shaft, ensuring stable torque transmission during rotation. System responses were measured using six non-contact gap sensors, which were installed at three axial positions along the shaft. At each location, two sensors were orthogonally arranged to capture lateral displacements in both horizontal and vertical directions, providing partial yet spatially distributed trajectory measurements of shaft motion.

Rotational speed was incrementally controlled from 150 RPM to 3000 RPM at intervals of 150 RPM, resulting in a total of 20 discrete operating conditions. Sensor signals were sampled at 25.6 kHz for 5-second durations, enabling the construction of dense time-domain datasets and high-resolution frequency-domain representations. For low-fidelity modeling, a finite element model (FEM) of the coupled motor–shaft–disk assembly was constructed. The FEM incorporated electromagnetic excitation forces induced by stator–rotor magnetic interactions, and structural dynamics were captured using a beam formulation that accounts for rotor asymmetry and attached disk masses. The output of the simulation model consisted of full-field displacement spectra across the entire shaft domain in the frequency domain.

To configure the training and evaluation datasets, 16 out of the 20 available operating conditions were selected for model training. The test set was specifically designed to include both interpolation cases (e.g., 1050 RPM, 1650 RPM), which lie within the range of training conditions, and extrapolation cases (e.g., 150 RPM, 3000 RPM), which extend beyond the training domain. This configuration enables a comprehensive evaluation of the surrogate model's generalization capabilities under both seen and unseen operating conditions. All datasets—whether derived from simulation or experimental measurement—were spatially and spectrally aligned to facilitate consistent comparisons. Coordinate points and frequency bins were matched to ensure that training and testing inputs shared a unified data structure.

To assess the effectiveness of the generative module, real sensor measurements were compared with synthetic high-fidelity responses generated from low-fidelity FEM inputs. For evaluating the surrogate modeling component, predicted full-field responses were validated against ground truth responses (either from experiments or high-fidelity synthesis), with particular attention to interpolation and extrapolation scenarios. Quantitative performance evaluation was conducted using two standard metrics: the Pearson correlation coefficient (PCC) and cosine similarity (CS). These metrics were computed pointwise and averaged over the spatial dimensions to provide a comprehensive measure of prediction fidelity.

3. RESULTS AND DISCUSSION

The performance of the proposed two-phase virtual sensing framework was quantitatively evaluated using vibra-tion response data acquired from a rotating shaft experimental testbed operating across 20 rotational speed condi-tions ranging from 150 to 3000 RPM. The two main components of the framework—PG-MAD-GAN for generating high-fidelity synthetic responses and PI-DADON for full-field surrogate prediction—were validated under both in-terpolation (e.g., 1050, 1650 RPM) and extrapolation (e.g., 150, 3000 RPM) scenarios.

In Phase A, the PG-MAD-GAN model successfully generated realistic, full-domain response spectra at representa-tive speeds including 600 RPM, 1500 RPM, and 2400 RPM. Two training configurations were compared: one with only adversarial loss and another with additional physics-based loss terms. The integration of physical constraints into the generative training yielded substantial improvements in prediction fidelity. Specifically, the average Pearson correlation coefficient (PCC) increased from 0.876 to 0.914, and the cosine similarity (CS) improved from 0.880 to 0.915 with the application of physics-guided regularization. Table 1 summarizes these improvements, providing results for three fault scenarios (normal condition, middle disk imbalance, and end disk imbalance), thereby con-firming that the benefit of physics-based losses generalizes across different mechanical configurations.

Table 1 Quantitative comparison of PG-MAD-GAN results under different training conditions across normal and faulty configurations.

Metric	Condition	FEM	w/o physics	w/ physics
PCC	Normal	0.281	0.808	0.861
	Middle disk	0.330	0.938	0.946
	End disk	0.278	0.881	0.937
	Average	0.296	0.876	0.914
CS	Normal	0.334	0.819	0.866
	Middle disk	0.346	0.939	0.945
	End disk	0.305	0.882	0.935
	Average	0.328	0.880	0.915

In addition to statistical metrics, training convergence patterns further validate the effectiveness of physics-informed learning. As visualized in Figure 1, the PG-MAD-GAN model trained with physics constraints consistently achieved higher PCC scores than the baseline MAD-GAN across various operating speeds (e.g., 300, 1800, and 3000 RPM). The physics-guided model also converged more rapidly, indicating increased training stability. These observations reinforce the role of domain knowledge in guiding generative processes toward physically valid solutions, particularly in spectral regions influenced by harmonics and resonance modes. These results demonstrate that the proposed generative network, when regularized by domain knowledge, is capable of producing realistic, full-domain response data that can serve as effective training targets for surrogate learning, especially in regions where physical sensors are unavailable.

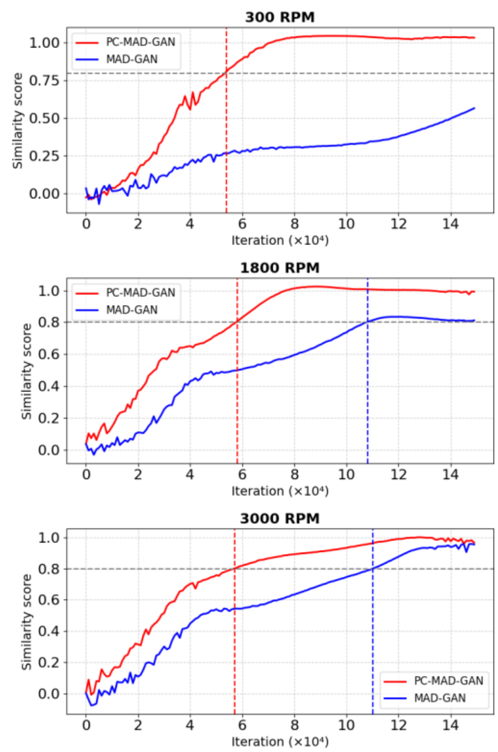

Figure 1 PCC comparison between PG-MAD-GAN and baseline MAD-GAN at three representative speeds.

In Phase B, the performance of the PI-DADON surrogate model was quantitatively assessed by comparing prediction accuracy before and after the integration of physics-informed constraints and synthetic high-fidelity data. At an extrapolated speed condition of 3000 RPM, the model trained without any physics guidance or synthetic augmentation showed poor agreement with ground truth, achieving a PCC of 0.078 and CS of 0.105. In contrast, the model trained with both PG-MAD-GAN-generated synthetic data and physics-based loss terms demonstrated near-perfect accuracy, reaching a PCC of 0.995 and CS of 0.999, as summarized in Table 2. These results underscore the necessity of both synthetic data augmentation and physics-informed regularization for achieving generalizable and accurate predictions in virtual sensing tasks, especially under extrapolation conditions. The synthetic data generated by PG-MAD-GAN effectively broadens the representational coverage of the training dataset, while the incorporation of domain knowledge via physics-based loss functions improves the model's robustness against data sparsity and distribution shifts.

Table 2 Surrogate model performance at 3000 RPM under various training conditions.

Model Configuration	PCC	CS
No synthetic data, no physics loss	0.078	0.105
With synthetic data, with physics	0.995	0.999

The evaluation results demonstrate that the proposed two-phase physics-informed framework effectively addresses the limitations of sparse sensor measurements and varying operational conditions in rotating machinery systems. Integration of simulation-informed generative modeling with physics-guided surrogate learning enables accurate and robust virtual sensing performance. The resulting methodology provides a practical foundation for achieving real-time, full-field monitoring and diagnostics in industrial environments where direct measurement is difficult or infeasible.

4. CONCLUSION

This study presented and rigorously validated a novel two-phase, physics-informed machine learning framework for virtual sensing in rotating machinery systems. The proposed methodology addresses the challenge of sparse and localized measurements by combining simulation-driven data generation and physics-aware surrogate modeling. In the first phase, low-fidelity finite element simulations were fused with limited high-fidelity experimental measurements via a physics-guided generative adversarial network. This approach enabled the synthesis of high-fidelity virtual data that preserve essential harmonic structures and dynamic characteristics across a broad spectrum of operating speeds. Building upon this enriched data, the second phase introduced a physics-informed, domain-adversarial deep operator network that enables accurate full-field response prediction. The surrogate model, trained with both synthetic and real data, successfully generalized across spatially unobserved regions and extrapolated operational conditions, even in high-speed regimes where sensor access is limited. The integration of physics-based loss terms further ensured physical consistency and improved robustness, confirming the value of embedding domain knowledge into both generative and predictive components. Overall, the proposed framework demonstrates strong generalization capability and high predictive accuracy under practical constraints, with only sparse sensor instrumentation. To further enhance the practical applicability of the framework, future work will incorporate mass imbalance fault conditions into both the data generation and model training processes. By embedding fault-specific physics and incorporating imbalance-induced spectral features, the framework can be extended to support robust condition monitoring and early-stage fault detection in real-world rotating systems. These extensions will enable the virtual sensing architecture to not only reconstruct unmeasured system states but also contribute to intelligent diagnostics and preventive maintenance strategies.

ACKNOWLEDGEMENT

This work was supported by the Air Force Office of Scientific Research [award number FA2386-23-1-4094], and Korea Institute of Machinery and Materials as part of the project 'Development of core technologies for digital transformation to enhance the total life-cycle safety of next-generation naval ship' [grant No. NK257A].

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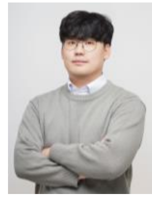
BIOGRAPHIES



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