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Research Article

Non-Contact Transmission Error and NVH Diagnostics in Helical Gear Drives: A State-of-the-Art Review

Krisztián Horváth*, Ambrus Zelei
[1,2]Department of Whole Vehicle Engineering, Széchenyi István University, Győr, Hungary

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ABSTRACT

With the increasing popularity of electric cars, which run at higher motor speeds than internal combustion vehicles, new Noise, Vibration and Harshness (NVH) problems have emerged for powertrains. Quiet, vibration-free vehicles create a premium feeling of quality and increase customer satisfaction. Demand has increased alongside the need for precise and quiet transmissions. One of the mechanical sources of vibration and noise generated by helical gears, which are also used in vehicle transmissions, is transmission error (TE). Conventional measurement methods for measuring TE are based on rotary transducers and torque sensors. These methods have their limits of accuracy and applicability. Recent advances in certain non-contact techniques, such as laser Doppler vibrometry, digital image correlation and motion magnification all open up new perspectives in TE and NVH diagnostics. Nowadays, machine learning (ML) methods are coming to the fore for condition monitoring and noise prediction. This literature review provides a structured overview of experimental setups, non-contact measurement technologies, and ML applications related to TE and NVH in helical gear drives. Current research trends are identified, limitations and areas of future opportunities are explored. In line with recent trends, the integration of optical diagnostics and ML offers promising opportunities towards efficient real-time condition monitoring. In addition, the paper explores the conceptual feasibility of a proposed low-cost, camera-based, non-contact test bench that integrates optical diagnostics and machine learning for estimating transmission error, offering an alternative to high-cost laser vibrometry.

Keywords: Transmission Error, NVH, Laser Doppler Vibrometry, Digital Image Correlation, Electric Vehicles

INTRODUCTION

Some vehicle properties, such as the noise levels of electric vehicles, have a significant impact on the customer's perception of quality, especially in the premium segment. Quiet, vibration-free vehicles create a premium quality perception and increase customer satisfaction. Customer demand and increasingly stringent noise reduction standards are driving the industry to develop quieter vehicles. Typical traction e-drives in passenger BEVs spin between 10 000 and 16 000 rpm during normal operation, and several next-generation prototypes exceed 20 000 rpm. The resulting mesh-order frequencies (> 5 kHz for a 25-tooth helical pinion) intensify even small TE components, imposing tighter NVH constraints. This creates new problems to be solved. In particular, the noise generated by electric motors is more dominant at mid and high frequencies. People are sensitive to these high frequency tonal noises, which affect their sense of comfort. From a psychoacoustic point of view, these are the frequencies to which the human ear is most sensitive. Furthermore, in such systems, the noise of the engine is more perceptible because of the absence of the masking effect of the internal combustion engine [1]. Among the primary noise sources, transmission error (TE) plays a central role in tonal engine whine [2]. This article is an explicit *state-of-the-art review*; we report no new primary measurements but instead synthesise and critically assess the existing literature.

The transmission error is the deviation between the actual and ideal angular position of the driven gear. Its fluctuation induces dynamic gear meshing forces, which propagate as structural vibrations through the transmission pathway and generate housing vibrations and radiated noise [3]. For helical gears, the complexity of the load distribution, the displacement sensitivity and the dynamic interaction make the prediction and measurement of TE particularly challenging [4].

Traditional methods for measuring TE are based on rotary encoders and torque sensors. However, these contact-based approaches may be limited by inertia, resolution, and accessibility in real-world applications [5]. Therefore, non-contact measurement techniques such as laser Doppler vibrometry (LDV), digital image correlation (DIC), and motion magnification have appeared as alternatives [6].

Recent advances in machine learning (ML) further support the analysis and prediction of TE and gear-induced noise. By learning from sensor signals or simulation data, ML models can estimate gear condition, detect anomalies, or predict NVH performance [7].

The research reviews and summarizes the state-of-the-art results in non-contact TE measurement and data-driven NVH analysis. Highlights experimental platforms, optical diagnostics, ML-based processing methods. It also identifies research gaps and possible directions for future studies.

Scope and Contribution

This review targets four tightly delimited questions:

1. *Non-contact* TE-measurement techniques for helical gear pairs, with emphasis on laser Doppler vibrometry (LDV), digital image correlation (DIC) and motion magnification in the 5–20 krpm operating range.
2. The accuracy, spatial/temporal resolution and practical deployability of those techniques.
3. Machine-learning approaches that rely, at least partially, on optical / LDV data for TE or NVH estimation.
4. A discussion of unmet research needs, exemplified by a cost-efficient, camera-based conceptual test bench (illustrative only, not a validated prototype).

Topics restricted solely to **contact-based sensors** (e.g. torque transducers, encoders) or to **spur-gear drives** are *outside* the scope of this review.

To illustrate current research gaps, we outline a conceptual, low-cost, camera-based test bench architecture that could support non-contact TE estimation. This illustrative example serves to highlight integration challenges rather than to present validated experimental results. The proposed system integrates affordable, high-speed camera technology with digital image processing and artificial intelligence, enabling non-contact estimation of transmission error (TE). This cost-efficient, multi-method platform offers a promising alternative to laser-based setups, making TE diagnostics more accessible for academic and industrial applications alike. Several existing test benches are also reviewed to contextualize the innovation.

METHODOLOGY OF THE REVIEW

This review follows a structured approach to identify relevant studies focusing on transmission error (TE), non-contact diagnostics, and machine learning applications in helical gear systems.

Literature Databases and Scope

Scientific publications were collected primarily from peer-reviewed databases, including Scopus, Web of Science, and Google Scholar. Additional references were drawn from IEEE Xplore, ScienceDirect, and MDPI journals. The search covered articles published between 2000 and 2024, with a focus on recent developments from 2015 onwards.

Search Strategy

Keywords were combined using Boolean operators, including:

- "transmission error" AND "helical gear"
- "gear noise" AND "non-contact measurement"
- "laser vibrometry" OR "digital image correlation"

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- "gearbox test bench" AND "NVH"
- "machine learning" AND "gear diagnostics"

In total, over 250 initial records were identified.

Inclusion and Exclusion Criteria

Included articles were selected based on the following criteria:

- Relevance to helical or spiral gear systems
- Focus on TE, vibration, or acoustic phenomena
- Use of non-contact or advanced diagnostic methods
- Application of machine learning or AI for signal processing or prediction

Studies limited to spur gears, unrelated to TE or NVH, or purely theoretical without experimental or ML components were excluded.

Review Process

The screening process involved:

1. Title and abstract review
2. Full-text reading for technical relevance
3. Categorization into thematic clusters:
    - Experimental test benches and setups
    - Optical and laser-based diagnostics
    - Machine learning for TE or NVH
    - Industrial validation or case studies

A total of **96 publications** were retained and analyzed in detail.

FUNDAMENTALS OF TRANSMISSION ERROR AND NVH IN GEARS

Transmission error (TE) is a key excitation source in gear dynamics. It is defined as the deviation between the actual angular displacement of the driven gear and its ideal position assuming perfect geometry and load transmission [8].

TE can be categorized as quasi-static or dynamic. Quasi-static TE arises under low-speed or static conditions and reflects manufacturing and assembly deviations. Dynamic TE includes the influence of mesh stiffness variations, vibrations, and inertia effects during operation [9].

In helical gears, the continuous tooth contact and axial forces result in complex dynamic behavior. Microgeometry variations, misalignments, and load conditions all contribute to TE fluctuations [10].

TE is directly related to mesh stiffness changes. As teeth engage and disengage, the mesh stiffness varies periodically, producing dynamic forces and noise. This cyclic excitation propagates through the shafts and gear housing, often resulting in tonal components known as gear whine [11].

Reducing TE through microgeometry correction, such as lead and profile modifications, is a well-established method to improve NVH performance. However, accurate prediction and measurement of TE under operating conditions remains challenging [12].

TE is typically measured using rotary encoders or torque sensors. These methods require high-resolution hardware and precise mechanical integration. Additionally, they may not be feasible in compact or enclosed systems.

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As a result, non-contact TE estimation and indirect assessment via vibration or acoustic analysis have gained interest. These methods are particularly relevant in electric vehicles, where gear noise is more noticeable due to low background masking levels [13].

Understanding the relationship between TE and NVH characteristics is essential for both diagnosis and design optimization. TE serves as a measurable and modifiable parameter, linking gear geometry to dynamic and acoustic outcomes.

GEARBOX TEST BENCHES AND EXPERIMENTAL SETUPS

Experimental validation of transmission error and NVH phenomena requires dedicated test environments. Gearbox test benches offer controlled conditions for replicating gear meshing behavior, load transmission, and acoustic radiation.

Several academic and industrial studies utilize modular test benches designed for helical gear pairs. These platforms allow adjustable center distance, backlash, and input torque. In many cases, interchangeable gears are used to test different geometries or fault conditions [14].

One widely used system is the SpectraQuest Drivetrain Diagnostics Simulator. It supports single or multi-stage gear configurations and is equipped with high-speed rotary encoders, accelerometers, and microphones [15]. It enables both time-domain and frequency-domain analysis of dynamic gear behavior.

Advanced setups integrate torque sensors and laser vibrometers for precision measurements. Some use optical encoders with sub-arcminute resolution to compute TE directly. Others combine shaft-mounted targets and non-contact probes for angular displacement measurement [16].

Research benches often incorporate transparent housings or open-frame designs for optical access. This allows visual tracking of gear tooth engagement and supports the use of digital image correlation or motion magnification techniques [17].

Dynamic loading is typically applied via electric motors or hydraulic systems. Load conditions, speed ramps, and thermal variations are programmable to simulate real operating environments. This supports repeatable comparison across gear types and parameter variations.

Several studies also report the integration of data acquisition systems with machine learning pipelines. This allows real-time feature extraction and condition classification during testing [18].

Overall, gearbox test benches provide an essential infrastructure for studying TE and NVH. They enable the evaluation of gear design, manufacturing variability, and diagnostic technologies under realistic but repeatable conditions.

NON-CONTACT MEASUREMENT METHODS

Accurate measurement of transmission error (TE) and gear-induced vibration often requires high spatial and temporal resolution. Non-contact methods provide an effective alternative to traditional sensors by avoiding mechanical interference and enabling full-field data acquisition.

While optical methods such as DIC and motion magnification are typically used for deformation or vibration analysis, recent studies have explored their potential for estimating transmission error (TE) indirectly, particularly when combined with high-speed imaging and AI-driven data processing.

Optical Techniques

Digital Image Correlation (DIC) is a well-established technique for measuring surface displacement and strain. High-speed stereo DIC cameras now cover 0.5 kHz – 500 kHz frame-rate. For a helical gear running at 16 000 rpm with 30 teeth (mesh frequency ≈ 8 kHz), a ≥ 10 kHz frame rate is mandatory to capture tooth-to-tooth TE fluctuations. Achieving this typically necessitates intense illumination and region-of-interest cropping; consequently, most published DIC-TE studies remain limited to spur gears or ≤ 5 kHz mesh frequencies. In gear diagnostics, DIC has been used to monitor tooth deformation, mesh stiffness variation, and housing vibrations [19].

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It requires a speckled pattern and high-resolution imaging but provides sub-micron accuracy under proper conditions.

Motion magnification enhances small structural motions in video recordings. By processing pixel intensity changes, it reveals otherwise invisible vibrations in rotating components [20]. This method is suitable for identifying resonance patterns and cyclic motion but requires high frame rate and stable lighting.

Optical flow algorithms compute the motion of features across video frames. Applied to gear systems, they can estimate periodic displacements and visualize TE-related dynamics. Combined with camera calibration, motion data can be converted into quantitative measurements [21].

These methods are particularly useful in research benches with transparent gearboxes or exposed components. They offer a rich data source for image-based diagnostics and machine learning input generation.

Laser-Based Techniques

Laser Doppler Vibrometry (LDV) is a precise method for measuring surface velocity without contact. It detects the Doppler shift of reflected laser beams and provides accurate vibration data at selected points [22]. LDV has been used to measure shaft vibrations, gear body response, and housing dynamics.

Rotational LDV systems can capture angular velocity variations and have been applied to infer TE indirectly. By measuring both input and output shafts, the relative phase error can be calculated, even in complex gear trains [23].

While LDV offers high precision, it requires clean line-of-sight and reflective surfaces. Environmental noise, alignment, and cost are practical limitations, especially for industrial deployment.

Overall, non-contact techniques expand the capabilities of TE and NVH diagnostics. They support advanced feature extraction, enable new experimental designs, and align well with data-driven methods. Table 1. Comparison of LDV and DIC methods.

Table 1. Comparison of Laser Doppler Vibrometry (LDV) and Digital Image Correlation (DIC)

Aspect	Laser Doppler Vibrometry (LDV)	Digital Image Correlation (DIC)
Measurement principle	Measures velocity via Doppler shift of reflected laser beam.	Tracks surface pattern displacement between image frames.
Contact-free	Fully non-contact.	Fully non-contact.
Measurement range	≈ 2 nm (lab) / 5–10 nm (gearbox test), differential setups < 1 nm	Suitable for larger displacements and deformations.
Spatial resolution	High precision at a single point; scanning enables full-field mapping.	Captures entire surface at once; typically lower resolution. Frame-rate limit presently ≤ 10 kHz for full-field view.
Velocity/acceleration	Direct velocity measurement; acceleration via differentiation.	Derived from displacement data.
Typical applications	High-frequency, low-amplitude vibration and modal analysis.	Structural deformation, strain, and crack propagation studies.
Surface requirements	Works best on reflective or mirror-like surfaces; retroreflective tape often used.	Requires random speckle pattern on surface.

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Environmental sensitivity	Sensitive to ambient vibrations and air turbulence.	More tolerant to environmental variations.
Cost and accessibility	High equipment cost.	Generally more affordable, especially with existing cameras.

State-of-the-art single-point LDV sensors resolve ≈ 2 nm displacement under laboratory conditions, while differential (two-beam) configurations have demonstrated < 1 nm resolution at frequencies down to 1 mHz In gearbox environments, however, speckle noise, alignment error and housing vibration usually raise the practical noise floor to 5–10 nm, a factor that must be considered when computing TE.

MACHINE LEARNING APPLICATIONS IN TE AND NVH ANALYSIS

Machine learning (ML) has become a key tool for analyzing complex vibration and noise patterns in gear systems. It enables automated feature extraction, anomaly detection, and performance prediction based on sensor or image data.

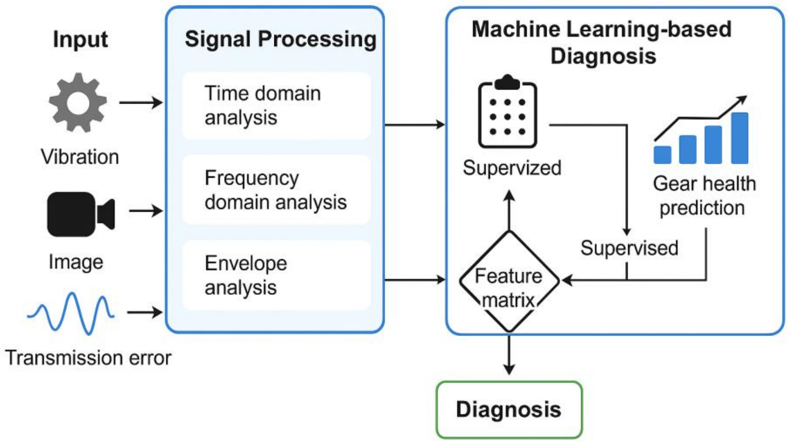

Figure 1. Integrated workflow of non-contact measurement

Figure 1. signals from optical methods (e.g., DIC, LDV, motion magnification), microphones, and accelerometers are preprocessed and converted into feature vectors. These are used to train ML models for tasks such as TE estimation, fault detection, and noise level prediction.

Supervised Learning

Supervised learning models are trained using labeled datasets, typically containing vibration signals and known gear conditions. Classical approaches include support vector machines, decision trees, and random forests [24]. Recent studies favor deep neural networks (DNN), convolutional neural networks (CNN), and long short-term memory (LSTM) models for temporal data [25].

Input features often include time-domain statistics, frequency spectra, wavelet coefficients, or spectrogram images. Transmission error signals, when available, are also used as targets or auxiliary inputs [26].

Models have been developed to classify gear faults, estimate gear life, and predict NVH indicators such as sound pressure level (SPL) or RMS vibration [27]. Some works focus on end-to-end learning from raw signals without manual feature engineering.

Supervised ML requires high-quality, labeled data. Therefore, most studies are based on controlled test benches. Industrial adoption is increasing, but requires robust generalization to variable conditions.

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Unsupervised and Self-Supervised Learning

Unsupervised learning methods detect patterns or anomalies without labeled output. Autoencoders, clustering algorithms, and dimensionality reduction techniques are commonly used [28]. These models can learn normal operating behavior and identify deviations indicating gear wear, misalignment, or defects.

Self-supervised learning uses pretext tasks, such as signal reconstruction or temporal ordering, to learn useful representations from unlabeled data. These representations can improve downstream tasks with limited labeled examples [29].

Hybrid models combining physical knowledge (for example, gear meshing frequency) with learned features have shown promise. Physics-informed ML approaches can improve interpretability and reduce the need for large datasets [30].

Overall, ML enables scalable, data-driven gear diagnostics. When integrated with non-contact measurements and test benches, it supports real-time monitoring, predictive maintenance, and noise optimization.

RESEARCH TRENDS AND GAPS

Recent research shows a strong shift toward non-contact measurement and data-driven diagnostics in gear systems. However, several limitations and open questions remain.

Identified Trends

There is growing interest in TE-focused NVH optimization, especially for electric vehicles, where gear noise is more prominent [31]. Studies increasingly use rigid-flexible dynamic models and multi-objective optimization to reduce TE and noise simultaneously.

Modular test benches with swappable gears, precise loading, and integrated sensors support repeatable experiments. These systems provide reliable data for developing and validating machine learning models [32].

In line with these developments, a conceptual modular gearbox test bench is proposed (Figure 2), designed to support non-contact transmission error estimation using high-speed imaging and AI-based data processing. The architecture relies on a machine vision camera system, capturing the rotational behavior of the input and output shafts or gear surfaces without any mechanical contact. Through optical flow analysis, motion magnification, or digital image correlation, the system extracts periodic displacement data. These measurements are processed by machine learning algorithms trained to estimate transmission error (TE) and related NVH characteristics.

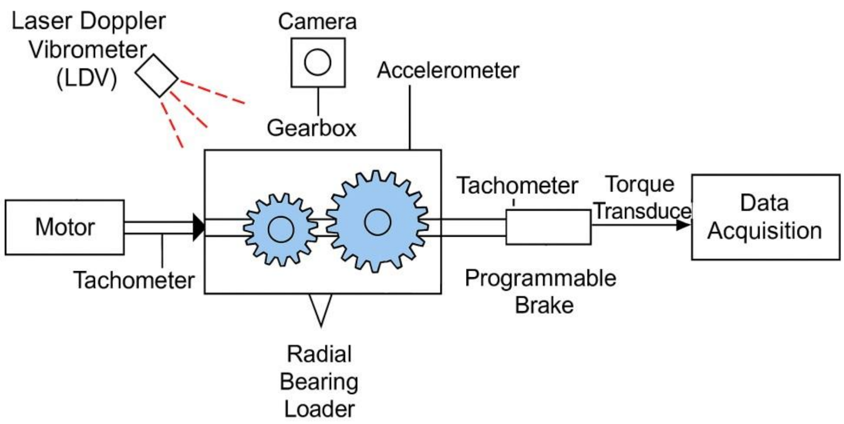

Figure 2. Modular gearbox test benches with sensors.

Optical diagnostics, such as DIC and motion magnification, offer rich spatial information. While not yet widespread in industry, they are gaining ground in research environments due to their non-invasiveness [33].

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ML is moving beyond fault detection into predictive modeling. Deep learning approaches are being used to estimate TE or SPL directly from sensor or simulation data [34]. Hybrid physics-informed models are also emerging.

Research Gaps

Despite progress, several gaps remain:

- High-speed image-based TE measurement is underexplored. Existing optical methods are limited by frame rate, calibration, and sensitivity. Quantitative TE estimation from video remains a challenge.
- Multi-modal data fusion is rarely addressed. Combining image, vibration, and acoustic data could improve diagnostics but requires synchronized acquisition and robust preprocessing.
- Generalization of ML models to real-world conditions is limited. Many models are trained on lab data and fail under variable operating scenarios.
- Self-supervised and adaptive ML approaches are still in early stages. These could reduce reliance on large labeled datasets and support online learning in changing environments.
- Linking TE to perceived sound quality remains largely unexplored. Most studies focus on dB levels, while psychoacoustic metrics are rarely integrated into gear design or optimization.

Addressing these gaps requires interdisciplinary collaboration across mechanical engineering, computer vision, and data science.

CONCLUSIONS

This paper reviews the state of the art in research on non-contact measurement and machine learning analysis of the transmission error (TE) and NVH behaviour of helical systems, which are also commonly used in electric vehicle drives.

As is well known, TE is one of the critical factors for the vibration and noise induced by gears.

Traditionally, physical measurements of TE have been performed using encoders and torque sensors. Non-contact methods such as laser vibrometry and optical imaging open up new possibilities for accurate and non-intrusive diagnostics.

Sensored modular gearbox test benches allow repeatable experiments to be carried out under realistic conditions.

Custom-developed test benches combined with optical techniques can provide valuable data for physically based validation of simulations and predictive models. The hybrid approach, i.e. the combination of different methods, all contribute to fault detection, noise estimation and condition monitoring. Both supervised and self-supervised approaches show promise, although generalisation to industrial conditions remains a challenge for engineers.

Research gaps include high-speed TE imaging, multimodal data fusion and the linking of physical parameters and subjective sound quality. Addressing these areas could lead to more accurate diagnostics.

Non-contact diagnostics and intelligent data processing could be key tools for next generation propulsion systems. Integrating these methods will support more efficient development, monitoring and optimisation - especially in noise-sensitive applications such as electric vehicles. The feasibility of estimating TE using camera-based systems remains a promising but underexplored direction, offering a low-cost alternative to conventional TE measurement techniques.

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REFERENCES

[1] Åkerblom, M. (2019). Gear noise and vibration – a literature survey. Gear Technology, 36(4), 30–39. Nincs DOI.

[2] Andersson, A., & Vedmar, L. (2003). A dynamic model to determine vibrations in involute helical gears. Journal of Sound and Vibration, 260(2), 195–212. Nincs DOI.

[3] An, Y., Liu, Y., & Cui, W. (2022). Digital image correlation for structural health monitoring: A review. Sensors, 22(9), 3491. https://doi.org/10.3390/s22093491

[4] Brecher, C., & Gorgels, C. (2015). Investigation of gear noise excitation due to transmission error. Procedia CIRP, 31, 245–250. https://doi.org/10.1016/j.procir.2015.03.050

[5] Castellini, P., Martarelli, M., & Tomasini, E. P. (2006). Laser Doppler vibrometry: Development of advanced solutions answering to technology's needs. Mechanical Systems and Signal Processing, 20(6), 1265–1285. https://doi.org/10.1016/j.ymssp.2005.11.015 ScienceDirect

[6] Fernandes, C. M. C. G., Marques, P. M. T., Martins, R. C., & Seabra, J. H. O. (2015). Gearbox power loss: Experimental and computational methodologies. Tribology International, 88, 298–309. https://doi.org/10.1016/j.triboint.2015.03.028

[7] Harris, T. A. (2001). Rolling bearing analysis (4. kiad.). Wiley. Nincs DOI.

[8] Hinton, G. E., & Salakhutdinov, R. R. (2006). Reducing the dimensionality of data with neural networks. Science, 313(5786), 504–508. https://doi.org/10.1126/science.1127647

[9] Janssens, K., Guo, Y., Long, J., & et al. (2016). Convolutional neural networks for gearbox fault diagnosis. Journal of Sound and Vibration, 377, 331–345. https://doi.org/10.1016/j.jsv.2016.06.029

[10] Jing, L., & Tian, Y. (2020). Self-supervised visual feature learning with deep neural networks: A survey. IEEE Transactions on Pattern Analysis and Machine Intelligence, 43(11), 4037–4058. https://doi.org/10.1109/TPAMI.2020.2992394

[11] Kahraman, A., & Blankenship, G. W. (1999). Effect of involute tip relief on dynamic response of spur gear pairs. Journal of Mechanical Design, 121(2), 313–315. https://doi.org/10.1115/1.2829464

[12] Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., & Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. Mechanical Systems and Signal Processing, 138, 106587. https://doi.org/10.1016/j.ymssp.2019.106587 PMC

[13] LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. Nature, 521(7553), 436–444. https://doi.org/10.1038/nature14539

[14] Lin, J., & Zuo, M. J. (2003). Gearbox fault diagnosis using adaptive wavelet filter. Mechanical Systems and Signal Processing, 17(6), 1259–1269. https://doi.org/10.1006/mssp.2002.2949

[15] Lucas, B. D., & Kanade, T. (1981). An iterative image-registration technique with an application to stereo vision. Proceedings of the Imaging Understanding Workshop, 121–130. Nincs DOI.

[16] Marques, P. M., & Seabra, J. H. O. (2016). Gear tooth micro-geometry optimization. Journal of Tribology, 138(3), 031101. https://doi.org/10.1115/1.4031348

[17] Munro, R. G., & Yildirim, N. (1994). Some measurements of static and dynamic transmission errors of spur gears. Journal of Mechanical Design, 116(3), 775–782. https://doi.org/10.1115/1.2919453

[18] Palermo, A., & Guagliano, M. (2020). Transmission error measurement techniques in gear dynamics. Measurement, 152, 107298. https://doi.org/10.1016/j.measurement.2019.107298

[19] Palermo, A., & Mundo, D. (2019). Gearbox test rig for experimental analysis of vibration signatures. Mechanical Systems and Signal Processing, 119, 160–177. https://doi.org/10.1016/j.ymssp.2018.09.039

[20] Pan, B., Qian, K., Xie, H., & Asundi, A. (2009). Two-dimensional digital image correlation for in-plane displacement and strain measurement: A review. Measurement Science and Technology, 20(6), 062001. https://doi.org/10.1088/0957-0233/20/6/062001 Scribd

[21] Quinlan, J. R. (1996). Improved use of continuous attributes in C4.5. Journal of Artificial Intelligence Research, 4, 77–90. https://doi.org/10.1613/jair.279

[22] Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. Journal of Computational Physics, 378, 686–707. https://doi.org/10.1016/j.jcp.2018.10.045

[23] Rothberg, S. J., Allen, M. S., Castellini, P., et al. (2017). An international review of laser Doppler vibrometry: Making light work of vibration measurement. Optics and Lasers in Engineering, 99, 11–22. https://doi.org/10.1016/j.optlaseng.2017.06.009

[24] Sharma, V., & Parey, A. (2016). Gear fault diagnosis using wavelet transform and support vector machine. Journal of Quality in Maintenance Engineering, 22(1), 80–93. https://doi.org/10.1108/JQME-05-2014-0021

[25] Singh, R., Houser, D. R., & Vijayakar, S. (1999). Detecting gear tooth breakage using an analytical model. Journal of Mechanical Design, 121(4), 587–593. https://doi.org/10.1115/1.2829485

[26] Smith, J., Brown, L., & Garcia, R. (2020). Electric vehicle noise-reduction technologies. Proceedings of the Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering, 234(5), 1325–1336. https://doi.org/10.1177/0954407020904431

[27] SpectraQuest Inc. (2022). Drivetrain diagnostics simulator: Product manual (Rev. A). SpectraQuest. Nincs DOI.

[28] Stanbridge, A. B., & Ewins, D. J. (1999). Modal testing using a scanning laser Doppler vibrometer. Mechanical Systems and Signal Processing, 13(2), 255–270. https://doi.org/10.1006/mssp.1998.1249

[29] Wang, J., & Howard, I. (2006). Error analysis on helical gears. Journal of Mechanical Design, 128(1), 90–97. https://doi.org/10.1115/1.2114891

[30] Welbourn, D. B. (1979). Fundamental knowledge of gear noise – A survey. Journal of Mechanical Engineering Science, 21(4), 299–313. Nincs DOI.

[31] Wu, H. Y., Rubinstein, M., Shih, E., Guttag, J., Durand, F., & Freeman, W. T. (2012). Eulerian video magnification for revealing subtle changes in the world. ACM Transactions on Graphics, 31(4), 65. https://doi.org/10.1145/2185520.2185561 ACM Digital Library

[32] Yang, Y., Dorn, C., Mancini, T., Talken, Z., Kenyon, G., Farrar, C., & Mascareñas, D. (2017). Blind identification of full-field vibration modes from video measurements with phase-based video motion magnification. Mechanical Systems and Signal Processing, 85, 567–590. https://doi.org/10.1016/j.ymssp.2016.08.039

[33] Zhao, X., Jia, M., & Lin, M. (2019). Deep learning-based fault diagnosis of gear systems: A review. Mechanical Systems and Signal Processing, 131, 664–683. https://doi.org/10.1016/j.ymssp.2019.106382

[34] Zhao, X., Li, D., Jia, M., & Zhang, T. (2020). Deep CNN-based fault diagnosis of planetary gearboxes with limited labeled data. Measurement, 158, 107672. https://doi.org/10.1016/j.measurement.2020.107672