THEORETICAL AND EXPERIMENTAL INVESTIGATIONS ON UNCERTAINTY ANALYSIS IN GEAR DESIGN AND ADAPTIVE LUBRICATION FOR SPUR GEAR FAULT PREDICTION USING MACHINE LEARNING TECHNIQUES

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Theoretical and Experimental Investigations on Uncertainty Analysis in Gear Design and Adaptive Lubrication for Spur Gear Fault Prediction Using Machine Learning Techniques

by

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Dedicated to

My parents (Sh. Moti Nath and Smt. Yashoda Devi) and my wife (Smt. Heera Devi).

and

(All the teachers)

Especially to my supervisor **Prof. Harish Hirani**

Certificate

This is to certify that the thesis entitled **"Theoretical and Experimental Investigations on Uncertainty Analysis in Gear Design and Adaptive Lubrication for Spur Gear Fault Prediction Using Machine Learning Techniques"** being submitted by Mr. **Kishan Nath Sidh** (Regd. No. **2022MEZ8327**) to the **Indian Institute of Technology Delhi**, New Delhi, India, for the award of the degree of **Doctor of Philosophy** is a record of bonafide research work carried out by him under my supervision and the candidate has fulfilled the requirements for the submission of this thesis. This thesis, in my opinion, meets the requirements for granting a Ph.D. degree from this institution. As per my awareness, the results contained in this thesis have not been submitted, in part or in full, to any other university or institute for the granting of a degree or certificate.

Hirani

Prof. (Dr.) Harish Hirani

Date...02.03.26...

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Abstract

Gears are important components of mechanical power transmission systems across various industrial sectors. Despite advancements in design and material processing, gear systems continue to experience failures primarily due to surface wear, contact fatigue, and lubricant degradation factors that collectively account for most gear-related breakdowns. These failures arise not only from deterministic causes but also from complex stochastic interactions among design parameters, surface roughness variations, manufacturing inaccuracies, and fluctuating lubrication conditions. Among these, lubricant degradation plays a critical role, occurring through mechanisms such as oxidation, water ingress, particle contamination, and acidification, which progressively alter lubricant load-carrying capacity and ultimately accelerating friction and surface wear. To address these challenges, the present study conducts a comprehensive uncertainty analysis of spur gear contact fatigue, integrating theoretical modeling with tribological experimentation. A unified framework is introduced, combining nano-additive-enhanced fresh and degraded lubricants with machine learning–based uncertainty quantification to evaluate and predict gear wear progression under diverse lubrication conditions, thereby advancing the reliability and predictive understanding of gear performance in real-world applications.

To simulate accelerated lubricant degradation in controlled laboratory settings, aqueous hydrochloric acid (HCl, 36%) was employed as a corrosive agent to induce oxidative and acidification-based degradation in gear lubricants. This approach enabled the systematic observation of lubricant property deterioration and its subsequent effect on wear and surface fatigue behavior. The degraded lubricants exhibited a substantial reduction in film-forming ability and anti-wear performance,

replicating conditions often encountered in long-duration or high-load industrial applications. To counteract this degradation, the study explored the incorporation of environment friendly nanoparticle additives such as carbon-based nanomaterials, which act as secondary lubricating agents. These nanoparticles were designed to form protective tribofilms, and reduce frictional heating at the asperity level. The doping of nanoparticles into the degraded lubricant demonstrated remarkable improvements in tribological behavior, including reduced wear scar diameter, lower coefficient of friction, and enhanced resistance to surface pitting. The tribological performance was evaluated using multiple tribometers, including the Block-on-Disk and Four-Ball configurations. In the Block-on-Disk setup, wear volume was determined through precise weight loss measurements, whereas in the Four-Ball tribometer, it was estimated using a geometry-based method.

However, the current geometry-based wear volume estimation techniques generally assume a flat wear scar, which fails to capture the true three-dimensional nature of wear morphology. To address this limitation, this study introduces the development of 3D wear volume characterization using advanced surface profilometry, thereby improving measurement accuracy and enabling a more comprehensive uncertainty quantification in wear assessment.

In parallel, the study employed real-time wear debris monitoring techniques to provide quantitative insights into wear severity and mechanism transitions. Debris samples were collected at various stages of gear operation and analysed using optical microscopy, and digital image processing methods. The morphological classification of debris ranging from rubbing and cutting wear particles to fatigue and corrosive debris served as a diagnostic indicator of lubrication health and gear surface deterioration. Ferrous debris count sensors were also utilized to measure debris concentration dynamically, thereby linking the lubrication degradation state with actual wear progression.

To handle the inherent uncertainties in the collected experimental data, the research integrated machine learning (ML) and probabilistic modeling approaches. Techniques such as Deep Learning (DL) and Non-Stationary Gaussian Process Regression (NSGPR) were applied for feature extraction, wear prediction, and uncertainty propagation analysis. DL models provided a nonlinear mapping between lubricant properties, operating parameters, and wear outcomes, while NSGPR facilitated probabilistic predictions with confidence intervals, enabling a more robust estimation of gear life under uncertain conditions.

The outcomes of this research provide an integrated perspective on tribological uncertainty, encompassing gear design, lubricant degradation, and real-time wear diagnostics. The results demonstrate that adaptive lubrication strategies incorporating nanoparticles can significantly mitigate the adverse effects of degradation, sustaining lubrication film integrity and reducing fatigue wear even in chemically compromised environments. Additionally, the developed uncertainty quantification model bridges the gap between experimental observations and theoretical predictions, offering a powerful tool for fault prognosis and predictive maintenance in gear-based transmission systems.

सार

गियर यांत्रिक शक्ति संचरण प्रणालियों के विभिन्न औद्योगिक क्षेत्रों में अत्यंत महत्वपूर्ण अवयव हैं। डिज़ाइन तथा सामग्री प्रसंस्करण में उन्नति के बावजूद, गियर प्रणालियाँ मुख्यतः सतही घिसाव, संपर्क थकान (fatigue) तथा स्नेहक (लुब्रिकेंट) अपघटन के कारण विफल होती रहती हैं, जो अधिकांश गियर-संबंधित खराबियों के लिए उत्तरदायी हैं। ये विफलताएँ केवल नियतात्मक कारणों से ही नहीं, बल्कि डिज़ाइन मापदंडों, सतही खुरदरापन में परिवर्तन, निर्माण संबंधी त्रुटियों तथा परिवर्तनीय स्नेहन स्थितियों के बीच जटिल () स्टोकेस्टिक अंतःक्रियाओं के कारण भी उत्पन्न होती हैं। इन कारकों में स्नेहक अपघटन की भूमिका अत्यंत महत्वपूर्ण है, जो ऑक्सीकरण, जल-प्रवेश, कणीय प्रदूषण तथा अम्लीकरण जैसी प्रक्रियाओं के माध्यम से होता है। ये प्रक्रियाएँ स्नेहक की भार-वहन क्षमता को क्रमशः प्रभावित करती हैं, जिससे घर्षण तथा सतही घिसाव में तीव्र वृद्धि होती है।

उपरोक्त चुनौतियों के समाधान हेतु प्रस्तुत अध्ययन में स्पर गियर संपर्क थकान का व्यापक अनिश्चितता विश्लेषण किया गया है, जिसमें सैद्धांतिक मॉडलिंग को ट्राइबोलॉजिकल प्रयोगों के साथ एकीकृत किया गया है। एक समेकित रूपरेखा प्रस्तुत की गई है, जिसमें नैनो-एडिटिव युक्त नवीन एवं अपघटित स्नेहकों को मशीन लर्निंग आधारित अनिश्चितता मात्रात्मककरण के साथ संयोजित कर विभिन्न स्नेहन परिस्थितियों में गियर घिसाव की प्रगति का मूल्यांकन एवं पूर्वानुमान किया गया है। यह दृष्टिकोण वास्तविक औद्योगिक अनुप्रयोगों में गियर प्रदर्शन की विश्वसनीयता तथा पूर्वानुमेयता को सुदृढ़ करता है।

इस अपघटन के प्रतिरोध हेतु पर्यावरण-अनुकूल कार्बन-आधारित नैनो-सामग्री जैसे नैनोकण एडिटिव्स के समावेशन का अध्ययन किया गया। ये नैनोकण द्वितीयक स्नेहक एजेंट के रूप में कार्य करते हुए सुरक्षात्मक ट्राइबो-फिल्म का निर्माण करते हैं तथा सूक्ष्म असमतलताओं (ऐस्पेरिटी) के स्तर पर घर्षणीय ताप को कम करते हैं। अपघटित स्नेहक में नैनोकणों के सम्मिश्रण से ट्राइबोलॉजिकल प्रदर्शन में उल्लेखनीय सुधार देखा गया, जिसमें घिसाव क्षरण व्यास में कमी, घर्षण गुणांक में कमी तथा सतही गड्ढानुमा क्षरण के प्रति प्रतिरोध में वृद्धि सम्मिलित है।

समानांतर रूप से, वास्तविक समय घिसाव मलबा निगरानी तकनीकों का उपयोग कर घिसाव की तीव्रता एवं तंत्र परिवर्तन के मात्रात्मक संकेत प्राप्त किए गए। गियर संचालन के विभिन्न चरणों में मलबा नमूने एकत्रित कर उनका प्रकाशीय सूक्ष्मदर्शी एवं डिजिटल छवि प्रसंस्करण विधियों द्वारा विश्लेषण किया गया। रबिंग, कटिंग, थकान तथा संक्षारक मलबा कणों की आकृतिगत वर्गीकरण स्नेहन स्वास्थ्य एवं गियर सतह क्षरण का निदानात्मक संकेतक सिद्ध हुआ। साथ ही, लौहयुक्त मलबा गणना सेंसरों का उपयोग कर मलबा सांद्रता का गतिशील मापन किया गया, जिससे स्नेहक अपघटन अवस्था एवं वास्तविक घिसाव प्रगति के मध्य प्रत्यक्ष संबंध स्थापित किया गया।

संग्रहित प्रायोगिक आंकड़ों में निहित अनिश्चितताओं के प्रबंधन हेतु मशीन लर्निंग एवं प्रायिकता-आधारित मॉडलिंग दृष्टिकोणों का समावेशन किया गया। फीचर निष्कर्षण, घिसाव पूर्वानुमान तथा अनिश्चितता प्रसार विश्लेषण के लिए डीप लर्निंग (DL) तथा गैर-स्थिर गॉसियन प्रोसेस प्रतिगमन (NSGPR) जैसी तकनीकों का उपयोग किया गया। डीप लर्निंग मॉडल ने स्नेहक गुणों, परिचालन मापदंडों एवं घिसाव परिणामों के मध्य गैर-रेखीय मानचित्रण प्रदान किया, जबकि NSGPR ने विश्वास अंतराल सहित प्रायिकतामूलक पूर्वानुमान उपलब्ध कराए, जिससे अनिश्चित परिस्थितियों में गियर आयु का अधिक सुदृढ़ आकलन संभव हुआ।

इस शोध के परिणाम ट्राइबोलॉजिकल अनिश्चितता के एकीकृत दृष्टिकोण को प्रस्तुत करते हैं, जिसमें गियर डिज़ाइन, स्नेहक अपघटन तथा वास्तविक समय घिसाव निदान को सम्मिलित किया गया है। अध्ययन से यह सिद्ध हुआ कि नैनोकण-आधारित अनुकूलनशील स्नेहन रणनीतियाँ रासायनिक रूप से प्रभावित परिस्थितियों में भी स्नेहन फिल्म की अखंडता को बनाए रखते हुए थकान घिसाव को उल्लेखनीय रूप से कम कर सकती हैं। इसके अतिरिक्त, विकसित अनिश्चितता मात्रात्मककरण मॉडल प्रायोगिक अवलोकनों एवं सैद्धांतिक पूर्वानुमानों के मध्य अंतर को पाटते हुए गियर-आधारित शक्ति संचरण प्रणालियों में दोष पूर्वानुमान एवं पूर्वानुमेय अनुरक्षण के लिए एक प्रभावी उपकरण प्रदान करता है।

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List of Abbreviation

AFM	–	Atomic Force Microscopy
AGMA	–	American Gear Manufacturers Association
ANOVA	–	Analysis Of Variance
ASTM	–	American Society for Testing and Materials
C_H	–	Hardness Ratio Factor
CI	–	Confidence Interval
C_L	–	Surface Life Factor
CM	–	Condition Monitoring
CNTs	–	Carbon Nanotubes
COF	–	Coefficient Of Friction
C_R	–	Reliability Factor
C_T	–	Temperature Factor
d	–	Pitch Diameter
DAQ	–	Data acquisition
DL	–	Deep Learning
DOE	–	Design Of Experiments
EDS	–	Energy Dispersive X-Ray Spectroscopy
E_g	–	Moduli Of Elasticity For Gear
E_p	–	Moduli Of Elasticity For Pinion
EP	–	extreme pressure
FEA	–	Finite Element Analysis
FESEM	–	Field Emission Scanning Electron Microscope
FFM	–	Friction Force Microscopy

FOS	–	Factor Of Safety
F_t	–	Transmitted Load
GPR	–	Gaussian Process Regression
GUM	–	Guide To The Expression Of Uncertainty In Measurement
H	–	Hardness
hBN	–	Hexagonal Boron Nitride
HCl	–	Hydrochloric Acid
I	–	Surface Geometry Factor
ISO	–	International Standards Organization
JGMA	–	Japan Gear Manufacturers Association
K_v	–	Dynamic Factor
L	–	Sliding Distance
m	–	Module
ML	–	Machine Learning
MoS_2	–	Molybdenum Disulfide
N	–	Speed
NSGPR	–	Non-stationary Gaussian Process Regression
NTA	–	Nanoparticle Tracking Analyzer
P	–	Load
Q	–	Margin Of Safety
R	–	Reliability
rGO	–	Reduced Graphene Oxide
RUL	–	Remaining Useful Life

T	–	Torque
TEM	–	Transmission Electron Microscope
V	–	Pitch Line Velocity
VMM	–	Visual Measuring Machine
WSD	–	Wear Scar Dia
wt%	–	Weight Percentage
Z_g	–	Number Of Teeth On Gear
Z_p	–	Number Of Teeth On Pinion
C_f	–	Surface Finish Factor
C_P	–	Elastic Coefficient
K_m	–	Load Distribution Factor
K_o	–	Overload Factor
K_s	–	Size Factor
S_c	–	Corrected Fatigue Strength
u_h	–	Height Uncertainty
u_r	–	Radial Uncertainty
v_g	–	Poisson's Ratios For Gear
v_p	–	Poisson's Ratios For Pinion
2D	–	Two-Dimensional
3D	–	Three-Dimensional