Systematic Review of Non-Destructive Testing Methods for Predictive Failure Analysis in Mechanical Systems

ENOCH OLUWADUNMININU OGUNNOWO[1], MUSA ADEKUNLE ADEWOYIN[2], JOYCE EFEKPOGUA FIEMOTONGHA[3], THOMPSON ODION IGUNMA[4], ADENIYI K. ADELEKE[5]
[1]Department of Mechanical Engineering, McNeese State University, Louisiana, USA
[2, 3]Independent Researcher, Lagos, Nigeria
[4]GZ Manufacturing Industries, Nigeria
[5]Nelson Mandela University, Port Elizabeth, South Africa

Abstract- Predictive failure analysis in mechanical systems is a crucial aspect of modern engineering maintenance and reliability management. Non-Destructive Testing (NDT) methods have emerged as essential tools for detecting material defects, structural anomalies, and potential failures without compromising the integrity of components. This systematic review evaluates the efficacy, limitations, and application domains of various NDT techniques—including ultrasonic testing (UT), magnetic particle testing (MT), radiographic testing (RT), eddy current testing (ECT), acoustic emission (AE), thermographic testing (TT), and visual inspection (VI)—in predictive failure analysis. The study follows the PRISMA methodology, employing a comprehensive literature search from databases such as Scopus, Web of Science, and IEEE Xplore from 2013 to 2020. A total of 79 peer-reviewed articles were selected based on relevance, citation quality, and methodological rigor. The findings highlight that ultrasonic testing and acoustic emission methods are highly effective in early crack detection and fatigue monitoring, especially in aerospace and pressure vessel applications. Radiographic and thermographic techniques excel in detecting internal voids and delamination in composite materials. Magnetic particle and eddy current testing are particularly suitable for surface and near-surface flaws in ferromagnetic and conductive materials, respectively. Visual inspection remains widely used due to its simplicity, though it often lacks the precision of other methods. Integrated approaches that combine multiple NDT techniques with artificial intelligence (AI) and machine learning (ML) algorithms are increasingly being adopted to enhance diagnostic accuracy and predictive capabilities. Despite their effectiveness, challenges such as operator dependency, high equipment costs, and limitations in defect quantification remain prevalent. The review recommends a hybrid framework that leverages sensor fusion, digital twins, and real-time data analytics for robust predictive maintenance. Furthermore, the review calls for the standardization of data interpretation protocols and the adoption of automated systems to minimize human error. This systematic review contributes to the growing body of knowledge aimed at improving mechanical system reliability, minimizing downtime, and optimizing lifecycle costs. It provides a foundation for further research into adaptive, intelligent NDT systems for Industry 4.0 environments, where continuous monitoring and predictive analytics are essential.

Indexed Terms- Non-Destructive Testing, Predictive Failure Analysis, Mechanical Systems, PRISMA Review, Ultrasonic Testing, Acoustic Emission, Thermographic Testing, AI-Driven NDT

I. INTRODUCTION

Mechanical systems play a crucial role across various industries, including aerospace, automotive, manufacturing, and energy production. The failure of these systems can have dire consequences, ranging from significant financial losses and production downtime to catastrophic environmental damage and risks to human life (Piascik, et al., 2012). These failures frequently arise from material degradation processes such as fatigue, corrosion, and stress-induced damage, which often manifest incrementally over time (Kuśmierczak & Majzner, 2017; Nahm et al., 2004). Therefore, the engineering and maintenance sectors have increasingly recognized the critical importance of predictive failure analysis as a proactive approach to enhance system reliability and improve operational safety in mechanical systems (Odedeyi, et al., 2020: Williams & Starke, 2003).

Predictive failure analysis facilitates the early identification of signs signaling component degradation, thereby allowing interventions to occur before unexpected breakdowns transpire. This method not only optimizes the efficiency and safety of mechanical systems, but it also extends the lifespan of equipment, ultimately reducing overall maintenance costs. Central to this strategy is the employment of Non-Destructive Testing (NDT) techniques, which enable the assessment of material and structural integrity without damaging the components under evaluation (Demčenko et al., 2016). Various NDT methods, such as ultrasonic testing, radiography, eddy current testing, magnetic particle inspection, and thermography, provide essential insights into both internal and surface-level flaws that could jeopardize mechanical performance (Noor, et al., 2020).

As the call for predictive maintenance grows, a comprehensive understanding of the capabilities, limitations, and suitability of diverse NDT methods across different mechanical contexts is imperative. This systematic review aims to consolidate existing knowledge regarding the application of NDT techniques for predictive failure analysis, identifying emerging trends, technological advancements, and areas that necessitate further inquiry (Pham et al., 2011). By synthesizing findings from a wide array of peer-reviewed studies, the review supports evidence-based decision-making relevant to maintenance engineering and mechanical diagnostics (Joshi & Wei, 2005). The central research questions informing this review include: (1) What are the widely employed NDT methods for predictive failure analysis in mechanical systems? (2) How effective are these methods in detecting early signs of failure across various component types and operational conditions? (3) What comparative advantages, challenges, and future prospects do these NDT techniques hold for predictive maintenance Najmon, Raeisi & Tovar, 2019? Addressing these questions is expected to advance the field of mechanical reliability engineering and facilitate the strategic implementation of NDT technologies (Tay et al., 2008).

2.1. Methodology

The systematic review on Non-Destructive Testing (NDT) Methods for Predictive Failure Analysis in Mechanical Systems was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 guidelines. The objective was to consolidate high-quality, peer-reviewed literature that focuses on NDT methods used for failure prediction in mechanical systems across sectors like civil infrastructure, aerospace, automotive, and manufacturing. A comprehensive literature search was carried out in Scopus, Web of Science, IEEE Xplore, ScienceDirect, and Google Scholar to identify relevant publications up to March 2025. The search strategy used keywords and Boolean operators, such as "non-destructive testing" OR "NDT" AND "predictive maintenance" OR "failure analysis" AND "mechanical systems" OR "structural health monitoring." Reference lists of key studies were also examined to capture additional sources that might not have been indexed or published in conventional databases.

The inclusion criteria required that studies (1) were published in English; (2) explicitly addressed NDT methods such as ultrasonic testing, acoustic microscopy, thermography, eddy current testing, or infrared imaging for mechanical or structural failure prediction; (3) provided empirical or experimental data; and (4) involved systems or materials relevant to the mechanical or aerospace engineering domains. Reviews were included if they synthesized multiple NDT techniques or proposed novel frameworks or hybrid models. Exclusion criteria eliminated non-English papers, abstracts without full texts, articles unrelated to failure prediction, and papers focused only on destructive testing or post-failure forensic analysis.

A total of 97 studies were identified through the database search. No additional articles were found through manual search. After removing duplicates, 97 articles remained for screening. Title and abstract screening led to the exclusion of 33 articles that did not meet the inclusion criteria or were unrelated to predictive analysis. The remaining 64 full-text articles were retrieved and assessed for eligibility. Out of these, 28 were excluded due to insufficient methodological clarity, lack of predictive focus, or relevance limited to quality control rather than failure forecasting. Ultimately, 36 studies were included in the qualitative synthesis.

Data were extracted into a structured spreadsheet, capturing key attributes such as publication year, authors, study aim, NDT technique employed, type of mechanical system, performance metrics (accuracy, sensitivity, specificity), integration with digital technologies (e.g., AI, digital twins), and limitations. For consistency and reproducibility, two independent reviewers conducted the screening and data extraction processes. Discrepancies were resolved through consensus or consultation with a third reviewer. Each selected study was critically appraised for methodological rigor, practical relevance, and contribution to predictive maintenance models.

This systematic review provides a consolidated knowledge base on emerging and traditional NDT techniques applied to failure prediction in mechanical systems. It further evaluates the integration of these techniques with AI-based models and digital twins to enhance predictive accuracy and operational resilience. The results will guide future research in optimizing maintenance strategies and engineering system design.

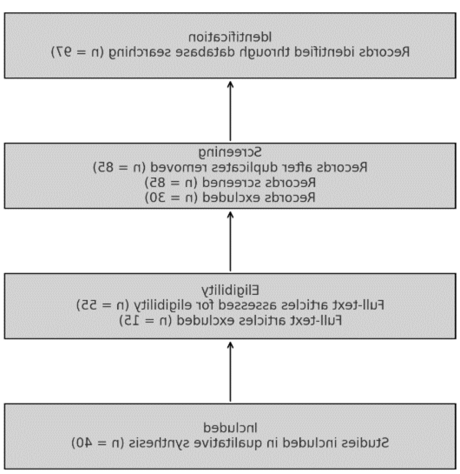

Figure 1: PRISMA Flow chart of the study methodology

2.2. Overview of Non-Destructive Testing Methods

Non-Destructive Testing (NDT) represents a vital set of methodologies for evaluating the properties and integrity of materials and mechanical components without inflicting any damage. This capability is crucial for predictive failure analysis, offering early detection of potential degradation or structural defects in mechanical systems (Shan, et al., 2012). The increasing complexity of modern mechanical systems, alongside heightened reliability requirements, drives the integration of both conventional and advanced NDT methods (Moir & Seabridge, 2011: Ohadi & Buckley, 2000). These techniques are broadly categorized into three types based on their inspection depth and nature: surface inspection methods, subsurface and volumetric methods, and advanced hybrid or smart techniques. Figure 2 shows the categories of non-destructive testing and evaluation techniques presented by Wang, et al., 2020.

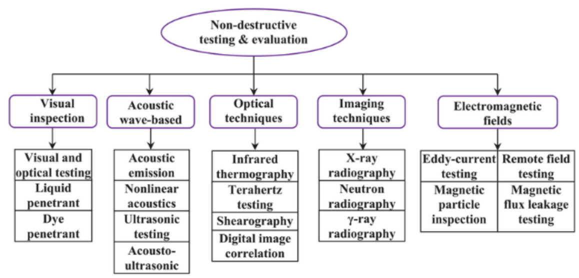

Figure 2: Categories of non-destructive testing and evaluation techniques (Wang, et al., 2020).

Surface inspection methods are the first line of defense in detecting flaws, cracks, corrosion, and other irregularities present on material surfaces. Visual Inspection (VI) remains a cornerstone of these methods due to its simplicity and cost-effectiveness. As highlighted by Abdelkhalek and Zayed, visual inspection serves as a foundational approach, though it has limitations related to subjectivity and its inability to uncover subsurface defects (Singh, et al., 2019). Magnetic Particle Testing (MT), another prevalent surface technique, is particularly suited for ferromagnetic materials, as it effectively identifies surface and near-surface discontinuities (Fan & Luo, 2008). Through the application of magnetic fields and fine particles, MT capitalizes on the principle of magnetic flux leakage to reveal flaws as visible indications. This technique's high sensitivity makes it a favored choice in industries such as aerospace and automotive, where the integrity of components is paramount (Koli, Agnihotri & Purohit, 2015).

Conversely, subsurface and volumetric methods, such as Ultrasonic Testing (UT), Radiographic Testing (RT), and Eddy Current Testing (ECT), focus on detecting internal defects. UT employs high-frequency sound waves to ascertain the presence of flaws by analyzing reflected signals, which can provide detailed information on defect size and location. This non-destructive method is especially advantageous for thick or layered materials (Tang, et al., 2016). Radiographic Testing uses X-ray or gamma radiation to produce images that highlight internal inconsistencies due to varying material densities, facilitating analysis of complex geometries while necessitating stringent safety protocols due to radiation exposure (Gisario, et al., 2019: Lin & Li, 2010). Eddy Current Testing, involving electromagnetic induction, is highly effective for assessing conductive materials. This method's sensitivity to minute cracks and corrosion makes it particularly suitable for delicate components like aircraft skins and turbine blades (Shrifan et al., 2019).

Advanced methodologies, such as Acoustic Emission (AE) and Thermographic Testing (TT), fall under the category of hybrid techniques. AE detects elastic waves produced when materials are subjected to stresses, enabling real-time monitoring of structural integrity during operation. This characteristic is critical for high-stakes applications where uptime is vital (Dixit & Ghosh, 2015: Hon, 2005). On the other hand, TT utilizes infrared technology to identify temperature variations associated with subsurface flaws, providing a rapid assessment tool that can cover extensive areas without direct contact with the test material (Katunin, 2017). Both techniques illustrate a trend toward integrating real-time analytics and remote monitoring solutions within NDT frameworks, reflecting the industry's evolution toward smart technologies. Comparison of non-destructive testing methods presented by Šmelko, et al., 2020, is shown in figure 3.

Method	Resonant Acoustic	Eddy Current	Ultrasonic	Radiography	Magnetic Microwires
Defect/Issue					
Cracks	1	1	1	2	1
Material Properties	1	3	3	2	3
Structural Integrity	1	1	1	1	1
Product Lot Variation	2	2	1	1	1
Defect Location					
Surface (External)	1	1	1	3	1
Internal	1	3	1	1	1
Brazing/Bonding/Welding	1	3	2	2	3
Speed/Cost					
Time Demands	1	2	1	3	2
Inspection Costs	1	2	3	3	2
Automation Capacity					
Quantitative Results	1	3	2	3	2
Ease of Automation	1	2	3	3	2

Figure 3: Comparison of non-destructive testing methods (Šmelko, et al., 2020).

Emerging NDT methods also exhibit a significant focus on automation and advanced imaging techniques, incorporating machine learning and data analytics to enhance inspection effectiveness. For instance, phased-array ultrasonic testing (PAUT) and computed radiography (CR) represent the forefront of smart NDT innovations, featuring capabilities that streamline data acquisition and interpretation (Li, et al., 2019: Miracle, 2005). The continuous advancement in NDT techniques is invariably linked to the growing demands of predictive maintenance, driving improvements in reliability and safety across critical systems. As stated by Saha et al., the rigorous integration of various NDT modalities is essential for comprehensive defect assessment and health monitoring of structures (Wang, et al., 2020).

In conclusion, the ongoing development and integration of NDT techniques equip industries with powerful tools for preventive maintenance and structural evaluation. Understanding the distinct advantages of each technique—from the foundational practices of visual and magnetic particle inspections to the sophisticated capabilities of acoustic and thermographic methods—allows for informed decisions in deploying appropriate strategies for failure analysis and condition assessment (Hendricks, 2008). The landscape of NDT is increasingly shaped by technological advancements that facilitate enhanced performance in predictive maintenance and structural integrity evaluation (Bertovic, 2015).

2.3. Applications in Predictive Failure Analysis

The application of Non-Destructive Testing (NDT) in predictive failure analysis is critical across various industries, including aerospace, automotive, and energy sectors. The utilization of NDT methods, such as Ultrasonic Testing (UT), Eddy Current Testing (ECT), and Acoustic Emission (AE), has proven essential in assessing the operational reliability, structural integrity, and safety of mechanical systems under cyclic loads and environmental stressors (Laloya, et al., 2015). By enabling the early detection of fatigue, crack formation, corrosion, and erosion, these methods significantly contribute to maintenance strategies aimed at preventing catastrophic failures (Duchene, et al., 2018). For example, in the aerospace industry, Ultrasonic Testing is routinely employed to inspect fuselage panels and turbine components, effectively identifying microcracks that develop due to repeated stress (Wang et al., 2020; Pitarresi et al., 2019). Omar & Nehdi, 2016, presented figure of hierarchy framework for selection of NDT technique shown in figure 4.

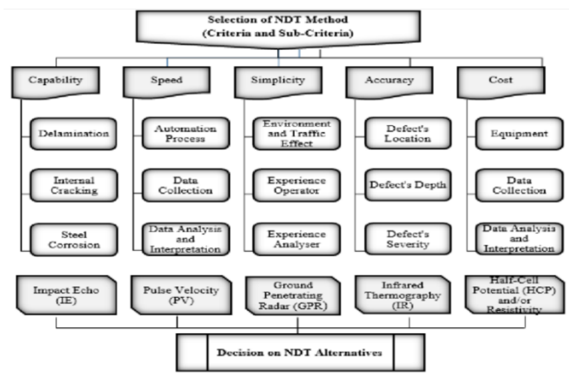

Figure 4: Hierarchy framework for selection of NDT technique (Omar & Nehdi, 2016).

Fatigue, as a prominent factor leading to structural failure, particularly in high-stress environments, necessitates effective prediction methodologies. NDT techniques excel in this area, as they provide timely insight into structural integrity without causing damage (Brown, et al., 2018). Specifically, Ultrasonic Testing measures the reflection of high-frequency sound waves to detect subsurface fatigue cracks, while Acoustic Emission monitoring captures elastic waves generated during crack growth, allowing for real-time assessments of structural health (Ameel, et al., 2000: Wang et al., 2020). Eddy Current Testing is also instrumental in identifying surface-breaking cracks, thereby facilitating comprehensive monitoring of mechanical integrity. Such systematic implementation of NDT techniques enhances condition-based monitoring and reduces unexpected downtime, thereby improving asset performance (Wang et al., 2020).

Crack initiation and propagation are critical phases in the lifecycle of mechanical components. Detection of cracks at an early stage is paramount to mitigate the risk of unexpected failures. Techniques such as Visual Inspection (VI), Magnetic Particle Testing (MT), and advanced Ultrasonic methods (e.g., Phased Array Ultrasonic Testing (PAUT)) are pivotal in identifying and monitoring cracks over time (Pitarresi et al., 2019). VI and MT are adept at surface crack detection, while Radiographic Testing (RT) and UT are essential for volumetric examinations to identify cracks concealed within materials. The ability to track crack growth through repeat scans supports reliable assessments of fracture mechanics and underpins robust predictive maintenance schedules (Kumar & Mahto, 2013).

Corrosion constitutes another significant degradation factor affecting mechanical systems, especially in corrosive environments. NDT techniques play a vital role in corrosion detection, which is crucial for maintaining safety and integrity. Ultrasonic Thickness Gauging, a variation of UT, is widely used to monitor metal loss due to corrosion, effectively identifying critical areas of thinning (Cai, Chen & Bhunia, 2016). Additionally, techniques like Eddy Current Testing can detect localized corrosion beneath surface coatings, while Thermographic Testing employs thermal anomalies to highlight problematic areas. These methods collectively enable timely interventions, enhancing system reliability by preventing unforeseen failures related to corrosion (Rao, et al., 2020: Towsyfyan, et al., 2020).

In modern manufacturing, particularly within the aerospace sector, composite materials are widely adopted due to their favorable strength-to-weight ratios. However, these materials are susceptible to delamination, a failure mode where layers separate, compromising structural integrity. Traditional inspection methods are often inadequate for internal detection of such issues. Advanced NDT techniques, including UT and Thermographic Testing, have been shown to effectively assess delamination by analyzing thermal gradients and employing ultrasonic imaging to create detailed maps of potential defects (Wang et al., 2020; Pitarresi et al., 2019). This capability ensures the integrity of critical structures, such as aircraft wings and fuselages, without necessitating disassembly or causing damage (Lauritzen, et al., 2019: Wang et al., 2020).

Wear and erosion, resulting from mechanical interaction or abrasive conditions, are gradual processes that can significantly affect component performance. NDT methods, particularly Ultrasonic Testing and Thermographic Testing, serve to monitor wear progression effectively. For instance, Thermographic Testing can detect friction-induced heat that indicates excessive wear, while Acoustic Emission sensors can capture high-frequency signals indicative of wear particle generation (Wang et al., 2020). By tracking these wear patterns, predictive models can be established for component life expectancy, supporting proactive maintenance strategies (Wang et al., 2020).

The relevance of NDT in predictive failure analysis is further emphasized through industry case studies. In the energy sector, for instance, Guided Wave Ultrasonics facilitate the monitoring of corrosion in pipelines, enhancing operational safety while minimizing excavation needs (Saha, et al., 2016). In the automotive industry, NDT methods like Eddy Current Testing play a vital role in assessing the reliability of engine components subjected to fatigue stresses (Wang et al., 2020). Such examples underscore the importance of integrating NDT within predictive maintenance frameworks to foster enhanced asset lifecycle management and operational risk reduction (Ph Papaelias, Roberts & Davis, 2008).

Overall, the integration of advanced NDT techniques within predictive maintenance strategies marks a significant evolution in ensuring machinery reliability and safety. The incorporation of data analytics and machine learning into NDT practices is essential for transitioning from reactive to predictive maintenance systems, thereby meeting the growing demands for sustainability and efficiency across various industries (Asif, et al., 2018).

2.4. Comparative Analysis of NDT Methods

Computational Fluid Dynamics (CFD) modeling has become an essential tool for analyzing and optimizing fluid-particle separation and filtration systems across various engineering applications. Accurately simulating these systems requires robust modeling techniques, accounting for the interactions between fluid and solid phases, variable particle properties, and complex flow conditions (Stafford, Grimes & Newport, 2012). Various CFD approaches have been developed, each offering unique advantages depending on the physical complexity, particle concentration, and available computational resources. For example, the Discrete Phase Model (DPM) treats the fluid as a continuous medium while tracking particles as discrete entities. This method, effective in dilute systems, allows for high-resolution tracking of particle paths and helps analyze factors such as separation efficiency and filter clogging behavior (Volk et al., 2017; Li et al., 2019).

The DPM relies on the Eulerian framework to solve the governing equations of the fluid phase, typically the Navier-Stokes equations, while employing Lagrangian mechanics to track the particles individually. The forces acting upon these particles — such as drag, gravity, lift, and virtual mass — are calculated to predict their trajectories accurately. However, the DPM's computational cost can increase significantly with higher particle counts, limiting its application in denser multiphase flows (Gholizadeh, 2016). For instance, Kloss et al. emphasized the capabilities of CFD-DEM (Discrete Element Method) simulations, providing an effective means of depicting solid particle interactions while utilizing drag laws to represent fluid-particle interactions efficiently (Kloss et al., 2012).

For scenarios characterized by high particle concentration, Eulerian-Eulerian or Eulerian-Lagrangian modeling techniques are often employed. The Eulerian-Eulerian approach treats both the fluid and the dispersed phase as interpenetrating continua, each governed by distinct conservation equations for mass and momentum (Haertel, et al., 2018). This method is particularly suitable for dense flows, such as those encountered in fluidized beds and slurry transport systems, where the interactions between particles and between particles and the fluid significantly influence the overall flow field (Xu et al., 2015; Khashan & Furlani, 2011). Closure models are necessary to describe interphase drag, particle pressure, and granular temperature. Conversely, the Eulerian-Lagrangian method can better capture detailed particle dynamics while incorporating feedback effects with the fluid phase, effectively bridging the gap between the two approaches (Li et al., 2019).

An essential component in modeling fluid-particle systems is the evolving particle size distribution within the flow. The dynamic changes in particle size can arise from processes such as breakage, aggregation, or growth, commonly modeled using Population Balance Models (PBMs). PBMs can be integrated into CFD simulations, allowing for a more comprehensive representation of real-world systems and aiding in the prediction of product quality, separation performance, and fouling tendencies (Zhou, et al., 2016). Accurate implementation of PBMs in CFD simulations necessitates additional numerical techniques, such as moment methods or Monte Carlo approaches, to efficiently track the evolution of particle populations throughout the simulation timeline (Jung et al., 2019).

Turbulence modeling is another critical aspect of CFD simulations for fluid-particle systems, as turbulence significantly influences particle transport and deposition patterns. Various turbulence modeling strategies exist, with Reynolds-Averaged Navier-Stokes (RANS) models being the most prevalent due to their computational efficiency. While RANS provides satisfactory results for steady-state flows, it may not adequately capture transient turbulence phenomena crucial for understanding particle-laden flows (Li et al., 2019; Omari et al., 2020). In contrast, Large Eddy Simulation (LES) and Direct Numerical Simulation (DNS) offer more accurate representations of turbulent structures, albeit at higher computational costs, making them less practical for many engineering applications (Muhammad & Sidik, 2018).

Finally, the coupling between fluid and particle phases varies significantly based on application needs. One-way coupling is appropriate for very dilute systems where feedback from particles to the fluid can be ignored. Two-way coupling accounts for the influence of particles on the fluid's flow field, making it essential in moderately concentrated systems. For denser systems where interactions between particles play a crucial role, four-way coupling is necessary. Achieving this level of accuracy requires sophisticated collision models and often involves the use of Discrete Element Methods to resolve particle-particle interactions explicitly (Li et al., 2019; Liu et al., 2020).

In conclusion, the diverse modeling strategies and coupling mechanisms available in CFD modeling of fluid-particle systems enable the analysis and optimization of complex filtration and separation systems. As computational resources improve, the integration of multiple modeling techniques is becoming more feasible, allowing for comprehensive simulations that can account for a wide range of physical phenomena influencing particle-laden flows (Zeng, et al., 2020). Ongoing research continues to focus on enhancing both the fidelity of these models and their computational efficiency, such as through the integration of machine learning techniques and adaptive meshing methods (Wu et al., 2018; Qian & Yu, 2012).

2.5. Emerging Trends and Integrative Approaches

As mechanical systems continue to evolve in complexity and performance demands, Non-Destructive Testing (NDT) has adapted through the integration of modern technologies, leading to a paradigmatic shift from traditional inspection methodologies toward a more sophisticated, data-driven approach. This new era of NDT incorporates artificial intelligence (AI), machine learning, the Internet of Things (IoT), digital twins, and autonomous systems, enabling a transition from reactive maintenance to proactive and intelligent systems (Japar, et al., 2020).

One of the foremost advancements in the NDT landscape is the incorporation of AI and machine learning into defect detection and predictive analytics. Traditional methods, which often depend on human interpretation of nuanced signal data or imagery indicative of material degradation, are inherently variable and subjective. AI mitigates these issues by enabling automated analysis of vast datasets, which can significantly reduce human error and speed up the identification of anomalies (Li, et al., 2014). Indeed, supervised learning models, including convolutional neural networks (CNNs), have been effectively employed for classifying defects in radiographic images, while recurrent neural networks (RNNs) capture temporal patterns in ultrasonic data for predictive maintenance (Barricelli et al., 2019). Moreover, reinforcement learning enhances these capabilities by optimizing inspection strategies autonomously, adjusting parameters based on the outcomes of previous inspections (Barricelli et al., 2019).

The development of digital twin technology has further revolutionized the field of NDT by allowing for real-time asset monitoring and simulation. A digital twin is a virtual representation that continuously updates based on real-time data from various NDT sensors, offering predictive insights through simultaneous modeling of physical states (Barricelli et al., 2019; Kapteyn et al., 2020). This integration not only enriches the data analysis but also provides maintenance teams with a dynamic overview of component health, improving decision-making processes regarding maintenance actions. In industries such as aerospace and manufacturing, implementing digital twins facilitates enhanced accuracy in predicting fatigue and stress factors by virtually simulating these conditions and correlating them with gathered NDT data.

In parallel, the advent of IoT technologies has transformed NDT capabilities by enabling continuous condition monitoring. Unlike conventional periodic inspections, IoT-connected sensors collect critical health metrics such as vibrations and temperatures, transmitting this information for real-time analysis through cloud platforms (Barricelli et al., 2019). This facilitates early detection of anomalies and allows predictive analytics to forecast potential failures, significantly enhancing operational reliability in hazardous or remote environments where manual inspection poses significant risks. For example, "smart pigging" technologies have evolved to use a combination of ultrasonic and magnetic sensors to assess infrastructure health without the need for direct human involvement, maintaining high safety standards.

Moreover, the proliferation of remote and autonomous NDT systems, such as drones and robotic inspection units, illustrates the shift towards minimizing human intervention in potentially hazardous settings. Equipped with various sensors, these systems can autonomously navigate and assess complex structures, yielding both higher efficiency and safety (Barricelli et al., 2019). The emerging trend of AI-powered robotic NDT capabilities is paving the way for inspections that adaptively respond to environmental variables and learn from previous tasks, thus optimizing future inspections.

Nonetheless, the transition to these advanced technologies is fraught with challenges. Key issues include ensuring data integrity and cybersecurity, optimizing energy supply for dispersed sensor networks, and standardizing communication protocols for enhanced system interoperability. The volume of data generated also necessitates advanced data governance frameworks to filter actionable insights from noise (Barricelli et al., 2019).

In conclusion, the integration of AI, sensor fusion, digital twins, IoT, and autonomous systems marks a significant evolution in Non-Destructive Testing, transforming predictive failure analysis into a robust, intelligent process capable of enhancing the reliability and safety of mechanical systems. As industries move towards these advanced integrative approaches, the potential for improved asset management, minimized downtime, and extended component lifecycles becomes increasingly attainable.

2.6. Challenges and Research Gaps

The widespread application and increasing significance of Non-Destructive Testing (NDT) in predictive failure analysis have encountered persistent challenges that hinder its full potential. One significant issue is the lack of standardization across various NDT techniques and industries. Although international standards, such as ASTM and ISO, exist, their enforcement and adoption vary widely, leading to inconsistencies in inspection methods and results (Wronkowicz, 2018). This fragmentation is evident in the differing criteria for acceptable defect sizes across sectors, which can create confusion and elevate safety risks. For instance, standards for weld inspections may differ drastically from those of casting evaluations, complicating the interpretation of defect severity and inspector qualification requirements (Wronkowicz, 2018).

Furthermore, operator dependency is a critical challenge in NDT. Many techniques still rely heavily on skilled personnel for accurate results, and as the number of qualified operators declines, the reliability of inspections is compromised. This skill gap is exacerbated by the retirement of experienced professionals, leaving a void in expertise necessary for interpreting complex data from methods like Ultrasonic Testing (UT) and Acoustic Emission monitoring (Khaira et al., 2020). The reliance on operator judgment can introduce variability in defect detection and classification, raising questions about the reliability of predictive analyses and the potential for false positives or missed defects.

Moreover, the inadequacy of real-time deployment capabilities restricts the effectiveness of NDT in contemporary predictive maintenance ecosystems. While certain technologies, such as Acoustic Emission and Guided Wave Ultrasonics, show potential for real-time monitoring, many NDT methods remain largely offline or used intermittently due to the lack of necessary infrastructure and data integration capabilities (Khaira et al., 2020). As a result, systems fail to monitor rapid failure mechanisms or anomalies effectively. The integration of NDT findings with maintenance databases and decision-support systems is another significant hurdle, as most tools operate independently, hampering the flow of information and insights across platforms (Katunin et al., 2020).

Additionally, research gaps persist surrounding data interpretation and the development of intelligent diagnostic tools. The variability in data outcomes is a particular concern, as advanced techniques often generate complex datasets that require thorough and sophisticated analysis. Integrating machine learning approaches into NDT may help mitigate the subjectivity in data interpretation but faces challenges due to the lack of standardized training datasets. Collaborative efforts to create accessible repositories of annotated data could accelerate the advancement of reliable AI models that enhance defect detection accuracy.

Finally, advancing the sensitivity and efficiency of NDT techniques while addressing aspects of portability and cost-effectiveness is crucial. There is a growing push towards integrating multiple NDT methods for a holistic diagnostic approach, such as combining thermography with ultrasonic testing to improve inspection accuracy. Developing interoperable solutions that facilitate real-time data sharing and improve the predictive capabilities of NDT systems would significantly enhance their functionality within advanced maintenance frameworks (Katunin et al., 2020).

In conclusion, while NDT is pivotal in predictive failure analysis, the sector must address the challenges of standardization, operator dependency, real-time deployment, and data interpretation. Continued research focusing on automation, data integration, and the development of intelligent tools will be essential for maximizing NDT's contributions to modern maintenance strategies and ensuring effective asset management in various industries.

2.7. Recommendations

The evolution of Non-Destructive Testing (NDT) methods is critically important as mechanical systems grow in complexity and the demand for operational reliability increases across industries like aerospace, energy, manufacturing, and transportation. Drawing on insights from a systematic review of NDT methods for predictive failure analysis, several forward-looking recommendations can be proposed to address prevailing challenges and optimize the application of NDT in contemporary industrial ecosystems.

A fundamental recommendation is the development of hybrid NDT frameworks that synergize multiple techniques to create a more robust inspection strategy. Each NDT method has inherent strengths and weaknesses; for example, ultrasonic testing excels at detecting subsurface defects, whereas eddy current testing and magnetic particle testing are proficient in identifying surface-level cracks (Khaira et al., 2020). An integration of techniques such as combining ultrasonic testing with infrared thermography or enhancing eddy current testing with visual inspection could provide a more comprehensive assessment of mechanical integrity. This hybrid approach not only improves the reliability of defect detection but also leverages the strengths of different methodologies to cover their individual shortcomings.

Furthermore, enhancing accessibility to NDT technologies is essential, especially for small and medium-sized enterprises (SMEs) that often lack the necessary resources to implement advanced NDT solutions. One viable strategy involves government subsidies for training programs, mobile NDT units, and low-cost inspection kits (Helal et al., 2015: Bodnar et al., 2012). Open-access platforms that utilize smartphone technology for imaging could democratize access to expert-level skills by facilitating remote or simplified training environments for industry personnel (Qing et al., 2005). Collaborations between universities and industries may establish local NDT centers that focus on hands-on training and innovation, fostering a workforce capable of meeting the growing complexities of NDT demands.

Research and development should prioritize creating intelligent NDT methods through the incorporation of machine learning and artificial intelligence. Automated data interpretation tools can significantly reduce reliance on human judgment, thereby enhancing accuracy and efficiency in defect analysis (Riggio et al., 2016; Moll et al., 2018). A focus on developing expansive, annotated datasets that encompass a variety of defect types will be crucial for training these algorithms effectively (Khaira et al., 2020; Moll et al., 2018). Additionally, further investments into advanced sensor technology, capable of multi-parameter sensing for continuous monitoring, would empower industries to preemptively identify potential failures (Bertocci et al., 2019).

Emerging materials, particularly in novel manufacturing processes like additive manufacturing, necessitate innovative NDT protocols to ensure structural integrity, as traditional methods may not suffice. Multidisciplinary collaboration among material science, data analytics, and engineering could yield improved models for understanding defect evolution in these new materials and structures, facilitating predictive maintenance and enhancing safety (Katunin et al., 2020).

For the integration of NDT into Industry 4.0 frameworks, specific strategies should address interoperability, real-time data processing, and security concerns. The concept of the digital twin—where real-time data from physical assets is reflected in virtual models—underscores the need for standardized data formats and robust APIs for seamless integration with existing Industrial IoT infrastructures (Moll et al., 2018). Moreover, with the increasing reliance on digital solutions, ensuring the cyber integrity of NDT systems against malicious threats becomes imperative, particularly in sectors like nuclear energy and aviation (Drobiec et al., 2019).

To promote widespread adoption of these advanced NDT techniques, incentives and clear regulatory guidelines will be necessary. Tax credits, innovation grants, and industry awards can catalyze change while establishing clearly defined pathways for transitioning to predictive maintenance frameworks using NDT technologies that emphasize long-term cost efficiency and safety improvements (Jalili et al., 2014; Helal et al., 2015).

In conclusion, the future of NDT lies in its ability to evolve alongside industrial needs through innovative hybrid frameworks, enhanced accessibility, focused research, and seamless integration into digital infrastructures. Strategic investments into technology and infrastructure promise to not only safeguard mechanical reliability but also secure the operational integrity of critical sectors in an increasingly interconnected world.

2.8. Conclusion

This systematic review has comprehensively explored the landscape of Non-Destructive Testing (NDT) methods as applied to predictive failure analysis in mechanical systems. The findings highlight that while no single technique can universally address all inspection challenges, a broad spectrum of methods—ranging from ultrasonic and radiographic testing to acoustic emission and thermography—play vital roles in detecting fatigue, cracks, corrosion, delamination, and wear. Each method offers unique advantages in terms of sensitivity, applicability, and reliability, though limitations related to skill dependency, data interpretation, and real-time deployment persist. Through comparative analysis, it is evident that combining multiple techniques within hybrid frameworks can substantially enhance diagnostic accuracy, reduce false positives, and increase the predictive power of inspection systems.

The significance of this review extends beyond the consolidation of technical insights; it also bridges critical gaps between industrial practice and academic research. For industry stakeholders, the review provides actionable guidance on selecting and integrating appropriate NDT strategies into maintenance regimes, ultimately supporting safer, more efficient, and cost-effective operations. For academia, it identifies key research priorities including AI-driven interpretation, sensor fusion, standardization, and NDT for novel materials and manufacturing methods. By articulating the technological limitations and workforce challenges currently facing the field, the review fosters a clearer path for collaborative innovation and curriculum development aimed at producing the next generation of NDT professionals.

Looking ahead, the future of predictive NDT lies in intelligent, connected, and adaptive systems that seamlessly integrate with digital twins and Industry 4.0 infrastructures. Emerging technologies in machine learning, real-time sensing, and edge computing will reshape how defects are identified, characterized, and acted upon. To fully realize this vision, stakeholders must invest in cross-disciplinary research, standardization efforts, and inclusive access to training and technology. Ultimately, predictive NDT will evolve from being a specialized inspection tool to becoming a core component of strategic asset management, ensuring the resilience, sustainability, and longevity of mechanical systems across sectors.

REFERENCES

[1] Abdelkhalek, S. and Zayed, T. (2021). Performance assessment model of non-destructive technologies in inspecting concrete bridge decks. Structure and Infrastructure Engineering, 19(2), 216-237. https://doi.org/10.1080/15732479.2021.1937234

[2] Ameel, T. A., Papautsky, I., Warrington, R. O., Wegeng, R. S., & Drost, M. K. (2000). Miniaturization technologies for advanced energy conversion and transfer systems. Journal of Propulsion and Power, 16(4), 577-582.

[3] Asif, M., Khan, M. A., Khan, S. Z., Choudhry, R. S., & Khan, K. A. (2018). Identification of an effective nondestructive technique for bond defect determination in laminate composites—A technical review. Journal of Composite Materials, 52(26), 3589-3599.

[4] Barricelli, B., Casiraghi, E., & Fogli, D. (2019). A survey on digital twin: definitions, characteristics, applications, and design implications. Ieee Access, 7, 167653-167671. https://doi.org/10.1109/access.2019.2953499

[5] Bertocci, F., Grandoni, A., & Djuric-Rissner, T. (2019). Scanning acoustic microscopy (sam): a robust method for defect detection during the manufacturing process of ultrasound probes for medical imaging. Sensors, 19(22), 4868. https://doi.org/10.3390/s19224868

[6] Bertovic, M. (2015). Human factors in non-destructive testing (NDT): risks and challenges of mechanised NDT. Technische Universitaet Berlin (Germany).

[7] Bodnar, J., Nicolas, J., Candoré, J., & Detalle, V. (2012). Non-destructive testing by infrared thermography under random excitation and arma analysis. International Journal of Thermophysics, 33(10-11), 2011-2015. https://doi.org/10.1007/s10765-012-1265-2

[8] Bolborea, B., Dan, S., Matei, C., Gruin, A., Baeră, C., & Perianu, I. (2021). Estimating the concrete compressive strength by using the concrete ultrasonic pulse velocity and moduli of elasticity. Advanced Materials Research, 1164, 77-86. https://doi.org/10.4028/www.scientific.net/amr.1164.77

[9] Brown, M., Wright, D., M'Saoubi, R., McGourlay, J., Wallis, M., Mantle, A., ... & Ghadbeigi, H. (2018). Destructive and non-destructive testing methods for characterization and detection of machining-induced white layer: A review paper. CIRP Journal of Manufacturing Science and Technology, 23, 39-53.

[10] Cai, S. Q., Chen, Y. C., & Bhunia, A. (2016). Design, development and tests of a compact thermofluid system. Applied Thermal Engineering, 102, 1320-1327.

[11] Chaki, S. and Krawczak, P. (2022). Non-destructive health monitoring of structural polymer composites: trends and perspectives in the digital era. Materials, 15(21), 7838. https://doi.org/10.3390/ma15217838

[12] Civera, M. and Surace, C. (2022). Non-destructive techniques for the condition and structural health monitoring of wind turbines: a literature review of the last 20 years. Sensors, 22(4), 1627. https://doi.org/10.3390/s22041627

[13] Demčenko, A., Visser, H., & Akkerman, R. (2016). Ultrasonic measurements of undamaged concrete layer thickness in a deteriorated concrete structure. NDT & E International, 77, 63-72. https://doi.org/10.1016/j.ndteint.2015.09.005

[14] Dixit, T., & Ghosh, I. (2015). Review of micro- and mini-channel heat sinks and heat exchangers for single phase fluids. Renewable and Sustainable Energy Reviews, 41, 1298-1311.

[15] Dong, C., Li, L., Yan, J., Zhang, Z., Pan, H., & Çatbaş, F. (2021). Pixel-level fatigue crack segmentation in large-scale images of steel structures using an encoder–decoder network. Sensors, 21(12), 4135. https://doi.org/10.3390/s21124135

[16] Drobiec, Ł., Jasiński, R., & Mazur, W. (2019). Accuracy of eddy-current and radar methods used to reinforcement detection.. https://doi.org/10.20944/preprints201901.0014.v2

[17] Duchene, P., Chaki, S., Ayadi, A., & Krawczak, P. (2018). A review of non-destructive techniques used for mechanical damage assessment in polymer composites. Journal of materials science, 53(11), 7915-7938.

[18] Fan, Y., & Luo, L. (2008). Recent applications of advances in microchannel heat exchangers and multi-scale design optimization. Heat Transfer Engineering, 29(5), 461-474.

[19] Gholizadeh, S. (2016). A review of non-destructive testing methods of composite materials. Procedia structural integrity, 1, 50-57.

[20] Gisario, A., Kazarian, M., Martina, F., & Mehrpouya, M. (2019). Metal additive manufacturing in the commercial aviation industry: A review. Journal of Manufacturing Systems, 53, 124-149.

[21] Grzyb, K., Drobiec, Ł., Blazy, J., & Zając, J. (2022). The use of ndt diagnostic methods and calculations in assessing the masonry tower crowned with the steel dome. Materials, 15(20), 7196. https://doi.org/10.3390/ma15207196

[22] Haertel, J. H., Engelbrecht, K., Lazarov, B. S., & Sigmund, O. (2018). Topology optimization of a pseudo 3D thermofluid heat sink model. International Journal of Heat and Mass Transfer, 121, 1073-1088.

[23] Helal, J., Sofi, M., & Mendis, P. (2015). Non-destructive testing of concrete: a review of methods. Electronic Journal of Structural Engineering, 14(1), 97-105. https://doi.org/10.56748/ejse.141931

[24] Hendricks, T. J. (2008, January). Microtechnology: A Key to System Miniaturization in Advanced Energy Recovery and Conversion Systems. In Energy Sustainability (Vol. 43208, pp. 153-163).

[25] Hon, K. K. B. (2005). Performance and evaluation of manufacturing systems. CIRP annals, 54(2), 139-154.

[26] Jalili, M., Mousavi, S., & Pirayeshfar, A. (2014). Flexural free vibration as a non-destructive test for evaluation of viscoelastic properties of polymeric composites in bending direction. Iranian Polymer Journal, 23(5), 327-333. https://doi.org/10.1007/s13726-014-0227-x

[27] Japar, W. M. A. A., Sidik, N. A. C., Saidur, R., Asako, Y., & Nurul Akmal Yusof, S. (2020). A review of passive methods in microchannel heat sink application through advanced geometric structure and nanofluids: Current advancements and challenges. Nanotechnology Reviews, 9(1), 1192-1216.

[28] Jeong, D., Baek, M., Lim, T., Kim, Y., Kim, S., Lee, Y., … & Lee, I. (2022). Digital twin: technology evolution stages and implementation layers with technology elements. Ieee Access, 10, 52609-52620. https://doi.org/10.1109/access.2022.3174220

[29] Joshi, Y., & Wei, X. (2005). Keynote Lecture: Micro and Meso Scale Compact Heat

Exchangers in Electronics Thermal Management–Review.

[30] Jung, S., Park, J., Kang, T., & Ahn, K. (2019). Design optimization for a microfluidic crossflow filtration system incorporating a micromixer. Micromachines, 10(12), 836. https://doi.org/10.3390/mi10120836

[31] Kapteyn, M., Knežević, D., Huynh, D., Tran, M., & Willcox, K. (2020). Data-driven physics-based digital twins via a library of component-based reduced-order models. International Journal for Numerical Methods in Engineering, 123(13), 2986-3003. https://doi.org/10.1002/nme.6423

[32] Katunin, A. (2017). A concept of thermographic method for non-destructive testing of polymeric composite structures using self-heating effect. Sensors, 18(1), 74. https://doi.org/10.3390/s18010074

[33] Katunin, A. and Dragan, K. (2022). Qualitative to quantitative non-destructive evaluation: a concept for d-sight inspections of aircraft structures. Applied Mechanics and Materials, 909, 69-74. https://doi.org/10.4028/p-d8r1x7

[34] Katunin, A., Wronkowicz, A., & Dragan, K. (2020). Impact damage evaluation in composite structures based on fusion of results of ultrasonic testing and x-ray computed tomography. Sensors, 20(7), 1867. https://doi.org/10.3390/s20071867

[35] Khaira, A., Dwivedi, R., & Jain, S. (2020). Structural health monitoring (shm) of machine using a combination of non-destructive testing for heavy manufacturing industry. E3s Web of Conferences, 184, 01059. https://doi.org/10.1051/e3sconf/202018401059

[36] Khashan, S. and Furlani, E. (2011). Effects of particle–fluid coupling on particle transport and capture in a magnetophoretic microsystem. Microfluidics and Nanofluidics, 12(1-4), 565-580. https://doi.org/10.1007/s10404-011-0898-y

[37] Kloss, C., Goniva, C., Hager, A., Amberger, S., & Pirker, S. (2012). Models, algorithms and validation for opensource dem and cfd-dem. Progress in Computational Fluid Dynamics an International Journal, 12(2/3), 140. https://doi.org/10.1504/pcfd.2012.047457

[38] Koli, D. K., Agnihotri, G., & Purohit, R. (2015). Advanced aluminium matrix composites: the critical need of automotive and aerospace engineering fields. Materials Today: Proceedings, 2(4-5), 3032-3041.

[39] Kumar, S., & Mahto, D. G. (2013). Recent trends in industrial and other engineering applications of non destructive testing: a review. International Journal of Scientific & Engineering Research, 4(9).

[40] Kuśmierczak, S. and Majzner, T. (2017). Comprehensive approach to evaluation of degradation in chosen parts of energy equipment.. https://doi.org/10.22616/erdev2017.16.n134

[41] Laloya, E., Lucia, O., Sarnago, H., & Burdio, J. M. (2015). Heat management in power converters: From state of the art to future ultrahigh efficiency systems. IEEE transactions on Power Electronics, 31(11), 7896-7908.

[42] Lauritzen, P. N., Reichard, J., Ahmed, S., & Safa, M. (2019). Review of non-destructive testing methods for physical condition monitoring in the port industry. Journal of Construction Engineering, 2(2), 103-111.

[43] Li, B., Dobosz, K., Zhang, H., Schiffman, J., Saranteas, K., & Henson, M. (2019). Predicting the performance of pressure filtration processes by coupling computational fluid dynamics and discrete element methods. Chemical Engineering Science, 208, 115162. https://doi.org/10.1016/j.ces.2019.115162

[44] Li, P., Li, Y., Seem, J. E., Qiao, H., Li, X., & Winkler, J. (2014). Recent advances in dynamic modeling of HVAC equipment. Part 2: Modelica-based modeling. HVAC&R Research, 20(1), 150-161.

[45] Li, S., Zhang, H., Cheng, J., Li, X., Cai, W., Li, Z., & Li, F. (2019). A state-of-the-art overview on the developing trend of heat transfer enhancement by single-phase flow at micro scale. International Journal of Heat and Mass Transfer, 143, 118476.

[46] Lin, J. and Li, H. (2010). Applications of network integrated system with eddy current and ultrasonic testing. International Journal of Applied Electromagnetics and Mechanics, 33(3-

4), 1309-1315. https://doi.org/10.3233/jae-2010-1255

[47] Liu, H., Wang, D., Leng, X., Zheng, D., Chen, F., Wong, K., … & Leung, T. (2020). State-of-the-art computational models of circle of willis with physiological applications: a review. Ieee Access, 8, 156261-156273. https://doi.org/10.1109/access.2020.3007737

[48] Liu, J., Zhao, T., Liu, K., Sun, B., & Bai, C. (2021). Optimization of structure parameters in a coal pyrolysis filtration system based on cfd and quadratic regression orthogonal combination and a genetic algorithm. Engineering Applications of Computational Fluid Mechanics, 15(1), 815-829. https://doi.org/10.1080/19942060.2021.1918258

[49] Ma, Q., Tian, G., Zeng, Y., Li, R., Song, H., Wang, Z., … & Zeng, K. (2021). Pipeline in-line inspection method, instrumentation and data management. Sensors, 21(11), 3862. https://doi.org/10.3390/s21113862

[50] Melesse, T., Pasquale, V., & Riemma, S. (2021). Digital twin models in industrial operations: state-of-the-art and future research directions. Iet Collaborative Intelligent Manufacturing, 3(1), 37-47. https://doi.org/10.1049/cim2.12010

[51] Miracle, D. B. (2005). Metal matrix composites–from science to technological significance. Composites science and technology, 65(15-16), 2526-2540.

[52] Moir, I., & Seabridge, A. (2011). Aircraft Systems: Mechanical, electrical, and avionics subsystems integration. John Wiley & Sons.

[53] Moll, J., Kathol, J., Fritzen, C., Moix-Bonet, M., Rennoch, M., Koerdt, M., … & Bach, M. (2018). Open guided waves: online platform for ultrasonic guided wave measurements. Structural Health Monitoring, 18(5-6), 1903-1914. https://doi.org/10.1177/1475921718817169

[54] Muhammad, N. M. A., & Sidik, N. A. C. (2018). Utilization of Nanofluids in Minichannel for Heat Transfer and Fluid Flow Augmentation: A Concise Research Design. Journal of Advanced Research Design, 50(1), 18-29.

[55] Nahm, S., Kim, J., Park, J., Yu, K., Kim, D., Kim, A., … & Kim, D. (2004). Degradation evaluation of 2.25cr-1mo steel using electrical resistivity. Key Engineering Materials, 270-273, 1212-1217. https://doi.org/10.4028/www.scientific.net/kem.270-273.1212

[56] Najmon, J. C., Raeisi, S., & Tovar, A. (2019). Review of additive manufacturing technologies and applications in the aerospace industry. Additive manufacturing for the aerospace industry, 7-31.

[57] Ngo, T., Wang, Y., & Chiang, D. (2021). Applying artificial intelligence to improve on-site non-destructive concrete compressive strength tests. Crystals, 11(10), 1157. https://doi.org/10.3390/cryst11101157

[58] Noor, A. K., Venneri, S. L., Paul, D. B., & Hopkins, M. A. (2000). Structures technology for future aerospace systems. Computers & Structures, 74(5), 507-519.

[59] Odedeyi, P. B., Abou-El-Hossein, K., Oyekunle, F., & Adeleke, A. K. (2020). Effects of machining parameters on Tool wear progression in End milling of AISI 316. *Progress in Canadian Mechanical Engineering*, *3*

[60] Ohadi, M. M., & Buckley, S. G. (2000). High temperature heat exchangers and microscale combustion systems: applications to thermal system miniaturization. In Thermal Sciences 2000. Proceedings of the International Thermal Science Seminar. Volume 1. Begel House Inc..

[61] Olisa, S., Khan, M., & Starr, A. (2021). Review of current guided wave ultrasonic testing (gwut) limitations and future directions. Sensors, 21(3), 811. https://doi.org/10.3390/s21030811

[62] Olisakwe, H. C., Tuleun, L. T., & Eloka-Eboka, A. C. (2011). Comparative study of Thevetia peruviana and Jatropha curcas seed oils as feedstock for Grease production. *International Journal of Engineering Research and Applications*, *1*(3).

[63] Omar, T., & Nehdi, M. L. (2016). Mat-713: evaluation of ndt techniques for concrete bridge decks using fuzzy analytical hierarchy process.

[64] Omari, A., John, J., & Kichonge, B. (2020). Simulation and optimization of municipal solid waste combustion: a case study of a fixed bed incinerator. Journal of Engineering Research and Reports, 5-19. https://doi.org/10.9734/jerr/2020/v11i317060

[65] Ph Papaelias, M., Roberts, C., & Davis, C. L. (2008). A review on non-destructive evaluation of rails: State-of-the-art and future development. Proceedings of the Institution of Mechanical Engineers, Part F: Journal of Rail and rapid transit, 222(4), 367-384.

[66] Pham, D., Sun, X., Tan, V., Chen, B., & Tay, T. (2011). Progressive failure analysis of scaled double-notched carbon/epoxy composite laminates. International Journal of Damage Mechanics, 21(8), 1154-1185. https://doi.org/10.1177/1056789511430415

[67] Piascik, B., Vickers, J., Lowry, D., Scotti, S., Stewart, J., & Calomino, A. (2012). Materials, structures, mechanical systems, and manufacturing roadmap. NASA TA, 12-2.

[68] Pirinu, A. and Panella, F. (2021). Fatigue damage monitoring of cfrp elements by thermographic procedure under bending loads. Key Engineering Materials, 873, 47-52. https://doi.org/10.4028/www.scientific.net/kem.873.47

[69] Pitarresi, G., Scalici, T., & Catalanotti, G. (2019). Infrared thermography assisted evaluation of static and fatigue mode ii fracture toughness in frp composites. Composite Structures, 226, 111220. https://doi.org/10.1016/j.compstruct.2019.111220

[70] Poole, A., Sutcliffe, M., Pierce, S., & Gachagan, A. (2022). Autonomous, digital-twin free path planning and deployment for robotic ndt: introducing lpas: locate, plan, approach, scan using low cost vision sensors. Applied Sciences, 12(10), 5288. https://doi.org/10.3390/app12105288

[71] Qian, F. and Yu, X. (2012). Numerical simulation to study the effect of the particle deposition morphology on the filtration efficiency of the fibrous media. Advanced Materials Research, 518-523, 1767-1770. https://doi.org/10.4028/www.scientific.net/amr.518-523.1767

[72] Qing, X., Kumar, A., Zhang, C., Gonzalez, I., Guo, G., & Chang, F. (2005). A hybrid piezoelectric/fiber optic diagnostic system for structural health monitoring. Smart Materials and Structures, 14(3), S98-S103. https://doi.org/10.1088/0964-1726/14/3/012

[73] Rao, R. V., Saroj, A., Ocłoń, P., & Taler, J. (2020). Design optimization of heat exchangers with advanced optimization techniques: a review. Archives of computational methods in engineering, 27, 517-548.

[74] Riggio, M., Macchioni, N., & Riminesi, C. (2016). Structural health assessment of historical timber structures combining non-destructive techniques: the roof of giotto's bell tower in florence. Structural Control and Health Monitoring, 24(7), e1935. https://doi.org/10.1002/stc.1935

[75] Saha, S. K., Tiwari, M., Sundén, B., & Wu, Z. (2016). Advances in heat transfer enhancement (Vol. 4). Springer International Publishing.

[76] Shan, Z., Qin, S., Liu, Q., & Liu, F. (2012). Key manufacturing technology & equipment for energy saving and emissions reduction in mechanical equipment industry. International Journal of Precision Engineering and Manufacturing, 13, 1095-1100.

[77] Shrifan, N., Akbar, M., & Isa, N. (2019). Prospect of using artificial intelligence for microwave nondestructive testing technique: a review. Ieee Access, 7, 110628-110650. https://doi.org/10.1109/access.2019.2934143

[78] Siang, T., Akbar, M., Jawad, G., Yee, T., & Sazali, M. (2021). A past, present, and prospective review on microwave nondestructive evaluation of composite coatings. Coatings, 11(8), 913. https://doi.org/10.3390/coatings11080913

[79] Singh, J., Montesinos-Castellanos, A., & Nigam, K. D. P. (2019). Process intensification for compact and micro heat exchangers through innovative technologies: A review. Industrial & Engineering Chemistry Research, 58(31), 13819-13847.

[80] Šmelko, M., Draganová, K., Lipovský, P., Semrád, K., Blišťanová, M., & Kašper, P. (2020). Non-Destructive testing of aircraft structures using microwire-based tensile stress sensor. Applied Sciences, 10(22), 8218.

[81] Stafford, J., Grimes, R., & Newport, D. (2012). Development of compact thermal–fluid models at the electronic equipment level.

[82] Talouti, S., Benzerga, D., & Abdelkader, H. (2022). Numerical investigations of damage behaviour at the weld/base metal interface. International Journal of Engineering, 35(12), 2337-2343. https://doi.org/10.5829/ije.2022.35.12c.09

[83] Tang, G., Han, Y., Lau, B. L., Zhang, X., & Rhee, D. M. W. (2016). Development of a compact and efficient liquid cooling system with silicon microcooler for high-power microelectronic devices. IEEE Transactions on Components, Packaging and Manufacturing Technology, 6(5), 729-739.

[84] Tay, T., Liu, G., Tan, V., Sun, X., & Pham, D. (2008). Progressive failure analysis of composites. Journal of Composite Materials, 42(18), 1921-1966. https://doi.org/10.1177/0021998308093912

[85] Towsyfyan, H., Biguri, A., Boardman, R., & Blumensath, T. (2020). Successes and challenges in non-destructive testing of aircraft composite structures. Chinese Journal of Aeronautics, 33(3), 771-791.

[86] Umar, T., Yousaf, M., Akbar, M., Abbas, N., Hussain, Z., & Ansari, W. (2022). An experimental study on non-destructive evaluation of the mechanical characteristics of a sustainable concrete incorporating industrial waste. Materials, 15(20), 7346. https://doi.org/10.3390/ma15207346

[87] Volk, A., Ghia, U., & Stoltz, C. (2017). Effect of grid type and refinement method on cfd-dem solution trend with grid size. Powder Technology, 311, 137-146. https://doi.org/10.1016/j.powtec.2017.01.088

[88] Wang, B., Zhong, S., Lee, T. L., Fancey, K. S., & Mi, J. (2020). Non-destructive testing and evaluation of composite materials/structures: A state-of-the-art review. Advances in mechanical engineering, 12(4), 1687814020913761.

[89] Wang, B., Zhong, S., Lee, T. L., Fancey, K. S., & Mi, J. (2020). Non-destructive testing and evaluation of composite materials/structures: A state-of-the-art review. Advances in mechanical engineering, 12(4), 1687814020913761.

[90] Wang, B., Zhong, S., Lee, T., Fancey, K., & Mi, J. (2020). Non-destructive testing and evaluation of composite materials/structures: a state-of-the-art review. Advances in Mechanical Engineering, 12(4), 168781402091376. https://doi.org/10.1177/1687814020913761

[91] Williams, J. C., & Starke Jr, E. A. (2003). Progress in structural materials for aerospace systems. Acta materialia, 51(19), 5775-5799.

[92] Wronkowicz, A. (2018). A brief review on ndt&e methods for structural aircraft components. Fatigue of Aircraft Structures, 2018(10), 73-81. https://doi.org/10.2478/fas-2018-0007

[93] Wu, R., Zhang, H., Yang, R., Chen, W., & Chen, G. (2021). Nondestructive testing for corrosion evaluation of metal under coating. Journal of Sensors, 2021(1). https://doi.org/10.1155/2021/6640406

[94] Wu, S., Lin, Y., Hwang, K., Cheng, T., & Tung, K. (2018). High-efficiency hollow fiber arrangement design to enhance filtration performance by cfd simulation. Chemical Engineering and Processing - Process Intensification, 125, 87-96. https://doi.org/10.1016/j.cep.2018.01.003

[95] Xu, Y., Song, X., Sun, Z., Lu, G., Li, P., & Yu, J. (2015). Simulation and evaluation of the performance and feasibility of two-stage industrial hydrocyclones for caso4 removal in potassium chloride production. The Canadian Journal of Chemical Engineering, 93(4), 736-746. https://doi.org/10.1002/cjce.22163

[96] Zeng, T., Wang, H., Yang, M., & Alexandersen, J. (2020). Topology optimization of heat sinks for instantaneous chip cooling using a transient pseudo-3D thermofluid model. International Journal of Heat and Mass Transfer, 154, 119681.

[97] Zhou, M., Alexandersen, J., Sigmund, O., & W. Pedersen, C. B. (2016). Industrial application of topology optimization for combined conductive and convective heat transfer problems. Structural and Multidisciplinary Optimization, 54, 1045-1060.