DIGITAL TECHNOLOGIES FOR PREDICTING THE OPERATIONAL RELIABILITY OF GLASS-FIBER MECHANICAL STRUCTURES.

Abstract. *This study provides a theoretical framework for the application of digital technologies to predicting the in-service reliability of glass-fibre-reinforced polymer (GFRP) engineering structures. The principal degradation mechanisms of GFRP composites are examined, including polymer-matrix cracking, fibre-matrix interfacial debonding, interlaminar delamination, local fibre failure, and progressive stiffness degradation. The effects of cyclic loading, temperature, moisture, vibration, and manufacturing defects on the evolution of structural condition are identified. A digital prognostic system is proposed as a closed-loop information and computational framework integrating a digital product passport, sensor-based monitoring, non-destructive testing, finite element modelling, a digital twin, and a prognostic module. The need for regular updating of the digital twin using in-service measurements and for accounting for the asset-specific loading history is substantiated. The integrated application of fibre-optic, piezoelectric, acoustic-emission, and strain sensors in conjunction with ultrasonic and thermographic inspection is shown to be appropriate. The potential of machine-learning techniques for sensor-data processing, diagnostic-feature extraction, and acceleration of prognostic calculations is examined. It is emphasised that such techniques should be applied in combination with physics-based models of composite deformation and failure. A probabilistic approach to remaining-useful-life assessment is proposed, accounting for measurement errors, data incompleteness, and uncertainty in degradation parameters. Implementation of the proposed framework provides a basis for transitioning from scheduled to condition-based*

maintenance, optimising inspection intervals, and reducing the risk of sudden failure of GFRP structures.

Keywords: *glass-fibre-reinforced structure, in-service reliability, digital twin, structural health monitoring, non-destructive testing, remaining useful life, machine learning.*

Relevance of the Research Problem. The use of glass-fibre-reinforced polymer (GFRP) composites in modern mechanical engineering has expanded considerably, particularly in the manufacture of housings, blades, storage tanks, pipelines, and thin-walled structural components. This trend is driven by their high specific strength, low weight, corrosion resistance, and the ability to tailor their mechanical properties to specific service conditions.

At the same time, the reliability of GFRP structures is strongly influenced by material heterogeneity and anisotropy, manufacturing defects, residual stresses, and the integrity of the fibre-matrix interface. Under cyclic loading, vibration, temperature variations, and moisture exposure, matrix cracks, interlaminar delamination, and local fibre damage progressively accumulate within the composite. Such damage may evolve over extended periods without producing readily observable external indications.

Conventional periodic inspections provide information on structural condition only at the time of assessment and do not support sufficiently accurate prediction of subsequent degradation. This limitation underscores the need for digital technologies that integrate structural health monitoring, non-destructive testing, numerical modelling, digital twins, and intelligent data analytics. Their implementation enables actual service loads to be considered, structural condition estimates to be updated, and remaining useful life to be predicted.

The relevance of the present study therefore arises from the need to establish a scientifically substantiated framework for the digital prediction of the in-service reliability of GFRP engineering structures. Implementation of this framework is expected to facilitate timely damage detection, enhance operational safety, and support the transition from scheduled to predictive maintenance.

Analysis of Recent Research and Publications. Recent research on the in-service reliability of polymer composites has been marked by the rapid development of digital methods for structural condition assessment and prognostics. S. Chaki and P. Krawczak systematised non-destructive testing methods for polymer composites [1], while M. M. Azad and L. B. Carani et al. examined composite damage mechanisms and advanced sensor technologies [2; 3]. J. Contreras Lopez et al. investigated condition-based maintenance strategies for composite structures [4]. The application of digital twins and thermographic inspection to damage diagnosis was addressed by D. Milanoski, X. Chen, Z. Sun, and their co-authors [5–7].

Advanced structural health monitoring techniques were systematised by A. Mardanshahi et al. [8]. The potential of machine learning for the investigation of fibre-reinforced composites and structural health monitoring was examined by A. Gomez-Flores, G. Scarselli, and their co-authors [9; 10]. Sector-specific applications of digital technologies to composite vessels, fibre-optic monitoring systems, and long-span structures were investigated by L. Bouhala, N. V. Golovastikov, M. Q. Tran, and their co-authors [11–13]. Nevertheless, the integrated application of these technologies to predicting the reliability of GFRP engineering structures remains insufficiently investigated, thereby defining the focus of the present study.

Main Results and Discussion. Predicting the in-service reliability of glass-fibre-reinforced polymer (GFRP) engineering structures requires an integrated assessment of their current structural condition and the mechanisms governing progressive damage accumulation. In contrast to metallic components, whose failure is frequently dominated by the propagation of a single macrocrack, degradation in GFRP composites results from the interaction of several damage modes. These include matrix cracking, fibre-matrix interfacial debonding, interlaminar delamination, local fibre fracture, and the associated progressive reduction in structural stiffness [2, p. 9524].

The initiation and evolution of these damage mechanisms are governed by the material architecture, fibre orientation, laminate stacking sequence, fibre volume fraction, impregnation quality, and manufacturing process. Their kinetics are further affected by the amplitude and frequency of cyclic loading, temperature and moisture variations, vibration, and exposure to aggressive environments. Consequently, geometrically identical structures may exhibit markedly different degradation trajectories and in-service lifetimes, even when operated under nominally comparable conditions [1].

Digital prognostics provides a framework for integrating design data, computational results, in-service measurements, and information on detected damage within a unified information environment. The digital product passport serves as the foundational data layer of this framework. It should include the structural geometry, reinforcement architecture, properties of the constituent materials, manufacturing deviations, baseline inspection results, and criteria defining the relevant limit states.

Throughout the service life of the structure, the digital product passport should be continuously supplemented with data on actual loading histories, temperature and moisture exposure, accumulated operating cycles, overloads, impact events, repairs, and periodic inspection outcomes. This continuous enrichment of the data record enables a transition from population-based assessment of a nominal structure to asset-specific prediction that accounts for the individual operational history of the component under consideration.

In-service data may be acquired using fibre-optic, piezoelectric, acoustic-emission, strain, and temperature sensors [3]. Fibre-optic sensing systems enable local or distributed measurements of strain and temperature, whereas piezoelectric transducers support damage identification through the analysis of elastic-wave propagation [12]. Acoustic-emission monitoring, in turn, provides information on transient events associated with matrix cracking, delamination growth, fibre-matrix debonding, and fibre fracture.

Continuous structural health monitoring should be complemented by periodic non-destructive testing. Ultrasonic, thermographic, and radiographic techniques provide more detailed information on the location, geometry, and extent of internal defects, whereas permanently installed sensors enable the temporal evolution of the structural response to be tracked [6]. The fusion of monitoring and inspection data improves the reliability of damage identification and reduces the likelihood that environmentally induced signal variations will be incorrectly interpreted as structural degradation [8]. Such an integrated monitoring approach is particularly important for safety-critical composite components, including storage tanks and pressure vessels, whose failure may result in severe operational consequences [11].

A key methodological challenge is to distinguish damage-related changes from variations induced by normal operating and environmental conditions. Temperature fluctuations, for example, may alter the strain and vibration response of a structure without being accompanied by actual damage growth. A reliable digital prognostic system must therefore compensate for environmental and operational variability, monitor sensor integrity, and automatically identify anomalous, inconsistent, or otherwise unreliable measurements.

A physics-based computational model provides the analytical core of the prognostic framework. The finite element method is particularly suitable for this purpose because it enables stress and strain fields to be determined, critically loaded regions to be identified, and the initiation and progression of damage to be simulated. To ensure adequate physical representativeness, the model should account for the anisotropic behaviour of individual plies, their spatial orientation, interfacial and contact interactions, boundary conditions, and the actual spectrum of service loads.

The initial parameters of the finite element model should be derived from mechanical characterisation of the constituent materials and representative laminate specimens. During operation, these parameters are updated using structural health monitoring and non-destructive testing data. Such model updating maintains consistency between the numerical representation and the evolving condition of the physical structure, thereby improving the credibility of subsequent reliability and remaining-useful-life predictions.

A normalised reduction in effective stiffness may be employed as an integral indicator of accumulated damage:

$$D_{(t)} = 1 - \frac{E_{(t)}}{E_0} \tag{1}$$

where *D (t)* is the damage index at time *t*; *E (t)* is the current effective elastic modulus; and E_0 is the initial elastic modulus of the undamaged material.

For an as-manufactured structure, the damage index approaches zero. Its progressive increase indicates stiffness degradation associated with the accumulation of internal damage. The permissible threshold value of the index should be established experimentally for the specific material system, structural configuration, and service conditions under consideration. Although this scalar parameter does not capture the full range of failure mechanisms inherent in GFRP composites, it can serve as an integral indicator of structural degradation.

The digital twin constitutes the core component of the proposed digital framework. It represents a continuously updated virtual model of a specific structure whose state evolves in accordance with changes occurring in its physical counterpart. Unlike a conventional computational model, the digital twin is periodically recalibrated using in-service measurements and non-destructive testing data [5]. It should incorporate the initial geometry and material properties, current damage state, effective structural stiffness, loading history, and the uncertainty associated with the estimated parameters. The general architecture of the digital system developed for predicting the in-service reliability of a GFRP structure is presented in Fig. 1.

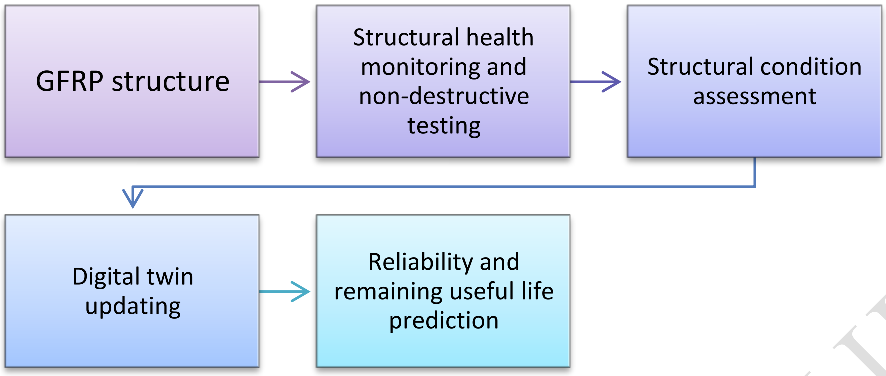

Fig. 1. Architecture of the digital system for predicting the in-service reliability of a GFRP structure

Source: developed by the author

Within the proposed framework, sensor-monitoring data are transferred to a preprocessing module, where noise filtering, temperature compensation, and signal-quality validation are performed. Damage-sensitive diagnostic features are subsequently extracted. The resulting feature values are used to update the parameters of the digital twin and predict the subsequent evolution of the structural condition.

Machine-learning methods may be employed to reduce the computational cost of prognostic analysis. These methods enable complex nonlinear relationships among loading parameters, sensor responses, damage characteristics, and remaining useful life to be identified [9]. Machine learning should not, however, entirely replace physics-based modelling, because the available training datasets generally do not encompass the full range of possible service conditions.

A hybrid modelling strategy provides the most scientifically substantiated solution. Within this framework, the physics-based model represents the fundamental mechanisms of deformation and failure, whereas machine-learning algorithms are employed to construct computationally efficient surrogate models, extract damage-sensitive features, and correct systematic model discrepancies. This combination improves the computational efficiency of the digital twin while preserving the physical interpretability and credibility of the resulting predictions [10].

Structural condition assessment should be formulated within a probabilistic framework. Even under nominally identical loading conditions, individual structures may exhibit different degradation rates because of variability in material properties and initial defect populations. Additional uncertainty arises from sensor errors, incomplete datasets, and simplifications inherent in the computational model. Prognostic results should therefore be expressed not as a single deterministic estimate of service life but as a range of possible values associated with a specified confidence level.

The probability that the structure will fail by time t may be determined from the reliability function as follows:

$$P_f(t) = 1 - R(t) \tag{2}$$

where $P_f(t)$ is the probability of failure by time t, and $R\ (t)$ is the probability that the structure will remain in an operational state over the corresponding time interval.

The remaining useful life is defined as the predicted period of continued operation between the time of assessment and the time at which the specified limit state is reached:

$$\mathrm{T}_{RUL} = t_{lim} - t_0 \tag{3}$$

where T_{RUL} is the remaining useful life; $t_0$is the time at which the assessment is performed; and t_{lim} is the predicted time at which the specified limit state is reached.

Because the time at which the limit state is reached depends on future loading and uncertain degradation parameters, remaining useful life should be treated as a random variable. Maintenance planning should therefore be based not only on the predicted mean value but also on its lower confidence bound. This approach reduces the risk of continuing to operate the structure after the required level of reliability has been lost.

The digital prognostic procedure should comprise the following sequence of operations:

- establishment of the digital product passport;
- acquisition of loading and environmental data;
- preliminary processing of sensor signals;
- extraction of damage-sensitive diagnostic features and assessment of the current structural condition;
- updating of the digital twin;
- simulation of future degradation;
- estimation of failure probability and remaining useful life;
- formulation of recommendations regarding the next inspection or repair.

The functional roles of the principal components of the digital system and the corresponding outputs are summarised in Table 1.

Table 1

Principal Components of the Digital Reliability-Prognostic System

Component	Function	Output
Digital product passport	Storage and management of the initial product characteristics	Baseline structural model
Sensor-based monitoring	Acquisition of loading data and structural-response measurements	In-service monitoring data
Non-destructive testing	Detection and localisation of internal defects	Damage parameters
Digital twin	Representation of the current structural condition	Updated computational model
Prognostic module	Simulation of subsequent degradation	Failure probability and remaining useful life
Decision-support module	Substantiation of maintenance decisions	Timing of inspection, repair, or replacement

Source: developed by the author

The credibility of digital predictions depends on the rigorous verification and validation of the models employed. Verification involves confirming the correctness of the numerical solution, assessing finite element mesh convergence, and evaluating algorithmic stability. Validation requires computational predictions to be compared with independent experimental data. Appropriate validation quantities include structural stiffness, strain fields, natural frequencies, the characteristics of detected defects, and residual load-bearing capacity.

The digital system should also identify and monitor the boundaries of its applicability. If the actual loading regime, temperature, or damage state falls outside the domain for which the model has been validated, the credibility of the resulting prediction decreases. Under such conditions, an additional structural examination or model recalibration is required.

The proposed framework provides a basis for transitioning from scheduled maintenance to condition-based maintenance. Decisions regarding continued operation, inspection, repair, or component replacement should be informed by the predicted degradation rate, remaining useful life, and acceptable failure risk. This approach enhances the safety of engineering structures while preventing the premature withdrawal of serviceable components from operation [4, pp. 1448–1449].

The practical implementation of digital prognostics requires explicit criteria for converting an assessed structural condition into a specific operational decision. The detection of damage alone does not necessarily justify the immediate cessation of operation. The critical factors include the defect type, dimensions, location, propagation rate, and influence on structural load-bearing capacity. Accordingly, the digital system should not only identify deviations in monitored parameters but also evaluate their criticality [7].

For this purpose, several structural condition states may be distinguished. The first corresponds to normal operation, in which the monitored parameters remain within their permissible limits and no evidence of progressive damage is observed. The second is characterised by minor changes that require enhanced monitoring but do not restrict structural operability. The third involves damage that affects structural stiffness or strength and therefore requires the interval before the next inspection to be shortened. The fourth represents a critical condition requiring the cessation of operation, repair, or replacement of the affected component.

Transitions between these condition states should be determined from a combination of diagnostic features rather than from a single indicator. For example, a local increase in acoustic-emission activity may not, in isolation, provide sufficient evidence of hazardous degradation. However, a simultaneous increase in acoustic-emission activity, reduction in stiffness, and alteration of the strain field indicates a higher probability of progressive structural damage. The integration of multiple monitoring channels reduces both the risk of failing to detect a safety-critical defect and the likelihood of generating an unjustified warning.

Periodic updating of the digital twin constitutes an essential component of the prognostic process. Following each inspection or the acquisition of a new sensor dataset, the estimated structural parameters should be compared with the preceding prediction. If the observed evolution of the structural condition is consistent with the predicted response, the model may continue to be used without substantial modification. Where a systematic discrepancy is identified, the degradation parameters should be re-estimated, the boundary conditions reassessed, and the adopted damage-accumulation law refined [13].

This approach enables uncertainty to be progressively reduced as in-service information accumulates. At the initial stage, predictions are based primarily on laboratory test results, standardised material properties, and computational models. As operation proceeds, data acquired directly from the specific structure assume a decisive role. Remaining-useful-life assessment thereby evolves from a population-based estimate to an asset-specific prediction.

An increase in data volume alone, however, does not necessarily improve prognostic accuracy. Sensor measurements may contain noise, missing values, systematic bias, and synchronisation errors. Moreover, progressive sensor degradation or debonding may produce signals resembling the structural response associated with damage. The digital system should therefore incorporate automated data-quality assessment, anomaly detection, and cross-validation of measurements obtained through different monitoring channels.

A complete history of changes in the digital-twin parameters should also be retained. Each model update should be accompanied by records of the update time, input data, identified parameter values, and resulting prediction. Such traceability enables the causes of changes in estimated remaining useful life to be analysed, predictions generated by different model versions to be compared, and the validity of maintenance and operational decisions to be evaluated.

The appropriate determination of inspection intervals is particularly important. Excessively short intervals increase maintenance expenditure and equipment downtime, whereas excessively long intervals increase the risk that progressive damage will remain undetected. Inspection frequency should therefore be established with regard to the current structural condition, predicted degradation rate, lower confidence bound of remaining useful life, and potential consequences of failure.

For a structure exhibiting stable behaviour, the interval between inspections may be extended. Conversely, if the digital twin indicates accelerated damage accumulation or a substantial widening of the prediction uncertainty interval, the next inspection should be conducted earlier. Inspection frequency thus becomes an adaptive parameter determined by the actual condition of the specific structure rather than by a fixed calendar-based schedule.

Digital prognostics also enables alternative future operating scenarios to be compared. Variations in loading, temperature regime, operating-cycle frequency, and environmental exposure can be simulated within the digital twin to evaluate their effects on the degradation rate. This makes it possible to determine whether reducing the operating load could extend the period of safe operation and to assess the feasibility of repair relative to structural replacement.

Decision-making should account not only for failure probability but also for the potential consequences of failure. An identical probability of damage cannot have the same operational significance for an auxiliary enclosure and a highly loaded blade. In the latter case, the consequences of failure are substantially more severe; consequently, both the acceptable risk level and the interval before the next inspection should be lower. Digital prognostics should therefore constitute an integral element of risk-informed structural health management.

Despite their technical advantages, digital systems are subject to several limitations. These include the need for representative databases, the difficulty of experimentally identifying degradation parameters, the high computational cost of high-fidelity models, and the limited transferability of results between structures with different reinforcement architectures. A model calibrated for one type of GFRP component cannot be applied directly to another without additional verification.

A further limitation is the incomplete observability of the composite’s internal condition. A sensor system records the structural response but does not always allow the damage mechanism, morphology, and spatial location to be identified unambiguously. Similar variations in measured signals may correspond to different combinations of matrix cracking, delamination, and fibre-matrix interfacial damage. Automated prognostic results should therefore be supplemented by engineering assessment, while safety-critical decisions should be verified using independent inspection methods.

Further advances in digital technologies for predicting the in-service reliability of GFRP structures are associated with improved heterogeneous data-fusion methods, the development of physics-informed machine-learning algorithms, and the construction of computationally efficient reduced-order degradation models. Particularly promising are digital twins capable of quantifying the credibility of their own predictions, detecting operation outside validated domains, and determining when additional inspection is required.

Thus, the digital prognostic system should be regarded as a closed-loop information and computational framework in which monitoring results are used to update the digital twin, the updated model supports degradation forecasting, and the resulting prediction informs decisions regarding subsequent operation. Implementing this framework enables a transition from fixed maintenance schedules to adaptive structural health management that accounts for the individual characteristics of each GFRP structure.

Conclusions. Thus, the in-service reliability of glass-fibre-reinforced polymer (GFRP) engineering structures should be predicted through the integrated application of structural health monitoring, non-destructive testing, finite element modelling, and digital-twin technology. This approach enables the actual loading history, service conditions, accumulated damage, and uncertainty in model parameters to be incorporated into the reliability assessment. The digital twin should be updated regularly using in-service data, whereas machine-learning techniques should be employed in conjunction with physics-based models. Probabilistic assessment of remaining useful life provides a basis for transitioning from scheduled to condition-based maintenance, optimising inspection intervals, and reducing the risk of sudden structural failure.

Further research should focus on improving heterogeneous diagnostic-data fusion, developing physics-informed machine-learning algorithms, and establishing criteria for evaluating the credibility of remaining-useful-life predictions.

References

1. Chaki S., Krawczak P. Non-destructive health monitoring of structural polymer composites: trends and perspectives in the digital era. *Materials*. 2022. Vol. 15, No. 21. Art. 7838. DOI: https://doi.org/10.3390/ma15217838
2. Azad M. M. et al. Failure modes and non-destructive testing techniques for fiber-reinforced polymer composites: a review**.** *Journal of Materials Research and Technology*. 2024. Vol. 33. P. 9519–9537. DOI: https://doi.org/10.1016/j.jmrt.2024.11.269
3. Carani L. B. et al. Advances in embedded sensor technologies for impact monitoring of composite structures: a review. *Journal of Composites Science*. 2024. Vol. 8, No. 6. Art. 201. DOI: https://doi.org/10.3390/jcs8060201

4. Contreras Lopez J. et al. A cross-sectoral review of the current and potential maintenance strategies for composite structures. *SN Applied Sciences*. 2022. Vol. 4. Art. 180. DOI: https://doi.org/10.1007/s42452-022-05063-3
5. Milanoski D., Galanopoulos G., Zarouchas D., Loutas T. Multi-level damage diagnosis on stiffened composite panels based on a damage-uninformative digital twin. *Structural Health Monitoring*. 2023. Vol. 22, No. 2. P. 1437–1459. DOI: https://doi.org/10.1177/14759217221108676
6. Chen X., Janeliukstis R., Sarhadi A. Thermographic data analytics-based damage characterization in a large-scale composite structure under cyclic loading. *Composite Structures*. 2022. Vol. 290. Art. 115525. DOI: https://doi.org/10.1016/j.compstruct.2022.115525
7. Sun Z. et al. Approach towards the development of digital twin for structural health monitoring with sensor fault resilience. *Sensors*. 2025. Vol. 25, No. 1. Art. 59. DOI: https://doi.org/10.3390/s25010059
8. Mardanshahi A. et al. Sensing techniques for structural health monitoring: a state-of-the-art review. *Sensors*. 2025. Vol. 25, No. 5. Art. 1424. DOI: https://doi.org/10.3390/s25051424
9. Gomez-Flores A., Cho H., Hong G. et al. A critical review on machine learning applications in fiber composites and nanocomposites: towards a control loop in the chain of processes in industries. *Materials & Design*. 2024. Vol. 245. Art. 113247. DOI: https://doi.org/10.1016/j.matdes.2024.113247
10. Scarselli G. et al. Machine learning for structural health monitoring of aerospace structures: a review. *Sensors*. 2025. Vol. 25, No. 19. Art. 6136. DOI: https://doi.org/10.3390/s25196136
11. Bouhala L. et al. Review of state-of-the-art of structural health monitoring in hydrogen composite pressure vessels. *Composites Part C: Open Access*.

2025. Vol. 18. Art. 100635. DOI: https://doi.org/10.1016/j.jcomc.2025.100635

12. Golovastikov N. V., Kazanskiy N. L., Khonina S. N. Optical fiber-based structural health monitoring: advancements, applications, and integration with artificial intelligence for civil and urban infrastructure. *Photonics*. 2025. Vol. 12, No. 6. Art. 615. DOI: https://doi.org/10.3390/photonics12060615

13. Tran M. Q. et al. A digital twin framework for structural health monitoring of existing large-span bridges. *Sensors*. 2026. Vol. 26, No. 11. Art. 3293. DOI: https://doi.org/10.3390/s26113293