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Machine Learning-Based Stress and Fatigue Prediction in Complex Piping Networks Recent Advances

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***Abstract*—The pipelines of oil and gas are very important in the transmission of energy but constantly subjected to mechanical stress, fatigue, and corrosion in complex conditions of operation. Finite element analysis and other traditional methods of physics have good mechanical interpretability and can be computationally costly and incapable of stochastic loading, material uncertainties, and nonlinear system response. The paper is a review of the current developments in machine learning (ML) methods, such as artificial neural networks, convolutional neural networks, and Gaussian process models, as effective and high-fidelity methods to stress distribution and fatigue life prediction. With the combination of data-based learning and the basic principles of mechanics, ML-based approaches are efficient to approach nonlinear relations and multi-axial stress states on the basis of sensor measurements, past experiences, and numerical modeling. In addition, hybrid frameworks and digital twins' technologies with the implementation of Bayesian inference are also discussed in terms of their ability to provide real-time structural health monitoring and predictive maintenance. These methods provide superior aptitude to ward off catastrophic breakdowns throughout industrial, marine, and water infrastructure piping infrastructure showing that the ML-based predictive modeling represent an efficient route to enhancing reliability, safety and lifecycle results of advanced piping networks.**

Keywords*—Pipeline integrity, structural health monitoring, corrosion fatigue, predictive maintenance, Gaussian process, probabilistic.

I. Introduction

In engineering systems, mechanical behavior is the basis of structural analysis and is controlled by the basic principles of stress-strain relations, elasticity, plasticity and fatigue damage mechanics [1]. These principles give the behavior of materials to outside forces and to other environmental influences and present the theoretical foundation on how to estimate the safety and structural endurance of structures [2][3][4]. correct mechanical modelling is needed to forecast deformation, stress concentration and failure mechanisms of load-bearing components. The most dependable and the least expensive form of transport system is through pipelines [5]. The integrity of the pipeline is extremely important to prevent disastrous effects of the burst failure [6][7]. Piping networks represent an important category of mechanical systems common in power plants, marine systems, chemical processing plants, and water distribution systems [8]. One of the most significant structural deterioration mechanisms is corrosion, and corrosion fatigue (CF) is caused by cyclic stress in the presence of corrosive media [9][10]. Numerous failures in oil and gas lines, offshore steel structures and even bridges such as the Silver River, and Minnesota are associated with corrosion From the mechanical standpoint, the system of piping is a complicated combination of straight pipes, bends, joints and supports, all of which is contributing to the uneven distribution of stress under working conditions [11]. Multi-axial stress states methodologies are brought about by the combination of internal pressure, thermal expansion, gravitational loads, and boundary constraints [12]. The most important failure modes in piping networks that would be affected by cyclic and time-varying loads include stress and fatigue. Progressive fatigue damage occurs when repeated thermal cycles, pressure changes and vibration are subjected to a structure, especially at geometrical discontinuities and support positions [13]. Classical fatigue models and stress-based evaluation methods have been in use in estimating service life but their usefulness reduces under random loading histories and complex working conditions stress and fatigue prediction in piping networks has essentially been based upon physics-based numerical techniques, including finite element analysis and empirical models of fatigue life [14][15]. mechanically interpretable, and design-conformable, they are computationally expensive and highly subject to modelling effects, material properties and boundary conditions. This restricts their use to large scale systems and real-time condition evaluation. Stress and fatigue prediction in highly complex piping networks based on machine learning paradigm [16][17]. experimental data and in-service monitoring measurements, machine learning models have the potential to learn nonlinear behavior and uncertainty in mechanical behavior [18]. Machine learning-based prediction, with integrating basic mechanical principles, allows stress estimation, fatigue life, and predictive maintenance to be effectively conducted, and is a potential avenue to confident and intelligent piping network control.

A. Structure of Paper

This paper is divided in the following way Section II stress and fatigue prediction in piping network. Section III Machine learning technique for stress and fatigue prediction, Section IV Application in complex piping network. Section V

Literature of review. Section VI describe conclusion with future work.

II. Stress and Fatigue Prediction in Piping Networks

The fatigue cracking problem is characterized by inherent stochasticity and is influenced by multiple sources of uncertainty and unpredictability. Particularly with fatigue-induced cracks in oil and gas pipelines, efficient and effective monitoring and inspection is key. It is not an easy effort to keep the pipeline transmission network in a safe and functional state because of its age and size [19]. With the help of cutting-edge scientific methods, must vehemently enhance and modernize the efficiency of monitoring and maintenance procedures. Fatigue is a probabilistic process, therefore there are a lot of unknowns, like the material's characteristics, the pipe's internal pressure, and the precision and reliability of condition inspection data.

A. Predictive Modeling Strategies

Fatigue is among the most critical material properties, particularly in industries where material failure can have catastrophic consequences [20]. Figure 1 shows the correct multi-physics and multi-scale complexity of fatigue deformation, as compared to physics-based models, which only capture the most essential aspects influencing fatigue and fail to account for the underlying physics. While models grounded in physics can only account for a subset of the variables that impact weariness.

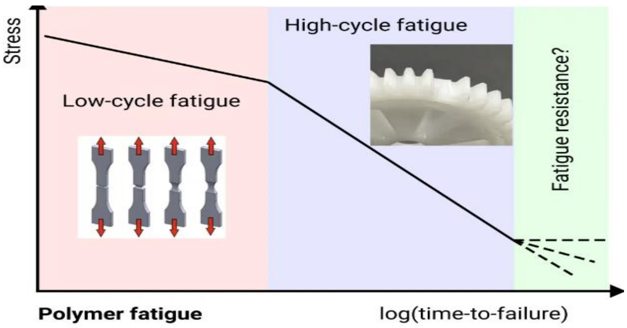

Fig. 1. Stress-Life (S-N) Curve Illustrating Low-Cycle and High-Cycle Fatigue

Fatigue deformation represents a complex phenomenon that involves dynamic interactions between multi-physics and multi-scale processes. Experimental evaluation of fatigue is time- and cost-intensive, because it requires conducting experiments involving large numbers of loading cycles and long periods to ensure the structural safety of materials. Conventional approaches for fatigue modelling typically employ physics-based models derived from knowledge of the governing physics laws.

B. Fatigue Life Prediction under Complex Loading

Piping networks operating in industrial environments are routinely exposed to complex and interacting loading conditions, including multi-axial stresses, thermal cycling, pressure fluctuations, and random vibrations in Figure 2. These additive loads have a serious impact on the accumulation of fatigue damage and tend to determine the service life of piping components, becomes necessary to determine predictable fatigue life under complex loading conditions as a reliable method of structural safety and maintenance strategy optimization [21].

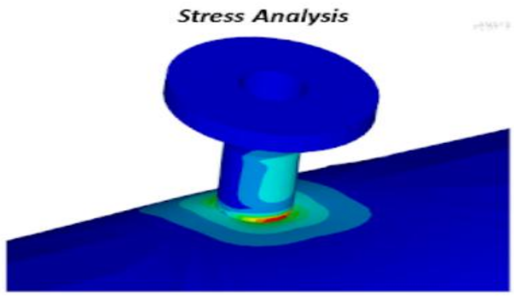

Fig. 2. Vibration of Induced Fatigue in Stress Analysis

1) Nature of Complex Loading

Piping networks are exposed to several interacting loads including internal pressure, thermal expansion, vibration and external constraints [22]. They usually occur in combination, creating multi-axis and time-varying stress condition which subsequently hastens fatigue damage.

2) Significance of Fatigue Life Prediction

To avoid failures that may not be predicted, operational safety, and maintenance optimization, it is important to have accurate fatigue life estimation. Damage due to fatigue is cumulative, and is usually not predicted with noteworthy result therefore predictive analysis is critical in managing the integrity of piping.

3) Traditional approaches towards fatigue

Conventional fatigue prediction methods usually use uniaxial stresses and constant amplitude loading. These simplifications can result in inaccurate estimates of life in applications to the real-world piping systems with random and multi directional loading.

4) Advanced Fatigue Prediction Approaches

Modern methods incorporate equivalent stress or strain In modern practices, the model of stress or strain has been equivalented to explain the effect of multi-axis loading conditions. These methods enhance the accuracy of sensitivity of prediction and the number of computations required especially in cases of random vibration and cyclic thermal loading.

5) Influence of Uncertainty and Environmental Effects

Uncertainties in material properties, load spectra, as well as, boundary conditions, and environmental factors including temperature variation and corrosion influence fatigue life prediction [23]. These uncertainties may cause great changes in fatigue behavior and they should be taken into account in realistic assessment.

These hybrid structures have great possibilities of improving the prediction accuracy, the ability to maintain the piping networks conditionally, and increasing the working life of such networks.

C. Integration of Data-Driven and Physics-Based Approaches

Data-driven and physics-based approaches has emerged as a powerful framework for improving stress and fatigue prediction in piping networks. Physics-based models, such as finite element analysis, provide mechanistic understanding of stress distribution and fatigue behavior based on material properties, geometry, and loading conditions, while data-driven methods leverage sensor data, inspection records, and historical operating information to capture complex, nonlinear patterns and uncertainties.

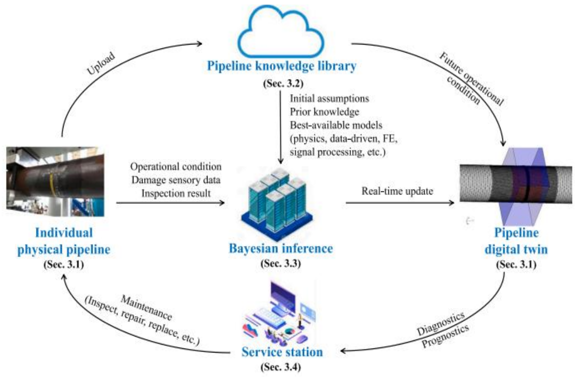

Fig. 3. Digital Twin Pipeline Fatigue

The digital twin of the pipeline is constructed using the physical pipeline and its associated knowledge library, as shown in Figure 3. Live updates on Bayesian inference the digital representation of the pipeline in accordance with data collected from each physical pipeline in the real world [24]. In order to keep the system running, the pipeline knowledge library supplies the starting point, background information, top models, and expected operating conditions.

The entity that is being monitored is a particular physical pipeline, or individual pipeline. "Individual" is used here to distinguish between a batch or group of physical pipelines. Pipeline knowledge library stands in for domain-related expertise because of the unit-to-unit volatility in batches and groups of pipelines [25]. In addition to receiving data from the various physical pipes, the knowledge library is also updated as the digital twin system runs. The best-available models, prior information, and initial assumptions for Bayesian inference are all part of the pipeline knowledge library.

There are a number of physical space uncertainty elements that cause the virtual and actual worlds to blend seamlessly. Natural uncertainty, sensing uncertainty, and model uncertainty are the three main types of these sources of uncertainty.

The term "pipeline digital twin" refers to an exact digital replica of a single physical pipe. Geometries, physical qualities, and future behaviour of the physical structure can be replicated in the virtual space by integrating various variables, scales, and domain knowledge.

The changing pressure is usually what causes the cycle loading. Welding the two loading pins into the pipe pipelines creates an off-center girth weld seam in the pipeline, as shown in Figure 4, and the operating load or force is measured at the hydraulic unit, which applies the load over the steel beam. As a result of the welding process, a crack that goes around the joint and widens as it progresses is expected. for example, nuclear pipe sensors placed in susceptible areas to collect damage sensory data.

Fig. 4. Pipe Fatigue Test Under Cyclic Load

1) Role of Physics-Based Models

Pipe systems' mechanical behaviour under various boundary conditions, loading scenarios, material qualities, and geometric considerations can be described using these models. They are also good at delivering trusted stress distribution as well as estimation of fatigue damage but can encounter difficulties in coping with uncertainties and variability in real time.

2) Data-Driven Methods

Machine learning and statistical models utilize sensor data, inspection records, and historical failures to learn nonlinear relationships and adapt to changing operating conditions. They are effective in handling large datasets and noise but often lack physical interpretability.

D. classification of Stress and Fatigue Prediction in Piping Networks

Stress prediction principally concerns the industrial piping, the prediction of the static, thermal, and dynamic stress, and fatigue prediction deals with fatigue life, and damage due to vibration under cyclic and random loading. Table I shows that by combining monitoring data with physics-based and machine learning models, along with other approaches for abnormality detection, the level of system-level evaluation can be further increased:

TABLE I. CLASSIFICATION OF STRESS AND FATIGUE PREDICTION IN PIPING NETWORK

Main Category	Sub-Category	Data Sources	Loading Conditions	Techniques	Piping Applications
Stress Prediction	Static stress estimation	Finite element simulations, material properties	Internal pressure, dead weight	Finite element analysis, ANN-based surrogate models	Steam and industrial piping
	Thermal stress analysis	Temperature and pressure measurements	Thermal expansion, temperature gradients	Thermo-mechanical modeling, ML regression	Power plant and high-temperature piping
	Dynamic stress prediction	Vibration sensor data	Cyclic and dynamic loads	Signal processing, ML-based regression	Vibration-prone piping systems
Fatigue Prediction	Fatigue life estimation	Stress–strain histories	Cyclic and multi-axial loading	Equivalent stress/strain methods, ML regressors	Marine, offshore, and process piping
	Vibration-induced fatigue	Frequency-domain vibration data	Random vibration loading	Time–frequency analysis, ML classifiers	High-pressure machinery piping
Abnormality Detection	Damage and defect detection	CCTV inspection images, sensor data	Operational variability	CNN-based classification, clustering techniques	Water and wastewater pipelines

	Stress anomaly detection	Structural health monitoring data	Variable operating conditions	Autoencoders, PCA-based anomaly detection	Large-scale piping networks
Hybrid Approaches	Physics-informed ML	FEM data and real-time sensor data	Combined thermo-mechanical loads	Physics-informed neural networks	Complex industrial piping networks
	Digital twin-based analysis	Live monitoring data streams	Real-time operational loads	Digital twin frameworks with ML models	Integrated piping plants

III. Machine Learning Techniques For Stress And Fatigue Prediction

Machine and structural designers need reliable methods for estimating fatigue life and for estimating forecast uncertainty. This is because there are numerous fatigue crack formation periods, each with its own unique physical damage mechanism, making the fatigue damage process very complex to model. Due to the inherent uncertainty in fatigue loadings, component shape, material characteristics, and microstructures, fatigue behaviour is often unpredictable. The semi-empirical fatigue models shown in Figure 5 are suggested to be replaced with an ML technique. A parametric version of the weariness model is chosen. When it comes to fatigue, one of the many ML methodologies used is the neural network (NN). Regression using the Gaussian process (GP) for fatigue life prediction uses. machine learning methods, which allow for conservative design by providing a probability distribution for the model's outputs.

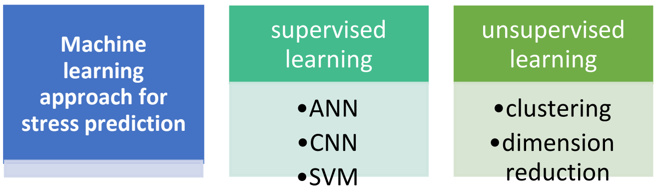

Fig. 5. Machine Learning Technique for Stress Prediction

A. *Machine Learning Models for Stress Prediction*

Stress distributions in piping systems are calculated by machine learning models more frequently as an efficient method to substitute traditional finite element analysis because it is computationally efficient. The models allow the stress responses to be estimated quickly in different loading and boundary conditions.

1) *Supervised Learning Technique*

Learning models are supervised with a set of labeled data, whereby input parameters (e.g., geometry, load, temperature) are correlated with known stress outputs, may be between finite element simulations or experimental data.

- **Artificial Neural Networks (ANNs):** ANN architecture predict the fatigue behavior of the components fatigue behavior, such as the fatigue crack [26] ANNs are widely used to approximate nonlinear relationships between input variables and stress responses. They are effective for predicting stress magnitude and distribution in complex piping geometries.
- **Convolutional Neural Networks (CNNs):** CNNs are especially effective when the stress field is required to be predicted in space and represented in images, e.g. stress contour maps or grid-based finite element results.
- **Support Vector Machines (SVMs):** SVMs are used in regression-based stress prediction, which has a good generalization performance with small datasets, particularly with medium-dimensional feature space.

2) *Unsupervised Learning Techniques*

unsupervised learning methods do not utilize any labelled output and are primarily applied to find patterns, anomalies, or hidden structures in stress-related data.

- **Clustering Algorithms:** Clustering patterns of stress reactions or an operating state can be done using methods like K-means, hierarchical clustering, and DBSCAN approaches. This can help identify anomalous stress responses or areas likely to be harmed.
- **Dimensionality Reduction Techniques:** PCA and autoencoders are employed to reduce data dimensionality, extract dominant stress features, and improve visualization and computational efficiency.

B. *Fatique life prediction*

The term used to describe the failure of welded structures and components is fatigue. Fatigue occurs when structures unknowingly undergo the introduction of residual loads or defects in welded joints.

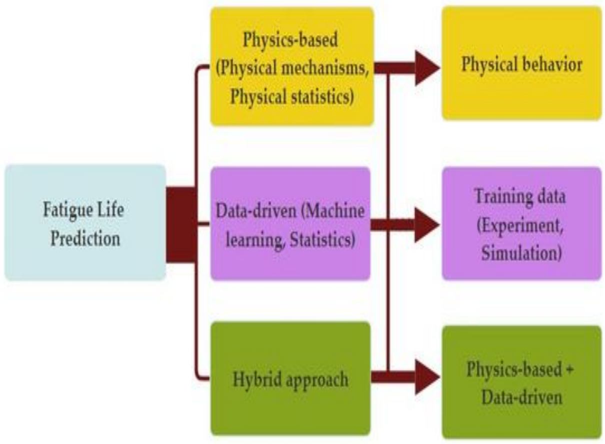

Fig. 6. : Fatigue Life Prediction

Additional variables that impact the fatigue lifetimes of these constructions include the weld toe angle, plate thicknesses, and the type of loading. Assessing the FL in welded connections is essential for guaranteeing the dependability, security, and longevity of diverse engineering structures and parts [27]. Based on the stress concentration factor, stress intensity factor, and fracture toughness, the FL phase may be divided into three distinct phases: initiation, crack growth, and final failure (Figure 6). Finite element analysis using ML has been implemented.

The FL of structures and components can be predicted using data-driven or physics-based approaches, or both. In order to increase safety and decrease production costs, fatigue testing of welded joints is a crucial industrial issue for forecasting the fatigue life of structures.

IV. Applications in Complex Piping Networks

Implementation of sophisticated stress and fatigue prediction methods is especially important, as the geometric complexity and the variability of the operating conditions, as well as the long service life, pose a considerable danger of structural degradation. Fluid distribution networks, where corrosion causes 21% of gas pipeline failures and 15% of chemical plant leaks (Figure 7), are among the more complex areas where recent advances in numerical modelling, machine learning, and hybrid methods have allowed for more effective assessment and management of such systems. The purpose of SHM systems is to assess a building's safety and health and then use auxiliary algorithms to estimate how much longer the building last .

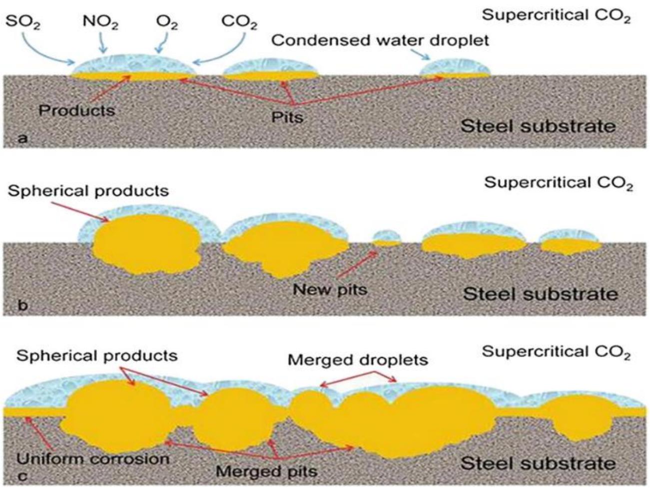

Fig. 7. Pitting Corrosion Mechanism in Pipelines

SHM techniques for pipelines, such as piezoelectric material-based impedance-based approaches for pipeline damage monitoring and real-time data monitoring based wireless sensor networks (WSN). The primary applications of fiber-optic (FO) sensors include tracking critical power system parameters like current, voltage, and temperature as well as stress changes in critical infrastructure like bridges, pipelines, and buildings.

A. *Failure Prediction and Maintenance Scheduling*

Pipelines encounter risks such as worn-out machinery, lack of upkeep, severe weather, accidents, and intentional acts of vandalism as they carry petroleum and natural gas from fields to processing facilities and consumers. For the detection and repair of underground pipeline concerns, particularly in remote locations, expert monitoring systems are necessary. Severe repercussions on the environment, economy, and safety might result from pipeline leaks or breakdowns [28]. Not having the ability to forecast future events in real time prevents proactive risk management. Advanced machine learning techniques have been employed for real-time anomaly detection and predictive maintenance forecasting.

B. *Simulation-Based Stress and Fatigue Analysis*

The design of structural components exposed to cyclic loads necessitates a comprehensive comprehension of the material's response under such conditions. The application of trustworthy material models and thorough experimental testing can yield this vital information. Ratcheting, the build-up of strain under stress-controlled cyclic loading with a non-zero mean stress, is a notable occurrence in cyclic plasticity models that occurs when materials undergo cyclic loading [29]. There have been numerous models put forward to mimic the cyclic behaviour of materials, with specific methods becoming widely used to represent creep-fatigue behaviour.

C. *Power Generation and Process Industries*

A significant portion of the electricity that is held for a lengthy period of time comes from pumped-storage hydroelectric stations [30]. However, societal retentions primarily limit further extension to compressed air energy storages and redox flow batteries for long-term storage. Elbow, weld joints, and support interfaces are the key areas where fatigue prediction techniques are used to assess the critical areas. Surrogate models that are trained on machine learning are becoming popular to offer fast estimation of stress and remaining life with the aim of facilitating condition-based maintenance and also decreasing unplanned downtime.

D. *Marine and Offshore Piping Systems*

A ship or offshore structure's pipes are the conveyance mechanisms for fluids or the opening and closing of air vents. A lot of control systems also rely on piping systems to function [31]. Aside from the weather deck, pipes enter nearly every interior room, shell above and below waterline, and nearly every restricted area [32]. An offshore structure or ship has the potential to severely damage or destroy the environment. Assembled components of piping include pipes, gaskets, bolts, flanges, flexible hoses, valves, housings for pumps, and supports. Along with pipes, ancillary components including heat exchangers, pumps, evaporators, and tanks make up piping systems.

E. *Water and Wastewater Infrastructure*

The proper management of wastewater and water treatment is essential for the preservation of both human and environmental health [33]. Treatment techniques purge wastewater of impurities, making it drinkable again, however sewage piping systems are vulnerable to environmental factors, transitory pressure variations, and changes in flow. Weak spots that could rip or rupture can be located using stress and fatigue prediction methods.

V. Literature Review

In this section, recent studies demonstrate the growing role of Machine Learning in stress and fatigue prediction for complex piping networks to automating vibration and structural analysis. Table II presents, their methodologies, principal findings, associated challenges, and anticipated future research.

Ling et al. (2025) an improved RAPID-based algorithm by employing a local SDC (LSDC) and reliability coefficient (RC) to ensure that damage is accurately detected. The LSDC is employed to enhance the sensitivity to damage by capturing localized signal variations, while the RC is developed to weigh the signal reliability. It maintained a strong overlap between the predicted and the actual defect locations, with an overlapping rate (OR) between 73.02% and 79.43% throughout all cycles [34].

Seo et al. (2025) an efficient 3-D PNN processor with LiDAR–PNN processor pipelined structure that eliminates the external memory between LiDAR and processor and hides sensing latency behind processing time by utilizing the mechanical characteristic of LiDAR with the following hardware features cylindrical partitioning core with novel cylindrical bin partitioning method loss pseudo-random number generator-based sampling unit and k-nearest neighbor searching cores with unified neighbor searching algorithm to reduce the computation cost linked-list memory management unit and predicted memory allocator to efficiently manage the point-cloud and support the parallel processing of neighbor searching and shared MLP [35].

Domiciano et al. (2025) The cooling heat transfer coefficient on the thermal performance of a loop heat pipe (LHP) was investigated. The diffusion-bonded LHP was specifically designed for electronics cooling, with overall dimensions of 76×60×1.6mm. As the heat transfer coefficient increased from approximately 62 to 641 W/m2 K, the LHP consistently exhibited the same start-up heat load across all cases. However, while the higher heat transfer coefficients enabled the device to dissipate greater heat loads thermal performance the critical importance of the condenser in the design and optimization of two-phase cooling systems [36].

Gunatilake and Miro (2024) The neural network consists of a feature extraction module, a convolutional base, and a classification head, which has been meticulously engineered through numerous experiments and iterations the proposed model surpasses conventional leak detection methods, accurately identifying different types of water leaks and achieving accuracies of up to 98%. Overall, the neural network model represents a notable practical step forward in the field of water leak detection by subcategorizing leaks and has the potential to revolutionize the way industry practitioners manage larger water infrastructure [37].

X. Wang et al. (2024) a PIPE-CovNet+ model with hyper-densely linked layers, gradient boosting methods, and convolutional neural networks (CNNs) with variable kernel sizes for detecting anomalies in wastewater pipe infrastructure. Overcoming the limitations of unbalanced data and over-fitting, the PIPE-CovNet+ model attained an accuracy of 85% and an F1-score of 84%. Incorporating PIPE-CovNet+ into a robotic system can make closed-circuit video (CCTV) inspections easier, faster, and less error-prone than with previous models; this is especially true when compared to other related models [38].

Y. Wang et al. (2024) the calculated primary and secondary stresses fall within the allowable stress range the stress assessment process for steam pipelines, including defining assessment objectives, collecting pipeline information, selecting appropriate software, creating geometric models of pipelines, setting constraint nodes, calculating load conditions, obtaining stress and displacement data, and verifying whether the stresses meet standard requirements stress analysis, the behavior characteristics of pipelines under different conditions can be evaluated [39].

Zhu et al. (2023) offered equivalent strain or stress is derived, further analysis can be conducted to assess the fatigue life. The life of structure is obtained by combining the formula of the life prediction of the method an efficient multi-axis random fatigue life prediction method the traditional method, the prediction accuracy is higher and the workload is greatly reduced. It provides theoretical support for multi-axis random vibration fatigue life analysis of key components of marine diesel engines [40].

TABLE II. RECENT STUDIES ON MACHINE LEARNING AND FATIGUE/STRESS ANALYSIS IN COMPLEX PIPING AND RELATED ENGINEERING SYSTEMS

Author	Study Focus	Key Findings	Approaches	Challenges	Future Work
Ling et al. (2025)	Structural damage detection using RAPID-based algorithms	Achieved strong agreement between predicted and actual defect locations with overlapping rates (OR) of 73.02%–79.43% across all cycles	Improved RAPID algorithm incorporating Local Signal Difference Coefficient (LSDC) for localized sensitivity and Reliability Coefficient (RC) for signal weighting	Performance may depend on signal quality and sensor placement; computational cost may increase with localization metrics	Extend validation to complex structures and noisy environments; real-time implementation
Seo et al. (2025)	Hardware acceleration for 3D point-cloud processing	Eliminated external memory bottleneck and hid LiDAR sensing latency; significantly reduced computation cost	3D PNN processor with LiDAR–PNN pipelined architecture, cylindrical bin partitioning, PRNG-based sampling, k-NN search cores, linked-list memory management	Hardware complexity and scalability for different LiDAR configurations	Adapt architecture for autonomous systems; optimize energy efficiency and scalability
Domiciano et al. (2025)	Thermal performance of loop heat pipes (LHPs) for electronics cooling	Startup heat load remained constant despite increasing heat transfer coefficient; higher coefficients allowed greater heat dissipation	Experimental analysis of diffusion-bonded LHP under varying condenser heat transfer coefficients	Performance strongly dependent on condenser design; limited to specific geometry and operating range	Optimize condenser design; integrate LHPs into high-power electronics and transient conditions
Gunatilake & Miro (2024)	Water leak detection using deep learning	Achieved up to 98% accuracy and outperformed traditional leak detection methods	Neural network with feature extraction module, convolutional base, and classification head	Requires large, labeled datasets; model generalization to varied pipe materials uncertain	Deployment in real-world infrastructure; integration with IoT-based monitoring systems
X. Wang et al. (2024)	Checking wastewater pipelines for anomalies	PIPE-CovNet+ successfully handled unbalanced data, achieving an accuracy of 85% and an F1-score of 84%.	Multi-kernel convolutional neural network (CNN) using gradient boosting and hyper-dense connections	Still limited by CCTV image quality and operational constraints of robotic inspection	Enhance robustness to noise; full-scale robotic deployment and real-time analysis
Y. Wang et al. (2024)	Stress assessment of steam pipelines	Calculated stresses met allowable standards, validating pipeline safety under operating conditions	Finite element stress analysis including geometry modeling, load definition, constraint setting, and verification	Relies on accurate modeling assumptions and input data	Incorporate real-time monitoring data; probabilistic stress and risk assessment

Zhu et al. (2023)	Fatigue life prediction under multi-axis random vibration	Higher prediction accuracy with reduced workload compared to traditional methods	Equivalent stress/strain derivation combined with efficient multi-axis random fatigue life prediction formulas	Validation limited to specific marine diesel engine components	Extend method to broader mechanical systems; experimental validation under varied loading conditions

VI. Conclusion with Future Work

Machine learning solutions to industrial, marine, and water infrastructure systems. Physical-based models (e.g., finite element analysis) are needed to understand mechanical behavior and meet design requirements; but they are expensive and not very adaptable to the uncertainty of stochastic loading and uncertain operating conditions, making them unsuitable to scale and real-time applications. ANNs, CNNs, and Gaussian process models are machine learning methods which have shown to be highly promising as efficient and precise alternatives in estimating stress. These models can represent nonlinear correlations and multi-axial stress field conditions that are challenging to articulate with conventional methods alone by using sensor data, historical records and numerical simulation to obtain hybridized systems and digital twin systems in continuous structural health monitoring and predictive maintenance. These methods can be used to increase reliability, minimize the unplanned downtime, and make condition-based decisions using complex piping networks Future efforts should aim at improving the quality and availability of data, creating uncertainty-aware and physics-informed machine learning algorithms, and validating predictions with long-term field data. Furthermore, real-time implementation, which is scalable, cybersecurity of monitoring systems, and standardization of prediction performance. These concerns will also contribute to the development of intelligent stress and fatigue management to be used in next-generation piping infrastructure.

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