Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 257 (2025) 896–903

Procedia Computer Science

www.elsevier.com/locate/procedia

The 8th International Conference on Emerging Data and Industry (EDI40)
April 22-24, 2025, Patras, Greece

Predictive Maintenance in Industry 4.0: A Review of Data Processing Methods.

Ietezaz ul Hassan[a], Krishna Panduru*, Prof Joseph Walsh

IMaR Research Centre, Munster Technological University, Co Kerry, V92 CX88, Ireland

Abstract

Industries require a revolution with the aim to improve productivity, sustainability, reduce costs, achieve customer satisfaction, and adopt emerging technologies. The current industrial revolution, known as Industry 4.0, is defined by smart technologies, which include robotics, big data, artificial intelligence (AI), and the internet of things (IoT). A breakdown in industrial process has consequences in terms of safety, productivity, and efficiency. Predictive maintenance is a cornerstone of Industry 4.0, which predicts the remaining useful life of equipment's, devices, and machines using condition monitoring, data analytics, and machine learning (ML). This article reviews a number of methods, including signal analysis, statistical analysis, and artificial intelligence-based methods, that can be used for performing predictive maintenance on the collected data from machines or equipment's. The signal processing and statistical analysis methods require domain knowledge, but the AI methods require labelled data (most of the data is healthy and lacks faulty data), which is a challenging task.

Keywords: Condition monitoring, Predictive maintenace, Non-invasive testing, Next generation heavy machinery, Smart machines.

1. Introduction

Industry 4.0, the fourth industrial revolution, is focused on the integration of digital technology into industrial and manufacturing processes, including automation, big data, smart systems, AI, and the IoT [1]. The fifth industrial revolution (also known as industry 5.0) continues to expand the idea of industry 4.0 by introducing human-machine

* Corresponding author. Tel.: +0-000-000-0000 ; fax: +0-000-000-0000 .
E-mail address: Krishna.Panduru@mtu.ie

10.1016/j.procs.2025.03.115

cooperation with the aim of customising production and sustainable practices [2]. The current industrial revolution is known as Industry 4.0; however, the fifth industrial revolution (Industry 5.0) is also in its early stages with a few developments. Industry 4.0 offers numerous advantages to business, economy, and society by integrating advanced technologies into industrial processes [3]. It improves efficiency and production by automation, real-time monitoring, and process optimisation. It also reduces costs by allowing predictive maintenance, energy optimisation, and resource efficiency.

Emerging data is generated by new and evolving technologies, such as societal activities and advanced industrial practices [4]. It is primarily collected through IoT devices, social media platforms, autonomous systems, and other digital systems, with high volumes, velocity, accuracy, and variety [5]. Industry 4.0 and emerging data are closely linked because industry 4.0 relies on data to improve efficiency, innovation, and productivity [6]. Emerging data and industry 4.0 are serving as catalysts for performing predictive maintenance. IoT sensors can generate continuous streams of data describing the status of equipment, tools, devices, or machines, such as temperature, pressure level, and vibration responses [7]. Industry 4.0 supports predictive maintenance systems by analyzing collected data to predict the remaining useful life (RUL) of equipment, reducing downtime and maintenance costs.

Machines, systems, equipment, and gadgets can break down for many reasons, including wear and tear, defective components, environmental conditions, and poor maintenance. After a breakdown, the maintenance team repairs the defective component that caused the breakdown, known as defective maintenance [8]. Defective maintenance has some limitations, such as increased downtime and high repair costs. Another alternative approach that reduces downtime is preventive maintenance, which keeps a regular inspection and replacement of equipment at scheduled intervals. But the preventive maintenance has a limitation of over maintenance, in which the components are replaced even they do not need to be replaced [9]. Predictive maintenance is a method that uses condition monitoring and data analytics to predict an equipment's RUL. It addresses the challenges brought by defective and preventive maintenance [10] and serves as a cornerstone of Industry 4.0 by converting traditional maintenance methods using real-time data, smart technologies, and advanced analytics.

Condition monitoring can be performed by collecting real-time data from equipment, machines, and tools, such as vibration, temperature, pressure, oil, and other data [11]. Several methods, such as signal processing, statistics-based techniques, and artificial intelligence-based techniques, can process the collected data. This article reviews the methods used to process the collected data to allow predictive maintenance.

2. Signal Processing

Signal processing-based methods are widely used for extracting meaningful information from data collected from machines and equipment, especially for performing condition monitoring [12]. Signal processing-based methods can use filters, transformations, and in-depth analysis to find data trends, patterns, and outliers. The methods may be the time domain, frequency domain, or advanced signal processing methods.

In signal processing, the time domain analysis is the simplest method [13] in which the signal amplitude is varied over time. The core features of a time domain signal are amplitude, mean, root mean square (RMS), zero crossing rate, and time domain averaging. The signal amplitude can represent the highest value of a signal in the time domain. If the amplitude of a signal crosses a threshold, it can indicate the presence of something wrong [14]. The average value of a signal over time is known as the mean value of the signal and can detect the bias in the signal. It can be used in condition monitoring by applying thresholding logic. For example, if the mean value exceeds a threshold, it can indicate the presence of misalignment, an imbalanced rotor, or other defects [15]. The root mean square (RMS) value of a signal can be used to measure the signal's effectiveness and detect the changes in both the amplitude and duration of the signal. A high RMS value can indicate defective conditions in machinery components, such as worn or misaligned bearings [15]. A zero-crossing rate is a measure that indicates the frequent oscillations in the signal caused by the speed of the rotating gear [16]. A fault in the rotating components, such as a bearing, gear, or loosened bolts, can be detected through the shift in zero-crossing rate. The time domain averaging combines many signal repetitions to reduce noise while highlighting the patterns or trends in the signal [17]. It is useful for improving the quality of noisy data, which is common in vibration analysis and acoustic emission testing. In comparison, autocorrelation is a metric that ensures that a signal is periodic [18]. If the periodicity decreases in a wind turbine vibration signal, it is an early-stage gear wear sign. The envelope detection is a method that separates the high-frequency components from the signal, which are necessary for fault detection [19]. For example, a developing crack can be detected by separating the high-frequency components in the vibration signal generated from an industrial motor.

A signal can be converted from the time domain to the frequency domain using methods such as Fourier transform and Fast Fourier transform, which helps in understanding the frequency components of the signal. The collected data from machinery in the form of signals can be processed in the frequency domain for condition monitoring purposes using power spectral density (PSD), Fourier transform [20], etc. The Fourier transform helps in the detection of the dominant frequencies in the vibration data collected by the rotating machinery [21], which is associated with individual components such as bearings, gears, and shafts. Meanwhile, if there is any deviation from the standard frequencies, it can indicate an issue [22]. The distribution of power across the frequencies can be illustrated by the PSD [23]. It can help detect frequencies representing the most energy and thus make it useful for fault detection in materials such as gear problems, bearing wear, etc.

Some signal processing methods can combine time and frequency domain information, providing a more accurate method in signal processing [8]. The spectrogram, wavelet transform, Continuous Wavelet Transform (CWT), and Discrete Wavelet Transform (DWT) are all popular time-frequency domain processing methods [24]. Some issues, such as cracks, gradual machine wear, and other factors, can create transient, high-frequency bursts that occur for a short time and can easily be identified in a spectrogram. The spectrogram is useful for analysing the collected signals for performing condition monitoring [29]. Meanwhile, wavelet transform is best suited for detecting sudden shifts or transients in signals caused by cracks or impacts in materials [30]. For example, in a wind turbine, the wavelet transform can detect a gradual rise in high-frequency vibration signals caused by a minor crack in the gearbox [31]. On the other hand, CWT is helpful when the signal has both low and high frequency components [32], changing over time. For example, in a compressor, a continuous wavelet transform can identify a bearing's constant deterioration by corresponding to high-frequency components. Similarly, if there are any misalignment issues with a wind turbine, the Short Time Fourier Transform (STFT) may indicate the dominant frequencies associated with the shaft's rotation over time [33]. These signal processing-based methods are outlined in Figure 1.

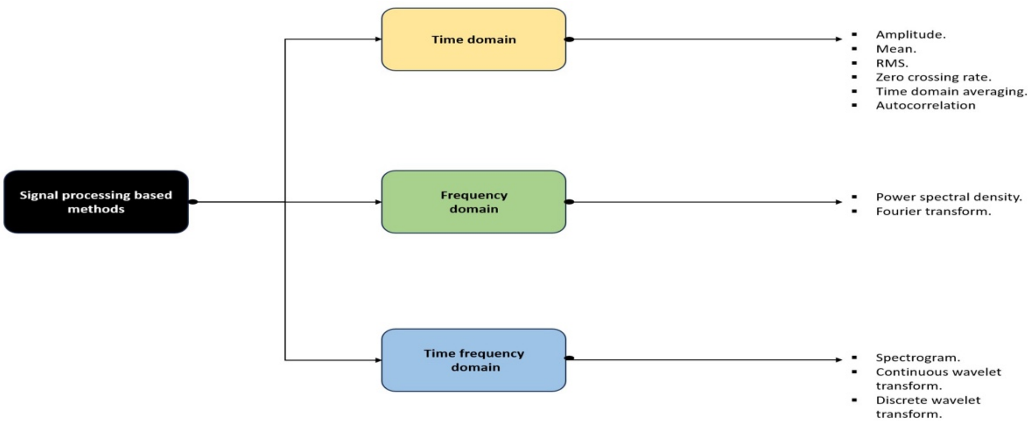

Figure 1. Classification of signal processing methods used in condition monitoring.

3. Statistical Analysis Based Methods

Data collected by condition monitoring methods for performing predictive maintenance can also be processed statistically [34]. The statistical analysis method extracts important features from data by applying mathematical models to analyze correlations, detect outliers, and evaluate machinery health [35]. Statistical analysis allows us to perform descriptive statistics, anomaly detection, and regression analysis.

A dataset's main characteristics can be summarised by its central tendency, dispersion, and distribution. Such measures provide an overview of a system's behavior under normal environments [36]. The median, mean, and mode measure central tendency, while variance, standard deviation, skewness, and kurtosis measure dispersion and distribution. Monitoring these parameters over time allows for the identification of trends and possible shifts in machine behavior. For example, if the mean value of a vibration level crosses a certain threshold, it may indicate an early-stage wear or imbalance. There is also statistical process control (SPC) charts used in descriptive statistics to monitor and control processes [37]. A control limit is defined in SPC charts, and when the attribute value exceeds the mean of these limits, it denotes a sign for an early warning. For example, if the amplitude of the vibration signal exceeds a threshold (lower or higher threshold), it can indicate that the equipment, such as gear or bearing, is starting to wear out.

Statistical methods, like threshold-based and outlier detection, are also used to detect anomalies. These outliers could indicate defects in machinery, materials, or objects. In threshold-based detection, when the value (corresponding to the attribute, which is under monitoring) exceeds a certain threshold, it can indicate a fault, such as an imbalance or a crack in a rotating gear [38]. A z-score-like outlier detection method can be used to detect outliers in the collected data, which can indicate unusual behavior at an early stage. For example, an outlier in sound wave (which might be acoustic emission data or ultrasonic testing data) can indicate a crack or internal defect [39]. On the other hand, regression analysis allows us to find the relationship between variables. Predictive maintenance is used to correspond machine temperature, acoustic emission levels, and vibration to operational conditions or possible failures [40]. Linear regression is used for studying the relationship between machine running time and level of wear. The slope of the regression line shows the wear rate [41].

4. AI-Based Methods

Artificial intelligence-based methods are useful for performing predictive maintenance on data collected via condition monitoring. These methods allow ML models to learn from data, find trends, detect anomalies, and predict equipment RUL without being explicitly programmed [42]. ML-based models are used to analyse the collected data for detecting patterns regarding the condition of materials, equipment, and machines. These models can detect faults, predict breakdowns, and improve maintenance schedules [43].

ML models can be classified as supervised, unsupervised, or semi-supervised learning models as reviewed in TABLE 2. Supervised models can be used for classification and regression problems. Supervised machine learning models map each input to its matching output (a status such as defective or healthy). Unsupervised learning is used when there is no labeled data. In that case, the model detects patterns and clusters data in groups without any guidance. Unsupervised learning models are primarily used for anomaly detection. An unsupervised learning model can detect anomalies in a signal's waveform that can show a hidden defect, such as a crack, during ultrasonic testing [44]. On the other hand, semi-supervised learning can be used when there is a large amount of unlabeled data but a limited amount of labelled data. Self-training models and graph-based algorithms are the most often used methods for semi-supervised learning. Self-training models are initially trained on labelled data, followed by unlabeled data predictions. After generating predictions, it integrates predictions with high confidence into the training dataset [45]. On the other hand, labels are generated in graph-based algorithms via a network of connected data points, by considering the similarities with labelled data.

Table 1: An overview of traditional machine learning methods for condition monitoring

ML TYPE	Technique	Description	Refs
Supervised learning	Classification	In classification problems, the models are initially trained to distinguish data between specific categories, such as normal, degraded, or failed states. Some well known algorithms used in this category are ML classifiers including decision tree, SVM, random forest etc.	[46]
	Regression	In regression problems, these models are used to predict continuous values, such as wear levels or the remaining useful life (RUL) value, for example linear regression model.	[47]
Unsupervised learning	Anomaly detection	Unsupervised model can detect anomalies in data, which represents early signs of failures or defects, for example, one class support vector machine.	[48]
	Clustering	Clustering algorithms group data in such a way that data within a group is similar to one another but different between clusters. K-mean clustering, principle component analysis (PCA), and auto encoders are all well-known unsupervised methods for processing data to allow predictive maintenance.	[49]
Semi supervised learning	Self training	Semi-supervised learning is commonly used for performing predictive maintenance, because labelling defects are costly and time-consuming. This is achieved by combining a large number of labelled data with a small number of labelled data. Zero shot learning and few shot learning, are its well-known examples.	[50]

Deep learning (DL), a subset of machine learning, analyses data using neural networks with many different layers. These models can be very useful for analyzing high-dimensional, complicated data, such as signals, images, or time series data obtained from sensors [51]. Convolutional neural network (CNN), recurrent neural network (RNN), and auto-encoders are some of the popular neural networks, and is very beneficial for processing condition monitoring data for allowing predictive maintenance. These neural network-based models are summarized in TABLE 2.

Table 2: An overview of neural networks for condition monitoring

Refs	DL Model	Description
[52]	CNN	Convolutional neural network (CNN) are well-suited for processing data such as signals, images. They are mostly used in computer vision to process data such as thermography, ultrasonic, or x-ray images. A CNN model can be used to detect tiny defects in materials that are invisible to the human eye.
[53]	RNN	RNNs and long short term memory (LSTM) are designed for processing sequential data. They are most suited for processing time series data, such as acoustic emission signals or vibrations recorded over time. The LSTM can be used to predict the RUL based on analyzing the collected signals. LSTM can learn temporal relationships from data, which allows them to detect anomalies. The LSTM model can also be used for predicting the future vibration pattern of a rotating machine.
[54]	Autoencoder	Autoencoders are unsupervised neural networks that learn, compress, and recreate data. If there is some variation between the input and output, it is classified as an anomaly, making it useful for defect detection. Auto-encoders are usually trained to create healthy data. If a signal is unhealthy, the reconstruction error will be high, indicating an anomaly or outlier. It can also be used to remove outliers from data, which allows more accurate analysis. For example, during acoustic emission testing, an auto-encoder is trained on normal sound waves. However, if the machine produces strange sounds, the auto-encoder reconstruction error will be high, which will indicate an issue.

5. Conclusion

Condition monitoring plays a vital role in improving the useful life of equipment, machines, and devices. Several data types, such as vibration, temperature, pressure, oil analysis, etc., can be used for condition monitoring and condition indicators to allow predictive maintenance in heavy machinery. These data processing methods can be classified as signal processing-based methods, statistical analysis-based methods, or artificial intelligence-based methods.

Signal processing methods can be further grouped as time-domain-based processing methods, frequency-domain-based processing methods, and time-frequency domain-based processing methods. Time domain processing methods easily detect noise and transient events, possess a low computational complexity, and are also more interpretable. Whereas the frequency domain-based processing methods allow for a more detailed picture of frequency analysis and fault patterns. But the time-frequency domain processing methods allow for handling non-stationary signals and allow for transient detections. These methods also have limitations, such as time domain methods being limited with frequency information and noise sensitivity. It can be used for basic monitoring, such as monitoring RMS, kurtosis, and amplitude. While the frequency domain processing methods lack time information & only allow for static analysis, and can be used for detecting repetitive faults. Similarly, the time-frequency domain processing methods are usually more costly and have complex interpretation, but they allow for early-stage fault detection, such as wavelet transform.

The statistical analysis-based methods involve monitoring some statistical features and then applying thresholding, for example, average value, mean, mode, variance, etc. The AI-based methods can be classified as either ML or DL based methods used for classification and clustering purposes. The major challenge associated with AI-based methods used for predictive maintenance is data labelling. In reality, there are more healthy samples and fewer faulty samples available. As a result of such data, the resulting model will be biased. This area can be improved further by exploring variational autoencoders, generative adversarial networks GAN), zero-shot learning, and few-shot learning for developing AI-based models for fault prediction trained on healthy data.

Acknowledgements

This paper would not be made possible without the help of the IMaR team at Munster Technological University, Co Kerry.

This work was supported, in part, by Science Foundation Ireland grant 13/RC/2094_P2 and co-funded under the European Regional Development Fund through the Southern & Eastern Regional Operational Programme to Lero-the Science Foundation Ireland Research Centre for Software.

References

[1] Ghobakhloo, M. Industry 4.0, digitization, and opportunities for sustainability. Journal of cleaner production 2020, 252, 119869.

[2] Huang, S.; Wang, B.; Li, X.; Zheng, P.; Mourtzis, D.; Wang, L. Industry 5.0 and Society 5.0—Comparison, complementation and co-evolution. Journal of manufacturing systems 2022, 64, 424–428

[3] Eslami, M.H.; Jafari, H.; Achtenhagen, L.; Carlbäck, J.; Wong, A. Financial performance and supply chain dynamic capabilities the Moderating Role of Industry 4.0 technologies. International Journal of Production Research 2024, 62, 8092–8109

[4] Osipov, V.S.; Semenova, G.N.; Adamova, G.A.; Larina, L.B. Industry 4.0 as the vector of industrial development in emerging economies in the age of intellectual machines: a financial aspect. International Journal of Economic Policy in Emerging Economies 2024, 19, 381–392

[5] Rath, K.C.; Khang, A.; Roy, D. The role of Internet of Things (IoT) technology in Industry 4.0 economy. In Advanced IoT technologies and applications in the industry 4.0 digital economy; CRC Press, 2024; pp. 1–28.

[6] Attaran, S.; Attaran, M.; Celik, B.G. Digital Twins and Industrial Internet of Things: Uncovering operational intelligence in industry 4.0. Decision Analytics Journal 2024, 10, 100398.

[7] Mallioris, P.; Aivazidou, E.; Bechtsis, D. Predictive maintenance in Industry 4.0: A systematic multi-sector mapping. CIRP Journal of Manufacturing Science and Technology 2024, 50, 80–103.

[8] Hassan, I.U.; Panduru, K.; Walsh, J. Review of Data Processing Methods Used in Predictive Maintenance for Next Generation Heavy Machinery. Data 2024, 9, 69.

[9] Wu, C.; Pan, R.; Zhao, X.; Wang, X. Designing preventive maintenance for multi-state systems with performance sharing Reliability Engineering & System Safety 2024, 241, 109661

[10] Es-sakali, N.; Zoubir, Z.; Kaitouni, S.I.; Mghazli, M.O.; Cherkaoui, M.; Pfafferott, J. Advanced predictive maintenance and fault diagnosis strategy for enhanced HVAC efficiency in buildings. Applied Thermal Engineering 2024, 254, 123910.

[11] Hassan, I.U.; Panduru, K.; Walsh, J. An In-Depth Study of Vibration Sensors for Condition Monitoring. Sensors 2024, 24, 740.

[12] M. Vejdannik, A. Sadr, V. H. C. de Albuquerque, and J. M. R. Tavares, "Signal processing for nde," Handbook of advanced non-destructive evaluation, 2018.

[13] F. P. G. Marquez and A. M. P. Chac ´ on, "A review of non-destructive testing on wind turbines blades," ´ Renewable Energy, vol. 161, pp. 998–1010, 2020.

[14] I. Lysenko, V. Eremenko, Y. Kuts, A. Protasov, and V. Uchanin, "Advanced signal processing methods for inspection of aircraft structural materials," Transactions on Aerospace research, vol. 2020, no. 2, pp. 27–35, 2020.

[15] W. Bi, Y. Zhao, R. Shen, B. Li, S. Hu, and S. Ge, "Multi-frequency gpr data fusion and its application in ndt," NDT & E International, vol. 115, p. 102289, 2020.

[16] Z. Fang, R. Su, L. Hu, and X. Fu, "A simple and easy-implemented time-of-flight determination method for liquid ultrasonic flow meters based on ultrasonic signal onset detection and multiple-zero-crossing technique," Measurement, vol. 168, p. 108398, 2021.

[17] N. Laroche, S. Bourguignon, E. Carcreff, J. Idier, and A. Duclos, "An inverse approach for ultrasonic imaging from full matrix capture data: Application to resolution enhancement in ndt," IEEE transactions on ultrasonics, ferroelectrics, and frequency control, vol. 67, no. 9, pp. 1877–1887, 2020.

[18] H. Zhang, J. Zhang, G. Fan, H. Zhang, W. Zhu, Q. Zhu, and R. Zheng, "The auto-correlation of ultrasonic lamb wave phased array data for damage detection," Metals, vol. 9, no. 6, p. 666, 2019.

[19] Y. El Masri and T. Rakha, "A scoping review of non-destructive testing (ndt) techniques in building performance diagnostic inspections," Construction and Building Materials, vol. 265, p. 120542, 2020.

[20] Ye, C.; Wang, Y.; Wang, M.; Udpa, L.; Udpa, S.S. Frequency domain analysis of magnetic field images obtained using TMR array sensors for subsurface defect detection and quantification. NDT & E International 2020, 116, 102284.

[21] Altaf, M.; Uzair, M.; Naeem, M.; Ahmad, A.; Badshah, S.; Shah, J.A.; Anjum, A. Automatic and efficient fault detection in rotating machinery using sound signals. Acoustics Australia 2019, 47, 125–139

[22] Randall, R.B. Vibration-based condition monitoring: industrial, automotive and aerospace applications; John Wiley & Sons, 2021.

[23] Mutlib, N.K.; Ismael, M.N.; Baharom, S. Damage detection in CFST column by simulation of ultrasonic waves using STFT-based spectrogram and welch power spectral density estimate. Structural Durability & Health Monitoring 2021, 15, 227.

[24] A. Akan and O. K. Cura, "Time–frequency signal processing: Today and future," Digital Signal Processing, vol. 119, p. 103216, 2021

[25] C. Guo, D. Fang, C. Wang, T. Qin, Z. Liu, Z. Liu, and Y. Zhang, "Ultrasonic flaw detection spectrogram characterization of vermicular graphite cast iron engine cylinder head," in Journal of Physics: conference series, vol. 1996, no. 1. IOP Publishing, 2021, p. 012005.

[26] M. Knak, E. Wojtczak, and M. Rucka, "Non-destructive diagnostics of concrete beams strengthened with steel plates using modal analysis and wavelet transform," Materials, vol. 14, no. 11, p. 3014, 2021

[27] M. S. Hameed, Z. Li, and K. Zheng, "Damage detection method based on continuous wavelet transformation of lamb wave signals," Applied Sciences, vol. 10, no. 23, p. 8610, 2020.

[28] N. H. Shrifan, M. F. Akbar, and N. A. M. Isa, "Maximal overlap discrete wavelet-packet transform aided microwave nondestructive testing," NDT & E International, vol. 119, p. 102414, 2021

[29] I. Fernandez-Osete, D. Bermejo, X. Ayneto-Gubert, and X. Escaler, "Review of the uses of acoustic emissions in monitoring cavitation erosion ´ and crack propagation," Foundations, vol. 4, no. 1, pp. 114–133, 2024.

[30] M. Knak, E. Wojtczak, and M. Rucka, "Non-destructive diagnostics of concrete beams strengthened with steel plates using modal analysis and wavelet transform," Materials, vol. 14, no. 11, p. 3014, 2021.

[31] A. A. Ogaili, M. N. Hamzah, A. A. Jaber, and E. Ghane, "Application of discrete wavelet transform for condition monitoring and fault detection in wind turbine blades: an experimental study," Engineering and Technology Journal, vol. 42, no. 1, pp. 104–116, 2024.

[32] C. Huang, Y. Liao, Q. Li, H. Yu, J. Liao, and C.-C. Chen, "Assessment of health of friction pair in sliding bearing using vibration sensor and continuous wavelet transform time-frequency images." Sensors & Materials, vol. 32, 2020.

[33] M. Alotaibi, B. Honarvar Shakibaei Asli, and M. Khan, "Non-invasive inspections: A review on methods and tools," Sensors, vol. 21, no. 24, p. 8474, 2021.

[34] H. Yun, R. Rayhana, S. Pant, M. Genest, and Z. Liu, "Nonlinear ultrasonic testing and data analytics for damage characterization: A review," Measurement, vol. 186, p. 110155, 2021.

[35] S. Hassani and U. Dackermann, "A systematic review of advanced sensor technologies for non-destructive testing and structural health monitoring," Sensors, vol. 23, no. 4, p. 2204, 2023.

[36] P. Guzik and B. Wieckowska, "Data distribution analysis–a preliminary approach to quantitative data in biomedical research," Journal of Medical Science, vol. 92, no. 2, pp. e869–e869, 2023.

[37] Y. Attaqwa, A. Hamidiyah, and F. A. Ekoanindyo, "Product quality control analysis with statistical process control (spc) method in weaving section (case study pt. i)," International Journal of Computer and Information System (IJCIS), vol. 2, no. 3, pp. 86–92, 2021

[38] Y. Chen, S. Schmidt, P. S. Heyns, and M. J. Zuo, "A time series model-based method for gear tooth crack detection and severity assessment under random speed variation," Mechanical Systems and Signal Processing, vol. 156, p. 107605, 2021.

[39] J. K. Shah, H. Wang, and S. El-Hawwat, "Detection of internal crack growth in polyethylene pipe using guided wave ultrasonic testing," Earthquake Engineering and Engineering Vibration, vol. 23, no. 2, pp. 319–329, 2024.

[40] T. Zvirblis, D. Vainorius, J. Matijo ˇ sius, K. Kilikevi ˇ cien ˇ e, A. Rimkus, ˙ A. Bereczky, K. Luk ´ acs, and A. Kilikevi ´ cius, "Engine vibration data ˇ increases prognosis accuracy on emission loads: a novel statistical regressions algorithm approach for vibration analysis in time domain," Symmetry, vol. 13, no. 7, p. 1234, 2021

[41] J. Sha, M. Fan, and B. Ye, "Intelligent hardness prediction of bearing rings using pulsed eddy current testing," IEEE Sensors Journal, vol. 22, no. 23, pp. 23 320–23 327, 2022

[42] Y. Himeur, K. Ghanem, A. Alsalemi, F. Bensaali, and A. Amira, "Artificial intelligence based anomaly detection of energy consumption in buildings: A review, current trends and new perspectives," Applied Energy, vol. 287, p. 116601, 2021

[43] T. R. Mohan, J. P. Roselyn, R. A. Uthra, D. Devaraj, and K. Umachandran, "Intelligent machine learning based total productive maintenance approach for achieving zero downtime in industrial machinery," Computers & Industrial Engineering, vol. 157, p. 107267, 2021.

[44] M. G. Mohammadi, D. Mahmoud, and M. Elbestawi, "On the application of machine learning for defect detection in l-pbf additive manufacturing," Optics & Laser Technology, vol. 143, p. 107338, 2021

[45] Y. Ding, J. Zhuang, P. Ding, and M. Jia, "Self-supervised pretraining via contrast learning for intelligent incipient fault detection of bearings," Reliability Engineering & System Safety, vol. 218, p. 108126, 2022.

[46] Q. Chen, J. Cao, and S. Zhu, "Data-driven monitoring and predictive maintenance for engineering structures: Technologies, implementation challenges, and future directions," IEEE Internet of Things Journal, vol. 10, no. 16, pp. 14 527–14 551, 2023.

[47] B. Ellis, P. S. Heyns, and S. Schmidt, "A hybrid framework for remaining useful life estimation of turbomachine rotor blades," Mechanical Systems and Signal Processing, vol. 170, p. 108805, 2022.

[48] P. Tanuska, L. Spendla, M. Kebisek, R. Duris, and M. Stremy, "Smart anomaly detection and prediction for assembly process maintenance in compliance with industry 4.0," Sensors, vol. 21, no. 7, p. 2376, 2021.

[49] N. H. Shrifan, G. N. Jawad, N. A. M. Isa, and M. F. Akbar, "Microwave nondestructive testing for defect detection in composites based on k-means clustering algorithm," IEEE Access, vol. 9, pp. 4820–4828, 2020.

[50] Y.-G. Yoon, C.-M. Kim, and T.-K. Oh, "A study on the applicability of the impact-echo test using semi-supervised learning based on dynamic preconditions," Sensors, vol. 22, no. 15, p. 5484, 2022.

[51] O. Serradilla, E. Zugasti, J. Rodriguez, and U. Zurutuza, "Deep learning models for predictive maintenance: a survey, comparison, challenges and prospects," Applied Intelligence, vol. 52, no. 10, pp. 10 934–10 964, 2022.

[52] W. Wang, J. Chen, G. Han, X. Shi, and G. Qian, "Application of object detection algorithms in non-destructive testing of pressure equipment: A review," Sensors, vol. 24, no. 18, p. 5944, 2024

[53] R. G. Nascimento and F. A. Viana, "Cumulative damage modeling with recurrent neural networks," AIAA Journal, vol. 58, no. 12, pp. 5459– 5471, 2020.

[54] Y. Fan, R. Rayhana, Y. Cao, C. Mandache, and Z. Liu, "A multimodal fusion-based autoencoder for nondestructive evaluation of aircraft structures," in NDE 4.0, Predictive Maintenance, Communication, and Energy Systems: The Digital Transformation of NDE, vol. 12489. SPIE, 2023, pp. 110–120.