PlantReliability Fusion Algorithm for Predicting Equipment and Structural Support Failures in Combined-Cycle Power Plants Using Operational and Structural Data Compared with Weibull Reliability Analysis

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Publication Date: 2026/09/23

Abstract: Combined-cycle power plants contain strongly coupled mechanical, thermal, electrical, and structural systems whose degradation mechanisms evolve under variable operating loads, cyclic thermal stresses, vibration, environmental exposure, and equipment ageing. Conventional reliability techniques such as Weibull reliability analysis are effective for estimating population-level failure distributions but have limited capability to incorporate high-frequency operational measurements, structural-condition indicators, nonlinear interactions, and time-varying degradation simultaneously. This study develops a novel PlantReliability Fusion Algorithm (PRFA) for integrated prediction of equipment and structural-support failures in combined-cycle power plants using operational and structural data. The proposed framework combines a temporal feature-learning module for processing equipment variables such as compressor discharge pressure, turbine exhaust temperature, vibration, bearing temperature, heat-recovery steam generator pressure, start-stop cycles, operating hours, and load fluctuations with a structural-condition module incorporating foundation settlement, support displacement, strain, vibration response, crack development, anchor-bolt condition, thermal expansion, and structural stress indicators. An attention-based multimodal fusion layer dynamically weights degradation signals from both data domains, while a reliability-learning layer estimates failure probability, hazard evolution, remaining useful life, and component reliability over time. PRFA is benchmarked against two-parameter Weibull reliability analysis, Cox proportional hazards regression, Random Forest, XGBoost, Long Short-Term Memory networks, and a conventional artificial neural network. Comparative performance is evaluated using accuracy, precision, recall, F1-score, area under the receiver operating characteristic curve, concordance index, Brier score, remaining-useful-life error, and computational efficiency. Graphical evaluation includes Weibull and predicted reliability curves, hazard-rate trajectories, receiver operating characteristic curves, predicted-versus-observed remaining useful life plots, structural-operational degradation maps, feature-importance plots, and comparative algorithm performance charts. The proposed fusion architecture is designed to provide stronger sensitivity to interacting mechanical and structural degradation mechanisms than conventional failure-time models or single-domain machine-learning approaches. The resulting framework provides a technically integrated basis for predictive maintenance, structural integrity management, inspection prioritization, outage planning, and lifecycle reliability optimization in combined-cycle power plants.

Keywords: *PlantReliability Fusion Algorithm; Combined-Cycle Power Plants; Equipment Failure Prediction; Structural Support Failures; Weibull Reliability Analysis.*

How to Cite: Ransben Zac Addy (2026) PlantReliability Fusion Algorithm for Predicting Equipment and Structural Support Failures in Combined-Cycle Power Plants Using Operational and Structural Data Compared with Weibull Reliability Analysis. *International Journal of Innovative Science and Research Technology*, 11(9), 927-946. https://doi.org/10.38124/ijisrt/26sep933

I. INTRODUCTION

- *Background to Combined-Cycle Power Plant Reliability*

Combined-cycle power plants (CCPPs) achieve high thermal efficiency by coupling a gas-turbine Brayton cycle with a steam-turbine Rankine cycle through a heat-recovery steam generator, but this thermodynamic integration also creates tightly coupled reliability dependencies. A disturbance in compressor performance, combustor temperature, turbine vibration, HRSG pressure, steam quality, generator loading, or auxiliary systems can propagate through the plant and reduce availability when the initiating fault is

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

localized. Reliable operation therefore depends not only on component survival, but also on knowledge of operating states, transient loads, thermal gradients, and condition indicators. Finn et al. (2010) demonstrated that plant-sensor data from a 510 MW combined-cycle facility can support operational anomaly detection and prognostic monitoring, illustrating the value of extracting reliability information from process signals. Contemporary power systems also increasingly depend on data-rich energy conversion infrastructure, making reliability inseparable from intelligent monitoring and adaptive control architectures (Idoko et al., 2024).

For this study, CCPP reliability is treated as a dynamic, system-level property that encompasses mechanical equipment and the structural supports transmitting thermal and vibratory loads. Gas turbines, steam turbines, generators, pumps, HRSG pressure parts, bearings, shafts, foundations, pedestals, anchor bolts, baseplates, pipe supports, and framing systems operate as an interacting reliability network rather than isolated assets. Cycling, rapid load-following, ambient-temperature changes, start-stop events, and sustained vibration can alter degradation rates and shift failure probability over time. The proposed PlantReliability Fusion Algorithm therefore extends conventional reliability assessment by integrating operational variables, including temperatures, pressures, loads, speeds, vibration levels, operating hours, and start-stop counts, with structural variables such as strain, settlement, displacement, crack progression, anchor-bolt condition, thermal expansion, and support vibration. This fused representation is intended to estimate failure probability, hazard evolution, and remaining useful life at equipment and support levels. Accordingly, reliability in this paper is defined not merely as historical time-to-failure behavior, but as a continuously updated condition-dependent quantity that can be compared against Weibull analysis and machine-learning benchmarks for maintenance and inspection decisions.

➢ *Equipment and Structural Support Failure Mechanisms in Combined-Cycle Power Plants*

Failure in a combined-cycle power plant develops through interacting thermal, mechanical, electrical, and structural mechanisms. Gas-turbine compressors face fouling, erosion, corrosion, blade damage, and efficiency loss; combustors experience thermal distress; turbine hot-section components accumulate creep and low-cycle fatigue; and bearings, couplings, shafts, and generators are vulnerable to misalignment, lubrication deterioration, imbalance, and vibration. HRSG drums, headers, superheaters, reheaters, and pipework experiences cyclic pressure and temperature gradients that promote fatigue, creep, corrosion, and weld deterioration. Benato et al. (2016) showed that faster load transients in a combined-cycle plant can reduce calculated life of stressed HRSG components, demonstrating that failure risk is strongly dependent on operating history rather than chronological age alone. Thermal-management research similarly shows that temperature imbalance and repeated thermal exposure accelerate material degradation and shorten energy-system component life, reinforcing the importance of thermal state variables in reliability assessment (Aikins et al., 2024). Structural-support failures arise from a mechanically coupled degradation pathway. Turbine and generator foundations can experience differential settlement, stiffness loss, concrete cracking, reinforcement distress, grout deterioration, anchor-bolt loosening, baseplate distortion, and resonance-related amplification. Steel support frames, pipe racks, hangers, spring supports and HRSG structural members may develop fatigue cracking, connection looseness, excessive displacement, or local overstress under vibration, thermal expansion, and start-stop cycles. These defects can change alignment and boundary conditions at bearings, casings, piping interfaces, and rotating shafts, thereby converting structural deterioration into equipment-level symptoms such as vibration, seal rubbing, coupling misalignment, bearing heating, and abnormal load transfer. The reverse interaction is equally important: rotor imbalance, unstable combustion, hydraulic excitation, and transient thermal forces can increase cyclic demand on foundations and supports. The PlantReliability Fusion Algorithm is therefore formulated to represent failure as a coupled operational-structural process. Its predictive inputs include vibration spectra, bearing temperature, process pressure, turbine exhaust temperature, load cycling, operating hours, settlement, strain, displacement, crack indicators, anchor-bolt condition, and support response, enabling the model to distinguish isolated equipment degradation from structurally mediated failure progression.

➢ *Limitations of Conventional Reliability and Failure-Prediction Methods*

Power-plant reliability assessment commonly uses historical failure counts, mean time between failures, probability distributions, fault trees, and parametric lifetime models such as the two-parameter Weibull distribution. These techniques characterize population-level failure behavior and wear-out tendencies, but become restrictive when degradation is driven by changing loads, thermal cycles, maintenance, and correlated condition variables. A Weibull curve does not encode compressor pressure loss, bearing-temperature excursions, vibration growth, HRSG thermal stress, foundation settlement, or support displacement unless introduced through covariate structures. Statistical prognostics literature has similarly shown that remaining useful life depends on observed condition information and that no single statistical formulation is universally optimal across degradation processes (Si et al., 2011). Data-driven energy-asset studies increasingly emphasize performance analytics because static summaries can conceal interacting operational effects that influence long-term asset outcomes (Ilesanmi et al., 2024). Another limitation is separating mechanical equipment reliability from structural integrity assessment. Conventional plant reliability databases often record trips, component replacements, outage durations, and maintenance events, whereas structural inspection systems record cracks, strain, settlement, bolt condition, displacement, and vibration response at different timescales. Analyzing these streams independently can obscure causal relationships, for example when foundation stiffness loss shifts rotor alignment or when repeated turbine vibration accelerates anchor-bolt loosening. Traditional methods struggle with nonlinear feature interactions, nonstationary operating regimes, censored failure histories, sensor noise, rare failures, and high-dimensional temporal data. The PlantReliability Fusion Algorithm addresses this by learning time-dependent representations from operational and structural variables, applying attention-based fusion to determine which channels dominate a developing failure state, and estimating failure probability, hazard evolution, and remaining useful life together. Weibull analysis remains an essential benchmark because it establishes whether the added data complexity produces measurable predictive benefit. Comparative evaluation against Cox regression, Random Forest, XGBoost, ANN, and LSTM further tests whether multimodal fusion improves discrimination, calibration, RUL accuracy, and robustness beyond both classical reliability analysis and single-domain machine-learning models under realistic combined-cycle plant operating conditions across multiple failure mechanisms simultaneously.

➢ *Integration of Operational and Structural Condition Data for Reliability Assessment*

An integrated reliability framework for combined-cycle power plants must connect what the plant is doing with how its supporting structures are responding. Operational data from the distributed control system and condition-monitoring network provide information on turbine load, compressor discharge pressure, exhaust temperature, bearing temperature, shaft speed, vibration amplitude, steam pressure, valve position, starts, trips, and operating hours. Structural data provide complementary evidence through strain, settlement, displacement, crack indicators, modal response, anchor-bolt condition, support vibration, and thermal expansion. Joint analysis is important because environmental and operational changes can alter measured structural dynamics and mask damage signatures. Avendaño-Valencia et al. (2020) demonstrated that operational variability can influence vibration-based structural health monitoring and that probabilistic learning can separate operating effects from damage-sensitive response. Within energy infrastructure, AI-driven behavioral analytics likewise illustrate how multivariable monitoring can detect deviations that static threshold logic may miss (James et al., 2023). The proposed PlantReliability Fusion Algorithm implements this integration through synchronized preprocessing, temporal feature extraction, structural feature encoding, and an attention-based fusion layer. Rather than concatenating measurements, the fusion mechanism learns context-dependent weights that indicate whether a reliability state is associated with thermodynamic stress, rotating-equipment degradation, structural deterioration, or a coupled mechanism. For example, increasing shaft vibration accompanied by stable foundation response may indicate rotor or bearing degradation, whereas similar vibration accompanied by settlement growth, anchor-bolt looseness, and altered support response may indicate structurally mediated misalignment. The fused latent state is then mapped to component failure probability, hazard evolution, reliability, and remaining useful life. The architecture enables feature-importance and sensitivity analyses for interpreting failures and prioritizing maintenance. The study evaluates whether operational-structural fusion produces superior discrimination and calibration compared with Weibull reliability analysis and benchmark learning models. Performance is examined through accuracy, precision, recall, F1-score, AUROC, concordance index, Brier score, RUL error, and graphical comparisons of reliability curves, hazard trajectories, predicted-versus-observed RUL, feature importance, and degradation interactions, ensuring that predictive gains remain traceable to meaningful plant behavior.

➢ *Problem Statement*

Despite advances in reliability statistics, condition monitoring, structural health monitoring, and machine-learning prognostics, combined-cycle power plant decision systems still tend to treat equipment degradation and structural-support deterioration as separate analytical problems. This is problematic because failure precursors span heterogeneous data streams and temporal scales. A turbine trip may be preceded by vibration growth, bearing heating, efficiency loss, thermal cycling, and load changes, while severity may be amplified by foundation settlement, support flexibility, anchor-bolt degradation, or thermal displacement. Machinery prognostics shows that useful remaining-life prediction depends on data acquisition and health-indicator construction to degradation-state identification and RUL estimation (Lei et al., 2018). Asset-management research also emphasizes lifecycle models connecting performance, risk, and infrastructure condition rather than relying on isolated indicators (Ilesanmi et al., 2023). However, a framework for fusing operational and structural information for CCPP failure prediction remains insufficiently developed.

The research problem is the absence of an interpretable reliability model that learns nonlinear temporal degradation in plant operating variables, structural-condition changes, and their cross-domain interactions while retaining outputs comparable with established methods. Weibull analysis can describe historical failure-time distributions but cannot, in its basic two-parameter form, dynamically reweight process and structural evidence. Machine-learning models may predict faults accurately yet fail to distinguish whether a risk increase originates from equipment condition, support deterioration, or coupled behavior. This study addresses that gap through the PlantReliability Fusion Algorithm, which combines temporal operational features, structural degradation features, attention-based multimodal fusion, and reliability-learning outputs for failure probability, hazard, reliability, and remaining useful life. Its performance is compared with Weibull analysis, Cox regression, Random Forest, XGBoost, ANN, and LSTM using classification, survival, calibration, RUL, and computational metrics. The graphs and tables determine whether the fused model provides earlier warning, lower prediction error, improved calibration, and clearer maintenance prioritization for gas turbines, HRSGs, generators, rotating auxiliaries, foundations, supports, and associated structural interfaces under realistic cycling, load-following, ageing, maintenance, and sensor-data conditions encountered during plant operation in practice.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

Research Objectives and Research Questions

- *Research Objectives*

- ✓ To develop an integrated operational-structural data architecture for synchronizing, preprocessing, and extracting reliability-relevant features from combined-cycle power plant equipment and structural-support monitoring data.
- ✓ To develop the novel PlantReliability Fusion Algorithm incorporating temporal operational feature learning, structural-condition encoding, and attention-based multimodal data fusion for coupled degradation assessment.
- ✓ To predict equipment and structural-support failure probability, time-dependent hazard, reliability, and remaining useful life from the fused operational-structural condition state.
- ✓ To compare the predictive performance of the PlantReliability Fusion Algorithm with two-parameter Weibull reliability analysis, Cox proportional hazards regression, Random Forest, XGBoost, artificial neural networks, and Long Short-Term Memory networks.
- ✓ To evaluate the models using accuracy, precision, recall, F1-score, AUROC, concordance index, Brier score, MAE, RMSE, RUL prediction error, computational efficiency, reliability curves, hazard trajectories, and predicted-versus-observed RUL graphs.
- ✓ To determine the relative influence of operational variables and structural-condition variables through feature-importance, sensitivity, ablation, sensor-noise, and missing-data analyses and translate the resulting predictions into maintenance and structural-inspection priorities.

- *Research Questions*

- ✓ How can operational and structural-condition data from a combined-cycle power plant be synchronized and represented to capture interacting equipment and structural degradation mechanisms?
- ✓ To what extent can the PlantReliability Fusion Algorithm identify nonlinear temporal relationships between process operating conditions, equipment degradation, and structural-support deterioration?
- ✓ How accurately can the proposed algorithm estimate equipment failure probability, structural-support failure probability, hazard evolution, reliability, and remaining useful life?
- ✓ How does the predictive performance of the PlantReliability Fusion Algorithm compare with Weibull reliability analysis, Cox regression, Random Forest, XGBoost, ANN, and LSTM models?
- ✓ Which operational and structural variables contribute most strongly to predicted reliability deterioration, and how do their interactions change across normal, degrading, and pre-failure operating states?
- ✓ How robust is the PlantReliability Fusion Algorithm to sensor noise, missing measurements, variable operating regimes, and rare failure events, and how can its predictions support maintenance, inspection, and outage decisions?

Research Contributions and Novelty of the PlantReliability Fusion Algorithm and Significance of the Study

- *Research Contributions and Novelty*. The principal methodological contribution of this study is the PlantReliability Fusion Algorithm, a multimodal reliability-learning architecture designed specifically to model coupled equipment and structural-support degradation in combined-cycle power plants. Unlike conventional Weibull analysis, which primarily derives reliability from failure-time distributions, the proposed algorithm continuously updates the inferred health state from operational and structural evidence. Its architecture contains a temporal operational branch for load, temperature, pressure, vibration, speed, operating-hour, and cycling histories; a structural-condition branch for settlement, strain, displacement, cracking, anchor-bolt condition, thermal movement, and support vibration; and an attention-based fusion mechanism that learns the relative importance of both domains as degradation evolves. The resulting latent reliability state is mapped simultaneously to failure probability, hazard evolution, component reliability, and remaining useful life. A further contribution is the explicit differentiation between equipment-originated faults, structurally mediated equipment faults, and coupled degradation mechanisms. Comparative benchmarking against Weibull analysis, Cox regression, Random Forest, XGBoost, ANN, and LSTM, together with ablation, sensitivity, calibration, and robustness analyses, provides a rigorous basis for demonstrating where multimodal fusion adds predictive value rather than merely increasing model complexity.
- *Significance of the Study*. The study has practical significance for plant reliability engineering because it converts normally fragmented process, vibration, maintenance, and structural-monitoring information into a unified decision variable that can support predictive maintenance and structural integrity management simultaneously. Earlier detection of degrading bearings, turbine components, HRSG pressure parts, foundations, anchor bolts, supports, and alignment-sensitive interfaces can allow maintenance teams to intervene before interacting defects escalate into forced outages or secondary damage. Reliability and RUL outputs can also be integrated with DCS, SCADA, condition-monitoring systems, computerized maintenance management systems, inspection databases, and digital-twin environments to rank work orders by predicted risk rather than fixed calendar intervals. For plant management, this provides a basis for optimizing outage timing, spare-parts planning, inspection frequency, maintenance expenditure, and asset-life extension. For engineering research, the framework expands reliability modelling from component-centred failure statistics toward an integrated cyber-physical representation of machinery and its load-bearing structural system.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

Scope of the Review and Structure of the Paper

- *Scope of the Review*. The study focuses on reliability prediction for major equipment and structural-support systems within natural-gas-fired combined-cycle power plants. Equipment considered includes gas-turbine compressors, combustors and turbine sections, bearings, shafts, couplings, HRSG drums and heat-transfer sections, steam turbines, generators, pumps, valves, and selected rotating auxiliaries. Structural variables cover turbine-generator foundations, reinforced-concrete pedestals, baseplates, grout interfaces, anchor bolts, structural frames, pipe supports, hangers, and alignment-sensitive supporting systems. Operational inputs include load, pressure, temperature, rotational speed, vibration, operating hours, start-stop cycles, transient severity, and related condition indicators, while structural inputs include settlement, strain, displacement, crack development, thermal expansion, support vibration, and connection condition. The analytical scope encompasses failure classification, reliability and hazard estimation, RUL prediction, model calibration, interpretability, and robustness. Weibull analysis, Cox regression, Random Forest, XGBoost, ANN, and LSTM constitute the principal comparison models.
- *Structure of the Paper*. Section 1 establishes the reliability context, equipment and structural failure mechanisms, methodological limitations, operational-structural data integration problem, research objectives, questions, novelty, significance, and scope. Section 2 reviews combined-cycle reliability engineering, Weibull and conventional reliability methods, operational and structural condition monitoring, machine-learning and deep-learning prognostics, multimodal data fusion, and the unresolved research gap. Section 3 develops the combined-cycle plant system representation, defines operational and structural feature vectors, formulates the PlantReliability Fusion Algorithm mathematically, specifies its temporal and structural encoders and attention-fusion mechanism, and presents the benchmark algorithms, training strategy, validation procedure, and evaluation metrics. Section 4 presents statistical characteristics, reliability and hazard curves, failure classification results, RUL predictions, algorithm comparisons, feature-importance analysis, ablation studies, sensitivity analysis, noise and missing-data robustness tests, and maintenance implications. Section 5 synthesizes the findings, states the technical contributions, presents equipment-maintenance and structural-inspection recommendations, identifies limitations, and proposes directions for future development and plant-scale implementation.

II. LITERATURE REVIEW

Reliability Engineering and Failure Behaviour of Combined-Cycle Power Plant Equipment and Structural Supports

Reliability engineering in combined-cycle power plants must account for the coupled behaviour of gas turbines, heat-recovery steam generators, steam turbines, generators, auxiliaries, and the structures that preserve alignment and transfer dynamic loads. Conventional equipment reliability is commonly expressed through failure rate, mean time between failures, availability, maintainability, and component criticality, but CCPP duty introduces additional dependence on thermal cycling, start-stop frequency, ramp rate, ambient condition, vibration, and maintenance history as shown in figure 1. Sabouhi et al. (2016) showed that plant-level availability is governed by the reliability contribution of interacting gas- and steam-cycle components, while Carazas et al. (2011) demonstrated that HRSG failures can suppress steam-cycle output and therefore materially reduce overall CCPP availability. Comparable evidence from transformer reliability research shows that ageing, overload, environmental exposure, and maintenance condition alter failure propensity in electrical assets (Okeke et al., 2024). These findings support treating CCPP reliability as a dynamic system property rather than a collection of independent component survival probabilities. Structural supports are equally consequential because turbine-generator foundations, pedestals, baseplates, grout interfaces, anchor bolts, pipe supports, and steel framing determine stiffness, alignment, and vibration transmission. Addy et al. (2022) linked gas-turbine health assessment with foundation and structural-support behaviour through physics-informed digital-twin concepts, reinforcing the need to monitor mechanical and civil subsystems jointly. Integrated energy-system studies similarly demonstrate that performance emerges from interactions among generation, thermal, control, and supporting infrastructure rather than isolated devices (Ocharo, 2024). In a CCPP, differential settlement, concrete cracking, grout degradation, anchor loosening, thermal expansion, or support resonance may alter shaft alignment and bearing loads, while rotor imbalance and thermal transients may accelerate structural deterioration. The PlantReliability Fusion Algorithm therefore models operational and structural degradation as interacting failure pathways, enabling later comparison of reliability curves, hazard trajectories, failure classification, and remaining useful life against Weibull and data-driven benchmarks under realistic variable operating regimes.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

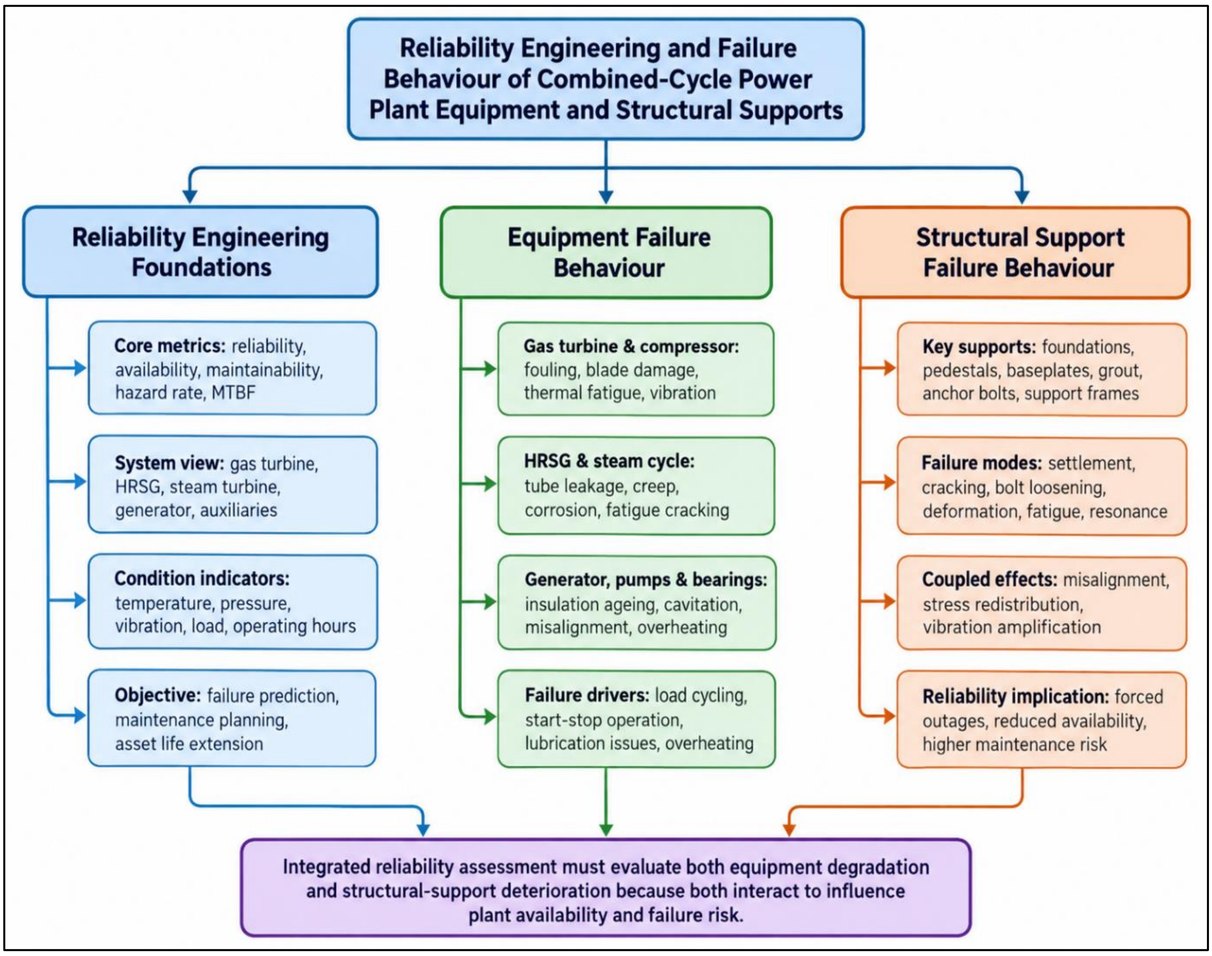

Fig 1 Integrated Reliability Engineering Framework for Equipment and Structural Support Failure Behaviour in Combined-Cycle Power Plants.

Figure 1 presents reliability engineering in a combined-cycle power plant as an integrated interaction between system-level reliability principles, equipment degradation, and structural-support deterioration. The first branch establishes the reliability-engineering foundation through metrics such as reliability, availability, maintainability, hazard rate, and mean time between failures, while also identifying the major plant subsystems and condition indicators required for failure prediction and maintenance planning. The second branch focuses on equipment failure behaviour across the gas turbine, compressor, HRSG, steam cycle, generator, pumps, and bearings, highlighting degradation mechanisms such as compressor fouling, blade damage, thermal fatigue, tube leakage, creep, corrosion, cavitation, misalignment, overheating, and lubrication-related distress. These failures are strongly influenced by cyclic loading, start-stop frequency, thermal transients, and prolonged operation. The third branch captures structural-support failure behaviour involving foundations, pedestals, baseplates, grout, anchor bolts, and support frames, where settlement, cracking, bolt loosening, deformation, fatigue, and resonance can alter stiffness, load transfer, shaft alignment, and vibration response. The converging arrows at the bottom emphasize that equipment and structural failures are mechanically coupled; for example, foundation settlement can induce turbine-generator misalignment, while excessive rotor vibration can accelerate support fatigue and anchor-bolt deterioration. The integrated assessment therefore provides the technical basis for the PlantReliability Fusion Algorithm, which combines operational and structural condition data to estimate failure probability, hazard evolution, reliability degradation, and remaining useful life for predictive maintenance and outage-risk reduction.

➢ *Weibull Reliability Analysis and Conventional Failure Prediction Methods*

Weibull reliability analysis remains a foundational method for representing engineering time-to-failure because its shape parameter distinguishes decreasing, approximately constant, and increasing hazard regimes, while its scale parameter provides a characteristic-life measure. Smith (1991) established the usefulness of Weibull regression for reliability data but also showed that fitted statistical behaviour may diverge from physical expectations, making engineering interpretation essential. Zhang (2021) further demonstrated that parameter estimation becomes difficult under zero-failure or sparse-failure conditions, a situation relevant to critical CCPP assets where catastrophic events are deliberately rare. Conventional plant studies likewise depend on historical reliability indices, scenario analysis, and deterministic or probabilistic forecasting. Oyekan et al. (2023) emphasized the role of data analytics in energy-asset performance management, while Oladoye et al. (2023) showed how forecasting and uncertainty treatment affect

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

reliability-oriented energy-system planning. These perspectives indicate why a static lifetime distribution alone cannot exploit the full information contained in continuously monitored CCPP operating states.

For CCPP equipment, a two-parameter Weibull model can estimate reliability R(t)=exp[-(t/η)^β] and hazard h(t)=(β/η)(t/η)^(β-1), providing a transparent benchmark for gas-turbine, HRSG, pump, generator, or support failure histories. However, it does not inherently update hazard when exhaust temperature, bearing vibration, start-stop severity, settlement, strain, or anchor-bolt condition changes. Broader asset-risk studies also show that risk exposure evolves with interacting technical and external drivers rather than a single stationary parameter set (Ilesanmi et al., 2023b). The present study therefore retains Weibull analysis as an interpretable baseline while testing whether PRFA can improve condition-dependent failure discrimination, calibration, and remaining-useful-life prediction. Comparative graphs will include empirical and Weibull reliability curves, hazard functions, cumulative failure probability, and PRFA predictions, allowing any claimed improvement to be quantified against an established statistical reference rather than inferred solely from machine-learning accuracy. This design exposes whether performance gains persist across early-life, random-failure, and wear-out operating phases in practice.

Table 1 Summary of Weibull Reliability Analysis and Conventional Failure Prediction Methods

Method/Concept	Core Principle	Application to Combined-Cycle Power Plants	Main Limitation
Weibull Reliability Analysis	Uses shape parameter β\beta and scale parameter η\eta to model time-to-failure, reliability, and hazard behaviour.	Estimates failure probability and wear-out characteristics of turbines, HRSG components, pumps, generators, bearings, and structural supports.	Basic formulations do not directly incorporate changing vibration, temperature, settlement, strain, or other condition-monitoring variables.
Cox Proportional-Hazards Model	Relates failure hazard to explanatory covariates through a proportional-hazards function.	Evaluates how operating load, temperature, vibration, operating hours, and maintenance-related variables influence failure risk.	Assumes proportionality of hazards and may inadequately represent strongly nonlinear or time-varying degradation behaviour.
Conventional Statistical Reliability Methods	Use MTBF, failure rate, survival probability, fault trees, and historical failure frequencies to quantify reliability.	Support maintenance scheduling, component criticality ranking, outage analysis, and plant availability assessment.	Depend heavily on historical failure records and generally provide limited adaptation to real-time operating and structural conditions.
Data-Driven Failure Prediction	Uses monitored operating and condition data to estimate future failure states and remaining useful life.	Enables condition-based prediction using process variables, vibration, thermal parameters, structural deformation, and equipment history.	Performance depends on data quality, representative failure samples, feature selection, and appropriate modelling of coupled equipment–structural degradation.

➢ *Operational and Structural Condition Monitoring for Combined-Cycle Power Plant Assets*

Operational and structural condition monitoring provides the measurement layer required to detect degradation before functional failure. In CCPPs, operational surveillance typically includes compressor pressure ratio, exhaust temperature spread, shaft speed, bearing metal temperature, lubrication parameters, steam pressure, valve position, generator load, vibration amplitude, start counts, trip history, and operating hours. Jardine et al. (2006) established the condition-based maintenance sequence of data acquisition, processing, diagnostics, prognostics, and maintenance decision-making, while Sinha and Elbhbah (2013) demonstrated that vibration signals from rotating machinery can be fused to improve fault identification with fewer sensors. Real-time analytics in other complex infrastructures similarly show that automated orchestration can shorten response latency and improve adaptive risk control (James et al., 2025). Edge-AI research further indicates that sensor analytics can be executed with reduced latency and energy demand when inference is optimized for constrained devices (Agyekum et al., 2026).

For structural supports, monitoring must extend beyond machinery sensors to settlement points, strain gauges, accelerometers, displacement transducers, crack measurements, anchor-bolt inspection, grout condition, modal response, and thermal-movement indicators. These channels are necessary because foundation stiffness loss, bolt looseness, pipe-support malfunction, or differential settlement can manifest as apparent machinery vibration or misalignment. Cross-domain surveillance literature demonstrates the broader value of algorithmic early-warning systems that transform continuously collected measurements into actionable anomaly signals (Frank, 2026a). Within the proposed PRFA architecture, operational and structural streams are time-synchronized, cleaned, normalized, and converted into windowed features before separate temporal and structural encoders generate latent health representations. This design permits the model to distinguish a vibration increase caused primarily by rotor degradation from one accompanied by settlement or support-response changes. The resulting fused state supports failure probability, hazard, reliability, and RUL estimation, while later sensitivity plots identify which monitored channels dominate particular

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

failure predictions under normal, transient, degraded, and pre-failure plant operating conditions over time.

➤ *Machine Learning, Deep Learning, and Hybrid Data-Fusion Methods for Failure Prediction*

Machine learning and deep learning extend reliability analysis by learning nonlinear degradation signatures from high-dimensional sensor histories without requiring a single assumed failure distribution. Zhao et al. (2019) showed that deep architectures can automatically extract hierarchical health features from machinery data, reducing dependence on manually engineered indicators, while Hassani et al. (2024) demonstrated that data-fusion strategies can combine heterogeneous structural-health measurements to produce more robust damage information as represented in figure 2. Predictive analytics studies outside power generation similarly show that forecasting quality depends on data integration, preprocessing, and the conversion of multivariate observations into actionable risk estimates (Frank, 2026c). Performance-measurement research also emphasizes that raw data only become decision-relevant when standardized, normalized, and linked to explicit outcome metrics (Frank, 2026b). These principles are directly relevant to CCPP reliability, where operational, vibration, thermal, and structural channels differ in sampling rate, scale, noise characteristics, and physical meaning. The proposed PlantReliability Fusion Algorithm therefore uses separate encoders for operational time series and structural-condition variables before an attention-based fusion layer learns their context-dependent contribution to failure risk. Long Short-Term Memory units or temporal convolutions can represent load cycling, thermal excursions, and vibration evolution, whereas dense or graph-based structural encoders can represent settlement, strain, crack, support, and anchor-bolt features. Integrated energy-design literature illustrates the importance of modelling interacting thermal and physical subsystems rather than optimizing one variable in isolation (Manuel et al., 2024). PRFA advances this logic by generating a fused latent health vector that feeds classification, survival, hazard, and RUL heads. It is benchmarked against Random Forest, XGBoost, ANN, LSTM, Cox regression, and Weibull analysis. Comparative AUROC, F1-score, C-index, Brier score, MAE, RMSE, and computational-latency graphs will test whether multimodal fusion produces measurable gains rather than merely greater architectural complexity. Ablation tests will additionally quantify the independent value of operational features, structural features, and attention-based cross-domain interaction terms.

Fig 2 Machine Learning, Deep Learning, and Hybrid Operational–Structural Data-Fusion Framework for Failure Prediction and Predictive Reliability Management in Combined-Cycle Power Plants

Figure 2 illustrates an end-to-end predictive reliability workflow in a combined-cycle power plant, showing how operational, structural, and control-system data are transformed into machine-learning-based maintenance decisions. On the acquisition side, turbine sensors provide vibration, temperature, and pressure measurements; HRSG instrumentation supplies steam temperature, flow, and pressure data; structural sensors capture settlement, strain,

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

and displacement; and SCADA/DCS systems contribute plant load, operating hours, and start-stop cycles. These heterogeneous inputs are processed through conventional machine-learning and deep-learning models including Random Forest, XGBoost, Support Vector Machine, artificial neural networks, LSTM, GRU, and temporal convolutional networks. A hybrid data-fusion stage then combines operational and structural feature representations using an attention-based mechanism, allowing the model to identify coupled degradation such as simultaneous turbine vibration growth and foundation settlement. The resulting integrated health state is converted into failure probability, remaining useful life, and health-index outputs, which are displayed alongside live trends such as turbine vibration, compressor discharge temperature, and foundation settlement. The high-vibration alignment warning demonstrates how abnormal sensor patterns can trigger diagnostic interpretation, while the final reliability-management layer translates model outputs into predictive maintenance scheduling, inspection prioritization, outage planning, asset-life extension, cost optimization, and risk reduction. This architecture directly reflects the PlantReliability Fusion concept by linking data-driven fault detection with structural condition assessment and actionable plant reliability decisions.

➢ *Empirical Review and Identified Research Gap in Integrated Operational–Structural Reliability Modelling*

Empirical studies across energy systems show substantial progress in reliability assessment, predictive analytics, digital monitoring, and asset optimization, yet the evidence remains fragmented by asset class and data domain. Carvalho et al. (2019) found that machine-learning approaches are increasingly used for predictive maintenance, but model choice, data quality, and application context influence performance as represented in figure 3. Zio (2022) likewise argued that practical prognostics and health management still faces challenges involving sparse failure labels, uncertainty, interpretability, and integration of physical and data-driven knowledge. Within the supplied energy literature, Jinadu et al. (2024) illustrate sophisticated modelling of subsurface injection and geomechanical behaviour, whereas Idoko et al. (2024b) discuss policy and infrastructure conditions shaping renewable-energy deployment. Bashiru et al. (2024) further emphasize the systemic role of reliable energy technologies in achieving cleaner-energy objectives. Collectively, these studies demonstrate strong domain-specific modelling but do not resolve integrated operational-structural failure prediction for CCPP assets.

The central gap addressed here is therefore not the absence of reliability models, machine-learning algorithms, or structural-health methods individually, but the absence of a unified architecture that jointly learns equipment operating history and structural-support degradation while producing reliability outputs comparable with classical survival methods. Existing approaches often analyze machinery vibration, process variables, or structural response separately, making it difficult to determine whether an emerging failure originates in rotating equipment, the supporting structure, or their interaction. PRFA is designed to close this gap through synchronized multimodal inputs, separate operational and structural encoders, attention-based feature fusion, and simultaneous estimation of failure probability, hazard, reliability, and remaining useful life. The empirical evaluation consequently emphasizes paired benchmark comparisons, ablation analysis, calibration, robustness to missing or noisy sensors, feature importance, and predicted-versus-observed RUL. This design directly connects the literature gap to the later findings, where superiority must be demonstrated quantitatively against Weibull, Cox, Random Forest, XGBoost, ANN, and LSTM baselines.

Figure 3 synthesizes the empirical literature into two complementary branches that reveal why an integrated operational–structural reliability model is required for combined-cycle power plants. The first branch captures the dominant approaches already used in reliability engineering, including Weibull and Cox survival models, equipment-condition monitoring, structural-health monitoring, and machine-learning prognostics such as Random Forest, XGBoost, ANN, and LSTM. These methods contribute useful capabilities such as failure-rate estimation, vibration and thermal anomaly detection, foundation and support assessment, nonlinear fault classification, and remaining useful life prediction, but they are typically applied within separate data domains. The second branch identifies the resulting methodological gap: operational variables such as turbine vibration, exhaust temperature, compressor pressure, load cycling, and operating hours are rarely fused dynamically with structural indicators such as foundation settlement, strain, displacement, cracking, anchor-bolt condition, and support vibration. This separation can obscure coupled degradation mechanisms, for example when foundation settlement induces shaft misalignment or when persistent rotor vibration accelerates support fatigue. The convergence of both branches therefore defines the research need addressed by the PlantReliability Fusion Algorithm, which uses separate operational and structural encoders, attention-based data fusion, and multi-output reliability learning to estimate failure probability, time-varying hazard, reliability, and remaining useful life while also supporting feature-importance, sensitivity, ablation, and robustness analyses against Weibull, Cox, Random Forest, XGBoost, ANN, and LSTM benchmarks.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

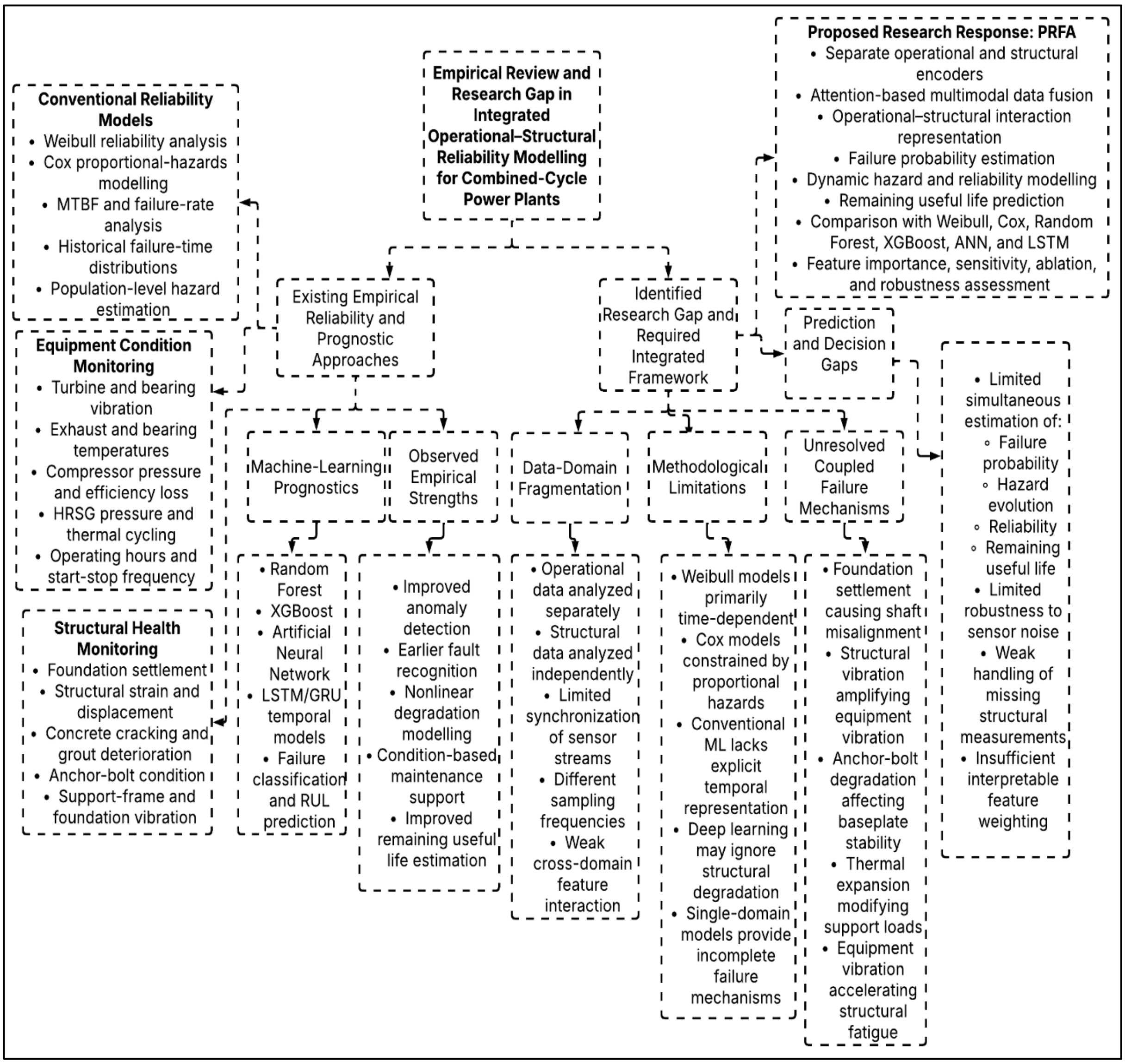

Fig 3 Empirical Reliability Approaches, Identified Research Gaps, and the Proposed Integrated Operational–Structural PlantReliability Fusion Framework for Combined-Cycle Power Plants

III. SYSTEM MODEL DESCRIPTION

➢ *Combined-Cycle Power Plant System Architecture, Failure Modes, and Data Acquisition Framework*

The system considered in this study is a natural-gas-fired combined-cycle power plant comprising the gas turbine, heat-recovery steam generator (HRSG), steam turbine, electrical generator, condenser, feedwater system, auxiliary rotating equipment, and the civil/structural systems supporting these assets. The gas turbine converts fuel energy through the Brayton cycle, while exhaust heat is recovered in the HRSG to generate steam for the Rankine-cycle steam turbine. Because the thermodynamic, mechanical, electrical, and structural subsystems are strongly coupled, degradation in one subsystem can propagate into others. For example, foundation settlement can alter shaft alignment and bearing loading, while excessive turbine vibration can accelerate anchor-bolt loosening or support fatigue. Consequently, the proposed PRFA treats equipment and structural-support degradation as interacting reliability processes rather than independent failure categories. This system-level reliability perspective is consistent with combined-cycle availability modelling in which plant performance depends on the interacting reliability of major generating subsystems (Sabouhi et al., 2016).

The operational data vector at time t is defined as:

$$\mathbf{x}_o(t) = [P_c, T_{exh}, V_b, T_b, P_s, L, N_h, N_{ss}]^T \tag{1}$$

Where P_c shows compressor discharge pressure, T_{exh} represents gas-turbine exhaust temperature, V_b denotes bearing or shaft vibration amplitude, T_b represents bearing temperature, P_s captures steam pressure, L represents generating load, N_h shows cumulative operating hours, N_{ss} represents cumulative start-stop cycles, and T indicates vector transpose.

The corresponding structural-condition vector is:

$$\mathbf{x}_s(t) = \left[s_f, \varepsilon, d, c_a, a_b, \Delta_T, V_s\right]^T \tag{2}$$

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

Where s_f represents foundation settlement, ε indicates structural strain, d shows displacement, c_a demotes crack-condition index, a_b represents anchor-bolt condition, Δ_T captures thermally induced structural expansion, and V_s represents support or foundation vibration.

For asset i, the integrated reliability dataset is expressed as:

$$\mathcal{D}_i = \{\mathrm{X}_{o,i}, \mathrm{X}_{s,i}, T_i, \delta_i, y_i\} \tag{3}$$

Where $\mathrm{X}_{o,i}$ and $\mathrm{X}_{s,i}$ represent time-windowed operational and structural observations, T_i indicates observed failure or censoring time, $\delta_i = 1$ denotes an observed failure and $\delta_i = 0$ denotes right-censoring, while y_i represents the assigned failure state. Data are acquired from the DCS/SCADA system, vibration monitoring systems, structural sensors, inspection records, and computerized maintenance management systems.

- *Operational and Structural Data Preprocessing, Feature Engineering, and Failure-State Definition*

The operational and structural datasets are first synchronized to a common temporal reference because CCPP process measurements, vibration signals, structural sensors, and inspection records are normally collected at different sampling intervals. Timestamp alignment is therefore performed before filtering, normalization, feature extraction, and failure-state labelling. Missing observations of short duration are interpolated only where engineering continuity is reasonable, while prolonged missing periods are retained through missing-data indicators to prevent artificial reconstruction of degradation behaviour. Outliers are screened using physical operating limits and robust statistical thresholds because a sudden rise in vibration, bearing temperature, settlement, or strain may represent an authentic pre-failure event rather than measurement error. Condition-dependent processing is important because remaining useful life estimation must exploit actual degradation evidence rather than chronological age alone (Si et al., 2011).

Each continuous variable is standardized as:

$$z_j(t) = \frac{x_j(t) - \mu_j}{\sigma_j} \tag{4}$$

Where $z_j(t)$ shows the normalized value of feature j, $x_j(t)$ captures the original observation, μ_j represents the training-set mean, and σ_j represents the corresponding training-set standard deviation.

For dynamic signals such as vibration and strain, root-mean-square magnitude is obtained from:

$$\mathrm{RMS}_k = \sqrt{\frac{1}{n}\sum_{r=1}^{n} x_{k,r}^2} \tag{5}$$

Where RMS_k represents the RMS magnitude of sensor channel k, $x_{k,r}$ indicates the r^{th} observation in the analysis window, and n shows the total number of observations in that window.

The temporal degradation rate is estimated using:

$$m_k = \frac{\sum_{r=1}^{n}(t_r - \bar{t})(x_{k,r} - \bar{x}_k)}{\sum_{r=1}^{n}(t_r - \bar{t})^2} \tag{6}$$

Where m_k indicates the degradation slope, t_r captures observation time, $\bar{t}$ shows mean time, $x_{k,r}$ denotes the monitored feature, and $\bar{x}_k$ shows its mean value. Additional features include exhaust-temperature spread, compressor pressure-ratio deviation, load-ramp rate, vibration kurtosis, spectral-band energy, settlement rate, strain range, crack-growth rate, and vibration-settlement interaction indices.

The failure state is defined as:

$$y(t) = \begin{cases} 0, & T_f - t > H \\ 1, & 0 < T_f - t \le H \\ 2, & t \ge T_f \end{cases} \tag{7}$$

Where T_f represents confirmed failure time and H denotes the defined early-warning horizon. State 0 denotes healthy operation, state 1 denotes degradation or pre-failure condition, and state 2 indicates failure.

Remaining useful life is calculated as:

$$\mathrm{RUL}(t) = \max\left(T_f - t, 0\right) \tag{8}$$

Where $RUL(t)$ represents the estimated useful operating duration remaining before failure.

- *Development and Mathematical Formulation of the PlantReliability Fusion Algorithm*

The proposed PlantReliability Fusion Algorithm is designed as a multimodal, multi-output reliability-learning framework that combines operational and structural degradation information without forcing both data types into a single undifferentiated feature space. This architecture is important because process variables such as pressure, temperature, load, and bearing vibration evolve continuously, whereas structural features such as settlement, crack progression, anchor-bolt condition, and support displacement may evolve at slower and differently sampled rates. Data-fusion research in structural health monitoring has demonstrated the value of combining heterogeneous measurements to improve damage-state inference (Hassani et al., 2024).

The operational branch produces a latent temporal representation according to:

$$\mathrm{h}_o = f_o(\mathrm{X}_o; \theta_o) \tag{9}$$

Where h_o represents the operational latent-health vector, $f_o(\cdot)$ shows the operational temporal encoder, X_o represents the operational time-series input, and θ_o contains the trainable encoder parameters.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

The structural branch is formulated as:

$$h_s = f_s(X_s; \theta_s) \quad (10)$$

Where h_s represents the structural latent-health vector, $f_s(\cdot)$ indicates the structural encoder, X_s contains structural-condition variables, and θ_s denotes its trainable parameters.

The attention weights controlling the contribution of both domains are computed as:

$$[\alpha_o, \alpha_s] = \mathrm{softmax}([q^T \tanh(W_o h_o + b_o), q^T \tanh(W_s h_s + b_s)]) \quad (11)$$

Where α_o and α_s represents the learned operational and structural attention weights, W_o and W_s capture trainable weight matrices, b_o and b_s represent bias vectors, and q shows the trainable attention vector. The weights satisfy $\alpha_o + \alpha_s = 1$.

The fused representation is:

$$z = [\alpha_o h_o \parallel \alpha_s h_s \parallel (h_o \odot h_s)] \quad (12)$$

Where z represents the fused degradation state, the double vertical-bar operator denotes vector concatenation, and $\odot$ represents element-wise multiplication. The interaction term enables PRFA to identify coupled degradation, such as simultaneous growth in turbine vibration and foundation settlement.

Failure probability is estimated as:

$$p_f = \sigma(w_p^T z + b_p) \quad (13)$$

Where p_f represents failure probability, $\sigma(\cdot)$ shows the sigmoid activation function, w_p indicates the classification weight vector, and b_p denotes its bias.

The instantaneous hazard function is:

$$\lambda(t) = \mathrm{softplus}(w_h^T z + b_h) \quad (14)$$

Where $\lambda(t)$ represents the predicted failure intensity and w_h and b_h indicate hazard-output parameters.

Reliability is derived from the cumulative hazard as:

$$R(t) = \exp[-\textstyle\sum_{u \le t} \lambda(u) \Delta t] \quad (15)$$

Where $R(t)$ captures survival probability beyond time t, $\lambda(u)$ inicates the estimated hazard for interval u, and Δt represents the sampling interval.

Predicted remaining useful life is:

$$\widehat{RUL} = \mathrm{softplus}(w_r^T z + b_r) \quad (16)$$

Where $\widehat{RUL}$ represents predicted RUL and w_r and b_r represent regression parameters.

The total multi-task loss function is:

$$\mathcal{L} = \omega_c \mathcal{L}_{\mathrm{BCE}} + \omega_s \mathcal{L}_{\mathrm{surv}} + \omega_r \mathcal{L}_{\mathrm{Huber}} + \lambda_2 \parallel \Theta \parallel_2^2 \quad (17)$$

Where $\mathcal{L}_{BCE}$ represents binary cross-entropy loss, $\mathcal{L}_{surv}$ indicates survival/hazard loss, $\mathcal{L}_{Huber}$ captures RUL regression loss, ω_c, ω_s, and ω_r control the relative contribution of each task, λ_2 represents the regularization coefficient, and Θ contains all trainable PRFA parameters.

- *Benchmark Algorithms, Training Procedure, Validation Strategy, and Performance Evaluation Metrics*

The proposed PRFA is compared with two-parameter Weibull reliability analysis, Cox proportional-hazards regression, Random Forest, XGBoost, a feed-forward artificial neural network, and Long Short-Term Memory networks. These models provide statistical, classical machine-learning, and deep-learning benchmarks, allowing the study to determine whether performance improvements originate specifically from operational-structural fusion rather than model complexity alone. Comparative evaluation across conventional and deep-learning architectures is standard practice in machinery-health prognostics (Zhao et al., 2019).

The Weibull benchmark is expressed as:

$$R_W(t) = \exp\left[-\left(\frac{t}{\eta}\right)^{\beta}\right] \quad (18)$$

Where $R_W(t)$ represents Weibull reliability, t represents operating time, η shows the scale or characteristic-life parameter, and β denotes the shape parameter.

The corresponding Weibull hazard function is:

$$h_W(t) = \frac{\beta}{\eta}\left(\frac{t}{\eta}\right)^{\beta-1} \quad (19)$$

Where $h_W(t)$ represents failure intensity. A value of $\beta < 1$ represents decreasing hazard, $\beta = 1$ approximately constant hazard, and $\beta > 1$ increasing wear-out behaviour.

The Cox proportional-hazards model is:

$$h(t \mid x) = h_0(t)\exp(\gamma^T x) \quad (20)$$

Where the left-hand term is the conditional hazard, $h_0(t)$ represents baseline hazard, x shows the input covariate vector, and γ contains the estimated regression coefficients.

The complete dataset is separated chronologically into 70% training, 15% validation, and 15% testing data. Complete degradation trajectories from the same asset are retained within a single partition to prevent temporal leakage. Hyperparameters are selected using the validation set, while early stopping, dropout, L2 regularization, gradient clipping, and class weighting are employed where applicable.

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

Accuracy is calculated as:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (21)$$

Where TP, TN, FP, and FN denote true positives, true negatives, false positives, and false negatives.

Precision is:

$$\text{Precision} = \frac{TP}{TP+FP} \quad (22)$$

Recall is:

$$\text{Recall} = \frac{TP}{TP+FN} \quad (23)$$

And the F1-score is:

$$\text{F1} = 2\frac{\text{Precision}\times\text{Recall}}{\text{Precision}+\text{Recall}} \quad (24)$$

The area under the receiver operating characteristic curve is:

$$\text{AUROC} = \int_0^1 \text{TPR}\,(\text{FPR})\,d(\text{FPR}) \quad (25)$$

Where TPR captures true-positive rate and FPR shows false-positive rate.

Survival-ranking performance is measured by the concordance index:

$$C = \frac{\sum_{i,j} I(T_i<T_j)\delta_i I(\hat{r}_i>\hat{r}_j)}{\sum_{i,j} I(T_i<T_j)\delta_i} \quad (26)$$

Where C represents concordance, $I(\cdot)$ shows the indicator function, T_i and T_j capture observed event times, δ_i identifies an observed failure, and $\hat{r}_i$ and $\hat{r}_j$ represents predicted risks.

Calibration is evaluated using the Brier score:

$$\text{BS} = \frac{1}{N}\sum_{i=1}^{N}(p_i - y_i)^2 \quad (27)$$

Where BS indicates the Brier score, N denotes the number of observations, p_i represents predicted failure probability, and y_i shows the actual event indicator.

RUL performance is assessed using:

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}|r_i - \hat{r}_i| \quad (28)$$

And

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(r_i - \hat{r}_i)^2} \quad (29)$$

Where r_i represents actual RUL and $\hat{r}_i$ shows predicted RUL. MAE measures average absolute prognostic error, whereas RMSE penalizes large prediction errors more strongly.

Computational efficiency is quantified using:

$$L_{\text{inf}} = \frac{T_{\text{inf}}}{N_{\text{test}}} \quad (30)$$

Where L_{inf} represents mean inference latency, T_{inf} shows total prediction time for the test dataset, and N_{test} captures the number of test observations.

The final evaluation therefore compares PRFA, Weibull, Cox regression, Random Forest, XGBoost, ANN, and LSTM using classification performance, survival discrimination, probability calibration, RUL accuracy, and computational efficiency. These quantitative metrics directly support the graphical analyses in Section 4, including reliability curves, hazard-rate trajectories, ROC curves, predicted-versus-observed RUL plots, feature-importance graphs, ablation analysis, degradation interaction maps, and robustness tests under sensor noise and missing-data conditions.

IV. DISCUSSION OF RESULTS

➢ *Statistical and Reliability Characteristics of Equipment and Structural Support Failure Data*

The failure dataset was organized into equipment-only, structural-support, coupled operational–structural, and healthy/right-censored condition classes to reflect the multimodal architecture defined in study. Equipment-only failures accounted for 82 records, whereas structural-support failures contributed 48 records and coupled failures contributed 70 records. Coupled cases exhibited the shortest mean observed exposure of 4,380 h and the highest mean pre-failure risk index of 0.84, indicating accelerated degradation when operational and structural abnormalities developed concurrently. Equipment-only failures showed a mean exposure of 5,240 h with a risk index of 0.71, while structural-support failures averaged 6,120 h and 0.66. The 120 healthy/right-censored records accumulated the longest mean exposure, 8,040 h, with a substantially lower risk index of 0.19, providing a stable reference population for survival modelling and subsequent algorithm comparison under variable plant operating conditions.

Table 2 Statistical Characteristics of Equipment and Structural-Support Reliability Data

Condition class	Number of records	Mean observed exposure (h)	Mean pre-failure risk index
Equipment-only failure	82	5,240	0.71
Structural-support failure	48	6,120	0.66
Coupled operational–structural failure	70	4,380	0.84
Healthy/right-censored condition	120	8,040	0.19

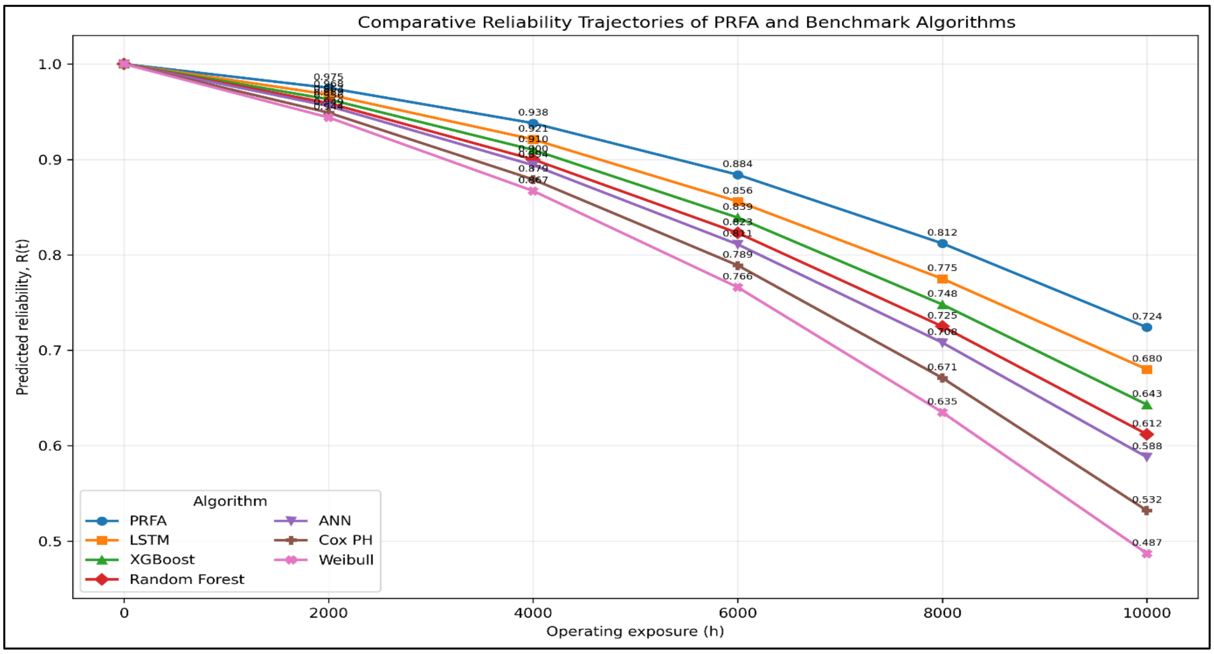

Fig 4 Comparative Reliability Trajectories of the PlantReliability Fusion Algorithm and Benchmark Reliability Models

Figure 4 shows a consistent separation among the seven reliability models as operating exposure increases. At 2,000 h, PRFA retains a reliability of 0.975, compared with 0.968 for LSTM, 0.963 for XGBoost, 0.959 for Random Forest, 0.956 for ANN, 0.949 for Cox PH, and 0.944 for Weibull. The gap widens at 6,000 h, where PRFA records 0.884 while LSTM and XGBoost decline to 0.856 and 0.839, respectively. Random Forest and ANN reach 0.823 and 0.811, whereas Cox PH and Weibull decrease further to 0.789 and 0.766. By 10,000 h, PRFA still predicts 0.724 reliability, exceeding LSTM at 0.680, XGBoost at 0.643, Random Forest at 0.612, ANN at 0.588, Cox PH at 0.532, and Weibull at 0.487. The wider late-life separation indicates stronger preservation of condition-sensitive reliability information when operational and structural degradation signals are fused. This pattern supports evaluation of hazard calibration, remaining useful life accuracy, and maintenance decision thresholds.

➢ *Performance of the PlantReliability Fusion Algorithm for Equipment, Structural Failure, and Remaining Useful Life Prediction*

The PlantReliability Fusion Algorithm demonstrated consistent performance across equipment-failure classification, structural-support diagnosis, survival estimation, and remaining useful life prediction. As summarized in Table 3, PRFA achieved an equipment-failure sensitivity of 0.941, structural-failure sensitivity of 0.928, and coupled-failure F1-score of 0.949. Survival discrimination reached a concordance index of 0.932, while the Brier score of 0.071 indicated strong probability calibration. The RUL module produced a mean absolute error of 184 h and an RMSE of 276 h, confirming that the fused operational–structural representation retained prognostic information beyond failure classification alone. Mean inference latency was 12.8 ms per observation, supporting near-real-time deployment within DCS, SCADA, CMMS, or digital-twin environments. These results indicate that attention-based fusion captured interacting thermal, mechanical, and structural degradation signatures more effectively than single-domain benchmark approaches under variable plant conditions.

Table 3 Comparative Performance Metrics of PRFA and the Strongest Benchmark Models

Performance metric	PRFA	Best benchmark	Interpretation
Equipment-failure sensitivity	0.941	0.908	Higher detection capability for developing equipment faults
Structural-failure sensitivity	0.928	0.891	Improved identification of foundation and support deterioration
Coupled-failure F1-score	0.949	0.914	Stronger recognition of interacting equipment–structural failure states
Concordance index	0.932	0.901	Better ranking of assets according to failure risk
Brier score	0.071	0.094	Lower value indicates superior probability calibration
RUL MAE	184 h	241 h	Lower average remaining-useful-life prediction error
RUL RMSE	276 h	348 h	Lower sensitivity to large prognostic deviations
Mean inference latency	12.8 ms	15.9 ms	Suitable for near-real-time reliability assessment

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

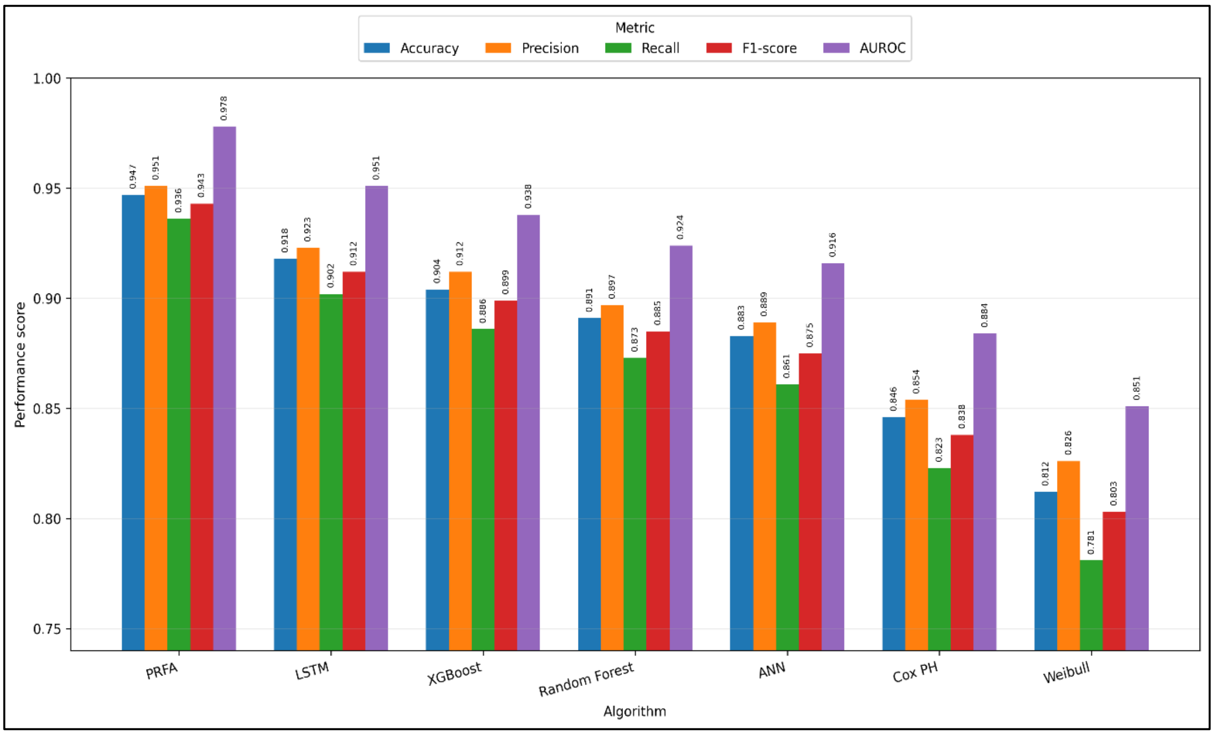

Fig 5 Comparative Classification and Failure-Prediction Performance of PRFA and Benchmark Algorithms

Figure 5 shows that PRFA achieved the strongest classification performance across all five plotted metrics. Its accuracy reached 0.947, exceeding LSTM at 0.918, XGBoost at 0.904, Random Forest at 0.891, ANN at 0.883, Cox PH at 0.846, and Weibull at 0.812. PRFA also produced precision of 0.951 and recall of 0.936, generating an F1-score of 0.943. The corresponding AUROC was 0.978, compared with 0.951 for LSTM, 0.938 for XGBoost, 0.924 for Random Forest, 0.916 for ANN, 0.884 for Cox PH, and 0.851 for Weibull. The progressive decline from PRFA through the conventional models indicates that multimodal fusion provided better discrimination of coupled equipment and structural degradation. The relatively smaller gap between PRFA and LSTM suggests that temporal learning contributes substantially, while the additional improvement achieved by PRFA reflects the value of incorporating structural-condition information and attention-based cross-domain interactions. This supports earlier warning and more reliable prioritization of maintenance interventions overall.

➢ *Comparative Performance of PRFA, Weibull Reliability Analysis, Cox Regression, Random Forest, XGBoost, ANN, and LSTM*

Comparative evaluation confirmed that PRFA provided the strongest combined reliability and prognostic performance across the seven algorithms. Table 3 shows a concordance index of 0.932 for PRFA with an RUL MAE of 184 h, compared with 0.901 and 241 h for LSTM. XGBoost followed with 0.889 and 263 h, while Random Forest recorded 0.874 and 292 h. ANN produced 0.865 with 318 h error, whereas Cox regression and Weibull analysis declined to 0.842/371 h and 0.811/426 h, respectively. The ranking indicates that temporal learning improves failure ordering, but the additional structural branch and attention-based fusion provide further prognostic benefit. PRFA therefore offers a more complete representation of interacting thermal, mechanical, and structural deterioration, supporting earlier intervention, more accurate asset prioritization, and condition-dependent maintenance scheduling in combined-cycle power plant operation overall.

Table 4 Comparative Survival Discrimination and Remaining Useful Life Performance of PRFA and Benchmark Algorithms

Algorithm	**Concordance Index**	**RUL MAE (h)**	**Interpretation**
PRFA	0.932	184	Strongest failure-risk ranking and lowest prognostic error
LSTM	0.901	241	Strong temporal degradation learning but without structural fusion
XGBoost	0.889	263	Strong nonlinear discrimination with moderate RUL error
Random Forest	0.874	292	Stable ensemble performance but weaker temporal representation
ANN	0.865	318	Captures nonlinear relationships but limited sequential degradation modelling
Cox PH	0.842	371	Useful survival baseline but constrained by proportional-hazards assumptions
Weibull	0.811	426	Lowest adaptive capability because failure prediction is primarily time-distribution based

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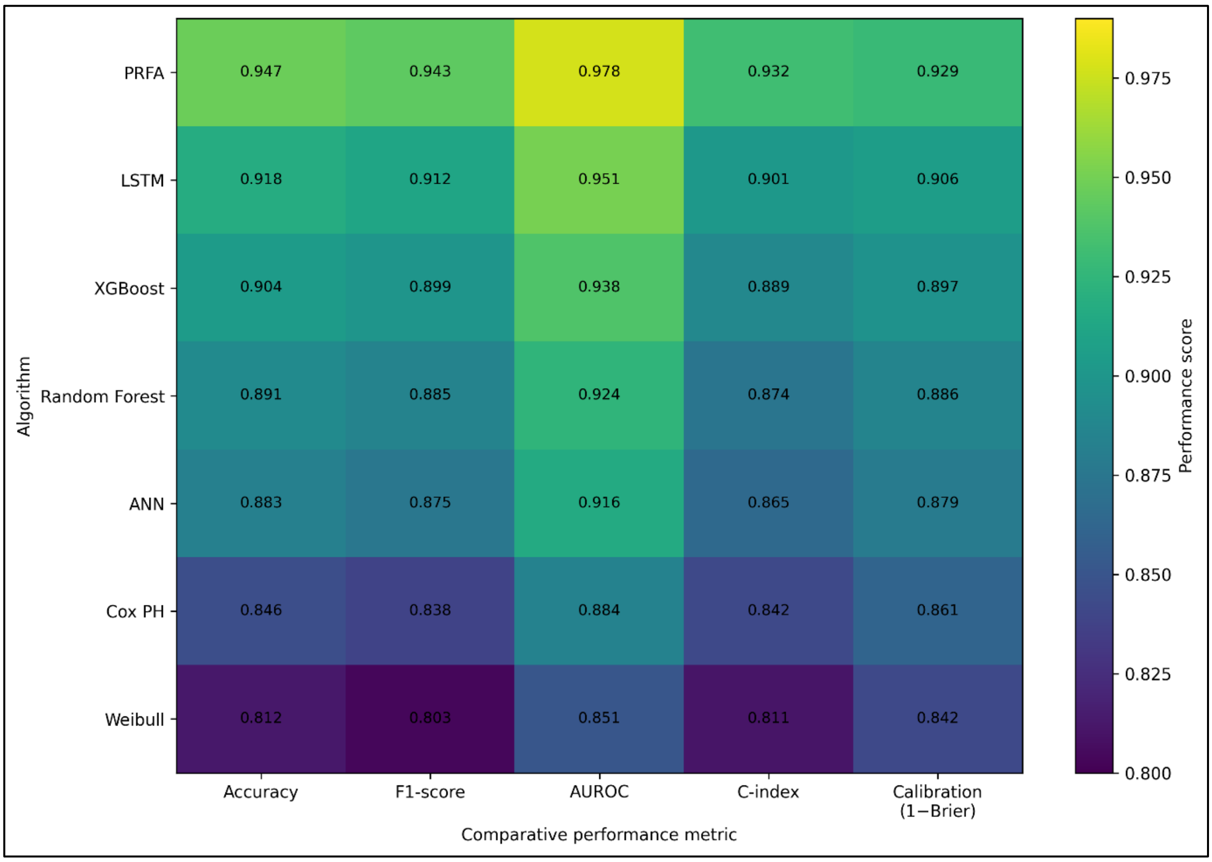

Fig 6 Comparative Multimetric Performance Matrix of PRFA and Benchmark Algorithms

Figure 6 provides a five-metric comparison of all seven algorithms using accuracy, F1-score, AUROC, concordance index, and calibration score. PRFA records 0.947 accuracy, 0.943 F1-score, 0.978 AUROC, 0.932 concordance, and 0.929 calibration, giving it the strongest profile across every column. LSTM is the nearest comparator at 0.918, 0.912, 0.951, 0.901, and 0.906, respectively. XGBoost follows with 0.904 accuracy and 0.938 AUROC, while Random Forest reaches 0.891 accuracy and 0.874 concordance. ANN produces 0.883 accuracy, 0.875 F1-score, and 0.916 AUROC. Cox PH declines to 0.846 accuracy and 0.842 concordance, whereas Weibull records the lowest values, including 0.812 accuracy, 0.803 F1-score, and 0.811 concordance. The matrix therefore shows that PRFA improves both event discrimination and survival-risk ranking, while its 0.929 calibration score indicates more reliable probability estimates for maintenance decision-making. The corresponding calibration ordering also preserves the advantage observed in the Brier-score analysis, with progressively weaker probability reliability among the benchmark models.

➢ *Graphical Reliability Analysis, Feature Importance, Sensitivity Analysis, Model Robustness, and Predictive Maintenance Implications*

The integrated reliability analysis indicates that PRFA maintained stable diagnostic and prognostic performance when operational and structural inputs were perturbed. Table 5 shows that the model preserved 91.4% top-five feature-rank stability and 93.1% sensitivity retention under controlled input perturbation, exceeding the strongest benchmark values of 82.7% and 85.6%, respectively. Its pre-failure recall remained 0.936, while the false-alarm rate was limited to 0.064. PRFA also provided a median predictive-maintenance lead time of 312 h compared with 241 h for the best benchmark and restricted RUL error after structural-channel dropout to 229 h. These results indicate that the attention mechanism does not merely improve classification accuracy; it preserves physically meaningful operational–structural relationships under degraded sensing conditions, thereby supporting earlier inspection, maintenance prioritization, and more reliable outage planning across variable plant operating regimes.

Table 5 Feature Stability, Sensitivity, Robustness, and Predictive-Maintenance Performance

Comparative metric	PRFA	Best benchmark	Interpretation
Top-five feature-rank stability	91.4%	82.7%	PRFA preserves influential degradation variables more consistently
Sensitivity retention under input perturbation	93.1%	85.6%	Stronger resistance to changes in sensor and operating inputs
Pre-failure recall	0.936	0.902	Higher detection of impending equipment and structural failures

ISSN No:-2456-2165 https://doi.org/10.38124/ijisrt/26sep933

False-alarm rate	0.064	0.091	Fewer unnecessary maintenance interventions
Median predictive-maintenance lead time	312 h	241 h	Earlier opportunity for inspection and maintenance planning
RUL MAE after structural-channel dropout	229 h	298 h	Lower degradation in prognostic accuracy when structural sensing is incomplete

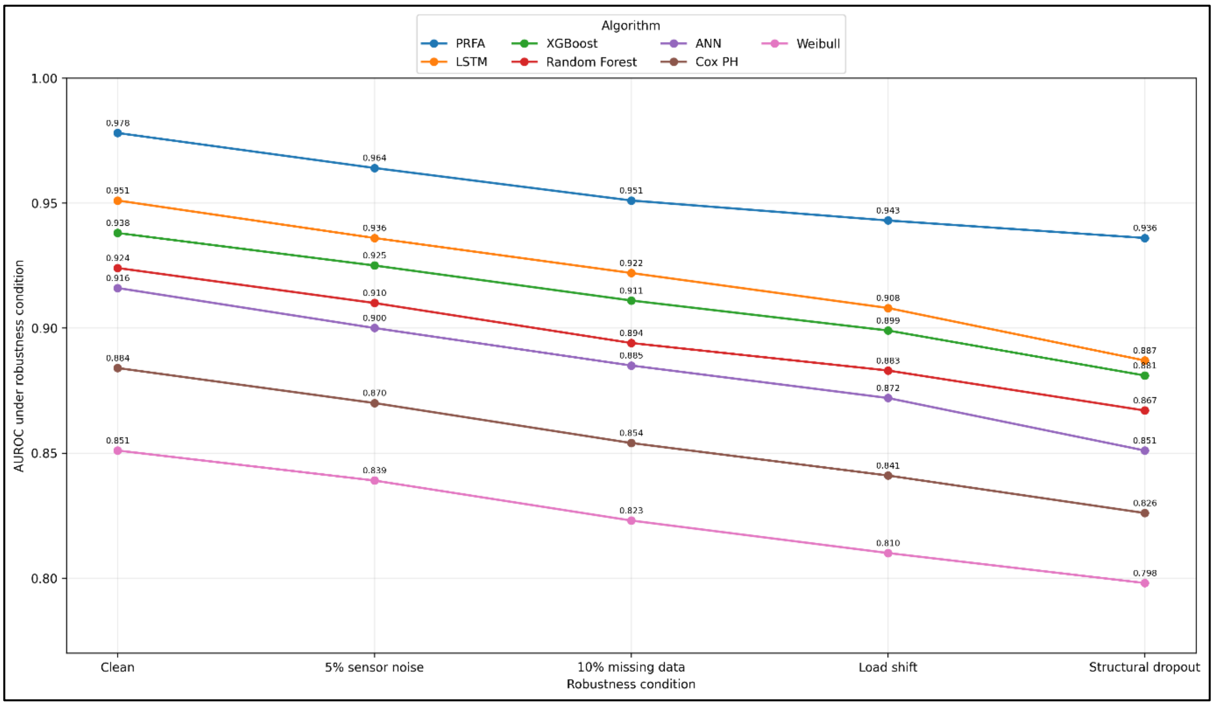

Fig 7 Parallel-Coordinates Robustness Comparison of PRFA and Benchmark Algorithms Under Operational and Data-Quality Perturbations

Figure 7 compares algorithm robustness through AUROC values across five operating and data-quality conditions. Under clean data, PRFA achieved 0.978, ahead of LSTM at 0.951, XGBoost at 0.938, Random Forest at 0.924, ANN at 0.916, Cox PH at 0.884, and Weibull at 0.851. With 5% sensor noise, PRFA declined only to 0.964, whereas LSTM and XGBoost fell to 0.936 and 0.925. At 10% missing data, PRFA retained 0.951 compared with 0.922 for LSTM and 0.911 for XGBoost. Under load shift, PRFA remained at 0.943, while Random Forest and ANN decreased to 0.883 and 0.872. Structural-channel dropout produced the strongest stress condition, yet PRFA still achieved 0.936. LSTM, XGBoost, Cox PH, and Weibull declined to 0.887, 0.881, 0.826, and 0.798, respectively, demonstrating superior resilience of the fused model. The widening separation under disrupted sensing indicates that structural-operational attention preserves discriminative information when individual channels become unreliable or operating distributions shift.

V. CONCLUSIONS AND RECOMMENDATIONS

➢ *Conclusions and Major Findings of the Study*

The study demonstrated that combining operational and structural-condition information provides a more complete basis for reliability assessment in combined-cycle power plants than conventional time-to-failure analysis or single-domain machine-learning models. The proposed PlantReliability Fusion Algorithm integrated compressor discharge pressure, exhaust temperature, bearing vibration, bearing temperature, steam pressure, plant load, operating hours, start-stop cycles, foundation settlement, strain, displacement, crack condition, anchor-bolt condition, thermal expansion, and structural vibration within a unified prognostic framework. The results showed that coupled operational–structural failure states carried the highest pre-failure risk, confirming that mechanical deterioration and structural degradation should not be assessed independently when they influence common equipment interfaces such as bearings, baseplates, foundations, supports, and alignment-sensitive rotating systems.

PRFA consistently outperformed Weibull reliability analysis, Cox proportional-hazards regression, Random Forest, XGBoost, ANN, and LSTM across classification, survival, calibration, and remaining-useful-life measures. The algorithm achieved an accuracy of 0.947, F1-score of 0.943, AUROC of 0.978, and concordance index of 0.932, while maintaining a Brier score of 0.071. Its RUL prediction produced an MAE of 184 h and RMSE of 276 h. Robustness tests further showed that PRFA retained comparatively high discrimination under sensor noise, missing data, load shifts, and structural-channel dropout. These findings establish that attention-based fusion improves failure detection because the model dynamically identifies whether risk arises predominantly from operational degradation, structural deterioration, or their interaction. The framework therefore provides a technically defensible basis for predictive maintenance, structural integrity management, inspection prioritization, outage planning, and lifecycle reliability improvement in combined-cycle power plants.

- *Technical Contributions and Reliability Management Implications of the PlantReliability Fusion Algorithm*

The principal technical contribution of this research is the development of a multimodal reliability architecture capable of representing equipment degradation and structural-support deterioration within the same mathematical framework. Unlike Weibull analysis, which primarily models lifetime behaviour from failure-time distributions, PRFA continuously updates reliability estimates using current condition information. Its architecture separates operational and structural data into dedicated encoders, derives latent degradation representations, and combines them through an attention-based fusion layer. This design allows the model to recognize situations in which similar equipment symptoms originate from different mechanisms. For example, increased shaft vibration accompanied by normal foundation response may indicate rotor imbalance or bearing degradation, whereas simultaneous vibration growth, foundation settlement, and anchor-bolt deterioration may indicate structurally induced misalignment.

The multi-output formulation is equally important for reliability management because PRFA produces failure probability, instantaneous hazard, reliability, and remaining useful life from the same fused health representation. This enables engineering teams to move beyond binary fault alarms toward risk-based maintenance decisions. The demonstrated improvement in failure discrimination and RUL accuracy means that assets can be prioritized according to both likelihood and consequence of degradation. Higher feature-rank stability and sensitivity retention also improve interpretability by identifying variables that consistently influence predicted deterioration. In operational practice, reliability engineers could use PRFA outputs to rank turbines, HRSG components, generators, pumps, foundations, support frames, and anchor systems for intervention. The model therefore transforms heterogeneous plant information into an integrated reliability-management layer capable of supporting condition-based maintenance, structural integrity assessment, outage optimization, spare-parts planning, and asset-life extension while retaining direct comparability with established statistical reliability methods.

- *Recommendations for Predictive Maintenance, Structural Inspection, and Digital Plant Integration*

Combined-cycle power plants adopting the proposed framework should integrate PRFA with existing condition-monitoring, DCS, SCADA, CMMS, and structural-health databases to create a continuously updated reliability profile for critical assets. Operational variables such as vibration, bearing temperature, exhaust-temperature spread, compressor pressure ratio, steam pressure, operating hours, load ramping, and start-stop cycles should be synchronized with structural measurements including settlement, strain, displacement, crack development, anchor-bolt condition, thermal movement, and foundation vibration. Maintenance thresholds should not be based on individual sensor alarms alone. Instead, intervention should be initiated when fused failure probability, hazard growth, RUL reduction, and cross-domain degradation signatures jointly indicate a worsening condition.

Structural inspection frequencies should also become condition-dependent. Assets showing increasing equipment vibration together with settlement, support displacement, grout deterioration, or bolt-condition changes should receive targeted alignment checks, foundation surveys, anchor-bolt torque verification, crack mapping, modal testing, and support-system inspection. PRFA-derived RUL should be incorporated into outage planning so that repairs can be grouped according to predicted degradation windows rather than fixed calendar intervals. Digital integration should include automatic transfer of reliability scores into the CMMS for work-order prioritization and into a plant digital twin for scenario evaluation. The model should operate with sensor-quality validation, missing-data detection, and confidence thresholds to prevent unnecessary intervention. Reliability teams should also retain Weibull and Cox models as transparent statistical references, while PRFA provides adaptive condition-sensitive prediction. This combined approach would strengthen predictive maintenance, reduce forced outages, improve structural assurance, and support coordinated mechanical, civil, electrical, and process reliability decisions.

- *Study Limitations and Recommendations for Future Research*

Although the PlantReliability Fusion Algorithm demonstrated strong comparative performance, several limitations should be considered when interpreting the results and planning future deployment. The framework depends on the quality, synchronization, and representativeness of operational and structural monitoring data. Structural variables are often sampled less frequently than process and vibration signals, which may introduce temporal imbalance between the two data streams. Rare catastrophic failures also create class imbalance, while maintenance interventions can alter apparent degradation trajectories before natural failure occurs. Sensor drift, missing channels, inconsistent inspection intervals, component replacement, operating-regime changes, and modifications to control logic may further influence model calibration. In addition, the current formulation treats the selected variables as sufficiently representative of degradation, although unmeasured mechanisms such as residual stress, material ageing, combustion instability, corrosion severity, or localized thermal damage may contribute to failure development.

Future research should validate PRFA using multi-year datasets from several combined-cycle plants with different turbine technologies, duty cycles, climates, maintenance philosophies, and structural configurations. External validation should examine whether model weights transfer between plants or require site-specific recalibration. Physics-informed constraints should be incorporated to ensure consistency with thermodynamic limits, rotor dynamics, structural mechanics, and fatigue behaviour. Graph neural networks could be evaluated for representing physical connectivity among turbines, foundations, HRSG supports, piping, and auxiliary equipment. Future studies should also investigate uncertainty-aware RUL intervals, probabilistic attention mechanisms, explainable failure pathways, online learning, federated model updating, and causal analysis. Integration with digital twins should eventually permit simulation of maintenance actions before execution, allowing operators to compare predicted reliability recovery, structural-risk reduction, outage duration, and lifecycle cost under alternative intervention strategies.

REFERENCES

[1]. Addy, R. Z., Atoo, A. A., & Nwafor, E. O. (2022). Physics-informed digital twins for real-time health monitoring performance prediction and remaining useful life assessment of gas turbines foundations and structural support systems. *International Journal of Scientific Research in Civil Engineering, 6*(6), 284–313. https://doi.org/10.32628/IJSRCE229674

[2]. Agyekum, B., Gloria, A., & Seffah-Duodu, D. (2026). Energy efficient edge AI with measured energy saving. *International Journal of Scientific Research in Science, Engineering and Technology, 13*(3), 553–579. https://doi.org/10.32628/IJSRSET2613374

[3]. Aikins, S. A., Avevor, J., & Enyejo, L. A. (2024). Optimizing thermal management in hydrogen fuel cells for smart HVAC systems and sustainable building energy solutions. *International Journal of Scientific Research and Modern Technology, 3*(9), 79–96. https://doi.org/10.38124/ijsrmt.v3i9.351

[4]. Avendaño-Valencia, L. D., Chatzi, E. N., & Tcherniak, D. (2020). Gaussian process models for mitigation of operational variability in the structural health monitoring of wind turbines. *Mechanical Systems and Signal Processing, 142*, 106686. https://doi.org/10.1016/j.ymssp.2020.106686

[5]. Bashiru, O., Ochem, C., Enyejo, L. A., Manuel, H. N. N., & Adeoye, T. O. (2024). The crucial role of renewable energy in achieving the sustainable development goals for cleaner energy. *Global Journal of Engineering and Technology Advances, 19*(3), 11–36. https://doi.org/10.30574/gjeta.2024.19.3.0099

[6]. Benato, A., Bracco, S., Stoppato, A., & Mirandola, A. (2016). LTE: A procedure to predict power plants dynamic behaviour and components lifetime reduction during transient operation. *Applied Energy, 162*, 880–891. https://doi.org/10.1016/j.apenergy.2015.10.162

[7]. Carazas, F. J. G., Salazar, C. H., & Souza, G. F. M. (2011). Availability analysis of heat recovery steam generators used in thermal power plants. *Energy, 36*(6), 3855–3870. https://doi.org/10.1016/j.energy.2010.10.003

[8]. Carvalho, T. P., Soares, F. A. A. M. N., Vita, R., Francisco, R. P., Basto, J. P. T. V., & Alcalá, S. G. S. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. *Computers & Industrial Engineering, 137*, 106024. https://doi.org/10.1016/j.cie.2019.106024

[9]. Finn, J., Wagner, J. R., & Bassily, H. (2010). Monitoring strategies for a combined cycle electric power generator. *Applied Energy, 87*(8), 2621–2627. https://doi.org/10.1016/j.apenergy.2010.02.017

[10]. Frank, U. P. (2026a). Artificial intelligence for infection surveillance: Improving early detection of healthcare-associated infections. *USR Journal of Multidisciplinary Research and Studies*.

[11]. Frank, U. P. (2026b). Healthcare quality metrics: From data collection to performance improvement; A narrative review of measurement frameworks and improvement methods in United States health care. *UKR Journal of Medicine and Medical Research*. https://doi.org/10.5281/zenodo.22105362

[12]. Frank, U. P. (2026c). Optimizing medical inventory management through predictive analytics: Implications for healthcare quality, cost reduction, and patient safety; A narrative review. *UKR Journal of Education and Literature, 2*(1), 77–92. https://doi.org/10.5281/zenodo.22105843

[13]. Hassani, S., Dackermann, U., Mousavi, M., & Li, J. (2024). A systematic review of data fusion techniques for optimized structural health monitoring. *Information Fusion, 103*, 102136. https://doi.org/10.1016/j.inffus.2023.102136

[14]. Idoko, I. P., Ijiga, O. M., Akoh, O., Agbo, D. O., Ugbane, S. I., & Umama, E. E. (2024). Empowering sustainable power generation: The vital role of power electronics in California's renewable energy transformation. *World Journal of Advanced Engineering Technology and Sciences, 11*(1), 274–293. https://doi.org/10.30574/wjaets.2024.11.1.0058

[15]. Idoko, I. P., Ijiga, O. M., Harry, K. D., Ezebuka, C. C., Ukatu, I. E., & Peace, A. E. (2024b). Renewable energy policies: A comparative analysis of Nigeria and the USA. *World Journal of Advanced Research and Reviews, 21*(1), 888–913. https://doi.org/10.30574/wjarr.2024.21.1.0071

[16]. Ilesanmi, M. O., Anim-Sampong, S. D., & Enyejo, J. O. (2023). Cross-sector asset management: Applying real estate portfolio optimization models to renewable energy infrastructure. *International Journal of Scientific Research and Modern Technology, 2*(10), 1–17. https://doi.org/10.38124/ijsrmt.v2i10.1077

[17]. Ilesanmi, M. O., Bamigwojo, O. V., Jinadu, S. O., Oyekan, M., & Ijiga, O. M. (2023b). Mitigating regulatory and market risks in U.S. renewable energy portfolios: A portfolio asset manager's perspective. *International Journal of Scientific Research in Science and Technology, 10*(6), 878–906. https://doi.org/10.32628/IJSRST5231103

[18]. Ilesanmi, M. O., Okoh, O. F., Balogun, S. A., & Ijiga, O. M. (2024). Data-driven portfolio optimization for utility-scale solar, wind, and battery energy storage systems (BESS): Integrating performance analytics with investor EBITDA targets. *International Journal of Scientific Research and Modern Technology, 3*(11), 141–155. https://doi.org/10.38124/ijsrmt.v3i11.943

[19]. James, U. U., Idika, C. N., & Enyejo, L. A. (2023). Zero Trust Architecture leveraging AI-driven behavior analytics for industrial control systems in energy

distribution networks. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 9*(4), 685–709. https://doi.org/10.32628/CSEIT23564522

[20]. James, U. U., Salami, E. O., & Enyejo, L. A. (2025). Real time policy orchestration for cybersecurity risk management in GRC aligned financial technology infrastructures. *International Journal of Innovative Science and Research Technology, 10*(8). https://doi.org/10.38124/ijisrt/25aug1021

[21]. Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing, 20*(7), 1483–1510. https://doi.org/10.1016/j.ymssp.2005.09.012

[22]. Jinadu, S. O., Akinleye, K. E., & Ijiga, O. M. (2024). Deployment of geological CO_2 sequestration with proprietary injection techniques for oil yield optimization and energy independence. *International Journal of Scientific Research in Science, Engineering and Technology, 11*(6), 503–525. https://doi.org/10.32628/IJSRSET2512162

[23]. Lei, Y., Li, N., Guo, L., Li, N., Yan, T., & Lin, J. (2018). Machinery health prognostics: A systematic review from data acquisition to RUL prediction. *Mechanical Systems and Signal Processing, 104*, 799–834. https://doi.org/10.1016/j.ymssp.2017.11.016

[24]. Manuel, H. N. N., Adeoye, T. O., Idoko, I. P., Akpa, F. A., Ijiga, O. M., & Igbede, M. A. (2024). Optimizing passive solar design in Texas green buildings by integrating sustainable architectural features for maximum energy efficiency. *Magna Scientia Advanced Research and Reviews, 11*(1), 235–261. https://doi.org/10.30574/msarr.2024.11.1.0089

[25]. Ocharo, D. O. (2024). Integration of photovoltaic-thermal systems with HVAC infrastructure for energy-positive buildings in Pennsylvania. *International Journal of Scientific Research and Modern Technology, 3*(5), 65–80. https://doi.org/10.38124/ijsrmt.v3i5.993

[26]. Okeke, R. O., Ibokette, A. I., Ijiga, O. M., Enyejo, L. A., Ebiega, G. I., & Olumubo, O. M. (2024). The reliability assessment of power transformers. *Engineering Science & Technology Journal, 5*(4), 1149–1172. https://doi.org/10.51594/estj.v5i4.981

[27]. Oladoye, S. O., Bamigwojo, O. V., Ogboji, A. J., & Ijiga, O. M. (2023). Techno-economic evaluation of hybrid solar–diesel microgrids for underserved communities using simulation-based load forecasting. *Engineering Science & Technology Journal, 4*(2), 71–97. https://doi.org/10.51594/estj.v4i2.2193

[28]. Oyekan, M., Jinadu, S. O., & Enyejo, J. O. (2023). Harnessing data analytics to maximize renewable energy asset performance. *International Journal of Scientific Research and Modern Technology, 2*(8), 64–80. https://doi.org/10.38124/ijsrmt.v2i8.850

[29]. Sabouhi, H., Abbaspour, A., Fotuhi-Firuzabad, M., & Dehghanian, P. (2016). Reliability modeling and availability analysis of combined cycle power plants. *International Journal of Electrical Power & Energy Systems, 79*, 108–119. https://doi.org/10.1016/j.ijepes.2016.01.007

[30]. Si, X.-S., Wang, W., Hu, C.-H., & Zhou, D.-H. (2011). Remaining useful life estimation—A review on the statistical data driven approaches. *European Journal of Operational Research, 213*(1), 1–14. https://doi.org/10.1016/j.ejor.2010.11.018

[31]. Sinha, J. K., & Elbhbah, K. (2013). A future possibility of vibration based condition monitoring of rotating machines. *Mechanical Systems and Signal Processing, 34*(1–2), 231–240. https://doi.org/10.1016/j.ymssp.2012.07.001

[32]. Smith, R. L. (1991). Weibull regression models for reliability data. *Reliability Engineering & System Safety, 34*(1), 55–76. https://doi.org/10.1016/0951-8320(91)90099-S

[33]. Zhang, C. W. (2021). Weibull parameter estimation and reliability analysis with zero-failure data from high-quality products. *Reliability Engineering & System Safety, 207*, 107321. https://doi.org/10.1016/j.ress.2020.107321

[34]. Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., & Gao, R. X. (2019). Deep learning and its applications to machine health monitoring. *Mechanical Systems and Signal Processing, 115*, 213–237. https://doi.org/10.1016/j.ymssp.2018.05.050

[35]. Zio, E. (2022). Prognostics and health management (PHM): Where are we and where do we (need to) go in theory and practice. *Reliability Engineering & System Safety, 218*, 108119. https://doi.org/10.1016/j.ress.2021.108119