THEORETICAL PRINCIPLES FOR DEVELOPING A METHODOLOGY OF ADVANCED DIGITAL TWIN CONSTRUCTION AND ITS APPLICATION IN PRODUCT RECOVERY PRODUCTION SYSTEMS

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Abstract - This paper presents a concept of technological support for the restoration of worn parts based on the application of digital twin technology. It is demonstrated that conventional repair and restoration approaches do not ensure the required accuracy and efficiency under modern demands for product reliability and service life. To address these limitations, an integrated digital restoration environment is proposed, combining 3D scanning technologies, CAD/CAE/CAM systems, digital modeling, and analytical methods.

Particular attention is given to the integration of the digital twin with reverse engineering processes, enabling the development of adaptive technological routes for part restoration, prediction of residual life, and evaluation of operational performance. A digital twin is considered as an integrated virtual–physical model that reflects the geometric state, operating parameters, and restoration history of a component in real time.

A structured architecture of a digital twin for worn parts is proposed, including modules for geometric analysis, sensor data monitoring, simulation modeling, and restoration lifecycle management. Based on the analysis of existing technological solutions, the feasibility of integrating CAD/CAE/PLM systems with IoT and artificial intelligence components is substantiated to ensure accurate condition monitoring and optimization of restoration processes.

The practical implementation of the proposed concept enables improved accuracy of wear assessment, reduced complexity of repair operations, and a transition toward adaptive and predictive maintenance strategies within the Industry 4.0 paradigm.

The novelty of the study lies in the development of a conceptual framework for technological support of part restoration that accounts for individual operating conditions, wear characteristics, and design features. The practical significance is associated with reduced production preparation time, lower repair costs, and enhanced accuracy of geometry restoration.

Keywords: Concept, Restoration, Worn part, Digital twins, Combination of technologies, Product reliability, Digital modeling, Reverse reengineering.

1. Introduction

This study addresses the need for a transition from static digital models to adaptive models capable of accurately reflecting the real-time technical condition of an object throughout its entire lifecycle, which is a key requirement of modern engineering development trends. A key direction in this field is the development of Extended Digital Twins, which integrate not only geometric data but also wear maps and material attributes of components. Such integration enables a more accurate representation of physical and mechanical processes and supports the implementation of predictive maintenance strategies.

However, existing approaches to digital twin development do not fully account for the influence of material properties and degradation processes, which reduces model accuracy and limits their applicability in real operating conditions. In addition, most existing methodologies are focused on high-tech or science-intensive industries, while there is a

dx.doi.org/10.17683/ijomam/issue24.39

lack of specialized studies addressing the needs of small and medium-sized enterprises (SMEs).

Therefore, the development of theoretical foundations for a methodology for constructing an extended digital twin with integrated wear maps and material attributes remains a significant challenge in modern engineering science.

2. Literature Review

The issues of technological support for the restoration of worn parts using digital twins have been widely addressed in recent studies. Existing research demonstrates a growing interest in integrating digital twin technologies, artificial intelligence, and advanced data processing methods into the lifecycle management of engineering systems.

Paper [1] analyzes the implementation of artificial intelligence (AI) in the technological support of the lifecycle of mechanical engineering products. The authors highlight key aspects of AI application aimed at improving the efficiency of all lifecycle stages, from design to disposal. In particular, the proposed conceptual framework for integrating AI into production control and maintenance processes enables data acquisition, condition prediction, and timely restoration of components in the presence of wear or damage. These results indicate the significant potential of AI-driven approaches for enhancing maintenance strategies. The use of digital twins for damaged objects is investigated in [2], where the authors provide a systematic overview of approaches for assessing technical condition and predicting the behavior of degraded structures. The proposed methodology offers a practical basis for restoration strategies under failure conditions. However, the study primarily focuses on structural assessment rather than on the integration of restoration-oriented technological processes.

In [3], the impact of digital twins and generative design on engineering workflows is analyzed, including transformations in CAD processes. The study demonstrates that generative approaches can significantly reduce the time required for geometry reconstruction of restored parts and can be effectively integrated into closed-loop digital twin frameworks. At the same time, the application of these approaches is mainly limited to design optimization, with insufficient consideration of material degradation and wear evolution.

Recent studies by autors [4-7] further extend these approaches by demonstrating the integration of digital twin technologies with spatial inspection methods, mobile sensing systems, and real-time data acquisition. These works highlight the potential of combining digital twins with image processing and sensor-based monitoring for improving the accuracy of component condition assessment and enabling adaptive restoration strategies. In particular, the use of mobile and distributed sensing environments provides new opportunities for scalable and cost-effective implementation of digital twins in industrial applications.

Dissertation [8] presents comprehensive methods for processing multimodal data (point clouds, images, and sensor data) for digital twins, including data fusion and fuzzy verification techniques. This work provides a valuable methodological foundation for integrating heterogeneous data sources, which is essential for combining 3D scanning results with wear measurements such as surface roughness and wear profiles. Nevertheless, the focus remains on data processing rather than on its direct application to restoration process optimization.

Study [9] addresses data acquisition, filtering, and quality control of spatial and temporal data for digital twins, emphasizing QA/QC techniques under conditions of noisy or incomplete data. While these approaches improve data reliability, they do not fully resolve the challenges of integrating such data into adaptive restoration models.

Paper [10] proposes a digital twin model updated using IoT sensor data for infrastructure degradation prediction, enabling the development of repair prioritization algorithms. This approach demonstrates the advantages of real-time monitoring but is primarily oriented toward large-scale infrastructure systems rather than individual engineering components.

Recent international studies have further advanced the development of digital twin architectures for lifetime prediction [11]. In particular, study [12] demonstrates real-time monitoring of tool wear by integrating sensor data streams with digital twin models. The authors emphasize the importance of adaptive wear maps and present examples of integrating extended Kalman filtering for micro-machining applications. These results confirm the effectiveness of combining statistical filtering methods with sensor data; however, they are mainly focused on monitoring rather than on comprehensive restoration strategies.

Of particular interest are the digital twin models with dynamic mechanistic modeling cores proposed in [13–15], which are applied for predicting milling tool wear. These approaches highlight the importance of integrating physical models with data-driven methods. Practical aspects of digital twin implementation in industrial environments, including PLM/CAD/CAE integration challenges, are discussed in [16]. Study [17] provides a comprehensive review of AI-based digital twins in manufacturing, emphasizing the integration of operators, products, and processes, as well as the inclusion of material attributes within digital twin architectures.

Overall, the reviewed studies demonstrate significant progress in the development of digital twin technologies, particularly in the areas of monitoring, data processing, and predictive analytics. However, a critical analysis reveals that the technological support of restoration processes for worn parts remains insufficiently addressed. Existing approaches tend to focus either on data acquisition and analysis or on design and simulation tasks, while the integration of geometric, material, and operational data into a unified restoration-oriented digital twin framework is still limited.

A digital twin enables the creation of a continuously updated dynamic model based on sensor data, operational measurements, and control systems, forming the foundation for predictive analysis and maintenance optimization. Nevertheless, there remains a clear research gap in the development of methodologies that explicitly incorporate wear maps, material degradation, and adaptive technological routes for restoration processes.

The aim of this study is to develop theoretical and methodological foundations that ensure the integrated representation of geometric, physical-mechanical, and wear-related characteristics of an object in real time using digital twin technology.

3. Main Content

Since its emergence, the digital twin (DT) has been recognized as an effective paradigm for integrating physical assets with their digital counterparts, attracting significant interest across industrial, technological, and policy-driven domains. A review of scientific publications indicates that traditional approaches to digital twin development are primarily focused on geometric and kinematic aspects, without adequately accounting for material properties and changes in the physical state of an object during operation. This limitation reduces the accuracy of digital models, particularly for components subjected to wear, fatigue, or material degradation.

In this context, it is proposed to develop an Extended Digital Twin (E-DT), which integrates geometric models with material attributes and wear maps, while ensuring temporal adaptability through integration with operational data streams [18]. A wear map is defined as a spatial model representing the degree of surface or volumetric material degradation within the coordinate system of a component, obtained from measurements, simulations, or signal analysis.

Approaches to modeling wear and material properties within digital twins can generally be classified into three main categories: physics-based (mechanistic) models [19], data-driven models based on machine learning and deep learning [20], and hybrid models that combine physical principles with data-driven approaches [21]. At the same time, wear maps are developed at different levels of complexity, ranging from global indices to spatially resolved surface and volumetric representations, including microstructural attribute layers. A review of existing studies indicates that hybrid approaches provide the most effective results, as they combine interpretable physical laws with the adaptability of machine learning to real-world data.

Machine Learning (ML), as a subfield of artificial intelligence, enables systems to learn from data without explicit programming, allowing for pattern recognition, prediction, and adaptive decision-making [22].

A digital twin is defined as an integrated virtual model of a physical object that reproduces its geometric, physical-mechanical, and functional characteristics in real time. In the context of component restoration, the digital twin serves as a foundation for condition assessment, wear prediction, and selection of optimal repair strategies. Traditionally, the restoration process has been fragmented: CAD systems are used only for geometry representation, technological departments independently plan repair operations, quality control is performed after restoration, and sensor-based diagnostics remain disconnected from CAD and PLM environments.

CAD (Computer-Aided Design) systems enable the creation, modification, and analysis of two- and three-dimensional models, improving design efficiency and accuracy. PLM (Product Lifecycle Management) represents a comprehensive strategy for managing all stages of a product’s lifecycle, from concept and design to production, operation, and disposal. It integrates data, processes, and resources, ensuring process optimization, cost reduction, and quality improvement.

Within the proposed theoretical framework, these components are integrated into a unified digital environment, where the digital twin of a component serves as the central element. This implies that each stage (wear → diagnostics → restoration → testing) continuously updates the digital model, preserving the complete history of changes.

The novelty of the proposed approach lies in the development of a fully functional digital twin that incorporates not only geometric data but also:

- sensor data (vibration, temperature, load, acoustic emission) reflecting the real physical state of the component;
- analytical and simulation models (e.g., FEM, thermomechanical analysis) for predicting future wear;

- a history of technological operations describing how, when, and by whom restoration was performed;
- CAD/PLM versioning to capture the evolution of the component after each repair cycle.

This enables the creation of a "living" digital representation of a component that accompanies it throughout its entire lifecycle.

The novelty of the proposed concept also extends beyond the digital model itself to a new approach to technological support. Technological parameters (e.g., deposition regimes, heat treatment, machining conditions) are directly linked to the digital twin. Based on sensor data analysis and simulation results, the system can automatically recommend optimal restoration parameters. A closed-loop quality control system is implemented, where post-repair results update wear models, forming a knowledge base for future restoration processes.

The significance of the proposed approach for mechanical engineering enterprises is reflected in technological efficiency, lifecycle management capabilities, engineering innovation, and economic and environmental benefits.

Technological efficiency is achieved through reduced decision-making time for repair (via automated wear assessment and resource prediction), increased restoration accuracy through comparison of 3D scans with reference CAD models, and reduction of rework and defects. This results in repair cost reduction of up to 25–30% and increased equipment availability.

Lifecycle management enables each component to obtain a "digital passport" containing wear history, repair records, and operational parameters. This supports predictive maintenance strategies based on actual condition rather than scheduled intervals and enables the creation of digital archives of component fleets, reducing unplanned downtime and optimizing spare parts management.

Engineering and innovation advantages arise from the development of new competencies in digital restoration, enabling personalized repair strategies based on component-specific data. This creates competitive advantages in after-sales service and leads to the formation of new business models such as "Repair-as-a-Service" based on digital twins.

Economic and environmental benefits include increased material reuse, reduction of waste and disposal costs, and optimized energy consumption through improved technological regimes, contributing to the transition toward green manufacturing models.

Thus, the novelty of the proposed concept of technological support for the restoration of worn components lies in the transition from conventional repair as a mechanical process to a digitally controlled, intelligent restoration paradigm, where the digital twin acts as an integration core linking technology, analytics, and operation. This approach enhances productivity, quality, and adaptability of repair processes within the framework of digital transformation in manufacturing.

Furthermore, the digital twin enables the creation of an integrated virtual–physical model of a component, reflecting its geometric state, operational parameters, and restoration history in real time.

4. Principles and Stages of Digital Twin Model Development

The development of a digital twin model is based on the following principles:

- *Geometric fidelity* – accurate reproduction of the shape and dimensions of a component, taking into account deviations and defects identified through 3D scanning;
- *Multiphysics representation* – the model considers not only geometry but also material properties (strength, hardness, microstructure), as well as the influence of operational loads;
- *Dynamic updating* – the digital twin is continuously updated based on diagnostic results throughout the component's lifecycle;
- *Integration with production processes* – the digital twin is connected with CAD/CAE/CAM systems and technological restoration routes.

The development of a digital twin for a worn component involves the following stages.

Stage 1. Data acquisition. 3D scanning of the component surface (laser, optical, or CT scanning); measurement of defect parameters (wear depth, cracks, erosion); recording of operating conditions (load, temperature, environment).

Stage 2. Creation of the base geometric model. Construction of a CAD model based on scanning data; alignment with the reference geometry (original component or design documentation); identification of wear zones through comparison with the reference model.

Stage 3. Analysis of material and mechanical properties. Application of materials science data (microhardness, microstructure); development of material property maps for different regions of the component; incorporation of these data into CAE models for strength analysis.

Stage 4. Integration with simulation models. Modeling of the stress–strain state of the component considering actual wear; prediction of residual life; selection of an optimal restoration strategy (e.g., cladding, additive repair, or hybrid approaches).

Stage 5. Formation of an integrated digital twin. Integration of geometric, material, and functional models into a unified environment; connection with technological routes (CAM systems, deposition or printing trajectories); implementation of feedback mechanisms for updating the model based on diagnostic data during operation.

The expected results of applying digital twin technology include:

- improved restoration accuracy through comparison of actual and reference geometry;
- residual life prediction, enabling estimation of service life after repair under specific operating conditions;
- adaptation of technologies, allowing the selection of individualized restoration strategies for each component;
- reduction of production preparation time through automated generation of technological routes in CAM environments.

5. Structural Model and Integration Mechanism of the Digital Twin of a Worn Component

The structural model of a digital twin for a worn component represents an information-functional system that integrates a virtual model of the component (developed in CAD/CAE), production and technological data (PLM level), and sensor data from the physical object reflecting its actual condition during operation. In other words, it is not merely a 3D model, but a dynamic "living" model that is continuously updated based on real-time measurements, including vibration, temperature, load, and acoustic emission (AE) signals (Table 1).

Table 1. Integration architecture: CAD → CAE → PLM → sensor network in the digital twin model

Level	Functions	Data Transferred	Technological Role
CAD (Computer-Aided Design)	Geometric modeling and 3D representation	Parametric geometry, materials, design relationships	Base model of the digital twin
CAE (Computer-Aided Engineering)	Engineering simulations: stress, thermal loads, material fatigue	Mechanical and thermal fields, FEM results	Comparison with sensor data
PLM (Product Lifecycle Management)	Lifecycle management, repair, modernization	Operational data, repair history, technical documentation	Formation of component history ("digital passport")
Sensor network (IoT)	Real-time measurements: vibration, AE, temperature, load	Sensor data streams, diagnostic parameters	Real-time updating of the digital twin

The integration of CAD/CAE/PLM systems with sensor data is implemented through a unified digital data environment (Digital Thread), which connects all system levels. The core principle is that any change in the physical object is automatically synchronized with its virtual representation. The integration mechanism includes the following steps:

1. IoT sensor systems (vibration, AE, temperature, force) collect real-time data;
2. Data are transmitted via an edge gateway to a digital platform (typically cloud-based or a PLM server);
3. An analytics/AI module compares sensor data with CAE simulation results;
4. In the case of deviations or detected wear, the system updates CAD model parameters (geometry, thickness, tolerances);
5. The PLM layer registers these changes as a new version of the digital twin, recording time, parameters, and operating conditions.

Feedback is implemented through a closed-loop cycle: "measurement → analysis → update → control." Its structure is as follows:

1. Sensors acquire signals (vibration, AE, temperature, load);
2. Data analysis is performed through comparison with reference models and CAE-based simulation results;
3. Model updating is carried out by automatic adjustment of CAD parameters (e.g., layer thickness, wear depth);
4. Decision-making is performed by the PLM system, which generates recommendations regarding restoration timing and technology selection;
5. Action is executed by transferring commands to manufacturing systems (e.g., additive manufacturing or cladding equipment).

This continuous loop enables predictive condition management of the component and is characterized by the following technological features:

1. Integration capability – combining multiple digital environments (CAD/CAE/PLM/IoT);
2. Adaptivity – the model evolves according to the actual state of the component;
3. Sensor-driven analytics – real-time signal analysis is embedded in the system;
4. Predictive capability – the system anticipates failure or loss of functionality;
5. Reconstruction capability – accurate restoration of geometry prior to repair.

The significance of this technological approach for production systems includes:

1. Repair optimization through reduced downtime and elimination of redundant operations;
2. Residual life prediction, enabling assessment of both current and future component states;
3. Material and energy efficiency through precise localization of restoration zones;
4. Improved quality and accuracy, ensuring compliance of restored components with design specifications;
5. Intelligent decision support through automated recommendations for engineers and control systems.

Thus, the digital twin of a worn component serves as a key element of the technological support framework for restoration processes, enabling the integration of diagnostics, modeling, and manufacturing into a unified system.

7. Concept of Digital Reproduction of the Component Restoration Process

Let us consider the essence of technological support for the restoration of worn components using digital twins. Its key distinguishing feature is an integrated cycle in which the digital twin (DT) serves as the central element linking the physical component, the diagnostic process, and decision-making regarding restoration. The main provisions of the proposed concept are as follows.

1. *Digital twin as a multi-layer model.* The digital twin of a worn component is not merely a CAD-based geometric representation but a multi-level model that includes:

- a geometric layer (precise 3D geometry);
- a physical/material layer (material properties, hardness distributions, microstructure);
- a behavioral layer (stress models, thermal models, loading conditions);
- historical data (digital passport including load cycles, repairs, and operating conditions).

2. *Digital thread.* The digital thread represents an automated data flow linking scanning → CAD → CAE → CAM → MES/enterprise systems. All information from diagnostics to final validation is stored, versioned, and used for decision-making.

3. *Intelligent restoration decision-making.* A system combining expert knowledge, machine learning, and physical models takes as input the digital twin and optimization criteria (cost, lifetime, accuracy) and generates an optimal restoration plan, including method, process parameters, and technological route.

4. *Hybrid technological chains.* The restoration process combines additive methods (e.g., laser cladding, directed energy deposition (DED)) with conventional machining and heat treatment to recover both geometry and material properties.

5. *Digital quality control.* Quality control is implemented in a digital environment through simulations (quantitative prediction of residual life), error models, testing plans, and automated inspection after restoration (3D scanning and comparison with the target digital model).

The mechanisms of digital twin application represent a technological architecture for product restoration (Fig. 1).

The essence of these mechanisms can be described as follows.

1. *Data sources (input):* 3D surface scanning (laser scanning, structured light, photogrammetry), CT or radiography for internal defects, ultrasonic testing (UT) for crack detection, coordinate measuring machines (CMM) for critical tolerances, operational sensors (temperature, vibration, strain gauges) for real-time updating, as well as chemical (EDS, OES) and microstructural analysis for material characterization.

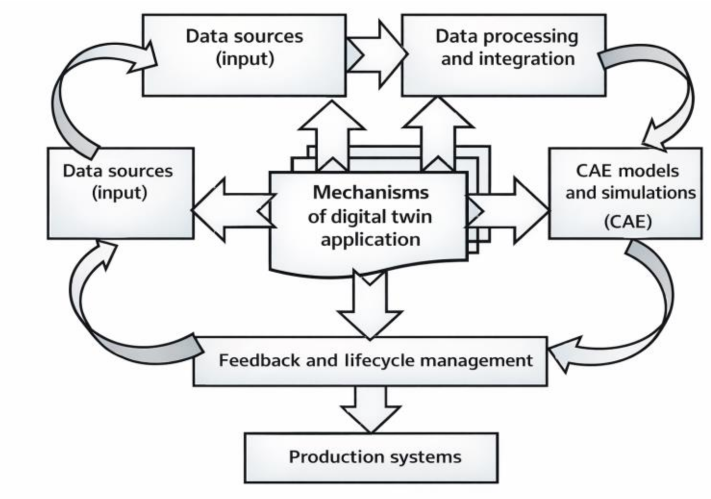

Figure 1: Mechanisms of digital twin application in a production restoration system

2. *Data processing and integration:* point cloud generation → noise filtering → registration → surface reconstruction (mesh) → conversion into parametric CAD models (NURBS, B-rep); feature recognition or creation of parametric templates; mapping of material properties (hardness, corrosion, wall thickness) onto geometry.

3. *Models and simulations (CAE)*: static and dynamic load analysis, thermodynamic models, fatigue modeling, simulation of additive deposition processes (thermal effects and residual stresses), and application of data assimilation methods (e.g., Kalman filtering, Bayesian updating, physics-informed machine learning) for model calibration based on non-destructive testing (NDT) data.

4. *Integration with production:* CAM (toolpath or deposition planning) → CNC or DED equipment → post-processing (machining, heat treatment); MES/PLM systems for version control, material management, and digital passport maintenance.

5. *Feedback and lifecycle management:* post-restoration inspection (3D scanning), comparison with the digital twin, process correction, and updating of the digital passport.

An improved approach to digital reproduction of the restoration process lies in transitioning from standardized repair templates to an adaptive "perception-based" system, where the actual condition of each component is compared with an ideal CAD model, and an optimal restoration strategy is automatically selected. This represents a shift from mass repair approaches to individualized, digitally controlled restoration.

Such an approach enables the development of a digital twin lifecycle methodology for components undergoing multiple repair cycles, taking into account CAD versioning and digital audit of changes.

The Digital Twin Lifecycle extends beyond technological aspects and directly influences business processes and marketing strategies. The lifecycle of a digital twin for repeatedly repaired components covers the entire operational period–from initial manufacturing to physical degradation–and includes several key components.

1. *CAD model versioning*. Each component has a complete digital history: initial CAD model, models after each repair cycle, and modifications due to design changes. Versioning ensures traceability of all geometric and parametric changes and guarantees that restoration is performed based on the most актуальна version. All versions are linked with technological data and analytical results (CAE, sensor data).

2. *Digital audit of changes*. All modifications are recorded, including time, type of change (geometric, material, technological), quality control results, and responsible entities (operator or automated system). This ensures full traceability required for certification and quality assurance.

3. C*yclic updating and adaptation.* After each repair, the digital twin is automatically updated: sensor data reflect the current condition, CAE models predict future performance, and CAD versions are corrected accordingly. This provides continuous lifecycle monitoring.

4. *Production advantages.* These include predicting residual life and next repair intervals, reducing defects and rework, optimizing resource planning, and providing full traceability of the component lifecycle.

The application of this lifecycle methodology forms the basis for transforming business models and marketing strategies. Products can be positioned as "intelligent" and digitally supported, offering customers traceability and predictable performance, thereby increasing trust. This enables the development of new service models such as Repair-as-a-Service (RaaS) and predictive maintenance contracts.

After-sales services include maintenance, spare parts supply, installation, technical support, and automated service notifications. The digital twin enables personalized repair strategies, providing additional competitive advantages.

Lifecycle data also enable the creation of analytical products, such as wear statistics, reliability assessment, maintenance recommendations, and personalized service offerings. These capabilities contribute to increased brand value through transparency and technological reliability.

Thus, the proposed concept demonstrates a direct impact on enterprise marketing strategies, including:

- positioning products as intelligent and digitally supported;
- development of service-oriented models (RaaS, predictive maintenance);
- use of analytics and personalization;
- enhancement of brand value through digital transparency;
- support of pricing strategies based on digital services.

Therefore, the digital twin lifecycle methodology integrates technological control with business innovation, enabling not only improved restoration efficiency but also the creation of new value propositions based on digital transparency and predictive capabilities.

The emergence of the "digital restoration" paradigm forms a new scientific direction at the intersection of reverse engineering, reliability theory, and digital technologies. A new system of performance criteria is introduced, where not only restoration accuracy but also predicted service life, material savings, and technological complexity are evaluated.

The practical significance lies in achieving a substantial reduction in repair costs and enabling rapid restoration of components, which is particularly important under crisis conditions. Digital twins allow restoration without waiting for documentation or spare parts, significantly improving operational efficiency. The creation of digital twin libraries further enables the development of unified restoration standards.

7. Conclusions

The theoretical foundations of technological support for the restoration of worn components have been developed, in which the digital twin serves as the central element for managing information flows and lifecycle control. The key novelty lies in transforming restoration from a conventional repair practice into a digitally controlled analytical process. Reverse engineering is complemented by digital validation of residual life, forming a basis for intelligent repair systems.

The proposed digital twin structure ensures integration between geometric data, sensor monitoring, analytical models, and real technological restoration processes.

The integration of CAD/CAE/PLM platforms with data acquisition and analysis systems enables the creation of a closed-loop digital quality management system for restoration and residual life assessment.

The implementation of the proposed technologies at repair and mechanical enterprises enables a transition to predictive maintenance and cost reduction through personalized digital support of components.

Future research should focus on the development of self-updating digital twin algorithms and their integration into clustered production and service systems.

Acknowledgement

The authors acknowledge that this research was conducted in alignment with the strategic priorities defined by the Strategy for the Development of the Domestic Aviation Industry of Ukraine up to 2030, approved by the Cabinet of Ministers of Ukraine (Resolution No. 851-r, July 8, 2020), and the State Target Scientific and Technical Program for the Development of the Aviation Industry of Ukraine for 2021–2030, approved by the Cabinet of Ministers of Ukraine (Resolution No. 951, September 1, 2021).

The authors also acknowledge that part of the results presented in this study was obtained within the framework of the research project No. 0126U000863, entitled “Design and technological support of abrasive processing processes of difficult-to-process materials by supplying additional types of energy to the cutting zone.

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