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A Review of Spur Gear Fault Diagnosis: Monitoring Methods, Predictive Models, and Industrial Challenges

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A B S T R A C T

Spur gears made from metal serve as central equipment in multiple mechanical configurations. They experience various defects like fatigue cracks, abrasion, and adhesion wear, pitting and scuffing. This review delivers a detailed analysis and performance review of research material from recent studies regarding spur gear failure modes, together with monitoring techniques and predictive models. Where detailed analysis through real-world examinations is conducted, wind energy applications are combined with automotive and manufacturing sector work environments to evaluate diagnostic system performance in practice. In this paper, both benefits and drawbacks across time-domain, frequency-domain, and time-frequency domain techniques are analyzed. This includes Fast Fourier Transform, empirical mode decomposition, wavelet transform, and Hilbert-Huang transform, as well as contemporary developments in machine learning diagnostic systems. The research sector identifies three main missing elements: limited availability of fault-labeled data, difficulties in maintaining operational condition generalization, and real-time system implementation. Future work and industrial use of spur gear fault diagnosis solutions need guidance to develop robust interpretive fault detection systems at a large operational scale.

1. Introduction

Power transmission systems depend on spur gears as their fundamental yet most employed mechanical component for efficient motion transfer. Spur gears demonstrate a straight and parallel configuration, which makes them efficient for transmitting rotational motion between parallel shaft systems that are simple to manufacture. Industrial sectors employ these gears within their range of applications, which span from automotive gearboxes to machine tools, wind turbines, and aircraft engines, along with heavy-duty industrial equipment. These components gain significance through their ability to control precise forces and movements, while also benefiting from simple installation and predictable load distribution systems [1].

The uncomplicated design of spur gears does not protect against significant mechanical difficulties and tribological complications that appear in industrial use. Industrial gears operate under conditions of changing loads, fast rotational movements, and temperature changes, alongside inadequate lubricating fluids [2]. Two main groups of degradation processes affect these components: fatigue cracking and abrasive and adhesive wear, besides scuffing and micro-pitting, which finally lead to tooth breakage [3]. Failures in gear systems degrade their performance and cause maintenance expenses, together with unexpected breakdowns and complete system breakdowns [4].

Out of all failure mechanisms, fatigue ranks as the most vital one. The damage begins in the stress-ridden areas surrounding the tooth root fillet. Under the repeated process of loading and unloading, microcracks start establishing and expanding into the gear tooth profile [5]. The combination of material inhomogeneities and residual stresses causes root failures in case-hardened gears to develop inside a 200 μm area around the maximum radius of root curvature, according to data [6]. Surface-initiated fatigue develops beach mark patterns and transgranular fracture pathways while tribochemical oxidation and lubricant-induced stress increase its rate of progression [7].

The primary form of gear deterioration, known as wear, produces diverse manifestations according to both lubricant state and operating environmental conditions [8]. The combination of asperity welding and subsequent material detachment leads to adhesive wear. Insufficient lubrication film thickness leads to the formation of this wear type. Abrasive wear occurs when hard particles within lubricants or between contact surfaces cause severe material surface deformation along with scratch marks.

Lubricants under high-pressure conditions cannot prevent contact surface separation because scuffing happens as a severe surface failure [9]. Metal-to-metal contact occurs when lubricants fail to provide surface separation, which causes sudden frictional heating, surface melting, and material transfer [10]. Surface scuffing initiates when ploughing grooves form along sliding directions, thus damaging gear tooth structures, and increasing frequencies of gear meshing vibrations [11]. Case-hardened steel components develop scuffing when flash temperatures at the contact interface reach values under either low lubricant supply or conditions of high sliding speed [12].

System dynamics, together with vibration characteristics, undergo substantial changes because of defective evolution in gears. Vibrations emitted from meshing gears exhibit modulated signals when meshing stiffness varies temporally and as geometrical imperfections emerge because of defect development. When defects such as cracks and pits occur in localized areas, they produce periodic impulses in time-domain signals [13], while distributed wear generates broadband noise that deforms the frequency band [14] .Sophisticated signal processing methods that include wavelet transform and empirical mode decomposition (EMD) and synchro-squeezing provide robust performance in identifying such technical indicators across diverse operational scenarios [15].

Finite element modeling (FEM) has proven itself as a key simulation framework for studying gears under defective states. The analysis capabilities of FEM include both stress evaluation and deformation tracking under loading conditions, which help researchers model fatigue propagation and spalling, and stiffness reduction. By uniting the Velex and Maatar models with FEM, researchers gained a clear understanding of how defective stiffness impacts gear rotational patterns and torque performance [16]. The recent advance integrates predictive maintenance procedures and Remaining Useful Life (RUL) estimators by combining these simulations with machine learning techniques [17].

Research investigations typically focus on single defects or diagnoses using a single approach, without conducting inter-technique assessments. Currently, current literature reveals a significant gap in adequately linking diagnostic data to real-life examples and established theoretical frameworks, such as contact mechanics, tribology, and fracture mechanics. Engineers and researchers face challenges in selecting diagnostic tools that are suitable for their unique application domains.

The presence of variable-speed operation represents a significant difficulty in industrial systems that employ this operation method. The analysis of signals using diagnostic methods requires stationary conditions because these conditions do not match actual operational patterns. Signal characteristics become indiscernible during variable-speed operations because they change their positions. The implementation of tacholess order tracking and generalized phase demodulation allows diagnostic systems to function without speed sensor dependency [18].

Gear fault diagnosis now uses artificial intelligence systems as one of the modern diagnostic techniques that has emerged in this field. Research has shown that Deep learning models, especially Convolutional Neural Networks (CNNs), combined with hybrid CNN–GRU architectures, deliver promising outcomes in diagnosing and categorizing gear defects by directly processing vibration data [19, 20]. The integrated dynamical system learns important input attributes from original data, which operates effectively when working with unpredictable or non-stationary sensing signals. The use of AI-based systems encounters challenges related to accessing necessary data, adapting to various hardware configurations and systems, and interpreting predictive outcomes from these systems.

The industrial need exists to merge gear health monitoring systems with Prognostics and Health Management operations to implement predictive maintenance as a replacement for reactive schedules [21]. PHM (Prognostics and Health Management) frameworks succeed because they require precise fault detection, system degradation modeling, and Remaining Useful Life estimations that enable predictive maintenance scheduling [22]. Real-time implementation of these systems demands computing speed along with flexible sensor networks and learning systems, which process poorly collected data [23].

The need for a thorough examination of existing gear failure techniques becomes crucial, as it affects operational and financial stability, and diagnostic systems are becoming more intricate. Such an evaluation system must implement both a systematic analysis of defect varieties and fault detection methods with modeling procedures.

2. Theoretical Background and Key Concepts

To understand the failure mechanisms behind spur gears, a combination of knowledge about gear meshing principles, together with mechanical stress analysis and lubrication dynamics principles, is needed. The fundamental knowledge required to understand the origins and development of regular gear failures exists in this section.

3. Gear Meshing Theory and Dynamics

Spur gears operate based on the fundamental principle of involute tooth engagement, where torque and rotational motion are transmitted between parallel shafts through repeated meshing of gear teeth. During rotation, the contact point, as shown in Fig. 1, between two teeth shifts along the line of action, creating dynamic variations in load and stiffness [24].

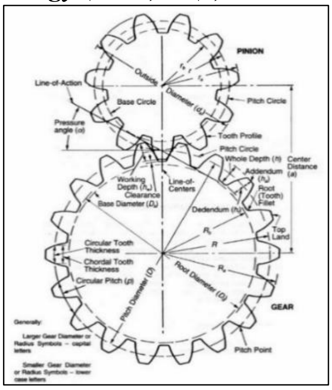

Fig. 1. Gear meshing showing contact point variation across the line of action [25]

4. Key Defect Types in Spur Gears

The operation of gears under industrial conditions produces multiple types of flaws that generate failure patterns:

The combination of repeated cycle loads produces fatigue, which initiates microcracks at high-stress points starting from the root fillet. The microcracks grow over time until they break the tooth into two parts.

Gears experience two types of wear, which start at inadequate lubrication sites as adhesive wear and emerge from surface scratching due to abrasive wear [26]. When wear occurs on gear surfaces, it changes geometry, causing loss of transmission accuracy and increased vibration [27].

Pitting forms due to surface fatigue, creating small pits at the gear teeth contact zone, which is induced by repeated Hertzian stresses [28]. The forces spread across the gears become impaired while the wear of gear components accelerates [27].

Surface failure, known as scuffing, emerges when lubricant films collapse, thus causing direct metal contact and resulting in surface melting and material transfer [29]. The occurrence of scuffing requires considerable pressure along with high-speed operation when loads are suddenly changed [30].

5. Time-Varying Meshing Stiffness (TVMS)

The different meshing connections lead to occasional fluctuations within the system dynamics. Under dynamic loads, the Time-Varying Meshing Stiffness (TVMS) controls the gear's response behavior [31]. When tooth engagement alters during rotation, the effective meshing stiffness changes, which modifies both vibration signatures and load transmission behavior. The modification of effective stiffness between meshing gear teeth, which occurs over time, is known as TVMS. TVMS depends on the number of teeth engaged in contact, as well as gear profile structure, material elasticity, and operating torque. An accurate model of TVMS is essential for proper gear vibration analysis together with fault diagnosis procedures, as shown in Fig. 2. TDVMS controls how systems transform under different loading conditions along with gear defects [32].

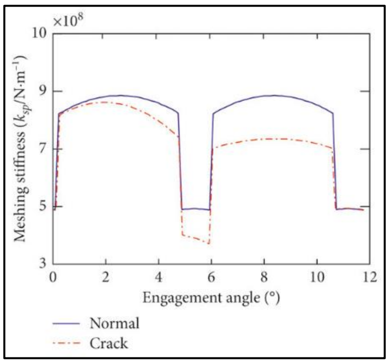

Fig. 2. TVMS variations during rotation – stiffness rises and falls with each tooth pair engagement [33]

VMS is also used in finite element models and simulation environments to replicate realistic operational behavior under defective or degraded conditions [34].

6. Hertzian Contact Stress and Lubrication Theory

Hertzian stress relates to the stress pattern that develops across the contacting curved surfaces of meshing gear teeth. The maximum contact stresses occur at the center spot, which spreads out radially into reduced levels, as shown in Fig. 3. These play an essential role in the formation of surface fatigue as well as pitting and microcracking [35].

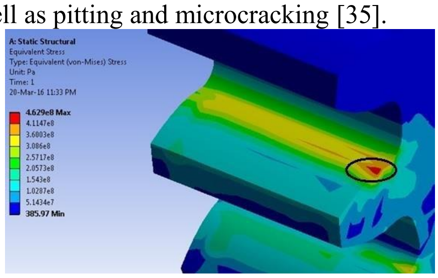

Fig. 3. Hertzian contact stress profile across gear facewidth [36]

Lubrication theory works to minimize the friction and wear that occur between contacting gear surfaces. A proper lubrication process develops a protective surface layer that prevents metal surfaces from touching each other while simultaneously carrying away heat. The absence of appropriate lubrication causes films to break down, leading to increased temperature, which in turn results in critical damage that includes scuffing and scoring. Lubrication regimes include:

Boundary lubrication develops at both the beginning and end of an operation because surfaces briefly come into contact. When combined, lubrication occurs, and the lubricant film becomes equivalent to the dimensions of surface irregularities [8]. The high-speed gear operation depends on electrohydrodynamic lubrication (EHL) because pressure-driven viscosity increases help preserve film integrity [37]. Surface fatigue and wear become highly probable when lubrication conditions fail to remain optimal, specifically when the system experiences either overloads or lubricant starvation events [8].

7. Classification of Gear Defects and Mechanisms

Various kinds of mechanical breakdowns afflict spur gears, which affect their operational characteristics and design lifetime duration, along with their dependability factors. Detailed comprehension of fatigue wear and pitting alongside scuffing and wear is crucial for diagnostic procedures and planned equipment maintenance [38].

7.1 Fatigue Mechanisms: Micro-Cracks and Spalling

Spur gears fail due to repetitive loading since this creates stress intensifications that affect the tooth root fillet region[39]. Cyclic loading at the tooth root fillet activates tiny micro-cracks that gradually become larger until the failure mode of spalling occurs when surface material breaks apart as fragments [40]. Spalling causes shallow pits on gears, which leads to decreased tooth strength together with increased noise production before causing total breakage of teeth [41, 42]. The endurance capacity of gears depends on their geometrical design, along with materials used, coatings applied, and naturally existing internal stresses [43, 44].

7.2 Wear Mechanisms: Adhesive, Abrasive, and Polishing

Wear constitutes a frequent failure mechanism in gears, which consists of the following components:

Adhesive wear occurs when inadequate lubrication causes surfaces to weld together, leading to subsequent splitting and material destruction. The process produces uneven surface patterns that heighten the amount of friction between surfaces [45, 26]. The hard particles or debris materials create abrasive wear damage by scratching and gouging surface material from teeth. The process produces deformed wheel gear geometry that limits transmission performance accuracy [45, 46]. Meshing operations undergo alterations in their contact dynamics because of prolonged changes in system width dimensions [47].

7.3 Pitting and Scuffing: Causes and Impacts

Surface fatigue occurs in pitting when repeated Hertzian contact stresses surpass material fatigue limits [48]. The initial appearance of pits manifests as small craters on the gear surface, which grow with time, thereby creating irregularities in contact points while increasing local tension forces [49, 50].

Surface failure through scuffing occurs as an abrupt, disastrous condition [51]. Under conditions of both high load and fast sliding, the lubricant film breaks down, allowing the presence of direct metal-to-metal contact between materials [44]. Gear surfaces experience local overheating and both tearing and smearing because of this condition [52]. The permanent damage to surfaces that results from scuffing behavior makes the gear fail quickly during operation. Tables (1) and (2) describe the different mechanisms of metallic gears' failures.

Table 1. Comparison between different defect mechanisms of metallic gears

Defect	Initiation Cause	Failure Mode
Fatigue	Cyclic stress, stress peaks	Crack growth, spalling
Adhesive Wear	Poor lubrication	Material welding/transfer
Abrasive Wear	Hard debris, contamination	Scratching, gouging
Polishing Wear	Fine particles, smooth load	Surface smoothening
Pitting	Contact fatigue stress	Subsurface crack & pit
Scuffing	Lubricant film collapse	Local melting, adhesion

Table 2. Comparison between different defect mechanisms of metallic gears (continued)

Defect	Surface Appearance	Effect on Performance
Fatigue	Flakes, pits, root cracks	Vibration, tooth failure
Adhesive Wear	Galled, torn areas	Increased friction, wear
Abrasive Wear	Grooves, linear scratches	Profile distortion, noise
Polishing Wear	Shiny, reflective finish	Altered tooth contact geometry
Pitting	Small craters or pits	Uneven loading, surface fatigue
Scuffing	Smeared, darkened areas	Sudden failure, overheating

8. Diagnostic Techniques: A Critical Comparison

The diagnosis of faults in spur gears requires effectiveness to ensure proper system reliability and efficiency. Researchers have established different. Diagnostic tools offer specific benefits but also confront certain obstacles. The analysis explores different diagnostic methods starting with time- and frequency-domain techniques, followed by time-frequency techniques, then artificial intelligence (AI) approaches [53].

8.1 Time- and Frequency-Domain Techniques

Traditional diagnostic procedures analyze vibration signals by generating results from time and frequency domain evaluations to identify gear faults [54].

FFT performs Fast Fourier Transform to transform time-based signals into frequency domains, which reveal gear fault-associated distinctive frequencies better [55]. The Fourier transform produces accurate results with steady signals yet has reduced effectiveness with unpredictable or rapid changes known as transient signals that typically occur within gear systems [56].

Time Synchronous Averaging (TSA) improves signal quality through the process of averaging signals that align with events such as gear meshing [57]. When the TSA is used in signal analysis, this method enables noise reduction that makes periodic gear fault components visible [58].

EMD analyzes complex signals by separating them into specific modes known as intrinsic mode functions (IMFs) to study data that presents non-linear and non-stationary characteristics [59].

8.2 Time-Frequency Techniques

The introduction of time-frequency techniques allows researchers to manage limitations found within traditional signal analysis methods.

This method performs multiple resolution signal decomposition through time-frequency components analysis using the Wavelet Transform [60]. Wavelet Transform effectively identifies short-time patterns together with brief disturbances that occur in gear signal data [61]. The selected wavelet function, together with its respective scale parameters, determines the effectiveness of the analysis [62].

The combination of Hilbert-Huang Transform (HHT) operates as an adaptive time-frequency representation through the integration of EMD with Hilbert Transform [63]. The technique is particularly suited for detecting nonlinear and non-stationary processes that exceed the capabilities of traditional methods. The mode mixing problems that come from EMD also exist in HHT and lead to degradation in its reliability levels [64].

9. Modeling and Simulation of Gear Defects

The behavior detection of spur gears during faulty operations relies fundamentally on modeling and simulation approaches [65]. The obtained tools enable predictions about failure initiation and escalation while they facilitate the creation of prognostic diagnostic systems. This writing section investigates different approaches, starting with Velex and Maatar's dynamic model, along with FEM, which supports real-time diagnostic system integration.

9.1 Velex and Maatar Model: Overview

The Velex and Maatar model functions as a dynamic lumped-parameter model, enabling simulations of gear transmission nonlinearity, including backlash effects and time-variant mesh stiffness, together with transmission errors and fault-induced excitations [66, 67]. The model exhibits gear system representation through masses and springs used to replicate mechanical processes.

The model works effectively for analyzing several phenomena.

1. Effects of profile modifications
2. Fault-induced variations in vibration response
3. Impact of meshing stiffness fluctuation

9.2 Limitations

In this section, the limitations of the Velex and Maatar models are summarized as follows.

1. The model makes assumptions about perfect geometric and material characteristics.
2. The model's resolution rate is not sufficient to detect surface pitting and crack initiation, along with other localized features.
3. This model cannot analyze physics-based problems, especially those involving rapid changes of stress fields or material examination on a microscopic level.
4. The Velex-Maatar system helps researchers understand the overall framework motion yet cannot replace the detailed capabilities of FEM modeling.

9.3 Finite Element Modeling (FEM): Simulation of Cracks, Wear, and Pitting

Finite Element Modeling serves as a simulation solution to precisely examine how stress and strains develop in gears while defects advance during loading situations [68, 69]. When gear geometry is divided into finite elements through FEM analysis, the system determines stress concentrations and material fatigue as well as crack initiation points.

Researchers have successfully implemented FEM approaches to their simulation efforts. The repetitive nature of cycle loads produces tooth root fatigue cracks [70]. The analysis incorporates Archard's wear law to study wear progression. The evolution mechanism can be modeled correctly through the combination of surface contact models together with fatigue damage mechanics [71]. The simulation models using advanced FEM now include thermal and tribological effects to replicate actual wear behavior during conditions of fluctuation [72]. The computations required for these simulations are both complex and require extensive input on material characteristics [73].

10. Integration with Diagnostic Systems

Data monitoring patterns now emphasize Digital Twin frameworks, which unite sensor readings from real-time operation with numerical modeling systems. Such integration enables the system to keep FEM simulations updated through live usage measurements of vibration or torque values [74]. Hybrid diagnostic systems incorporate FEM together with lumped models to provide quick response times alongside accurate results [75].

11. Comparison of Modeling Approaches

In this section, a comparison is summarized describing the different defect modelling types in metallic gears, as shown in Table 3.

Table 3. Comparison of Gear Defect Modeling Approaches

Model	Strengths	Limitations	Use Case
Velex-Maatar Model [76]	Fast simulation, functional for system-level dynamics	Low spatial resolution, simplified material assumptions	Dynamic vibration analysis
FEM [77]	High accuracy, detailed stress analysis	Computational cost, complex setup	Crack/wear /pitting simulation
Hybrid Models [78]	Balance between accuracy and speed	Integration complexity	Real-time diagnostics with moderate detail

12. Case Studies

This section examines multiple case studies from various industries for their practical gear fault detection methodologies. The analysis focuses on wind turbines and automotive transmissions, as well as manufacturing machinery, to study diagnostic method performance. The case studies detail the real-world installations together with the sensors that collect data, like vibration signals or SCADA data, and they explain the selected diagnostic methods as well as the achieved results. Each case analysis includes discussions about practical difficulties like data quality and noise performance, environmental effects, and integration problems. Tables 4 and 5 contain a comprehensive comparison of the examined case studies.

Table 4. Diagnostic of Gear Fault Case Studies

Case Study (Industry)	Sensors & Diagnostic Method
Wind Turbine Gearbox (Planetary stage fault) [79]	SCADA + high-frequency vibration; hybrid ML with

	anomaly detection and data fusion
Automotive Transmission (Test bench gearboxes) [80]	Vibration via five accelerometers; wavelet transforms + morphological filtering
Cement Plant Gearbox (Planetary gearbox in roller press) [81]	IoT accelerometers; time-domain trending + shock pulse spectral analysis

Table 5. Comparison of Gear Fault Detection Cases

Case Study	Key Outcomes	Challenges
Wind Turbine Gearbox (Planetary stage fault) [79]	Detected fault weeks earlier than conventional methods; pinpointed the planetary stage as the fault source	Non-stationary conditions, signal complexity, and the need for data fusion to distinguish actual faults from fluctuations
Automotive Transmission (Test bench gearboxes) [80]	Differentiated bearing vs. gear faults; suitable for automated quality control on production lines	Variable regimes in real-world conditions require clean labeled datasets; signal complexity from engine & drivetrain
Cement Plant Gearbox (Planetary gearbox in roller press) [81]	Detected early bearing failure, avoiding ~36 hours of downtime; confirmed by post-replacement vibration drop	Harsh environment (dust, vibration), large data handling, integration of edge + cloud diagnostics, human trust in the system

12.1 Wind Turbines (Gearbox Monitoring in Wind Energy)

The detection of faults in wind turbines becomes difficult since the wind turbine gearboxes experience changing speed conditions and load patterns [82]. Research presented that a multi-MW wind turbine's planetary gearbox suffered a developing fault in its planetary stage according to the standard analysis methods [83]. Among many planetary components, standard single-source data analysis proves inadequate for planetary gearset fault detection in this situation.

The diagnostic methodology of the study combined SCADA sensors and high-frequency vibration sensors, using a hybrid machine learning infrastructure [84, 85]. The SCADA anomaly detection system based on autoencoders operated in tandem with vibration models to confirm developing equipment flaws [86]. The combined system uses multiple detection and identification techniques, starting with SCADA performance anomaly monitoring, followed by vibration signal diagnostic analysis [87].

The impending planetary stage failure became detectable in time for maintenance scheduling, thus stopping a potential catastrophic breakdown. The critical need to identify failing components in complicated machines can be resolved through sensor channel analysis of anomaly metrics [88]. The analysis process that combined operational data of lower frequencies with vibration data enabled the detection of subtle operational signatures, including minor temperature drifts and vibration energy variations [89]. A combined ML solution proves capable of circumventing the deficiencies that appear when using a diagnostic technique separately.

The wind turbine case reveals multiple operational obstacles. The planetary gearbox fault signatures became indiscernible due to the intricate vibration path involving turbine control systems. Industrial gear fault modeling displays success in this case study through data fusion of SCADA and vibration measurement and machine learning methods, which delivered an early warning that went beyond traditional monitoring approaches alone [90].

12.2 Automotive Transmissions (Vehicle Gearbox Fault Diagnosis)

The automotive transmission sector demonstrates another diagnostic area with its fast-speed operations, shifting, and acceleration transient events. A major challenge for implementing the technologies in automotive systems arises from the wide range of operational conditions. Active vehicle gearboxes experience multiple gear shifts along with changing torque levels, as well as engine-produced vibrations that create masking effects on fault detection indicators.

Research analyzed a group of automotive gearboxes with ten healthy units combined with three faulty units containing bearing defects, along with a cracked gear tooth [91]. A series of accelerometers was installed on the gearbox housing for signal acquisition while the machine operated under different gear linkages and operating speeds [92]. The diagnostic approach implemented vibration signal processing alongside pattern recognition as its significant features. The five mounted accelerometers covered complete gearbox components by detecting vibrations that originated from shafts, both gears, and bearings. The analysis measured energy characteristics (signal entropy and wavelet packet energy within targeted frequency ranges) for testing purposes, which enabled researchers to assess gearbox condition changes. The investigators created a signal processing method by merging morphological pattern spectrum analysis with selective band-pass filtering to improve fault detectability. The method strengthened unique indicators such as gear-mesh frequency sidebands and bearing fault modulations throughout the vibration spectral analysis [92]. Researchers discovered significant differences between healthy and faulty gearbox vibration feature indices, according to the study. Damaged gearboxes presented both increased signal entropy and divergent pattern spectrum measurements that proved the gearbox contained faults compared to baseline measurements. When the method detected changes in both frequency bands and morphological features, it inferred where the fault occurred. Technicians detected characteristic patterns across signal spectra to identify faults in which bearing faults appeared as high-frequency rolling element vibrations, while cracked teeth in gears affected gear-mesh harmonics. The diagnostic system reached a sensitivity that qualified it for incorporation into automated gearbox quality control systems, which would identify possible production-line component faults [92]. The research demonstrates that vibration-based machine learning strategies can identify automotive gearbox malfunctions, highlighting the importance of developing processing algorithms that manage non-stationary conditions and high background noises found in automotive applications.

12.3 Manufacturing Machinery (Industrial Gearbox in Cement Plant)

The industrial manufacturing sector utilizes heavily loaded large gearboxes within various equipment systems [93]. A cement plant operates its crushers through a high-pressure roller press, which employs a big planetary gearbox that powers the material-crushing rollers [94]. The failure of gearboxes within such equipment presents substantial threats that result in significant losses from production halts. A planetary gearbox located on a 2 MTPA cement roller press became part of an IoT vibration monitoring solution providing continuous data collection in the Infinite Uptime (2022) report [81]. The goal focused on recognizing early-stage problems that affect the multi-staged planetary gear train system, even though it operates under challenging conditions involving heavy dust and high pressures while experiencing complex gearbox load distribution. According to the input stage, the bearing of the gearbox suffered from abrasive wear because of the contaminated lubricant.

Studies used wireless accelerometer nodes positioned on strategic gearbox areas (refer to white dots in the gearbox schematic). According to the sensors, vibration data was transmitted through a cloud-based platform, and the diagnostic strategy combined both time-domain trends and spectral examinations [95]. The diagnostic system measured two main indicators: overall vibration acceleration level and shock pulse spectrum, which detects high-frequency acceleration signals from impacts [96]. The system monitored vibration metrics throughout several months, which confirmed the faulty condition through increased total acceleration and velocity amplitude patterns between late 2021 and May 2022 [81]. The examination in spectral space showed that bearing outer race defect signatures presented through high-frequency peaks that matched ball-pass frequency patterns [81].

The inspection revealed "line marks" and "circumferential grooving" as wear indicators on both rollers and raceway surfaces, which indicated abrasive wear together with false brinelling (fretting damage during standstill). Incident diagnosis enabled the plant to change bearings before experiencing a destructive failure incident. This predictive maintenance approach eliminated 36 hours of unexpected gearbox malfunctions that could have occurred. The study proves that planetary gearbox diagnoses can be successfully conducted through the analysis of overall acceleration combined with shock pulse metrics, even in intricate gearbox systems. The system performed dual functions by identifying the fault and demonstrating improvement before and after the bearing replacement, thereby verifying the fault's resolution. The study also revealed that lubricant contamination was a source of failure, causing wear. Consequently, the team proposed using anti-wear additives and vibration control to prevent false brinelling.

Among practical limitations, manufacturing settings in cement plants impose both environmental noise and harsh operating conditions on sensor equipment. The vibration signals contained signals from multiple gear meshing stages as well as from other operating equipment in the system. The system managed to extract bearing fault signatures from overall vibration noise when it detected high-frequency shock waves. Complex gear trains with planetary systems present a challenge when it comes to fault isolation because a single problem with a planet gear will produce equivalent sensor responses in all components. The bearing displayed a clear signature, yet identifying a slight gear tooth crack would present challenges to the equipment inspection team [81]. Table 6 summarizes the methodologies and the findings of this study.

Table 6. Summarized references that discussed the diagnoses of spur gears

Author	Methodologies	Findings
[1]	Simulated S-gear designs under various loads were compared with standard gear shapes, and then, evaluated steel and polymer gear combinations with FEM validation, with the creation of a new shape factor to improve stress calculations.	The tooth stress depends on shape, material, and load. Contact ratio increase reduces the stress effect, which varies by material. The new model is more precise than the old methods (e.g., ISO 6336).
[2]	Experimental Observation: Real-world monitoring of gearboxes under different operating conditions. Modeling fault behavior to replicate diverse operating conditions and study their impact on gearbox health. The study reviews both experimental setups and theoretical frameworks employed in existing gearbox failure research.	Gearbox monitoring is essential for preventing unexpected machinery failure and reducing operational downtime. A combination of experimental and simulation-based methods yields a more comprehensive understanding of fault evolution under various conditions.
[20]	1D Convolutional Neural Network (1D-CNN): Trained using acoustic emission (AE) signals and extracts local spatial features from high-frequency AE data. Gated Recurrent Unit (GRU) Network: Trained using vibration signals. Captures temporal dependencies in vibration signal data. Seven distinct gear pitting fault conditions were evaluated. Evaluation involved variations in load conditions and learning rates to assess robustness.	The integrated CNN-GRU method achieved over 98% accuracy, even with limited training samples. The approach demonstrated strong robustness across varying mechanical loads and hyperparameter settings (like learning rates). It is noted that this deep learning structure is scalable and can be extended to other sensor modalities in future diagnostic applications.
[40]	6-DOF) A dynamic model of a one-stage spur gear transmission was used to simulate vibration signals for both healthy and cracked gear teeth at various crack levels (25%, 50%, 75%, 100%) in two ways: Standard gears: symmetric profile (20°/20°). Asymmetric gears: two variations (20°/25° and 20°/30°).	The study successfully demonstrated that gear tooth asymmetry can significantly enhance the performance of deep learning-based fault diagnosis systems. The proposed 1-D CNN model, coupled with dynamic simulations and statistical validation, offers a robust approach for early detection of gear tooth cracks
[55]	A heterodyne technique, adapted from telecommunications, was developed to reduce the AE signal frequency to below 50 kHz. This method enables sampling rates as low as 20 kHz, aligning AE data acquisition with conventional vibration sensors. A notional split torque gearbox was used with seeded gear tooth cut faults at varying levels. AE and vibration data were collected and comparatively analyzed.	AE-based diagnosis successfully identified fault severity levels, outperforming traditional vibration analysis in consistency. AE signals were less susceptible to mechanical resonance and ambient noise compared to vibration signals. The developed AE-based techniques made it possible to reuse well-established vibration analysis methods on AE signals.
[60]	diagnosis technique based on Structured Sparsity Time-Frequency Analysis (SSTFA). SSTFA employs mixed-norm priors on time-frequency coefficients, enabling detailed modeling of complex signal structures.	Separating transient features from noisy vibration signals. Preserving inner time-frequency structures. Delivering superior resolution and diagnostic clarity compared to existing methods.
[81]	Roller Sensor nodes enabling fault diagnosis for the gearbox were mounted at various positions. These sensors communicate with a cloud dashboard and provide comprehensive vibration signal analysis and fault diagnosis.	Bearing and gear faults in a complex planetary gear train can be observed and diagnosed using parameters such as total Acceleration and shockwave, thanks to the Infinite Uptime auto-diagnostics features. The goal is to prevent unplanned downtime for this equipment.

13. Discussion of Case Studies

The examined case studies checked the parallel patterns that become evident inside. The use of vibration sensors stands as an essential diagnostic method throughout all domains. Multiple data integration began to provide early detection in the wind turbine and cement plant cases through the combination of SCADA operational data and multiple accelerometer channels. Diagnostic outcomes show machines can be accurately diagnosed for their distinct failure modes through analysis tuning for individual equipment characteristics. The identification process becomes complicated for complex systems since traditional vibration spectrum analysis produces obscure outcomes when applied to planetary gearboxes. Apart from that, we see how quantitative thresholds together with trending maintain crucial importance in this process. Industrial settings demonstrated success with the cement plant, where they performed feature time tracking and detected meaningful changes. The wind turbine approach detected drifts starting "some weeks in advance" through an error metric generated from an ML model, according to the reference. The combination of time-domain analysis together with intelligent system models produces warning indicators in advance.

The practical hurdles identified across these use cases will remain, such as managing operation state changes in wind turbines and vehicles, and noise reduction requirements across all systems, particularly affecting industrial applications and maintenance system integration steps. The practice implementation of wind turbine data analytics required new algorithms because previous research had minimal experience with multi-source data fusion. The acquisition of adequate fault data proved difficult in the automotive application because researchers struggled to obtain data that replicated actual operating circumstances throughout the vehicle fleet's operational range. The practical experiences highlighted the importance of investigating existing research gaps and how developing technologies plan to resolve them.

13.1 Future Work

Automated feature extraction and classification are now possible through the combination of AI and machine learning technology for gear fault diagnosis processes. CNNs enable the computerized learning of hierarchical features directly from raw vibration data, thereby eliminating the need for manual feature engineering. The training of CNNs heavily depends on extensive collections of labeled datasets, but such resources may sometimes prove challenging to obtain.

Support Vector Machines (SVMs) deliver top results for classification purposes when working with datasets that are restricted in number. The application of pre-designed features helps SVM models operate optimally, but these models cannot detect complex patterns to the extent of deep learning models. A combination of modern techniques involves using CNNs initially for extracting features before employing SVMs for classification to exploit their individual advantages. Hybrid models utilizing these techniques exhibit better performance when dealing with situations characterized by restricted labeled database availability.

13.2 Gaps in Current Gear Fault Modeling and Diagnostics

The main obstacle to creating diagnostic models is obtaining scarce labeled fault data together with unbalanced class representations. The frequency of catastrophic gear failures remains low within one machine, because training datasets contain exclusively healthy condition examples rather than fault instances. Generalizable model performance becomes challenging for supervised machine learning and deep learning techniques because they need multi-fault type examples for training purposes. Real-world detection of gear faults requires limited labeled data because this approach leads to practical results, according to research findings.

The process of obtaining fault-labeled equipment data proves expensive because it demands machine modification testing through artificial fault generation or natural failure observation. Some failure modes, including specific gear tooth cracks, cannot be identified in historical machine data, which prevents the model from detecting all faults. The training of models based on single datasets leads to performance difficulties in machine applications and fault recognition for new devices due to inadequate data collection. The problem of scarce labeled data has received attention from researchers who explore techniques of transfer learning and semi-supervised learning to make the most out of generalization and Domain Shift (Varying Conditions) pose a challenge to traditional gear fault diagnostic methods because they are built under assumptions of identical training-deployment operating conditions. Terrestrial gear systems experience working conditions with continuously changing speeds, loads, and environmental factors while operating, which results in signature changes referred to as non-stationarity. When a model is trained using fixed speed or operational loads, it will fail to identify new patterns that evolve when the operational conditions vary. The performance of this classified gearbox operating at 1800 RPM would suffer changes in speed or fluctuating load conditions at 1200 RPM [97, 98]. The breach of identical distribution between test and training data results in lower prediction accuracy.

Real-world sensor data recovery becomes challenging due to environmental noise, deteriorating signal quality, and complex operating conditions. The presence of multiple machine vibrations along with environmental noises such as engines and wind sounds threatens to degrade gear vibration signals in industrial, automotive, and aerospace environments. Several deep learning models demonstrate excellent performance on prepared datasets, although they tend to lose operational robustness whenever the environment becomes noisy.

The process of implementing an algorithm into online monitoring systems reveals complexities that challenge its real-time deployment, even though it performs effectively in offline tests. The industrial requirement for gear fault diagnosis now calls for

Immediate analysis at the machine level is particularly crucial when dealing with essential assets that require early detection alerts.

The powerful computational requirements of deep neural networks, along with their cloud or offline operation requirements, do not fulfill the real-time and on-site cost benchmarks needed for industrial monitoring systems. Complex model designs require compromise with processing time. The current research highlights the need for developing minimal hardware-intensive diagnostic tools that provide rapid predictions through edge computers with minimal accuracy deterioration.

Existing industrial systems that use PLCs and SCADA software need analyzable outputs from AI solutions for proper integration. Maintenance engineers require visual indicators showing anomaly scores or confidently identified faults instead of receiving black-box predictions from diagnostic systems. The absence of clear explanations from AI models functions as a gap in the field because current deep learning models succeed in gear fault detection, but their functioning remains unclear to humans. The gap's resolution will guide practitioners to trust and accept new diagnostic tools for advanced use. Table 7 summarizes the advantages and disadvantages of this paper's methodologies.

Table 7. The advantages and disadvantages of the methods utilized in this research

Time-Frequency Method	Advantages	Disadvantages
Wavelet Transform (WT)	Excellent time localization at high frequencies More adaptable than STFT Offers a variety of wavelet functions	Involves convolution with predefined basis functions, which can distort the signal Selecting an appropriate mother wavelet is often difficult.
Hilbert Transform (HT)	High time-frequency resolution Avoids the use of pre-established basis functions	Risk of misinterpreting results due to low-frequency IMFs (Intrinsic Mode Functions)
Short-Time Fourier Transform (STFT)	Simple to implement and beginner-friendly Requires low computational effort	Uses fixed frequency resolution across the entire signal Finding an efficient algorithm for its calculation can be complex.
FFT (Fast Fourier Transform)	Simple and rapid to apply.	Ineffective for capturing time-localized or transient characteristics.
Spectral Analysis	Detects abrupt signal variations effectively; offers improved spectral resolution over FFT.	Complex techniques necessitate expert knowledge for proper implementation and interpretation.
SVM	Compatible with large and complex data sets, high accuracy	DiAcult to determine the appropriate kernel to be applied, performs poorly when the data contains noise

Fig. 4 describes the percentages of numerical to experimental references. While Fig. 5 illustrates the number of references according to the publishing year as follows.

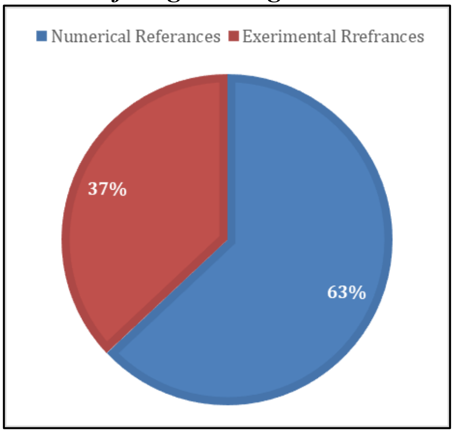

Fig. 4. The percentages of numerical and experimental references.

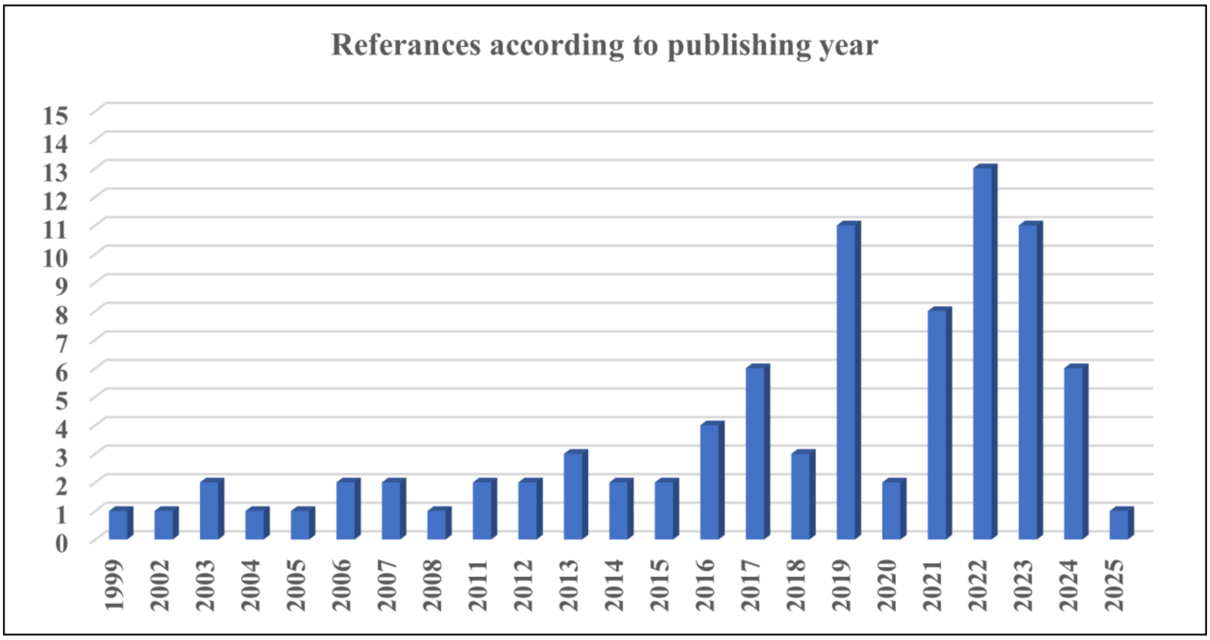

Fig. 5. Sorting the references according to the publishing year

Table 8 summarizes the number of references mentioned in this review according to different failing modes.

Table 8. Describes the analysis of the references with respect to the gear failing modes

Failure Type	Number of References	Example Reference Numbers
Wear	12 references	3, 8, 14, 27, 28, 29, 30, 31, 36, 38, 71, 72
Scuffing	05 references	9, 11, 30, 51, 52
Fatigue	10 references	5, 7, 11, 13, 28, 32, 35, 48, 70, 77
Pitting	06 references	20, 28, 32, 41, 42, 77

14. Conclusion

This review has investigated present-day gear fault detection and modeling practices, which range from practical implementation cases to new academic discoveries. The analysis of wind turbine systems alongside automotive gearboxes and manufacturing equipment highlighted both the capabilities and existing obstacles in current diagnostic approaches.

The implementation of reliable gear fault detection requires potent sensing methods that are paired with innovative signal interpretation algorithms and advanced signal processing techniques.

The fundamental connection between diagnostic and modeling systems via analytical modeling showed its potential in fault detection enhancement.

Future research approaches are built from the motivation generated by identified gaps. Real-time gear health assessments at the equipment location are now achievable through sensor fusion technology and edge computing, which enables initiative-taking maintenance instead of only reactive maintenance.

The development of adaptive diagnostic systems, along with intelligent systems, helps direct the maintenance approach from reactive to predictive maintenance for gear systems.

The significance of this innovation stands high because gears play essential roles in numerous machines, while their operational reliability supports the safety and efficiency of transportation and energy industries. Through precise gear behavior analysis coupled with data-driven diagnostic systems, maintenance operations will become more efficient and targeted.

The future of gear maintenance appears bright because research deficiencies will lead to an automated system based on equipment condition for predictive maintenance practices.

Advanced monitoring equipment will identify minor developing faults with precision, then suggest the best maintenance responses to keep equipment operational longer and reduce down time. The fusion of classical engineering with modern AI through self-learning diagnostic approaches will lead gear fault detection methods into the future for sustaining the operational condition of critical gear systems.

Ongoing advancements covered in this study create solid groundwork for the future by bringing forth a new period of gear maintenance excellence. Advanced diagnostic methods will lead to operational safety while reducing maintenance expenses and delivering an enhanced understanding of machine health status.

List of abbreviations

Term	Meaning
RUL	Remaining Useful Life
CNN	Convolutional Neural Networks
GRU	Gated Recurrent Unit
PHM	Prognostics and Health Management
TVMS	Time-Varying Meshing Stiffness
EHL	Electrohydrodynamic Lubrication
FFT	Fast Fourier Transform
TSA	Time Synchronous Averaging
FEM	Finite Element Modeling

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