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Dynamics of Rotating Machinery: Modeling, Fault Diagnosis, and Control Strategies

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***Abstract*—The rotating machinery forms the foundation of modern industrial systems, and major industries, including power generation, petrochemicals, aviation and aerospace, are greatly reliant on rotating machinery. Due to continuous service under high mechanical, thermal, and aerodynamic loads, such machines are very vulnerable to failures such as imbalance, misalignment, wear of the bearings, cracks along the shaft, lubrication damage and defective gears. The complicated rotor-stator interactions in the form of fluid-structure interactions, thermal stress interaction, as well as vibration phenomena are necessary in understanding the reliability, operational safety, and cost-effective maintenance. In this paper, the modeling, fault diagnosis and control methods employed in rotating machinery have been surveyed in detail. The advanced analytical and numerical modeling methodology, e.g., the finite element method, transfer matrix method, and modal analysis are discussed to model the dynamic behavior in various working conditions. Furthermore, the work delves into the most recent advancements in defect diagnostic approaches that include signal processing, vibration analysis, and artificial intelligence. It highlights the growing trend of information-based predictive maintenance. Also, recent control schemes, such as passive and active vibration control schemes, smart and fault-tolerant and resilient control structures are discussed in terms of their contribution to stability in the system and failure prevention.**

Keywords—Rotating Machinery, Fault Diagnosis, Condition-Based Maintenance, Rotor Dynamics, Vibration Analysis.

I. INTRODUCTION

Modern industrial systems revolve around rotating machinery, which includes equipment whose main function relies on rotational movement, which includes steam turbines, gas turbines, compressors, pumps, and aircraft engines. These machines are used in a variety of industries that prioritize dependability, continuous operation, and safety, including power generation, petrochemicals, metallurgy, aviation, and aerospace. Rotating machinery structurally involves a rotor-stator assembly which is subjected to constant stress in the long-term operation [1][2]. Consequently, these systems are likely to fail due to imbalance, misalignment, bending of the shaft, fatigue cracks, lubrication erosion, wear of bearings, and gear flaws that can impair the integrity of the operation, efficiency, and can potentially result in disastrous industrial accidents.

The interactions between complex physics, fluid structure interactions are significant, aerodynamic load, thermal effects, and are all strongly influencing the dynamics of rotating machinery. The interactions between fluid that are characteristic of turbine, compressors, and pumps, make the fluids unstable through instability expressed in the form of fluid induced vibrations, rotor whirl, and flow induced noise [3]. Such problems have also enabled the timeless advancements in studies in rotor dynamics [4], especially with the current machines being directed in their orientation to be faster, lighter, and efficient. This is also enhanced by the fact that the greater knowledge regarding the rotor dynamic behavior under stochastic wind loads and structural flexibility is needed owing to increased use of a renewable energy system, such as wind turbines [5]. Against the background of such complexities, fault diagnosis of rotating machinery (FDRM) nowadays is an extremely popular research and engineering area [6]. An efficient FDRM system comprise of four basic tasks, i.e. fault detection, fault isolation, severity assessment, fault prediction [7]. They relate with the accurate identification of the abnormal conditions, the identification of their emergent failures, the identification of its severity and prediction of the degradation progression to rule out the sudden failure.

Various sophisticated vibration analysis, signal processing techniques, data-driven learning algorithms, and digital twin tools have led to the progressive enhancement of the diagnostic accuracy and the possibility of transitioning to predictive maintenance [8]. Another dimension of relevance is the control measures of the vibration suppression as well as stability enhancement. Active balancing and active vibration control have proven to be effective measures to control forces that are caused by imbalance. Nevertheless, traditional methods tend to tie imbalance estimation and control measures, without an explicit model to maximize their interplay [9]. Ideally, the control inputs can not only cause reduction in vibration but also enable the accurate evaluation of imbalance and consequently enhance the machine performance, life cycle of component fatigue and the general operation costs.

A. *Structure of the Paper*

The paper is structured as follows: Section II presents the rotating machinery and its dynamics. Section III discusses advanced modeling and analysis techniques. Section IV focuses on fault diagnosis & control strategies in rotating machinery. Section V surveys recent literature that combines theoretical modeling, sensor-based monitoring, and AI-driven diagnostics Finally, Section VI concludes the paper and outlines promising future research directions.

II. ROTATING MACHINERY AND IT'S DYNAMICS

A rotating system is an essential component of mechanical systems for motion and has numerous uses in fields including energy, aeronautics, and astronautics. A number of these uses are vital in both civilian and military settings, and they include things like electric generators, gas turbines, and aero-engines [10]. Understanding the many dynamical phenomena that arise during machine operations and being able to analyze and forecast the vibration responses of complex rotor systems are two of the biggest issues faced by researchers and engineers working in rotating machinery [11]. To guarantee the safe and smooth operation of such rotating systems, the engineering community is constantly focusing on hotspots like robust dynamic characteristics analysis, design optimization, and effective maintenance.

A. Types of Rotating Machinery

Following are the Types of Rotating Machinery:

1) Compressors

Heating and cooling systems have made use of rotary compressors, a kind of rotatory engine. A fluid can have its pressure increased by using a compressor, which is a mechanical device. Two main types of compressors are positive displacement compressors and dynamic compressors. In the former, the fluid gains momentum through the transformation of kinetic energy into pressure energy by means of rotating blades or impellers. One of the primary uses of a compressor is the rolling piston [12]. A roller within a cylinder is attached to the driveshaft's eccentric cam to form the rolling piston mechanism. The suction chamber and the compression chamber are separated by the roller's contact with the inner cylinder wall, as shown in Figure 1.

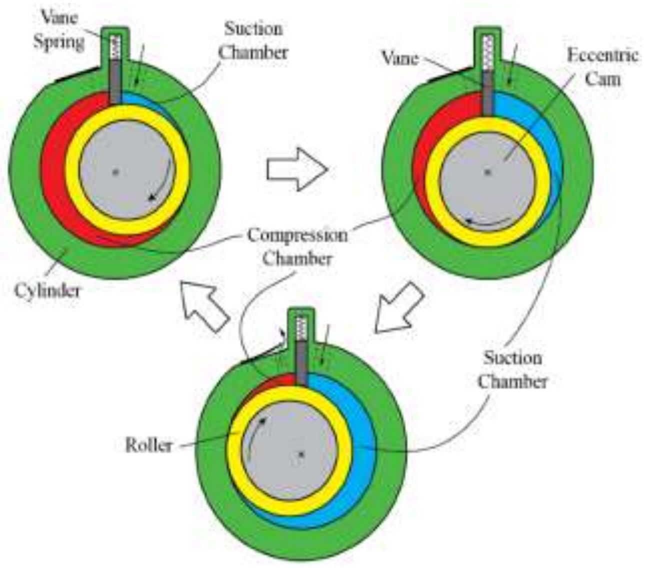

Fig. 1. Rolling Piston Compressor Working

2) Gas Turbines

A gas turbine (GT) is among the most expensive pieces of machinery used in aviation and stationary mechanical applications; it finds extensive use in the oil, gas, petrochemical, and power generation sectors, where its accessibility and dependability are deemed paramount. A gas turbine is a type of thermal machine that operates best when subjected to extreme heat, pressure, and stress. All sorts of mechanical, electrical, and hydraulic systems are integrated into one complicated piece of machinery [13]. The low-pressure and high-pressure compressor cooling air is retrieved from the middle and last stages. Figure 2 shows what is known as a three-shaft gas turbine.

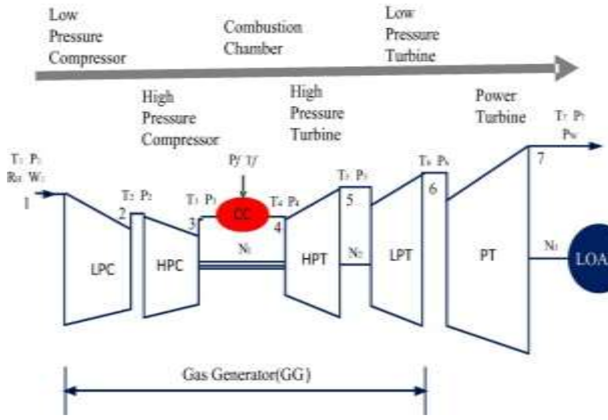

Fig. 2. Three-Shaft Gas Turbine

3) Steam Turbines

The most adaptable and long-standing prime mover in the history of electricity generation has been steaming turbines. Steam turbines are mechanical devices that transform pressurized steam into usable mechanical work by removing thermal energy from the steam [14][15]. Its superior thermal efficiency and power-to-weight ratio have led to its near-total replacement of the reciprocating piston steam engine. Plus, there's no need for a linkage system to transform reciprocating action into rotational motion because the turbine itself produces rotating motion. According to Figure 3.

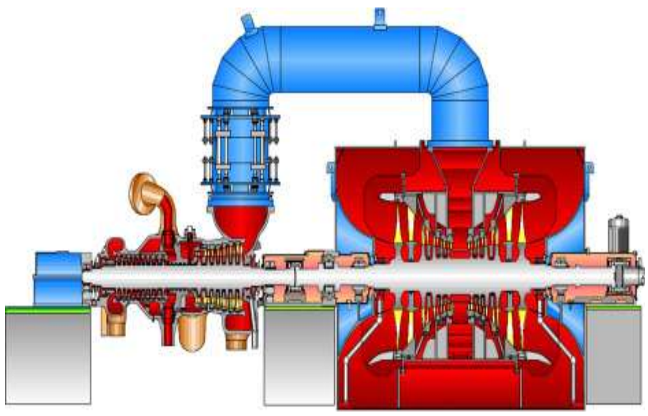

Fig. 3. Steam Turbine Structure

B. Governing Equations

The driving equations of motion for a full rotor-bearing-support system are found by putting together the equations of motion for each part. This is usually done using the Lagrangian method.

The equation of motion can be expressed as Equation (1):

$$\frac{d}{dt}\left(\frac{dL}{dq}\right) - \frac{dL}{dq} + \frac{dR}{dq} = 0 \quad (1)$$

the Lagrangian L is defined as the dispersion of the kinetic energy T and the potential energy U, as demonstrated in Equation (2).

$$L = T - U \quad (2)$$

The energy dissipation in the system as a result of internal friction and damping is represented by the dissipation function, R.

q is the generalized displacement vector.

The kinetic and potential energy components can be easily calculated by applying either the Bernoulli-Euler or the Timoshenko beam theory [16]. Both the angular and rotational inertial effects of the disc and shaft contribute to the total kinetic energy. In order to obtain a vector differential equation that describes the system's motion, the Lagrange equation is enlarged using the energy formula. see this in Equation (3).

$$M\ddot{q} + C\dot{q} + G\dot{q} + Kq = Fex \tag{3}$$

C. Vibrational Analysis

The analysis explains the response of various rotor parts with asymmetrical imbalance, which is essential in enhancing the process of balancing and minimal vibrations. Balancing of a turbo generator is a process that is done with carefulness in order to provide stability in the operation and efficiency of the machinery. In the process of this, the vibrations of the support are often measured, as well as the relative vibrations of the rotor at different distances to the support [17]. These data are supplemented by the data of rotor vibration in the plane of the support that makes it possible to perform precise balancing and draw accurate pictures of the elastic lines of the rotor before and after balancing.

The study of how shafts behave when vibrated is known as rotor dynamics. Both torsional and lateral vibrations are encompassed in this. An essential consideration when dealing with lateral vibrations is the critical speed. At this speed, the rotational frequency aligns with one of the rotor's inherent bending frequencies. It is recommended that crucial speeds be kept out of pumps' functioning ranges. Particularly in cases of poor rotor damping, this becomes crucial [18]. Thoroughly studying the rotor's vibrational behaviour is crucial for ensuring the operational durability of high-head pumps. It has long been believed that bearings are the sole components connecting the rotor and casing when analyzing the rotor dynamics. Solving the stability challenge of rotor dynamics has been a recent focus. As shown in the Figure 4.

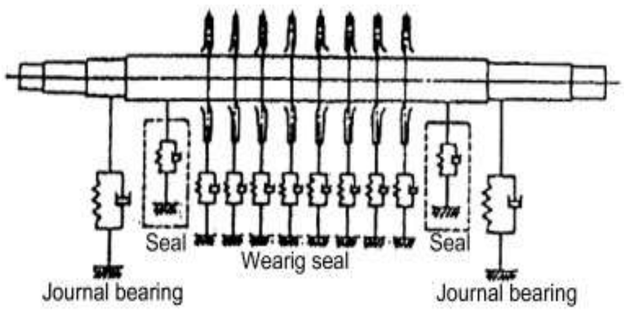

Fig. 4. Rotor Dynamics for Vibrational Behavior

III. Modeling Techniques for Rotating Machinery

A variation in the amplitude of the vibration signal is a basic harmonic motion that may be used to monitor and display all problems in rotating machinery. In order to keep this rotating machinery in good working order, it is necessary to monitor them periodically. In order to keep an eye on the rotating machinery and make it last longer, all of the maintenance techniques play a significant part [19]. Several factors contribute to these rotating machinery faults, including cyclic loading, the indisputable tolerance limits provided when fitting the rolling bearing elements between the shafts of the machinery, and human error on the part of maintenance workers. Techniques are as follows:

A. Finite Element Method

One way to get close to the answer to an engineering problem is to use the finite element method (FEM), a numerical analysis tool. Finding the governing equations by piecewise approximation is the goal of a finite element model [20]. A solution region can be analytically modelled or approximated by replacing it with an assembly of discrete components (discretization), which is the underlying premise of the FEM. These components can stand in for extremely complicated geometries because to their malleability.

B. Modal Analysis

A lot of mechanical and structural breakdowns in buildings and other public buildings started with vibrations. If wants to know what causes vibrations in structures, it's necessary to extract their dynamic properties. Dynamic properties of a system, such as mode shapes, damping ratios, and natural frequencies, can be discovered by modal analysis [21]. A few examples of modal analysis's practical uses include structural health monitoring, damage detection, and designing structures and machines to withstand dynamic loading situations. Three methods are utilized in modal analysis: operational modal analysis (OMA), experimental modal analysis (EMA), and a relatively new method known as impact synchronous modal analysis (ISMA). While operational maintenance and inspection take place in a controlled setting, EMA is carried out in a simulated one.

1) Transfer Matrix Method

Vibrations in various structures, including beams, sheets, and shells, can be studied analytically using the transfer matrix approach. The transfer matrix can be found by computing the inverse of "zero matrices" using this technology. Computer programming becomes more computationally expensive when the inverse matrix has to be calculated. In order to get the inverse matrix's order down from 2n to n, a technique is offered [21]. To do this, swap the rows of the state vector and the constant coefficients vector; as a result, the transfer matrix is transformed into a block diagonal matrix, offering improved efficiency for computing the inverse matrix. According to Figure 5.

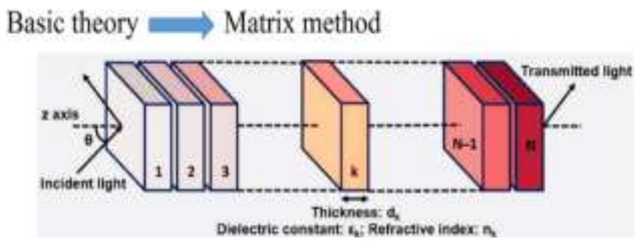

Fig. 5. Summary of Transfer Matrix Method

IV. Fault Diagnosis & Control Strategies in Rotating Machinery

The two main processes of defect detection and feature extraction make up FDRM, which is fundamentally a pattern recognition problem. These steps can be addressed using signal processing and AI technology. There have been many industrial uses for signal processing technology for quite some time; this is a significant area of study in FDRM. The four main steps of fault diagnosis of rotating machinery (FDRM) are as follows: identifying the machines or critical components that may be experiencing an abnormal condition, locating the beginning of a failure and its source, gauging the severity of the failure, and finally, forecasting the trend of the fault's progression [22]. To prevent catastrophic system failures and outages, it is critical to employ efficient FDRM that can cut down on offline time, predict residual life, lessen productivity loss, and avert abnormal event development.

A. Common Fault Types

A condition monitoring scheme's speed of detection is its most essential feature. Figure below shows the typical progression of several types of faults from the incipient to the extremely advanced stage [23]. In this study, early failure identification is the primary focus. When looking for signs of impending rotor failure, only partially broken bars are evaluated, whereas completely broken bars indicate a developed issue. The reason behind this is that when a bar is fully cracked, the crack quickly spreads to neighboring bars, which in turn harms the stator winding and makes it impossible to fix. As shown in Figure 6.

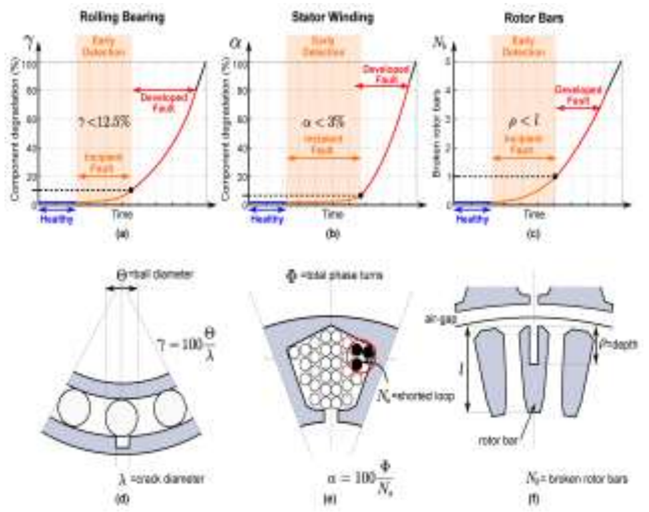

Fig. 6. Degradation stages of induction motor components: (a) rolling bearing degradation, (b) stator winding degradation, (c) rotor bar degradation, (d) rolling bearing schematic, (e) stator winding schematic, and (f) rotor bars schematic.

B. Machine Learning and AI in Fault Detection

The ability to detect induction motor faults before they cause the motor to completely shut down is crucial for various sectors. Great promise exists for problem detection that makes use of condition monitoring and machine learning [24]. Error detection is one area where machine learning can be effectively utilized. It is crucial to handle induction motor defects promptly to save losses. When applied to the field of fault identification, machine learning algorithms offer a dependable and efficient method for preventative maintenance.

The primary emphasis is on predicting and preventing failures through durability testing of Permanent Magnet Synchronous Motors for use in automobiles, with the help of Autoencoders (AEs) [25]. This artificial intelligence (AI) defect detection method uses acceleration data from electric motors that have been tested in demanding environments with large fluctuations in speed and torque. This method is an extension of fault detection under steady-state conditions. Upon the examination of Neural Networks, variational autoencoders (VAEs), convolutional neural networks (CNNs), and long short-term memory (LSTM) networks, the performance of six AI models are compared: AE, VAE, 1D CNN AE, 1D CNN VAE, LSTM AE and LSTM VAE. The 1D CNN AE was the best network in fault detection as it possessed high accuracy, stability and computational efficiency.

C. Control Strategies of Rotating Machinery

Rotating machinery control measures are important in ensuring operational stability, wear and tear reduction and guaranteeing safety and efficiency in the numerous industrial practices. Nonlinear and dynamic nature of rotating systems, particularly during the variation of loads, speeds and faults, requires the deployment of advanced control tools. Through the years, the discipline has changed its conventional methods of passivity to effective active and smart control methods.

1) Passive and Active Control Methods

There are two major directions of studying the flow behavior, active flow control and passive flow control. Through the control and regulation of the fluid flow process, the flow in various areas can be realized efficiently and controlled. This paper discuss the concepts and use of active flow control and passive flow control, and study how these control methods can be used in real-life situations [26]. The fundamental concept of active flow control is that the direction, speed and stability of fluid flow can be controlled through variations in fluid velocity, pressure, and temperature. Active flow control is aimed at attaining the accurate control of the fluid flow behavior in order to satisfy certain requirements. As Shown in Figure 7.

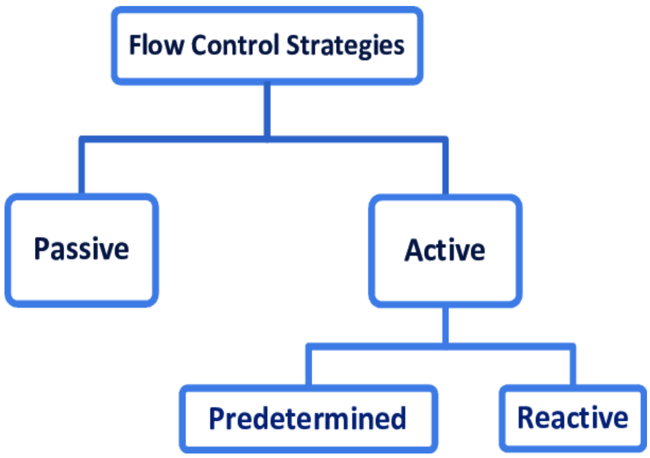

Fig. 7. Flow Control Strategies

2) Intelligent and Data-Driven Control

Rational modeling and optimization algorithms based on data in industrial processes. The integration of advanced data analytics, machine learning, and artificial intelligence has become central as Industry 4.0 employs advanced technologies to open up new opportunities in their efficiency, sustainability, and quality assurance [27]. The papers in this Special Issue also show innovative research in the area of work-sampling data analysis, data-driven process choreography discovery, the intelligent ship scheduling of maritime rescues, the process variability monitoring, the hybrid optimization algorithms of economic emission dispatches, and the intelligent controlled oscillations in smart structures.

3) Fault-Tolerant and Resilient Control

In FTRCs, there exists a FDI module, re-configurable mechanism, and re-configurable controller. The FDI unit's main job is to compare its internal output with actual plant values. Any deviation of a specified value thus be defined as a fault, whereas no error between the estimated and real value is considered fault free [6]. However, when there is error detection, isolation of the faulty component occurs, followed by estimation of the possible value. This is known as the reconfigured control law. FTRC has been used to handle issues surrounding: 1) sensor faults and 2) actuator faults. The FTRC can be seen in Figure 8.

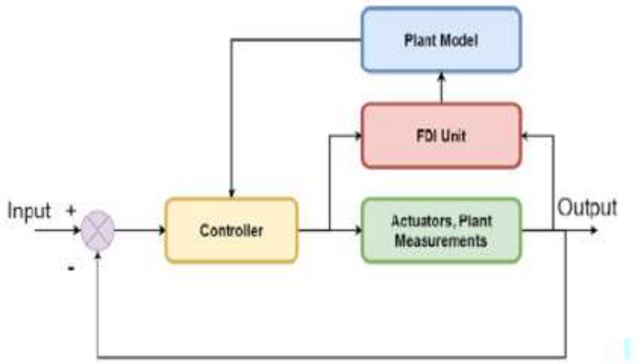

Fig. 8. Fault-Tolerant and Resilient Control

V. Literature Review

Modern developments in condition-based maintenance and fault diagnostic methods for rotating machinery are highlighted in the literature study. Several innovative approaches are explored, such as using shaft voltage for gear fault detection without additional sensors, and deep learning models.

Chen et al. (2025) investigates both the theoretic and practicable aspects of the application of shaft voltage for gear fault detection in induction motor drivetrain. To begin with, the shaft voltage signal is generated analytically taking into account common-mode and differential-mode sources, eccentricity and unbalance, rotor slotting effect, and fault excitation. The fault modulation signatures of the signal are therefore uncovered, and confirmed by experiments subsequently [28].

Bi et al. (2025) rolling bearings are important parts of rotating equipment that directly influence the service life and equipment reliability. The degradation of bearing is a complex issue that can be forecasted successfully by applying the best possible strategies to assure the safety and stability of the system. But, the evolution of degradation process of bearings is complex multi-stage, with local non-stationarities and irregular fluctuations, which makes it difficult to model them because of the heterogeneity of global and local dynamics. To address this issue, proposed a Multi-Scale Mamba-Transformer Model (MSMT) and employed it for bearing degradation prediction [29].

Li et al. (2024) Digital Twin (DT) can help comprehensively monitor and predict the remaining useful life (RUL) of rolling bearings by generating a high-fidelity model of the physical object. Due to the varying working conditions faced in real industrial applications, the existing DT model of rolling bearings urgently needs continuous dynamic evolution ability and resource-efficient updating method. It is proposed that an end-edge-cloud based DT architecture for rolling bearings, which includes two stages: DT construction and DT update. For adapting to dynamic changes of physical entities under various working conditions, a Condition-Adaptive Dynamic Continual Learning Digital Twin Model (CADCL-DTM) is designed, which applies different penalties to continual learning tasks in both intra-condition and inter condition scenarios [30].

Mekhalfia et al. (2024) is to examine the influence of electromagnets on stationary blades and thus build up a theoretical basis. To account for the uncertainties, the Timoshenko beam theory is used to analyze vibration characteristics such as frequency and amplitude. In this case, the theoretical analysis is referred to as being complemented by numerical modeling through the finite-element method, as well as by experimental measurements using laser Doppler vibrometer (LDV). Accordingly, the findings have shown that electromagnetic excitation can indeed be used effectively to produce controlled vibrations in static blades [31].

Yang et al. (2023) The customizable bearing dynamics and lack of friction are only two of the many benefits that have led to the widespread usage of active magnetic bearings (AMBs) in rotating machinery. When it comes to optimizing controls, monitoring conditions, and diagnosing faults, calibration of AMB model parameters is crucial. There are issues with the applicability and accuracy of traditional calibration methods when it comes to AMB. These approaches mostly rely on sampling and statistical methodologies [32].

Kurvinen et al. (2023) Product simulations grounded in physics are increasingly interacting with their real-world counterparts. One important development is the ability for dynamic simulation to work in real time, which allows simulation models to coexist with real-time machinery. It is because of this capability and state observer techniques like Kalman filtering that the real world and simulation are now in sync with each other. Virtual sensing, which involves estimating unmeasured quantities, or improving the quality of measured signals are two applications of state estimator approaches. Many potential applications exist for synchronized models; however, from a commercial standpoint, the most advantageous and practical use cases are now being defined by value generation and business model development [33].

Jiang et al. (2022) Rotating machinery relies on bearings. Their efficiency has a knock-on effect on the machine's overall health. Sudden stops of spinning machinery due to bearing failure can cause accidents and financial losses. An established approach to preventing bearing failure and enhancing machinery dependability and safety is the prediction of bearing remaining useful life (RUL). Various bearing life prediction characteristics were computed, such as the time domain features of the vibration signal, the energy characteristics obtained by Fourier transform, and the Shannon entropy of the vibration signal [34].

Shen et al. (2021) An approachable tool is introduced by Adaptive and Non-Recursive Mode Functions (IMF). While excessive background noise has a significant impact on the model number setup, which could result in data loss or an over-decomposition issue. In this research, a novel method called Generalized Variational Mode Decomposition (GVMD) is suggested as an upgraded version of VMD. It can adaptively extract fault characteristic information from vibration signals. It is then possible to use the retrieved parameters to build the Normalized Feature Vector (NFV). Using the aforementioned techniques as a foundation, present an innovative intelligent method for quantitatively diagnosing gear faults in dynamic work environments by integrating GVMD with NFV extraction [35].

Table I, the summary table systematically organizes eight key research studies based on their publication year, main findings, methodologies, addressed challenges, and identified limitations.

TABLE I. SUMMARY OF LITERATURE ON MODERN FAULT DIAGNOSIS AND DIGITAL-TWIN-BASED MAINTENANCE OF ROTATING MACHINERY

Author (Year)	Key Findings	Methods / Approach	Challenges Addressed	Limitations / Future Gaps
Chen et al. (2025)	Demonstrated that shaft voltage can act as a built-in indicator for drivetrain and gear faults in induction motors.	Analytical modeling of shaft-voltage signals considering CM/DM sources, eccentricity, unbalance, rotor slotting, and modulation effects; Experimental validation.	Avoids extra sensors by using motor-inherent signals; Reveals fault modulation signatures.	Needs validation under diverse industrial loads and variable-speed conditions; Sensitivity under high noise environments remains unclear.
Bi et al. (2025)	Proposed MSMT model for accurate multi-stage rolling-bearing degradation prediction with improved trend forecasting.	Multi-Scale Mamba-Transformer Model capturing global–local dependencies and non-stationary degradation signals.	Addresses heterogeneity in degradation stages and irregular fluctuations.	Model complexity is high; Real-time deployment and generalization to different bearing types need investigation.
Li et al. (2024)	Developed a condition-adaptive DT for rolling bearings with continual evolution across operating conditions.	End-edge-cloud DT architecture; CADCL-DTM with dynamic continual learning penalties for intra- and inter-condition updates.	Handles varying working conditions and need for continuous model updates.	Requires high computational resources; Scalability for large industrial fleets and long-term drift remains a challenge.
Mekhalfia et al. (2024)	Verified that electromagnetic excitation effectively generates controlled vibrations in static blades.	Timoshenko beam theory; FEM simulation; Laser Doppler Vibrometer experiments.	Establishes theoretical basis for controlled vibration of blades and validates excitation mechanisms.	Results limited to controlled lab settings; Complex blade shapes and operational loads not fully model
Yang et al. (2023)	Highlighted the importance of precise AMB parameter calibration for optimized control and fault diagnosis.	Review and evaluation of traditional sampling/statistical calibration techniques for AMBs.	Need for accurate and applicable calibration under real industrial conditions.	Traditional methods have limited accuracy; Advanced data-driven or adaptive calibration approaches needed.
Kurvinen et al. (2023)	Showed synchronization between real-time simulation models and operating machinery enables virtual sensing and enhanced system monitoring.	Real-time dynamic simulation + Kalman filtering for state estimation and signal enhancement.	Allows estimation of unmeasured states and improves signal quality; Supports digital twin-like monitoring.	Business adoption and value realization still emerging; Limited discussion on robustness under sensor faults.
Jiang et al. (2022)	Identified useful time-domain, frequency-domain, and entropy-based features for bearing RUL prediction.	Feature extraction: vibration time-domain metrics, FFT energy features, Shannon entropy.	Addresses need for reliable RUL prediction to prevent sudden failures.	Traditional features may not capture nonlinear degradation; Deep learning models needed for improved accuracy.
Shen et al. (2021)	Proposed GVMD for adaptive extraction of fault features under noisy and variable conditions; Enabled quantitative gear fault diagnosis.	Generalized Variational Mode Decomposition + Normalized Feature Vector construction.	Overcomes IMF number selection issues, noise sensitivity, and over/under decomposition in traditional methods.	GVMD computational cost may be high; Performance under extreme variable-speed conditions requires further testing.

VI. CONCLUSION AND FUTURE WORK

Rotating machine is highly dynamical machine that has presented a comprehensive review of machinery, focusing on their dynamic behavior, common fault types, and modern diagnostic and control strategies. The analysis included the principles of rotor dynamics and governing equations, the classification and working principles of the most important types of machinery, which are compressor, gas turbine, and steam turbine. Further modeling procedures such as the transfer matrix method, modal analysis, and FEM were mentioned to emphasize their usefulness in the simulation of complicated machinery. Moreover, the latest advances in fault diagnostics models based on signal processing, machine learning, and artificial intelligence were discussed, with a focus on the capacity to improve the condition monitoring, minimize the downtime, and enhance the system reliability. The combination of smart control solutions, such as fault-tolerant and data-driven approaches, is evidence of a great transition to predictive and adaptive maintenance models.

One of the priorities is the development of future analysis running in real-time and edge-deployable models that may be effective in the conditions of variable and noisy industrial processes. Better coordination of digital twin solutions with machine learning models particularly continual and federated learning would allow more adaptive and scalable predictive maintenance. There is also increasing need to have common framework that takes several sensor modalities like acoustic emission, shaft voltage and thermal data to ensure more robust fault detection. Studies of lightweight and understandable AI models will also play a critical role in enhancing trust and use in safety-critical applications. Lastly, by standardizing datasets and benchmarking techniques in various industries, it is possible to hasten the creation and validation of genericized fault diagnosis systems.

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