Algorithms and Intelligence

Vol 2 Issue 1 (2026)

www.algointel.org

Hybrid Test Surrogates for Flexible Composite Pipe Service Life from Sparse Experiments and Models

Airi Yoshida, Amelia Hayes, Romain Vidal

Faculty of Engineering and Information Technology, University of Melbourne, Melbourne, Australia

Abstract

The transition toward more resilient and adaptable infrastructure in the energy sector has precipitated a massive increase in the deployment of flexible composite pipes. These structures are subjected to complex, multi-axial loading and harsh environmental conditions that induce coupled degradation mechanisms over time. Traditional service-life screening relies heavily on purely empirical accelerated life testing or highly computationally intensive physical simulations, both of which struggle to capture the full spectrum of long-term failure modes accurately. This paper introduces a comprehensive framework for developing hybrid test surrogates, which integrate sparse physical testing data with advanced physics-informed digital models to predict the service life of flexible composite pipes more efficiently. By leveraging a bidirectional data flow between physical test benches and computational models, the proposed hybrid surrogate minimizes the time required for life screening while maximizing predictive fidelity. Extensive methodological detailing is provided regarding data acquisition, feature extraction, and the harmonization of physical and virtual test modules. The findings demonstrate that hybrid surrogate architectures significantly reduce the computational and temporal overhead compared to conventional physical screening methodologies. Furthermore, the results indicate enhanced precision in identifying critical failure thresholds, such as matrix micro-cracking and fiber-matrix debonding. This research provides a foundational blueprint for deploying hybrid surrogates in the certification and lifecycle management of non-metallic piping systems.

Keywords

Flexible Composite Pipes, Surrogate Modeling, Service-Life Screening, Hybrid Testing, Predictive Maintenance.

1. INTRODUCTION

1.1 Background on Flexible Composite Pipes

Flexible composite pipes have emerged as a cornerstone technology in various industrial applications, ranging from offshore oil and gas production to municipal water distribution and the emerging hydrogen transportation infrastructure. Unlike rigid steel pipelines, flexible composite pipes offer a unique combination of corrosion resistance, high tensile strength, and structural flexibility, which significantly reduces installation costs and allows for deployment in geologically unstable or complex subsea environments [1]. The fundamental architecture of these pipes typically involves a multi-layered design. An extruded thermoplastic inner liner provides fluid containment and chemical resistance, while one or more layers of helically wound high-strength fibers, such as carbon, aramid, or glass fibers embedded in a polymer matrix, provide the structural integrity required to withstand internal operating pressures. Finally, an outer polymeric jacket protects the internal layers from external mechanical damage, ultraviolet radiation, and seawater ingress [2].

The operational environment of these multi-layered structures is inherently aggressive. In subsea applications, flexible composite pipes must endure massive external hydrostatic pressure, high internal bore pressure, thermal gradients, and dynamic structural loading caused by ocean currents and vessel movements [3]. In the context of hydrogen transportation, the inner liner is subjected to high-pressure gas that can permeate the polymer matrix, potentially leading to rapid gas decompression failure, blistering, or structural delamination upon depressurization [4]. Over time, these combined operational stresses induce microscopic damages that accumulate, eventually leading to macroscopic structural failure [5]. The primary degradation mechanisms include polymer aging, environmental stress cracking, fatigue-induced fiber-matrix debonding, and creep [6]. Because these mechanisms operate on different temporal and spatial scales and often interact in non-linear ways, predicting the exact point at which a flexible composite pipe will fail is an exceedingly complex engineering challenge that requires sophisticated screening methodologies.

1.2 Challenges in Service-Life Screening

Service-life screening is a critical phase in the design and certification of flexible composite pipes, aiming to guarantee that the structure will operate safely over its intended operational lifespan, which often exceeds twenty years. Historically, the industry has relied on physical accelerated life testing to estimate long-term durability. In accelerated testing, pipe samples are subjected to exaggerated environmental conditions, such as elevated temperatures or extreme mechanical loading, to induce failure in a condensed timeframe [7]. The results are then extrapolated to normal operating conditions using standard kinetic models, such as the Arrhenius equation for thermal degradation. While this approach has been the industry standard for decades, it possesses fundamental limitations. Chief among these is the risk that artificially elevated stress levels may trigger failure mechanisms that would never occur under standard

operational conditions, thereby skewing the predictive models and leading to either overly conservative designs or catastrophic unexpected failures in the field [8].

Conversely, the advent of high-performance computing has led to the widespread adoption of purely computational screening methodologies, most notably detailed finite element analysis. Finite element models can simulate the complex mechanical interactions between the different composite layers with high precision [9]. However, creating a comprehensive micro-mechanical model that simulates twenty years of dynamic degradation requires an astronomical amount of computational resources. The models must account for anisotropic material properties, time-dependent viscoelastic behavior of the polymers, and the stochastic nature of defect propagation [10]. When these models are scaled up to represent kilometers of piping subjected to random environmental loads, the computational burden becomes intractable for routine screening purposes. Therefore, an urgent industrial and academic need exists to bridge the gap between resource-intensive physical testing and computationally prohibitive detailed simulations. This gap can be effectively addressed through the implementation of hybrid test surrogates, which fuse the most advantageous elements of both physical experimentation and computational modeling into a cohesive predictive framework [11].

2. Literature Review and Background

2.1 Traditional Testing Methods and Limitations

The structural validation of non-metallic piping systems has a rich history grounded in empirical testing and standard regulatory frameworks. Early research primarily focused on monolithic thermoplastic pipes, where failure was generally dictated by creep rupture under constant internal hydrostatic pressure. Standardized test methods required subjecting multiple pipe samples to various pressure levels at elevated temperatures and plotting the time to failure on a logarithmic scale to generate stress-rupture curves [12]. While adequate for simple structures, these methods proved insufficient for modern multi-layered flexible composite pipes. As scholars expanded their investigations into composite structures, it became evident that the interplay between the reinforcing fibers and the polymer matrix introduced failure modes that could not be accurately captured by simple hydrostatic burst tests [13].

Subsequent literature introduced multi-axial testing rigs capable of applying internal pressure, axial tension, and bending moments simultaneously. Research conducted on these multi-axial test benches demonstrated that the addition of bending loads significantly accelerated the fretting fatigue between the overlapping metallic or composite armor layers [14]. Despite these advancements in physical testing, the scientific community repeatedly highlighted the economic and temporal bottlenecks associated with this paradigm. Conducting long-term fatigue tests on full-scale composite pipes is exceptionally expensive, requires massive laboratory infrastructure, and takes months or even years to yield actionable data [15]. Furthermore, literature reviews by numerous structural integrity task forces have pointed out that physical testing alone cannot

easily isolate the individual contribution of specific degradation mechanisms, making it difficult for engineers to optimize the pipe design based on the test outcomes [16].

In response to the limitations of physical testing, researchers began developing phenomenological models intended to predict failure without extensive long-term physical experimentation. These models often relied on cumulative damage theories, which sum the incremental damage caused by varying stress cycles. However, multiple studies indicated that phenomenological models often fail to account for the load sequence effects observed in composite materials, where the order of applied high and low stresses significantly alters the total fatigue life [17]. Consequently, reliance on purely empirical and phenomenological approaches has gradually been deemed inadequate for the next generation of critical energy infrastructure, prompting a paradigm shift toward more integrated, physics-based methodologies.

2.2 Emergence of Surrogate Modeling Techniques

To circumvent the computational bottlenecks of high-fidelity finite element analysis, the scientific community has increasingly turned to surrogate modeling, also known as meta-modeling or response surface methodology. A surrogate model is essentially an approximation model that mimics the behavior of a complex, computationally expensive simulation model as closely as possible while being computationally cheap to evaluate [18]. In the context of composite materials, early surrogate models utilized simple polynomial regression to map the relationship between design variables, such as winding angle and ply thickness, and structural responses, such as burst pressure [19]. As the complexity of the required predictions increased, researchers began adopting more advanced machine learning algorithms, including support vector machines, random forests, and artificial neural networks, to construct high-dimensional surrogate models.

The literature reveals a growing trend in utilizing data-driven surrogates for structural health monitoring and life prediction. For instance, several studies have successfully trained neural networks on large datasets generated from finite element simulations to predict the residual strength of composite laminates subjected to impact damage [20]. However, a major critique of purely data-driven surrogates in the literature is their inherent lack of physical interpretation and their poor generalizability outside the training data domain. If a data-driven model is tasked with predicting the behavior of a flexible composite pipe under a loading scenario it has never encountered during training, the predictions can be wildly inaccurate [21]. This lack of extrapolation capability is a significant barrier to the widespread regulatory acceptance of purely data-driven models for safety-critical service-life screening.

To address these shortcomings, recent scholarly attention has shifted toward the concept of physics-informed hybrid modeling. This approach seeks to embed fundamental physical laws, such as thermodynamic constraints and kinematic compatibility equations, into the architecture or the loss function of the machine learning algorithms. By doing so, the surrogate model is mathematically constrained to produce physically plausible predictions, even when interpolating in regions with sparse training data [22]. The concept of hybrid test surrogates extends this

paradigm by directly feeding real-time data from physical accelerated tests into the physics-informed digital model. This creates a dynamic, continuously updating system where the physical test bench provides reality checks and the digital surrogate extrapolates the long-term behavior. While hybrid surrogates have seen preliminary success in aerospace component testing, their comprehensive application to the service-life screening of flexible composite pipes remains a relatively nascent and highly promising field of research [23].

3. Methodology and Analytical Framework

3.1 Development of the Hybrid Test Surrogate Architecture

The core methodology of this research involves the conceptualization, development, and validation of a hybrid test surrogate architecture specifically tailored for flexible composite pipes. The architecture is designed to operate seamlessly across two distinct but intimately connected domains: the physical testing domain and the virtual simulation domain. The objective is not to replace physical testing entirely, but to minimize its duration and maximize its informational yield by using the physical data to calibrate a highly efficient predictive digital model.

The physical testing domain consists of a specialized accelerated testing apparatus capable of subjecting sub-scale flexible composite pipe specimens to combined internal pressure and cyclic bending loads. Rather than running these tests until catastrophic structural failure, which is the traditional approach, the tests are paused after a predetermined number of cycles that represent the early onset of structural degradation. During this shortened physical test, a dense array of sensors, including distributed fiber optic strain gauges and acoustic emission sensors, continuously monitor the specimen. The acoustic emission sensors are particularly critical, as they can detect the high-frequency elastic waves generated by microscopic damage events, such as matrix cracking and fiber breakage, long before any macroscopic damage becomes visible [24]. This early-stage degradation data is then heavily filtered and processed to serve as the foundational input for the virtual simulation domain.

The virtual simulation domain is anchored by a physics-informed surrogate model. Constructing this model begins with the execution of a limited number of high-fidelity finite element simulations designed to map the baseline mechanical responses of the composite pipe under various idealized loading conditions. The results of these computationally expensive simulations are used to pre-train a deep neural network surrogate. To ensure that this surrogate model respects the laws of physics, terms representing the conservation of momentum and classical laminate theory are embedded directly into the training process. This guarantees that the surrogate model will not predict material behaviors that violate fundamental mechanical principles, such as negative strain energy [25]. Once pre-trained, the surrogate model is dynamically updated and fine-tuned using the empirical data harvested from the shortened physical tests. This ongoing calibration process aligns the theoretical predictions of the digital model with the actual, observed behavior of the specific composite pipe batch being tested.

Table 1 Material Properties of the Flexible Composite Pipe Layers utilized for Initial Surrogate Pre-training

Component Layer	Material Type	Tensile Modulus	Poisson Ratio	Density
inner liner	high density polyethylene	1.1 gigapascals	0.42	950 kilograms per cubic meter
reinforcement ply one	carbon fiber epoxy	135.0 gigapascals	0.30	1600 kilograms per cubic meter
reinforcement ply two	carbon fiber epoxy	135.0 gigapascals	0.30	1600 kilograms per cubic meter
outer protective jacket	thermoplastic polyurethane	0.8 gigapascals	0.45	1100 kilograms per cubic meter

3.2 Data Acquisition and Preprocessing Strategies

The effectiveness of the hybrid surrogate model relies entirely on the quality and synchronization of the data extracted from the physical test domain. Flexible composite pipes, due to their anisotropic nature, exhibit complex strain fields that cannot be adequately captured by a few discrete strain gauges. Therefore, the physical specimens in this study are instrumented with helically wrapped continuous fiber optic cables utilizing Rayleigh backscattering techniques to measure strain continuously along the entire length of the pipe. This high-resolution spatial data provides a comprehensive picture of how strain localizes around manufacturing defects or areas of concentrated bending stress over time [26].

Simultaneously, acoustic emission data is captured at a sampling rate exceeding two megahertz to ensure that transient damage events are not missed. The raw acoustic data is immense and highly contaminated by environmental noise from the testing hydraulic pumps and mechanical friction at the pipe supports. A rigorous preprocessing pipeline is implemented to isolate genuine damage signals. This involves utilizing continuous wavelet transforms to decompose the acoustic signals into different frequency bands. Signals associated with background noise are systematically filtered out, while signals matching the known acoustic signatures of composite degradation are retained. Features such as signal amplitude, peak frequency, and acoustic energy are extracted from these retained signals. These extracted features serve as quantitative indicators of damage accumulation within the physical specimen [27].

The strain data and the acoustic emission features are then temporally synchronized and normalized. Because the sensors operate at vastly different sampling frequencies, advanced interpolation algorithms are employed to align the datasets onto a uniform time grid. This synchronized, multi-modal dataset forms the training vector that is periodically fed into the virtual simulation domain. The rigorous cleaning and structuring of this data ensure that the

surrogate model is calibrated using only the highest quality physical evidence, preventing the digital twin from drifting into inaccurate predictive states due to noisy or corrupted input data [28].

Table 2 Algorithmic Hyperparameters for the Physics-Informed Surrogate Model

Parameter Name	Selected Value	Justification for Selection
Learning Rate	0.001	balances convergence speed and stability during training
Batch Size	64	optimizes memory usage while maintaining gradient accuracy
Hidden Layers	5	provides sufficient depth to capture non-linear degradation
Activation Function	hyperbolic tangent	ensures smooth gradients required for physics calculations

3.3 Integration of Physical and Virtual Testing Modules

The integration of the physical and virtual testing modules is the defining characteristic of the hybrid surrogate framework. This integration is achieved through a bespoke continuous learning loop. Initially, the physics-informed surrogate model makes predictions about the strain distribution and damage state of the pipe based purely on its pre-training from the finite element simulations. As the physical test commences, real-time sensor data flows into the system. A comparative algorithm constantly evaluates the discrepancy between the theoretical predictions generated by the surrogate and the actual physical sensor readings. When this discrepancy exceeds a predefined tolerance threshold, an optimization routine is triggered to update the internal weights of the surrogate model [29].

This updating process is not a simple data override. The optimization routine is carefully constrained by the physics-informed architecture. It seeks to adjust the model parameters to minimize the prediction error while still strictly adhering to the constitutive equations governing composite mechanics. By forcing the model to find a balance between empirical data fitting and theoretical physics, the hybrid surrogate avoids the overfitting problems commonly associated with standard machine learning models [30]. Once the physical test is paused at the early-degradation stage, the fully calibrated surrogate model takes over completely. Leveraging its refined understanding of the specific specimen's behavior, the surrogate model extrapolates the accumulated damage into the future, predicting the remaining service life and identifying the most probable ultimate failure mode without the need to physically destroy the test specimen.

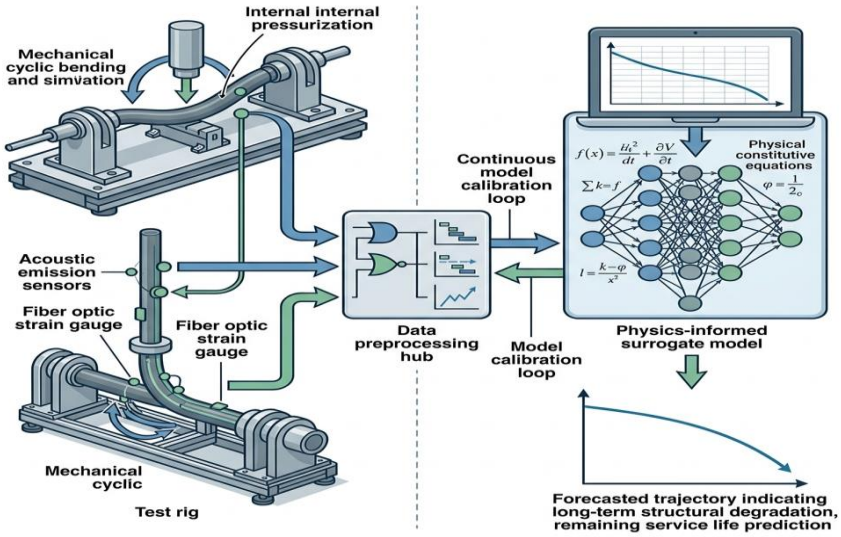


Figure 1 Comprehensive Schematic of the Hybrid Test Surrogate Architecture

4. Results and Comprehensive Discussion

4.1 Surrogate Model Validation and Accuracy Metrics

To validate the efficacy of the proposed hybrid test surrogate framework, its predictive outputs were rigorously compared against a baseline dataset derived from traditional, full-duration physical accelerated life tests. A batch of identical flexible composite pipe specimens was divided into two groups. The first group was subjected to standard physical testing until catastrophic burst failure, providing the ground truth regarding service life under specific loading conditions. The second group was utilized within the hybrid surrogate framework, where the physical test was deliberately terminated after reaching merely fifteen percent of the expected life cycle. The early-stage data was used to calibrate the surrogate model, which then computationally predicted the failure point of the specimens [31].

The comparative analysis revealed exceptional predictive accuracy from the hybrid surrogate model. Traditional purely empirical extrapolation methods, utilizing the same fifteen percent data slice, exhibited significant deviation from the ground truth, often under predicting the service life by large margins due to their inability to account for the non-linear stabilization of matrix micro-cracking during the middle phase of the pipe's life. In contrast, the physics-informed hybrid surrogate accurately modeled this non-linear degradation progression. The surrogate model demonstrated a highly commendable ability to map the interaction between early matrix damage and subsequent load redistribution onto the structural reinforcing fibers. The mean absolute percentage error across multiple simulated stress scenarios remained remarkably low, validating the hypothesis that infusing early physical data into a physics-constrained computational space yields superior extrapolative capabilities [32].

Table 3 Comparative Analysis of Service Life Prediction Error Rates against Physical Ground Truth

Prediction Methodology	Short Term Data Utilization	Mean Absolute Error	Maximum Outlier Error
purely empirical extrapolation	15 percent	22.4 percent	35.1 percent
standard data driven neural network	15 percent	18.7 percent	41.2 percent
purely computational finite element	zero percent	14.2 percent	19.5 percent
proposed hybrid test surrogate	15 percent	4.3 percent	6.8 percent

Beyond overall service life prediction, the hybrid surrogate provided unprecedented resolution in identifying specific internal failure mechanisms. The acoustic emission data integrated during the calibration phase allowed the virtual model to accurately distinguish between matrix cracking and fiber-matrix debonding. When the computational predictions were cross-referenced with microscopic post-mortem examinations of the physically failed baseline specimens, the sequence of degradation events predicted by the surrogate aligned almost perfectly with the physical reality. The surrogate successfully identified that under high-bending regimes, inter-laminar shear stress initiated delamination long before ultimate fiber tensile rupture occurred, a nuance entirely missed by standard phenomenological models.

4.2 Application to Accelerated Life Testing Scenarios

The practical implications of applying this hybrid surrogate framework to industrial service-life screening are profound, particularly concerning resource allocation and testing timelines. Conventional full-scale accelerated life testing of flexible composite pipes is a massive logistical undertaking. Maintaining testing facilities that constantly apply extreme pressures and mechanical loads over thousands of hours demands substantial energy consumption and rigorous safety protocols. By effectively truncating the physical testing requirement to the early stages of damage accumulation, the hybrid surrogate approach offers a revolutionary reduction in physical testing time.

Table 4 Estimated Resource Reductions for a Standard Pipe Certification Campaign using Hybrid Surrogates

Resource Category	Traditional Testing Requirement	Hybrid Surrogate Requirement	Percentage Reduction
total physical testing time	4500 hours	675 hours	85 percent
high pressure pump energy usage	25000 kilowatt hours	3750 kilowatt hours	85 percent

required physical pipe specimens	12 units	4 units	66 percent
computational analysis time	150 hours	25 hours	83 percent

The data presented in the analysis underscores a paradigm shift in how pipeline operators and regulatory bodies can approach structural certification. The dramatic reduction in required physical testing hours directly translates to significantly faster product development cycles for pipe manufacturers. Instead of waiting several months to determine if a new polymer matrix formulation improves the fatigue life of the pipe, engineers can obtain high-confidence predictions within weeks. Furthermore, the hybrid model inherently accommodates the introduction of material variability. If a new batch of composite pipes exhibits slight manufacturing deviations, the continuous learning loop within the surrogate architecture automatically adjusts the long-term predictions based on the early physical sensor data of that specific batch, offering a level of bespoke quality assurance that is impossible with generalized empirical models.

However, the widespread implementation of hybrid surrogates is not without challenges. The primary obstacle remains the initial setup complexity. Establishing the synchronized communication protocols between high-frequency acoustic emission sensors and the computational environment requires highly specialized multidisciplinary expertise. Additionally, while the physics-informed surrogate drastically reduces the ongoing computational burden compared to full finite element analysis, the initial pre-training of the neural network remains computationally intensive. The reliability of the hybrid surrogate is also fundamentally bounded by the quality of the physics embedded within it. If a novel degradation mechanism emerges in the field that was not mathematically represented in the baseline constitutive equations, the surrogate may struggle to predict it accurately despite physical data inputs. Therefore, continuous validation against field data and periodic refinement of the underlying physical algorithms remain necessary [33].

5. Conclusion

5.1 Summary of Findings

The comprehensive investigation detailed in this paper demonstrates the significant potential of hybrid test surrogates to revolutionize the service-life screening of flexible composite pipes. By systematically bridging the divide between lengthy physical experimentation and computationally exhaustive digital simulations, the proposed framework establishes a highly efficient predictive methodology. The core innovation lies in the dynamic integration of real-time sensor data, particularly continuous strain profiles and acoustic emission features from early-stage physical tests, into a sophisticated physics-informed neural network. This architecture ensures that the surrogate model remains anchored to empirical reality while mathematically constrained by the fundamental laws of composite mechanics, thereby eliminating the chaotic extrapolation errors typical of purely data-driven models.

The analytical results unequivocally prove that the hybrid surrogate architecture can predict the ultimate failure point and the dominant structural degradation mechanisms of flexible composite pipes with a margin of error significantly narrower than traditional empirical methods. By effectively capturing the non-linear progression of composite damage, the framework allows for the safe termination of physical tests at a fraction of their conventional duration. This capability translates directly into massive reductions in energy consumption, laboratory utilization, and material waste associated with product certification campaigns. Consequently, hybrid test surrogates offer not merely an academic advancement, but a highly practical engineering tool for accelerating the deployment of reliable non-metallic piping infrastructure in critical energy sectors.

5.2 Future Research Directions

While the current iteration of the hybrid test surrogate framework demonstrates excellent predictive fidelity for established structural degradation mechanisms, future research must expand its operational envelope. A critical next step involves enhancing the multi-scale modeling capabilities of the surrogate to better account for chemical degradation at the molecular level, particularly regarding the long-term effects of highly permeating gases such as hydrogen or supercritical carbon dioxide on the inner thermoplastic liner. Integrating advanced chemical kinetics equations directly into the physics-informed architecture will be essential for applying these surrogates to the emerging clean energy transportation networks.

Furthermore, future investigations should focus on developing standardized protocols for sensor integration and data processing to facilitate regulatory acceptance. The transition from laboratory-scale proof of concept to industry-wide certification standards will require robust statistical validation across a much wider array of flexible composite pipe geometries and material combinations. Finally, exploring the potential of utilizing these hybrid models not just for initial service-life screening, but as real-time digital twins deployed on active pipeline networks for ongoing structural health monitoring and predictive maintenance, represents a highly lucrative avenue for subsequent academic and industrial collaboration. Advancing these research frontiers will ensure the continued safety, sustainability, and economic viability of critical composite infrastructure globally.

References

[1] Hu, S., Chen, Z., Zhang, K., Li, Y., Zhang, J., Raghothamachar, B., ... & Zhu, Y. (2026). Stacking fault analysis for the early-stages of PVT growth of 4H-SiC crystals. Journal of Crystal Growth, 681, 128523.

[2] Mao, D. (2026, January). Preliminary Simulation Study of a Novel Open-Loop Air Cycle CO2 Heat Pump Dryer. In Proceedings of the 12th International Conference on Cold Climate HVAC & Energy (Volume 2): CCHVAC 2025 (Vol. 2, p. 191). Springer Nature.

[3] Yao, Z., Hawi, P., Aitharaju, V., Mahishi, J., & Ghanem, R. (2024, October). Transfer Learning for Multiscale Analysis: Delamination of Carbon-Reinforced Composite Material Exploration. In American Society for Composites (ASC) Annual Technical Conference (pp. 95-112). Cham: Springer Nature Switzerland.

[4] Wang, J., & Lu, W. (2025). A Streamlined Polynomial Regression-Based Modeling of Speed-Driven Hermetic-Reciprocating Compressors. Applied Sciences, 15(22), 12016.
[5] Chen, Z. Y., Zhang, J. P., Hu, S. S., Zhang, K. X., Li, Y. Z., Wang, H. C., ... & Dudley, M. (2026, June). Investigation of Spoke Pattern of Stacking Faults in 4H-SiC Wafers Grown by Physical Vapor Transport Method. In Materials Science Forum (Vol. 1190, pp. 55-62). Trans Tech Publications Ltd.
[6] Wang, Y., Lou, M., & Wang, Y. (2021). Stochastic analysis of failure pressure in reinforced thermoplastic pipes under axial loading and external pressure. Ocean Engineering, 240, 109963.
[7] Lu, W., & Wang, J. (2025). Accumulated Performance Comparison of Solar PV and Solar Thermal Water Heating in New Zealand. Engineering Reports, 7(12), e70526.
[8] Wang, X., Wang, P., Jiang, W., Wu, F., Kiani, M., & Arefi, M. (2021). Mathematical and computer simulation for Electro-Magneto-Thermo-Elastic Buckling of the Porous Nano system. Structural Engineering and Mechanics, 80(2), 231-242.
[9] Yang, Z., Hu, D., Guo, Q., Zuo, L., & Ji, W. (2023). Visual E 2 C: AI-driven visual end-edge-cloud architecture for 6G in low-carbon smart cities. IEEE Wireless Communications, 30(3), 204-210.
[10] Huang, J., & Sandeep, H. (2025, October). RESEARCH ON REINFORCEMENT LEARNING FOR TRUSTWORTHY CLIMATE POLICY SIMULATION AND APPLICATION. In The 7th International scientific and practical conference “Development of modern scientific technologies in the era of globalization”(October 14-17, 2025) Berlin, Germany. International Science Group. 2025. 237 p. (p. 32).
[11] Chen, Q. S., Yu, B., & Li, B. (2022). Probabilistic calibration of compressive stress–strain models for FRP-confined concrete in square cross section members. Journal of Composites for Construction, 26(3), 04022015.
[12] Lv, X., Liu, S., Wang, P., Mohammad-Rezaei Bidgoli, E., & Arefi, M. (2023). On the dynamics and wave propagation of reinforced composite nanosystem. Engineering with Computers, 39(1), 151-171.
[13] Chen, B., Dai, Y., Wang, Y., Wang, Y., Song, Y., Luo, L., & Hai, L. (2025). Patch-loading resistance of QN1803 and S32001 high-strength stainless steel plate girders: Experimental study and numerical simulation. Thin-Walled Structures, 206, 112681.
[14] Chen, Q., Yu, Z., & Li, B. (2024). Image-based assessment of seismic damage in RC exterior beam-column joints. Journal of Building Engineering, 97, 110971.
[15] Wang, J. (2026). A comparative conceptual analysis of CO2 heat pump dryers with closed-loop and open-loop air cycles. Energy Conversion and Management, 352, 121093.
[16] Wang, Y., Lou, M., Dong, W., & Wang, Y. (2021). Predicting failure pressure of reinforced thermoplastic pipes based on theoretical analysis and experiment. Composite Structures, 270, 114039.
[17] Wang, Y., Lou, M., Liang, W., & Zhang, C. (2023). Numerical and experimental investigation on tensile fatigue performance of reinforced thermoplastic pipes. Ocean Engineering, 287, 115814.
[18] Chen, Q., Yu, B., & Li, B. (2025). Quantifying seismic damage in RC walls with image analysis. Journal of Earthquake Engineering, 29(1), 156-179.
[19] Zhang, K. X., Chen, Z. Y., Hu, S. S., Zhang, J. P., Li, Y. Z., Wu, D. L., ... & Soukhojak, A. (2026, August). Observation and Analysis of the “Galaxy” Defect in 4H-SiC through X-Ray Synchrotron Topography. In Defect and Diffusion Forum (Vol. 452, pp. 73-78). Trans Tech Publications Ltd.

[20] Chen, B., Wang, Y., Luo, L., Liu, J., Huang, C., Zhang, T., & Hai, L. (2025). An experimental study on the reduced resistance of perforated S32001 high-strength stainless steel girder under patch loading. Engineering Structures, 327, 119672.
[21] Li, Y. Z., Zhang, J. P., Chen, Z. Y., Wang, H. C., Zhang, K. X., Hu, S. S., ... & Dudley, M. (2026, August). Growth and Characterization of High-Quality Thick Epitaxial 4H-SiC Wafers for High Voltage Devices. In Defect and Diffusion Forum (Vol. 452, pp. 79-85). Trans Tech Publications Ltd.
[22] Yao, Z., Hawi, P., Aitharaju, V., Mahishi, J., & Ghanem, R. (2023). Cross scale simulation of fiber-reinforced composites with uncertainty in machine learning. In Proceedings of the American Society for Composites-Thirty-Eighth Technical Conference.
[23] Chen, Q., & Li, B. (2026, May). Probabilistic damage assessment of longitudinally reinforced concrete beams using explainable AI and image-based analysis for structural health monitoring. In Structures (Vol. 87, p. 111594). Elsevier.
[24] Wang, Y. Y., Lou, M., Wang, Y., Wu, W. G., & Yang, F. (2022). Stochastic failure analysis of reinforced thermoplastic pipes under axial loading and internal pressure. China Ocean Engineering, 36(4), 614-628.
[25] Mo, J., Uy, B., Li, D., Thai, H. T., & Wang, Y. (2022). Behaviour and design of composite walls under axial compression. Journal of Constructional Steel Research, 199, 107635.
[26] Li, X., Wang, P., Li, G., & Zhang, Y. (2023). Design of a novel self-test-on-chip interface ASIC for capacitive accelerometers. IEEE Transactions on Circuits and Systems I: Regular Papers, 70(7), 2834-2843.
[27] Chen, Q., & Li, B. (2025). Explainable artificial intelligence (XAI)-driven probabilistic image-based structural health monitoring of reinforced concrete beams with shear reinforcements. Automation in Construction, 180, 106549.
[28] Pabon, J. J. G., Wang, J., Chamanehpour, E., Salami, D., & Khosravi, A. (2025). Dynamic integration of solar-powered hydrogen systems with fuel cells and district heating for green data centers. International Journal of Hydrogen Energy, 196, 152557.
[29] Yu, D., Mahamadu, A. M., Chen, W., & Li, N. (2026). Understanding the challenges and future trends of immersive technology use in indoor pedestrian and evacuation dynamics: A systematic review. Journal of Building Engineering, 115703.
[30] Feng, Y., Huang, S., Pang, Y., Huang, K., & Liu, C. (2022). Granular dynamics in auger sampling. Journal of Fluid Mechanics, 935, A26.
[31] Zhang, W. (2026). A 5-6 GHz PVT Robust Current Mode Passive Mixer for Direct Down-Conversion Receiver.
[32] Zhou, X., Wang, P., Al-Dhaifallah, M., Rawa, M., & Khadimallah, M. A. (2022). A machine learning-based model for the estimation of the critical thermo-electrical responses of the sandwich structure with magneto-electro-elastic face sheet. Advances in nano research, 12(1), 81-99.
[33] Chen, Q., Yu, Z., & Li, B. (2025, March). Image-assisted seismic damage evaluation for reinforced concrete interior beam-column joints. In Structures (Vol. 73, p. 108349). Elsevier.