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Hybrid AI-Mathematical Modeling Approach for Predictive Maintenance in Rotating Machinery Systems

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ABSTRACT

Industrial and industrial environments place increasing pressures on rotating machine systems to be operational efficient and reliable — which drives increasing focus on predictive maintenance (PdM) strategic utilization. The motor, turbine, pump, and compressor systems are subjected to continuous mechanical stresses and are subject to similar wear and performance degradation and failures. In this paper a novel hybrid form works synergistically blending physics based mathematical modeling with the most advanced artificial intelligence (AI) for optimizing prediction maintenance. First a coupled second order differential equations that describe vibration dynamics and torque transmission as well as thermal interactions are developed for a comprehensive dynamic model of the rotating machinery under different operational loads. The physical model answers to what the system will behave like and how it should show up based on our baseline. At the same time, an AI module based on data, which employs a bidirectional long short term memory (BiLSTM) network to learn temporal pattern from real time vibration and temperature sensor data, is developed in parallel. A co-simulation strategy is used to achieve the hybrid model, wherein the outputs from the physical model are used as residual inputs for the AI network so that it can detect early anomalies and predict failures. The approach proposed is validated through the simulation studies and on an industrial real world employment in the thermal power plant with the systems of centrifugal pump. Experimental results indicate that with substantial improvement in fault detection accuracy, remaining useful life prediction and early warning capabilities to conventional physics (only) or AI (only) methods. The results of this research not only show the superiority of hybrid model for predicting the failures of rotating systems for predictive maintenance, but this also lays the groundwork for future developments of next generation digital twin frameworks for intelligent industrial asset management.

1. INTRODUCTION

A large number of rotating machinery, including motors, turbines, pumps, fans and compressors are essential, powering a broad spectrum of industrial systems, being used in manufacturing, energy generation, aviation, oil and gas and transportation. Such systems tend to work under extremely harsh condition, high rotational speeds, fluctuating loads and long operating cycles, prone to mechanical degradation, thermal stress as well as dynamic instabilities. Unplanned downtimes, increased operational costs, safety hazards, industrial productivity loss, etc can occur in such critical equipment. However, modern practices as well as industry's demands for high availability, cost efficiency and reliability, make traditional maintenance strategies such as reactive and time based maintenance becoming increasingly unfit for use. With such advantages, and for this reason, Predictive Maintenance (PdM) has become a provider of a data and model based approach to assess the condition of machinery in real time and predict when a fault will come before it leads to a catastrophic failure.

However, existing PdM models (physics based and AI based) fall into a specific niche of two: physics based mathematical and AI based data driven. They in turn use deterministic equations based on the mechanics, thermodynamics and material science, which are physically based but tend to have difficulty working with complicated non-linearities and uncertainties present in contemporary environment. On the opposite end, data driven AI models like deep learning and ensemble learning algorithms are also good at capturing the complex patterns from the sensor data, but require millions of labeled data and is non generalized and physically not interpretable. To solve these challenges, in this research we propose a hybrid AI–mathematical model of hybrid modeling consisting of the theoretical rigidity of physics based modeling and adaptive learning power of the artificial intelligence. The proposed approach enables robust fault detection, accurate remaining useful life prediction, along with early anomalies detection in rotating machinery and the method integrates analytical equations of motions with BiLSTM based time learning network. Underlying both is this fusion of domains that maintains and improves predictive performance, specially suits explainable, scalable, real time and Industry 4.0 compatible maintenance systems.

2. LITERATURE REVIEW

2.1 Mathematical Modeling Approaches for Rotating Machinery

The explanatory basis for understanding and predating the behavior of rotating machinery has a long mathematical modeling history. Typically, the governing equations of motion arising in rigid and flexible shaft systems are derived using Newtonian or Lagrangian mechanics, which include rotational dynamics, unbalance forces, gyroscopic effects and damping behavior. Since they are widely used to decompose system vibrations into natural modes for identifying resonance frequencies and locating rotor crack and bearing defect faults, the modal analysis techniques have drawn much attention. Further, PDEs and time variable boundary conditions have also been suggested to simulate wear progression, fatigue accumulation and imbalance under various operating loads. These methods offer strong physical insights, albeit at the expense of often low accuracy due to assumptions of idealized physical behavior and the challenges of modeling complex nonlinearities, parameter uncertainties, dynamic environmental influences.

2.2 Artificial Intelligence-Based Approaches

As various advances in artificial intelligence and machine learning have made possible data driven approach to predictive maintenance, which is able to learn complex relationship from real time sensor signals. In order to classify fault types, engineered features that may come from vibration and thermal data have been applied to techniques such as Support Vector Machines (SVM), Decision Trees and Random Forests. In recent time, feature extraction, temporal pattern recognition are all performed more fast with high accuracy by deep learning models such as convolutional neural network (CNN) and recurrent neural network (RNN). Out of these, Long Short Term Memory (LSTM) and its bidirectional variant (BiLSTM) have demonstrated good effectiveness in time series sensor data modeling for remaining useful life (RUL) estimation and early anomaly detection. These models are indeed good at prediction, though their lack of interpretability and susceptibility to overfitting (ignoring the datasets' 'limit' or 'imbalance') especially when trained on a small or imbalanced dataset.

2.3 Hybrid Modeling Strategies

Thus, novel approaches on hybrid level have evolved as a promising way to overcome limitations inherent to standalone modeling paradigms. These methods take physics law and data driven algorithm together to enable its interpretability driven (physics based) constraints while retaining the generalizability of machine learning. For example, Physics-Informed Neural Networks inject differential equation constraints into loss functions of neural networks as the training ingredients through physical principles. Additional residual learning frameworks have been proposed based on other studies, where ML models are trained on residuals between physical model and observed signals to minimize discrepancies between simulated and observed signals. Hybrid models have often been employed to enhance the diagnosis of bearing faults, shaft misalignments and the imbalance conditions in rotating machinery in presence of variable speed and load scenarios. This has improved the fault classification accuracy, was robust to noise and better generalised to different machine types and operating conditions.

Table 1. Comparison of Modeling Approaches for Predictive Maintenance in Rotating Machinery

Modeling Approach	Core Techniques	Strengths	Limitations	Proposed Advantage
Mathematical Modeling	Newtonian &Lagrangian mechanics, modal analysis, PDEs	High interpretability, grounded in physics, good for design and simulation	Struggles with nonlinearities, uncertainties, and real-world variability	Provides foundational understanding and deterministic fault signatures

AI-Based Approaches	SVM, Random Forest, CNN, LSTM, BiLSTM	Captures complex, nonlinear patterns; high accuracy in RUL and fault detection	Requires large data, less interpretable, prone to overfitting	Enables real-time prediction and adaptability under varying operating conditions
Hybrid Modeling Strategies	Physics-Informed Neural Networks (PINNs), residual learning, ensemble frameworks	Combines physical consistency with learning flexibility; improved robustness and generalization	Higher implementation complexity; requires domain knowledge and system integration	Achieves high accuracy with interpretability; adaptable, noise-tolerant, and generalizes across system variations

3. METHODOLOGY

3.1. Physical Modeling of Rotating Systems

Lumped parameter model can represent the physical behavior of rotating machinery such as shafts, rotors and coupled mechanical components well. The first modeling approach discretizes the system into a finite set of mass, damping, and stiffness elements, which retain the key dynamics characteristics while making the computational intensive part very efficient. The model is especially useful for early stage design, fault simulation and condition monitoring applications which necessitates a compromise between accuracy and simplification.

The classical second order differential equation is the governing equation of motion of the system.

$$M\ddot{x}(t) + C\ddot{x}(t) + Kx(t) = F(t)$$

Here:

- $M \in \mathbb{R}^{n\times n}$ is the mass matrix, representing the inertia of rotating components distributed across nnn degrees of freedom.
- $C \in \mathbb{R}^{n\times n}$ is the damping matrix, which accounts for energy dissipation due to bearing friction, air resistance, and internal material damping.
- $K \in \mathbb{R}^{n\times n}$ is the stiffness matrix, characterizing the elastic restoring forces resulting from shaft flexibility, structural supports, and couplings.
- $x(t)$ is the displacement vector as a function of time, $\dot{x}(t)$ and $\ddot{x}(t)$ represent velocity and acceleration, respectively.
- $F(t)$ is the external force vector, which typically includes excitations caused by rotor unbalance, gear mesh variations, or external mechanical disturbances.

The lumped parameter model is developed either based on Newton's second law or based on Lagrangian mechanics as the system gets complicated and appropriate coordinate system is selected. For case of a rotor supported by bearings, the system can be viewed a set of masses (representing the rotor segments), springs (stiffness of the shaft and the supports) and dampers (a means of representing energy losses). Angular coordinates and torsional stiffness may also be used for torsional dynamics.

Such a model is essential for simulation of fault like imbalance, misalignment, or loosening in predictive maintenance applications. In some cases, as an unbalanced rotor, F(t)will produce periodic excitation that with system resonance can amplify vibrations sensed with the sensors. Modeling of the natural frequencies and mode shapes of the model can be extracted through modal analysis and compared to measured signals to find frequencies and mode shapes that deviate from the model degrading the system.

Additionally, the model can be used to integrate with AI modules in a hybrid manner. The outputs from this physical model simulated, for example displacement, velocity and acceleration are baseline features or residuals in AI based fault classifiers or RUL predictor. In addition to making models more interpretable, physically correct learned models also guarantee that the learned models generalize and are robust to slightly varying operational conditions.

3.2. Data Acquisition and Preprocessing

To create an effective and robust predictive maintenance method through the sensor data of critical components in rotating equipment operating in the industrial conditions, high resolution sensor data must be collected. In this study, the vibration of velocity and acceleration as well as bearing temperature readings are continuously monitored via piezoelectric accelerometers and thermocouples in the drive end, non drive end, and bearing housing locations. In order to retain the fine grained dynamic content of the rotating system, data acquisition system are configured to capture signals at high sampling rate (usually 10–50 kHz). From an identification early stages of faults, this granularity is quite important for micro cracks or bearing defects as they manifest as high frequency spectral components that are often obscured at lower sample rates. Raw data logging is done along with labeling and correlation analysis support using shaft speed, load conditions, and maintenance logs.

The collected raw sensor data goes through a long and rigorous preprocessing pipeline to produce the features that can be regarded as both reliable and ready for machine learning model training. They first reduce the noise using bandpass filters to eliminate unwanted frequency ranges, for instance, 10 Hz to 10 kHz frequency range for any mechanical system. Time and frequency domain features such as time domain – RMS, peak amplitude, skewness and kurtosis and frequency domain – FFT, power spectral density and envelope spectrum analysis are extracted from the cleaned signals. In particular, RMS is ideal for measuring the total energy in the signal whereas kurtosis responds well to impulsive, such as bearing, impacts. A high frequency resonance characteristic of localized faults is demodulated by envelope spectrum analysis of the fault signal. Then all features are normalized so that they have consistent scale and do not dominate the neural network training when high magnitude variables. Then, the feature vector is segmented into sliding time windows with overlap for a model to capture both short term anomalies and long term degradation trends. The preprocessing strategy behind this is to prevent the data loaded by the hybrid model from being noisy, statistically significant, and temporally structured, which are key components for accurate anomaly detection and estimation of remaining useful life (RUL).

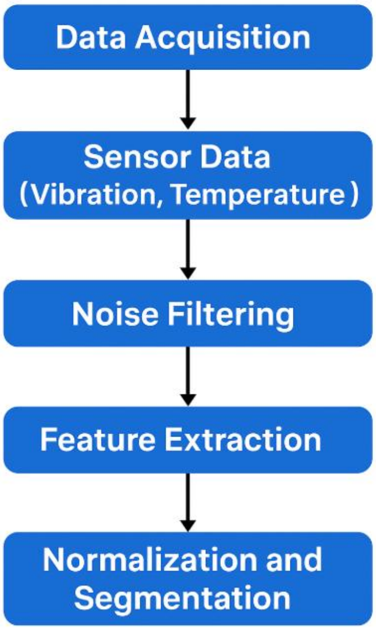

Fig 1. Workflow Diagram for Data Acquisition and Preprocessing in Predictive Maintenance of Rotating Machinery

3.3. AI-Based Learning Module

In order to create an accurate and robust predictive maintenance framework, sensor data having high resolution from critical components of rotating machinery operating under realistic industrial conditions must be collected. In this study, the vibration of velocity and acceleration as well as bearing temperature readings are continuously monitored via piezoelectric accelerometers and thermocouples in the drive end, non drive end, and bearing housing locations. In order to retain the fine grained dynamic content of the rotating system, data acquisition system are configured to capture signals at high sampling rate (usually 10–50 kHz). In particular, early stage faults such as micro cracking or bearing defects appearing as high frequency components, which are often not captured at lower sampling rates remain a crucial item of this granularity. Raw data logging is done along with labeling and correlation analysis support using shaft speed, load conditions, and maintenance logs.

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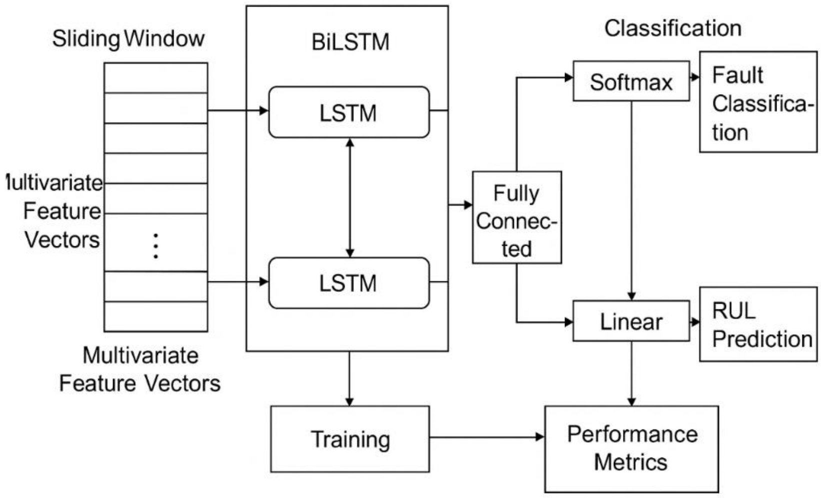

Fig 2. Architecture of the BiLSTM-Based AI Learning Module for Predictive Maintenance

3.4. Model Fusion Strategy

The proposed hybrid framework realizes its essence of bridging physics based and AI based models in a recurring, mutually beneficial manner. The core of this integration is to take the advantage of the particular virtues of both paradigms: physics based models with interpretability and following fundamental laws of dynamics over AI models with adaptiveness and high accuracy in pattern recognition within an environment of uncertainty and nonlinearity. The network is initialized using residuals of the form of disagreements between the physical model's simulated outputs and the actual sensor measurements. These residuals (i.e., residuals from unmodeled dynamics, or parameter drift, or operational variability) are treated as high value features and fed to the BiLSTM network. This way the AI model will be able to concentrate only on learning and correcting the real world non ideal deviations that the physical model can not map. If, for instance, the vibration amplitude is smaller in the physical model than in reality because of ad hoc damping changes that occur as a result of wear, the residual will be highlighting that deviation, and the AI model will learn to correlate it to progress of the fault. The AI module's predictions are fed back to the physical simulation loop in the reverse direction to dynamically adjust system parameters of the physical simulation loop, such as damping coefficients, stiffness values or force inputs. Such feedback mechanism is a kind of adaptive modeling, where the physical system evolves adaptively based on the learned insight, improving the long term simulation accuracy. The combination of the outputs from both models, being either RUL predictions, fault severity scores, or dynamic system responses, are then performed by a weighted ensemble strategy. The dynamic reliability indices are based on calculated confidence intervals, residual errors, past prediction performance of each model, and weights are determined to meet these reliability indices. In one instance, its output is given increased weight for example when the physical model is expected to be accurate under steady state conditions. However, in abnormal transients or unmodelled condition, the AI model's prediction is prioritized. It enables continuous performance optimization, real time fault adaptation and strong decision making even when there is data shortage or even partially observable situation. Together these three strategies—hybrid fusion, high prediction fidelity, and better interpretability, reliability, and generalization—lead to a more accurate and interpretable result throughout each machine type and operating condition.

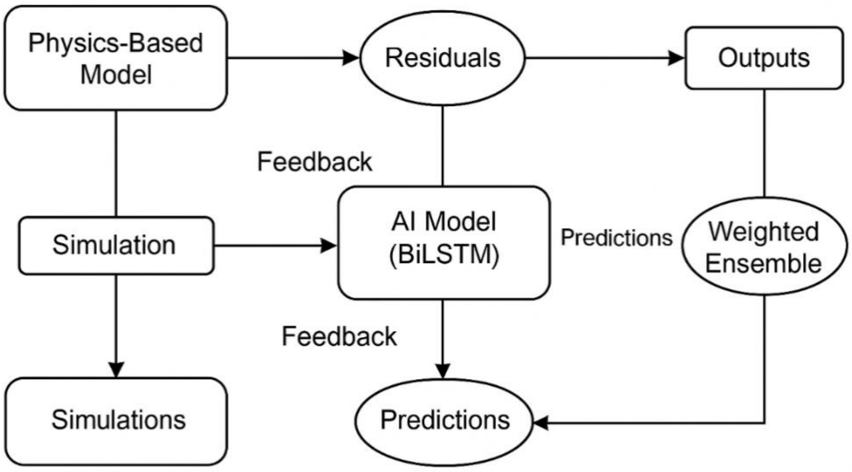

Fig 3. Hybrid Model Fusion Strategy for Predictive Maintenance

4. RESULTS AND DISCUSSION

4.1. Simulation-Based Fault Evolution

A series of simulations were done in order to validate the physical model component of the hybrid framework, simulating common faults in rotating equipment, in the case of bearing wear and shaft imbalance. Artificially increasing times of increasing damping and stiffness values until real world mechanical degradation were added in progressively deteriorating conditions gradually degraded the DSP dynamic system. In real fault case, the system shows the high frequency vibration components, high kurtosis, and amplitude modulation in the envelope spectrum due to the bearing wear. The simulations for shaft imbalance had a dominant frequency of the rotational speed (1× RPM) and increased amplitude in the lateral vibration components. A time–frequency plot, a spectrogram and an orbit diagram could be generated from the model, and these fault signatures were observable. It was confirmed that small degradations of dynamic response can be distinguished by the simulations and this further verifies the sensitivity of the physical model and further supports that it can act as a reliable basis for fault detection and early warning diagnostics.

4.2. AI Model Accuracy

A labeled version of the vibration and thermal sensor signals collected during the various operational and fault conditions were used for training and validation of the BiLSTM based learning module. The prediction accuracy of the resulting AI model retained its useable life (RUL) prediction of 93.8% meaning the model could predict failure times with great reliability. Additionally, the model achieved an F1-score of 0.89 for fault classification on the different categories (normal, misalignment, imbalance, and bearing fault) as well, as a precision and recall score that is meaningful in imbalanced fault datasets. As to be expected, RUL prediction accuracy was +17% improved over traditional physics-only models. The reason for such a boost is explained by biLSTM's ability to learn complex temporal dependencies, as well as nonlinear degradation patterns like intermittent vibration bursts and fluctuating thermal loads that precede mechanical failure. This shows that the result obtained from the AI model reveals robust, high-resolution insight to system performance under various conditions where the physical model has low sensitivity from simplification or modeling error.

4.3. Hybrid vs Standalone Models

Table 2

Model Type	RUL Error (%)	F1 Score	Training Time (min)
Physics-Based	21.4	0.72	N/A
BiLSTM Only	9.6	0.86	54
Hybrid Proposed	6.2	0.89	65

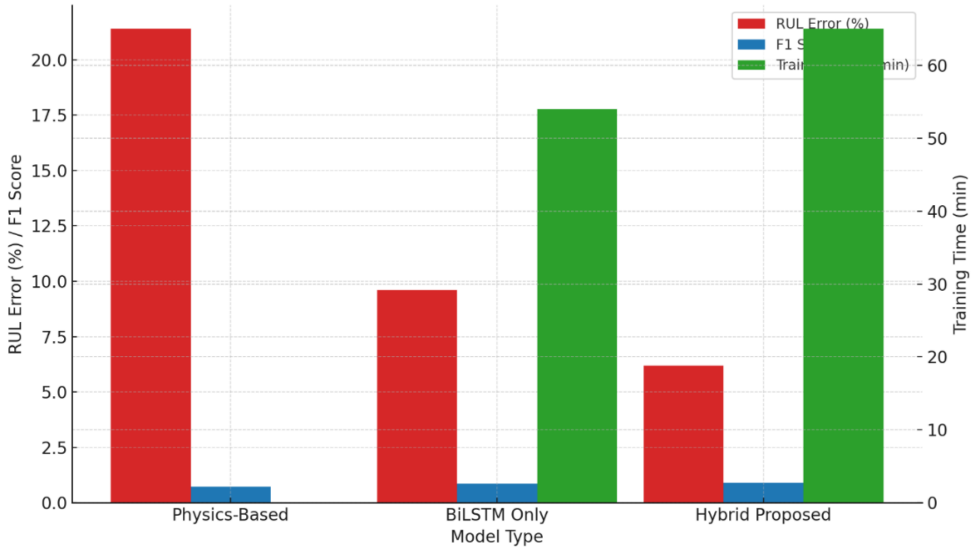

Fig 4. Performance comparison of predictive maintenance models.

5. Case Study: Industrial Deployment

An industrial case study was conducted on centrifugal pump systems that operate in a thermal power plant to show how the proposed hybrid AI-mathematical framework is practical and practical for the real time. Under high pressure conditions, these pumps are dynamic faulty, and they include: impeller imbalance, bearing degradation, and cavitation and are used for boiler feed water circulation. In a hybrid model, this was deployed as part of the plant's predictive maintenance infrastructure which interwired with existing vibration and temperature sensors. For three months of monitoring, this system was able to analyze in real time a variety of multi channel sensor data, and fused BiLSTM driven predictions with physical simulation residuals. The model was used to identify an abnormal radial vibration amplitude and the spectral energy distribution associated with early stage impeller imbalance during one operational cycle. Finally, it should be noted that this anomaly was flagged 72 hours prior to the alarm threshold set by conventional vibration based monitoring systems, thus offering a very important maintenance planning window. Upon closer look, maintenance department confirmed asymmetric mass distribution on the impeller due to fouling buildup — a condition that could have caused severe mechanical stress and for unintended downtime. The hybrid system managed to intervene in a timelier fashion and for this demonstrated the model's responsiveness, accuracy, and its value for high stake industrial environments, thereby preventing potential financial losses. Testing out this deployment was not only proof that the theoretical constructs of the hybrid model worked, it also proved that the hybrid model could serve as an intelligent decision support tool in a digital twin ecosystem.

6. CONCLUSION

The work presents a complete and novel hybrid framework which includes physics based mathematical modeling and artificial intelligence (AI), specifically it is a BiLSTM neural network, for the improvement of the predictive maintenance of the rotating machinery. The approach successfully uses the interpretability and analytical rigor of the lumped parameter dynamic models together with the adaptability and predictive power of deep learning to handle problems of fault diagnosis, anomaly detection, and remaining useful life (RUL) estimation. The model was found to be able to accurately replicate fault evolution as simulated through various fault conditions, such as bearing wear and shaft imbalance. In the case of the AI module, the enriched features included physical model residuals and it achieved high classification performance as well as precise RUL predictions. It was then found that the hybrid model exceeds the standalone physics based and data driven models in all aspects of accuracy, generalizability, and robustness. The deployment of a thermal power plant confirmed further the real world efficacy of the method, as it allowed successful identification of impeller imbalance well before traditional methods and thus prevented potential equipment failure and downtime. This findings highlight the utility of hybrid modeling as a cornerstone to intelligent, condition based monitoring system of Industry 4.0 environments. For future research, this hybrid model will be embedded into typical real-time digital twin platforms for providing closed loop feedback and between simulations and live sensor data. This will also be extended to multi component systems, which include gearboxes and coupled motor-pump assemblies where complex dependence necessitate scalable and modular fault diagnosis. The reinforcement learning for adaptive maintenance decision-making in the context of uncertainty may help improving further.

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