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Pregled metoda prediktivnog održavanja zasnovanih na veštačkoj inteligenciji za degradaciju i pouzdanost lopatica gasnih turbina

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Apstrakt: Gasnoturbinski motori predstavljaju ključne pogonske sisteme u savremenoj vazduhoplovnoj industriji, pri čemu turbinski delovi rade u ekstremnim eksploatacionim uslovima koje karakterišu visoke temperature, velika centrifugalna naprezanja i agresivno gasno okruženje. Turbinske lopatice, kao najkritičnije i najopterećenije komponente, izložene su kombinovanom delovanju termičkih i mehaničkih opterećenja, što dovodi do razvoja složenih mehanizama degradacije materijala.

U ovom preglednom radu razmatra se ponašanje turbinskih lopatica u uslovima dugotrajne eksploatacije, sa posebnim osvrtom na dominantne mehanizme degradacije, kao što su puzanje, oksidacija, termički i visokociklični zamor, kao i mikrostrukturne promene koje prethode inicijaciji i propagaciji pukotina.

Posebna pažnja posvećena je mogućnostima primene savremenih metoda veštačke inteligencije u okviru okvira prediktivnog održavanja, sa fokusom na procenu preostalog radnog veka (RUL), detekciju anomalija i analizu obrazaca degradacije. Rad daje kvalitativni pregled mehanizama degradacije materijala i pristupa prediktivnog održavanja zasnovanih na veštačkoj inteligenciji, uz naglašavanje njihovog potencijalnog doprinosa unapređenju pouzdanosti vazduhoplovnih sistema.

Ključne reči: gasnoturbinski motori, mikrostrukturna degradacija, prediktivno održavanje, preostali radni vek (RUL)

A Review of AI-Based Predictive Maintenance Methods for Gas Turbine Blade Degradation and Reliability

Abstract: Gas turbine engines represent key propulsion systems in the modern aerospace industry, with their turbine section operating under extreme service conditions characterized by high temperatures, significant centrifugal stresses, and aggressive gaseous environments. Turbine blades, as the most critical and highly loaded components, are subjected to combined thermal and mechanical loading, leading to the development of complex material degradation mechanisms.

This review discusses the behavior of turbine blades under long-term service conditions, with particular emphasis on dominant degradation mechanisms such as creep, oxidation, thermal and high-cycle fatigue, as well as microstructural changes preceding crack initiation and propagation.

Special attention is given to the potential application of modern artificial intelligence methods within predictive maintenance frameworks, focusing on remaining useful life (RUL) estimation, anomaly detection, and the analysis of degradation patterns. The paper provides a qualitative overview of material degradation mechanisms and AI-based predictive maintenance approaches, highlighting their potential role in supporting reliability improvement in aerospace systems.

Keywords: gas turbine engines, microstructural degradation, predictive maintenance, remaining useful life (RUL)

1. Introduction

Aerospace systems represent one of the most complex classes of engineering systems, in which safety, reliability, and material degradation management are of critical importance. In the modern aerospace industry, gas turbine engines occupy a central role as propulsion systems, operating under conditions of high thermal, mechanical, and aerodynamic loads, as well as stringent requirements in terms of reliability and operational availability.

A particularly critical region is the turbine section of the engine, especially the turbine blades located in the hot section. The “hot section” of a gas turbine engine refers to the combustion chamber and turbine stages, which operate under extremely high temperature conditions and represent the zone of most intensive thermal and microstructural material degradation. During operation, these components are exposed to high temperatures, significant centrifugal stresses, and an aggressive gas environment, making them the most highly loaded and critical elements from the standpoint of material degradation and failure initiation.

The reviewed literature indicates that dominant degradation mechanisms include creep, oxidation, thermal fatigue, high-cycle fatigue, and thermo-mechanical fatigue (Kurz & Brun, 2000). These processes lead to progressive deterioration of the material microstructure, with Ni–Cr-based superalloys being widely used due to their high-temperature resistance, although they remain susceptible to long-term degradation. Microstructural damage, such as intergranular cracking and grain boundary weakening, represents a key indicator of progressive failure. Therefore, continuous monitoring of turbine blade condition is essential for reliability assessment and failure prevention.

Advances in sensor technologies and condition monitoring systems have enabled a transition from traditional maintenance strategies based on fixed intervals to condition-based and predictive maintenance approaches. Preventive maintenance relies on predefined schedules, whereas predictive maintenance utilizes real-time operational data to assess component health and estimate Remaining Useful Life (RUL), often supported by machine learning and data-driven methods.

The literature used in this study was identified through a structured search of scientific databases, including Scopus, Web of Science, and Google Scholar. The initial search was performed using combinations of keywords such as “gas turbine blade degradation”, “remaining useful life”, “predictive maintenance”, “prognostics and health management”, “condition monitoring”, and “artificial intelligence in maintenance”.

In addition to the database search, a snowballing approach was applied to ensure a comprehensive coverage of relevant literature. This included backward citation tracking (screening reference lists of selected papers) and forward citation tracking using Google Scholar’s “cited by” and recommendation features. This approach enabled the inclusion of both recent studies and earlier seminal works that form the theoretical foundation of gas turbine degradation and reliability analysis.

The review therefore includes a combination of recent publications (2005–2025), primarily focused on artificial intelligence and predictive maintenance methods, as well as earlier foundational studies addressing gas turbine degradation mechanisms and material behavior. Preference was given to peer-reviewed journal articles and conference papers written in English. The search results were screened based on titles, abstracts, and full texts to select studies relevant to the research focus.

2. Operating Conditions and Degradation of Gas Turbine Blades

Gas turbine engines represent key propulsion systems in modern aerospace engineering, with their turbine components operating under extreme service conditions characterized by high temperatures, large centrifugal stresses, and aggressive gas environments (Mattingly, 2002; Saravanamuttoo et al., 2001). Turbine blades, as the most critical and highly loaded components, are located in the hot section of the engine and are exposed to severe thermal conditions. Gas temperatures typically range from approximately 800 °C in the early stages to values exceeding 1000–1100 °C in high-pressure turbine sections, depending on engine design and cooling efficiency (Behera et al., 2023). Higher overall gas-path temperatures, reaching up to approximately 1300 °C, have also been reported in gas turbine systems (Bohidar et al., 2013). In localized hot-spot conditions, metal temperatures may further increase and approach or exceed 1200 °C, making these components particularly susceptible to progressive material degradation and failure initiation.

Under such conditions, complex degradation mechanisms occur, including creep, oxidation, thermal fatigue, high-cycle fatigue, and thermo-mechanical fatigue. Experimental studies on service-exposed turbine blades have shown

that long-term exposure to elevated temperatures leads to γ' precipitate coarsening and rafting, carbide transformation, grain boundary degradation, and crack initiation, resulting in progressive deterioration of mechanical properties and reduced blade life (Najmi & Migbagheri, 2023; Kolagar et al., 2017). These processes lead to gradual deterioration of the material microstructure and are recognized as the primary causes of progressive turbine blade damage. In addition, erosion and fouling phenomena significantly influence component performance by altering blade geometry and surface condition, thereby affecting aerodynamic flow characteristics through the turbine (Kurz et al., 2000; Kurz et al., 2014).

Nickel (Ni) based alloys with chromium (Cr) play a particularly important role due to their high-temperature resistance; however, they still exhibit significant sensitivity to long-term operational loading. Their degradation is manifested through microstructural changes, including phase coarsening, grain boundary weakening, and intergranular damage (Sujata et al., 2010). Furthermore, the interaction of airborne particles with blade surfaces leads to erosive wear, the intensity of which depends on particle velocity, impact angle, and temperature, and can be predicted using numerical simulations of particle trajectories in a three-dimensional flow field (Tabakoff et al., 1998).

In real operational conditions, additional contributions to degradation arise from oxidation and thermal corrosion, as well as the initiation and propagation of microcracks along grain boundaries. These phenomena represent direct indicators of deteriorated operating conditions and often precede catastrophic blade failure (Ejaz, 2006). Moreover, increased clearances and sealing system degradation result in additional losses and flow disturbances, thereby affecting overall turbine performance (Kurz et al., 2000).

Therefore, monitoring component condition and understanding degradation mechanisms are of critical importance for reliability assessment and maintenance planning. In this context, modern approaches include the development of both simplified and complex models for degradation simulation, as well as methods for detecting performance changes during operation (Kurz et al., 2000; Kurz et al., 2014). In addition, the application of protective coatings, such as ceramic and metallic layers deposited using advanced processes (e.g., CVD), has proven to be an effective method for reducing erosive wear and extending blade service life (Tabakoff et al., 1998).

3. Traditional and modern maintenance approaches

Maintenance of gas turbine engines in aviation has traditionally been based on preventive and corrective strategies, which form the foundation of airworthiness and system safety management. Preventive maintenance involves scheduled interventions at predefined time or cycle intervals, independent of the actual condition of components, whereas corrective maintenance is performed after failure occurrence.

The periodicity of preventive maintenance for gas turbine engines can be determined using multi-criteria decision analysis methodologies (Biocanin et al., 2024) or reliability-based models (Biocanin, 2024).

In the case of turbine blades, such approaches have significant limitations, as material degradation is a continuous and progressive process that cannot always be reliably detected through discrete inspections. In practice, technical diagnostic methods such as visual inspections, non-destructive testing (NDT), and service data analysis are used to assess component condition; however, these methods are limited by inspection intervals and subjective interpretation.

Aircraft maintenance is largely governed by regulatory requirements of the European Union Aviation Safety Agency (EASA), particularly through regulations such as Part-M and Part-145, which define inspection procedures, maintenance actions, and documentation requirements. Although these standards ensure a high level of safety, they are primarily based on conservative assumptions regarding degradation and predefined maintenance intervals.

For this reason, condition-based maintenance (CBM) and predictive maintenance approaches are gaining increasing importance in modern practice. These concepts may support decision-making based on the actual condition of components, supported by continuous monitoring of operational parameters. This is particularly important for components such as turbine blades, where degradation directly affects system reliability and safety. The evolution of maintenance strategies in aviation, from traditional approaches to modern data-driven and AI-based methods, is illustrated in Figure 1.

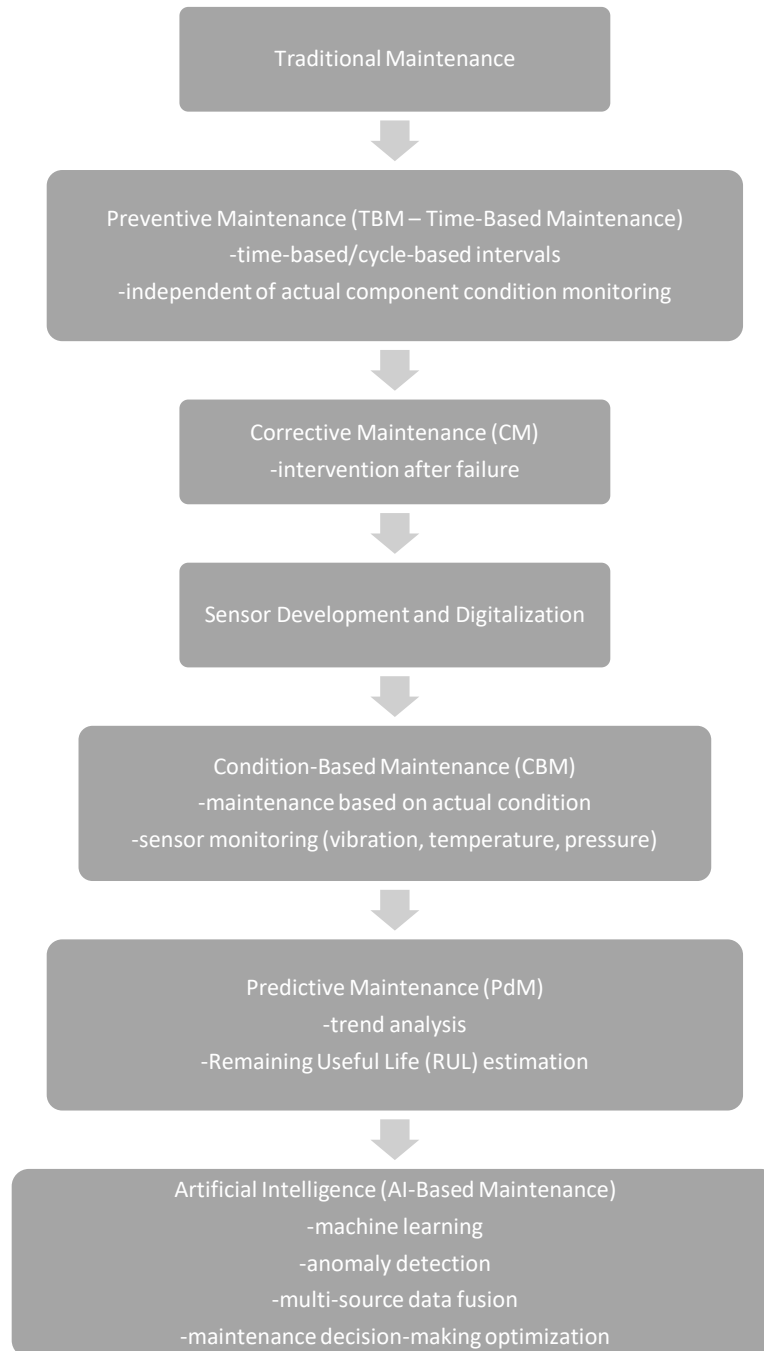


Figure 1: Conceptual framework of AI-based predictive maintenance for turbine blade degradation (Data generated by the authors)

4. Application of artificial intelligence in predictive maintenance

Artificial intelligence represents a key tool for analyzing data collected during the operation of gas turbine engines, including temperature regimes, vibrations, pressures, and other parameters relevant to assessing the condition of turbine blades.

This paper does not aim to develop or experimentally validate specific artificial intelligence algorithms, but rather to provide a qualitative and conceptual overview of their potential application within predictive maintenance frameworks.

Within these approaches, machine learning methods reported in the literature show potential for identifying degradation patterns that are not always detectable using classical analytical techniques. A broad overview of machine learning- and deep learning-based approaches for fault diagnosis and prognostics in industrial systems has been extensively discussed in the literature (Lei et al., 2018; Zonta et al., 2020), particularly in the context of predictive maintenance and Industry 4.0 applications. The most commonly applied techniques include neural networks, decision tree-based methods (random forest—an ensemble method that combines multiple decision trees to achieve more robust classification), and support vector machines (an algorithm that determines the optimal hyperplane separating classes in the data space), which have been applied for anomaly detection, state classification, and degradation trend analysis.

Modern approaches within Prognostics and Health Management (PHM) are based on the integration of physical degradation models and machine learning methods. Such hybrid models may support more reliable condition assessment by combining an understanding of degradation mechanisms with operational data analysis. The PHM and condition-based maintenance (CBM) framework has been widely established as a structured approach for maintenance optimization in engineering systems (Jardine et al., 2006; Tsui et al., 2015). A particularly important aspect is the estimation of Remaining Useful Life (RUL), where historical and real-time data are used to predict the time to failure. This approach represents one of the key concepts of predictive maintenance and may support optimization of maintenance intervals, especially for components exposed to intensive degradation such as turbine blades (Szrama et al., 2025).

Experimental investigations of service-exposed turbine blades have shown that microstructural evolution, hardness variation, and degradation of mechanical properties are strongly correlated with service exposure time, emphasizing the importance of degradation monitoring for RUL estimation and predictive maintenance strategies (Li et al., 2023). A structured overview of commonly applied artificial intelligence methods in predictive maintenance, including their applications, input data, expected outputs, advantages, and limitations, is presented in Table 1.

Table 1: Overview of AI methods in predictive maintenance of gas turbine engines

AI Method	Application	Input Data	Output	Advantages	Limitations
Neural Networks	Remaining Useful Life (RUL) prediction	Temperature, vibration, pressure	Time to failure	Models nonlinear degradation; suitable for time-series data	Limited interpretability; large datasets required
Random Forest	Fault detection and classification	Sensor data, operational parameters	Fault type/health state	Robust to noise and overfitting	Limited temporal sequence modeling
Support Vector Machine (SVM)	System health classification	Engine performance parameters	Health state category	Good performance in high-dimensional spaces	Sensitive to parameter selection

Table 2 presents a synthesized relationship between dominant turbine blade degradation mechanisms, observable operational indicators, typical input data, and corresponding artificial intelligence applications within predictive maintenance frameworks. The table is compiled based on findings reported in the literature on gas turbine degradation and condition monitoring systems (Mattingly, 2002; Saravanamuttoo et al., 2001; Kurz et al., 2014; Viswanathan, 2006). As shown, different degradation processes can be associated with specific measurable parameters obtained from engine monitoring systems, including temperature, vibration, pressure, and operational cycle data. The reviewed literature suggests that AI-based methods may support the identification of degradation trends, anomaly detection, fault classification, and Remaining Useful Life (RUL) estimation, depending on the type of degradation mechanism and available data sources.

Table 2: Synthesized relationship between turbine blade degradation mechanisms, observable indicators and AI-based predictive maintenance tasks (compiled by the authors based on reviewed literature)

Degradation mechanism	Observable indicators	Typical input data	AI task/application
Creep	Progressive deformation, temperature increase	Temperature history, operating cycles	Remaining Useful Life (RUL) estimation
Oxidation / thermal corrosion	Surface degradation, efficiency loss	Temperature data, exhaust gas parameters	Anomaly detection
High-cycle fatigue	Vibration anomalies, crack initiation	Vibration signals, rotational speed	Fault detection and classification
Thermo-mechanical fatigue	Thermal stress fluctuations	Temperature and load profiles	Degradation trend analysis
Crack initiation and propagation	Changes in vibration and acoustic response	Vibration and acoustic emission data	Fault detection and prognostics
Erosion and fouling	Reduced aerodynamic efficiency	Pressure ratio, airflow parameters	Performance degradation analysis

In general, the application of artificial intelligence in predictive maintenance of gas turbine engines follows a structured data-driven workflow consisting of data acquisition, preprocessing, model development, and output interpretation. Operational data such as temperature, vibration signals, rotational speed, and pressure are collected from engine monitoring systems and serve as input variables for machine learning models. These data are then processed and used to train algorithms capable of identifying degradation patterns and predicting system behavior.

The typical workflow can be represented as a pipeline: sensor data → feature extraction → machine learning model → diagnostic or prognostic output. In this framework, different AI methods are applied depending on the specific task. For example, neural networks are commonly used for Remaining Useful Life (RUL) estimation due to their ability to capture nonlinear degradation trends, while Random Forest models are effective for fault classification based on structured sensor datasets (Tsui et al., 2015; Szrama et al., 2025). Support Vector Machines (SVM) are widely used for health state classification due to their robustness in high-dimensional feature spaces.

The integration of these methods enables both diagnostic (fault detection and classification) and prognostic (RUL estimation) capabilities within a unified predictive maintenance framework. This may support maintenance-related decision-making processes and may contribute to improving the reliability of aerospace propulsion systems.

In addition, digital twin concepts are increasingly important and may support real-time simulation of component behavior and degradation prediction. Digital twin frameworks have been widely recognized as an enabling technology for integrating physical models, sensor data, and machine learning methods in predictive maintenance and smart manufacturing systems (Qi & Tao, 2019). However, the application of artificial intelligence in aviation requires high-quality data, model validation, and compliance with regulatory requirements to ensure reliability in safety-critical systems.

5. Risk, limitations, and application of artificial intelligence in turbine blade degradation analysis

The application of artificial intelligence in predictive maintenance of gas turbine engines, particularly in turbine blade condition analysis, offers significant potential for improving system reliability. However, it also introduces several limitations arising from the safety-critical nature of aerospace applications.

One of the main challenges concerns the reliability of prognostic models, as errors in Remaining Useful Life (RUL) estimation may directly affect system safety and operational availability. Another key issue is the limited availability of real failure data, since such events are rare but essential for model validation and training.

An additional complexity is related to model interpretability, especially in deep neural networks, which often function as “black boxes”. In aerospace systems, where clear justification of decisions is required, this represents a significant limitation and necessitates additional verification and validation methods.

The regulatory framework of aviation further slows down the implementation of advanced algorithms, as standards require rigorous certification, testing, and reliability demonstration processes. Therefore, hybrid approaches that combine physical degradation models with machine learning methods are increasingly favored in practice, as they improve robustness and regulatory acceptance.

In this context, turbine blade degradation represents a central problem in gas turbine engine reliability analysis. These components operate under extreme conditions at temperatures, under the simultaneous influence of high centrifugal, thermal, and aerodynamic loads, leading to complex degradation mechanisms.

Dominant damage mechanisms include creep, oxidation, thermo-mechanical and high-cycle fatigue, as well as crack initiation and propagation. Microstructural changes in Ni-based superalloys are particularly important, manifested through grain boundary degradation, phase coarsening, and intergranular cracking. These changes represent reliable indicators of accumulated material damage.

In real operating conditions, direct monitoring of these processes is limited; therefore, degradation analysis is based on indirect indicators such as temperature, vibration, and engine operating regimes. This is precisely where artificial intelligence methods play a crucial role.

Machine learning methods may enable data fusion from multiple heterogeneous sources, including sensor measurements, historical records, and physical degradation models, potentially improving the detection of hidden damage patterns not observable through classical analytical methods. A particularly important application is in Remaining Useful Life (RUL) estimation, where failure time prediction may be performed by combining historical data, sensor measurements, and degradation models. The importance of RUL estimation and uncertainty quantification in prognostics has been widely discussed in the literature (Si et al., 2011).

Modern PHM approaches increasingly explore hybrid modeling strategies that integrate physical principles with machine learning techniques. Physics-Informed Neural Networks (PINNs) provide a framework for embedding governing physical laws into data-driven models (Raissi et al., 2019). Recent research has proposed Bayesian extensions of such models to incorporate uncertainty quantification through probabilistic inference over network parameters (Yang et al., 2021). In parallel, Bayesian neural network approaches have been applied in Remaining Useful Life estimation and PHM frameworks to improve predictive uncertainty handling and enhance decision-making reliability in safety-critical systems. These developments highlight the growing interest in probabilistic and physics-informed learning methods for uncertainty-aware prognostics. Within modern PHM frameworks, hybrid models that combine physical degradation mechanisms (e.g., creep and fatigue) with machine learning methods are gaining increasing importance. This approach may provide a better understanding of material behavior and improves prediction reliability compared to purely data-driven models. Prognostics and Health Management (PHM) represents an integrated framework that includes condition monitoring, diagnostics, and system behavior prediction, aiming to improve reliability, safety, and sustainability during operation (Tsui et al., 2015).

The application of PHM approaches in aerospace also extends to other critical subsystems, including landing gear, where AI methods are used for failure detection and remaining life estimation, thereby potentially improving maintenance efficiency and safety (Raouf et al., 2025).

Modern prognostic approaches in gas turbine engines are based on trend analysis of operating parameters such as turbine temperatures, rotational speeds, and pressures. Data-driven algorithms may support identification of degradation patterns and estimation of remaining useful life of components (Szrama et al., 2025).

In addition to turbine blades, similar principles can be applied to other engine subsystems, such as compressors, fuel systems, and lubrication systems, supporting comprehensive reliability assessment of the entire propulsion system. However, turbine blades remain the most critical element due to their essential role and high sensitivity to degradation processes.

6. Conclusion

This paper provides a qualitative review of the behavior of gas turbine engine blades under long-term operational conditions, with particular focus on dominant material degradation mechanisms, including creep, oxidation, and various forms of thermal and mechanical fatigue. The reviewed literature suggests that nickel-based superalloys containing chromium and other alloying elements, although designed for high-temperature operation, are still susceptible to complex microstructural changes that may lead to progressive damage and reduced component reliability.

Traditional maintenance approaches based on time- or cycle-based intervals show limitations in early degradation detection, especially for components in which damage develops gradually at the microstructural level. In this context, condition-based and predictive maintenance approaches represent a conceptual advancement, as they enable decision-making based on actual operational data.

The reviewed studies suggest that artificial intelligence methods have considerable potential for supporting turbine blade condition analysis, particularly in anomaly detection and Remaining Useful Life (RUL) estimation. The integration of multi-source data and the use of hybrid models combining physical degradation mechanisms and machine learning methods may support more reliable interpretation of complex degradation processes.

However, the application of these methods is still limited by the availability of high-quality failure data, issues related to model interpretability, and strict regulatory requirements in aviation. Therefore, the reviewed literature suggests that a cautious and phased implementation approach may be appropriate when deploying these technologies in safety-critical aerospace systems.

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Conflicts of Interest

The authors declare no conflict of interest.

References

1. Behera, A., Sahoo, A. & Mahapatra, S. (2023). Application of Ni-based superalloy in aero turbine blade: A review, *Proceedings of the Institution of Mechanical Engineers, Part E: Journal of Process Mechanical Engineering*, 09544089231219104.
2. Biočanin, S., & Timotijević, M. (2024). Determination of a reliability model for an engine low pressure pump. In *Proceedings of the Sustainable Aviation Symposium*. Belgrade.
3. Biočanin, S., Timotijević, M., Bulatović, Ž., & Mišić, M. (2024). Determination of the model of preventive maintenance of special-purpose vehicles. *Vojnotehnički glasnik*, 72(4), 1–37. <https://doi.org/10.5937/vojtehg72-50491>
4. Bohidar, S. K., Dewangan, R., & Kaurase, P. R. (2013). Advanced materials used for different components of gas turbine. *International Journal of Scientific Research and Management*, 1, 366–370.
5. Ejaz, N., & Tauqir, A. (2006). Failure due to structural degradation in turbine blades. *Engineering Failure Analysis*, 13(3), 452–463.
6. Jardine, A., Lin, D. & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483-1510.
7. Kolagar, A.M., Tabrizi, N., Cheraghzadeh, M., Shahriari, M.S. (2017). Failure analysis of gas turbine first stage blade made of nickel-based superalloy, *Case Studies in Engineering Failure Analysis*, 8, 61-68, ISSN 2213-2902, <https://doi.org/10.1016/j.csefa.2017.04.002>.
8. Kurz, R., & Brun, K. (2000). Degradation in gas turbine systems. *Journal of Engineering for Gas Turbines and Power*, 123(1), 70–77. <https://doi.org/10.1115/1.1340629>
9. Kurz, R., Meher-Homji, C., & Brun, K. (2014). Gas turbine degradation. In *Proceedings of the 43rd Turbomachinery & 30th Pump Users Symposia*. Houston, TX.
10. Lei, Y., Li, N., Guo, L., Li, N., Yan, T & Lin J. (2018). Machinery health prognostics: A systematic review from data acquisition to RUL prediction. *Mechanical Systems and Signal Processing*, 104, 799-834.
11. Li, D., Liu, J., Sun, J., Huang, W., Li, N & Yang, L. (2023). Microstructure and mechanical degradation of K403 Ni-based superalloy from ultra-long-term serviced turbine blade. *Journal of Alloys and Compounds*, 957, 170378, ISSN 0925-8388, <https://doi.org/10.1016/j.jallcom.2023.170378>.
12. Mattingly, J. D. (2002). *Aircraft engine design*. AIAA.

13. Najmi, M. & Migbagheri, A.M.H. (2023). CM88Y superalloy blade metallurgical degradation in a gas turbine. *Engineering Failure Analysis*, 146, 107110.
14. Raissi, M., Perdikaris, P., & Karniadakis, G. E. (2019). Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations. *Journal of Computational Physics*, 378, 686–707.
<https://doi.org/10.1016/j.jcp.2018.10.045>
15. Raouf, I., Kumar, P., Cheon, Y., et al. (2025). Advances in prognostics and health management for aircraft landing gear—Progress, challenges, and future possibilities. *International Journal of Precision Engineering and Manufacturing-Green Technology*, 12, 301–320.
<https://doi.org/10.1007/s40684-024-00646-4>
16. Sankararaman, S. (2015). Significance, interpretation, and quantification of uncertainty in prognostics and remaining useful life prediction. *Mechanical Systems and Signal Processing*, 52–53, 228–247, <https://doi.org/10.1016/j.ymssp.2014.05.029>.
17. Saravanamuttoo, H. I. H., Rogers, G. F. C., & Cohen, H. (2001). *Gas turbine theory*. Pearson Education.
18. Si, X. S., Wang, W., Hu, C. H., & Zhou, D. H. (2011). Remaining useful life estimation – A review on the statistical data driven approaches. *European Journal of Operational Research*, 213(1), 1–14, <https://doi.org/10.1016/j.ejor.2011.02.013>
19. Sujata, M., Madan, M., Raghavendra, K., Venkataswamy, M. A., & Bhaumik, S. K. (2010). Identification of failure mechanisms in nickel base superalloy turbine blades through microstructural study. *Engineering Failure Analysis*, 17(6), 1436–1446.
20. Szrama, S., Szymański, G., & Mokrzan, D. (2025). Aircraft propulsion health status prognostics and prediction. *Advances in Science and Technology Research Journal*, 19(5), 321–335.
21. Tabakoff, W., Hamed, A., & Shanov, V. (1998). Blade deterioration in a gas turbine engine. *International Journal of Rotating Machinery*, 4, Article 621028.
<https://doi.org/10.1155/S1023621X98000190>
22. Qi, Q. & Tao, F. (2018). Digital Twin and Big Data Towards Smart Manufacturing and Industry 4.0: 360 Degree Comparison, *IEEE Access*, 6, 3585–3593.
23. Tsui, K. L., Chen, N., Zhou, Q., Hai, Y., & Wang, W. (2015). Prognostics and health management: A review on data-driven approaches. *Mathematical Problems in Engineering*, 2015, Article 793161.
<https://doi.org/10.1155/2015/793161>
24. Yang, L., Meng, X., & Karniadakis, G. E. (2021). B-PINNs: Bayesian physics-informed neural networks for forward and inverse PDE problems with noisy data. *Journal of Computational Physics*, 425, 109913, <https://doi.org/10.1016/j.jcp.2020.109913>.
25. Viswanathan, R. (2006). *Damage mechanisms and life assessment of high-temperature components* (4th ed.). ASM International.
26. Zonta, T., Costa, C., Righi, R., Lima, M., Trindade, E. & Li, G. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review, *Computers & Industrial Engineering*, 150, 106889, ISSN 0360-8352, <https://doi.org/10.1016/j.cie.2020.106889>.