

Advanced Analytics for Reliability Improvement in Electric Grid Components

Tashi Wangchuk

Department of Information Systems,
Royal University of Bhutan, Thimphu, Bhutan

VOLUME 02 ISSUE 02 (2026)

Published Date: 31 Dec 2025// Page no.: - 45-52

ABSTRACT

The increasing complexity of modern electric power systems has intensified the need for advanced reliability management strategies capable of ensuring continuous operation, reducing unexpected failures, and improving asset lifecycle performance. Conventional reliability assessment and maintenance approaches primarily depend on periodic inspections, historical failure statistics, and corrective interventions after equipment degradation becomes evident. However, the emergence of advanced analytics, machine learning (ML), Internet of Things (IoT)-enabled monitoring, and data-driven decision frameworks has created new opportunities for transforming electric grid maintenance from reactive and preventive paradigms toward predictive and reliability-centered approaches. This research paper investigates the application of advanced analytics techniques for improving the reliability of electric grid components through intelligent condition monitoring, failure prediction, risk assessment, and maintenance optimization.

The study develops a conceptual analytical framework by synthesizing reliability engineering principles with machine learning-based predictive maintenance methodologies. The proposed framework integrates data acquisition, preprocessing, feature extraction, predictive modeling, reliability evaluation, and decision-support mechanisms to enhance the operational resilience of critical grid components such as transformers, transmission assets, circuit breakers, and distribution equipment. Insights are derived from existing predictive maintenance research, reliability engineering methodologies, physics-informed machine learning approaches, and industrial analytics applications. Previous studies have demonstrated that machine learning-driven maintenance systems can identify degradation patterns, estimate remaining useful life, and support optimized maintenance planning in complex engineering systems (Xu and Saleh, 2021; Theissler et al., 2021).

The research emphasizes that electric grid reliability improvement requires a balanced integration of data-driven intelligence and engineering knowledge. While purely statistical approaches may provide predictive capability, their effectiveness can be limited by insufficient failure data, changing operational conditions, and lack of physical interpretability. Therefore, hybrid approaches combining machine learning algorithms with reliability engineering principles and physics-based understanding provide a more robust pathway for grid asset management. Predictive maintenance approaches specifically designed for electric power systems have shown potential for reducing operational risks, improving maintenance scheduling, and increasing equipment availability (Philip, 2025).

The findings indicate that advanced analytics can significantly improve reliability decision-making by enabling early fault detection, dynamic risk evaluation, and optimized resource allocation. However, challenges related to data quality, cybersecurity, model transparency, and integration with existing grid infrastructures remain important barriers. This research contributes a comprehensive analytical perspective on how advanced analytics can support next-generation electric grid reliability management and provides directions for future research involving intelligent, adaptive, and physics-informed maintenance systems.

Keywords: Advanced analytics; Electric grid reliability; Predictive maintenance; Machine learning; Condition monitoring; Reliability engineering; Smart grid; Asset management; Failure prediction.

INTRODUCTION

Electric power systems represent one of the most critical infrastructures supporting modern societies, industrial activities, communication networks, and essential services. The reliability of electric grids depends heavily on the operational performance of numerous

interconnected components, including transformers, transmission lines, protection systems, substations, and distribution equipment. Failure of these components can lead to service interruptions, economic losses, safety risks, and reduced system resilience. As electricity networks become more interconnected and exposed to increasing operational complexity, traditional reliability management approaches

face significant challenges in maintaining high levels of availability and performance.

Historically, electric grid maintenance strategies have relied on corrective maintenance and time-based preventive maintenance. Corrective maintenance addresses failures after occurrence, often resulting in unexpected downtime and expensive emergency interventions. Preventive maintenance improves reliability by scheduling inspections and replacements based on predetermined intervals; however, it may result in unnecessary maintenance activities because component conditions are not always directly correlated with operating age. Reliability engineering has therefore increasingly focused on condition-based maintenance (CBM) and predictive maintenance strategies that utilize operational information to estimate degradation patterns and anticipate potential failures.

The rapid development of sensing technologies, communication systems, and computational capabilities has enabled the collection of large-scale operational data from engineering assets. Advanced analytics techniques can transform these data streams into actionable reliability insights by identifying abnormal behavior, predicting failure probabilities, and supporting maintenance decisions. Machine learning algorithms are particularly valuable because they can recognize complex nonlinear relationships between operational variables and equipment health indicators. Research in reliability engineering has highlighted that machine learning provides significant opportunities for improving failure prediction and safety analysis when integrated appropriately with domain knowledge (Xu and Saleh, 2021).

Electric grid components present unique challenges for predictive analytics implementation. Unlike controlled manufacturing environments, power system assets operate under continuously changing electrical loads, environmental conditions, and network constraints. Equipment failures are also relatively rare compared with normal operating events, creating difficulties in developing accurate predictive models. Zhang et al. (2021) emphasized that reliability assessment under conditions of limited failure data remains a major challenge, requiring advanced methods capable of extracting meaningful information from incomplete datasets. These challenges make the development of robust analytical frameworks essential for practical deployment in power infrastructure.

The transition toward intelligent grid management requires approaches that combine advanced analytics with established reliability engineering methodologies. Machine learning-based predictive maintenance systems developed for industrial applications demonstrate how

sensor data, historical records, and analytical models can support proactive maintenance planning. Arena et al. (2022) proposed decision-support approaches based on machine learning to improve predictive maintenance strategies, demonstrating the importance of integrating analytical outputs with maintenance decision processes rather than focusing only on prediction accuracy.

For electric power systems specifically, predictive maintenance approaches have demonstrated potential in reducing unexpected failures and improving asset utilization. Philip (2025) examined machine learning-based predictive maintenance for electric power systems and highlighted the ability of analytical models to support early fault identification, maintenance optimization, and improved operational reliability. Such approaches represent an important evolution from traditional reliability practices toward adaptive maintenance systems capable of responding to real-time equipment conditions.

Despite these developments, several research gaps remain. First, many existing predictive models focus primarily on algorithm performance while insufficiently addressing reliability engineering requirements such as explainability, risk assessment, and integration with maintenance strategies. Second, electric grid applications require analytical models capable of handling limited failure events, heterogeneous data sources, and safety-critical decision environments. Third, there is a need for frameworks that combine data-driven learning with physical system knowledge to improve model reliability and operational acceptance.

This research addresses these gaps by developing a comprehensive conceptual framework for applying advanced analytics to reliability improvement in electric grid components. The objectives of this study are to:

1. Examine the theoretical relationship between advanced analytics, predictive maintenance, and reliability engineering.
2. Analyze machine learning and data-driven approaches applicable to electric grid component reliability improvement.
3. Develop an integrated framework combining data acquisition, analytics, reliability evaluation, and maintenance decision support.
4. Identify practical challenges, limitations, and future opportunities associated with intelligent reliability management.

The scope of this research focuses on analytical methods for improving the reliability of electric grid components through predictive and condition-based maintenance approaches. The study does not propose a specific commercial implementation but provides a research-oriented framework based exclusively on existing reliability analytics literature. The significance of

this work lies in demonstrating how advanced analytics can support the transition toward more resilient, intelligent, and sustainable power systems.

LITERATURE REVIEW

Reliability engineering has traditionally focused on understanding failure mechanisms, estimating component lifetimes, and developing strategies to minimize system interruptions. Conventional reliability methods rely heavily on statistical failure analysis, reliability block diagrams, failure mode analysis, and scheduled maintenance programs. Although these approaches remain valuable, they often struggle to accommodate the increasing complexity and dynamic operating conditions of modern engineering systems.

Recent advances in machine learning and data analytics have introduced new possibilities for reliability improvement. Xu and Saleh (2021) reviewed the current status of machine learning applications in reliability engineering and safety analysis, emphasizing that ML techniques can identify hidden patterns within complex operational datasets. Their study highlighted that machine learning is particularly useful where traditional analytical methods face limitations due to nonlinear system behavior and large-scale data availability.

The development of predictive maintenance represents a major transformation in reliability management. Instead of performing maintenance according to fixed schedules, predictive approaches estimate equipment health conditions and determine optimal intervention timing. Theissler et al. (2021) investigated machine learning-enabled predictive maintenance applications and identified significant benefits, including improved equipment availability, reduced maintenance costs, and enhanced operational decision-making. However, they also emphasized challenges related to data preparation, model validation, and industrial deployment.

In manufacturing environments, predictive maintenance frameworks have demonstrated how real-time data can improve reliability decisions. Ayvaz and Alpay (2021) developed a machine learning-based predictive maintenance system using IoT-generated production data, showing that continuous monitoring and analytical processing can identify potential failures before production disruption occurs. Although developed for manufacturing systems, the underlying principles are highly relevant to electric grid applications because both domains involve complex assets requiring continuous reliability monitoring.

METHODOLOGY

3.1 Research Design and Analytical Framework

This research adopts a conceptual framework development methodology based on synthesis of reliability engineering theories and advanced analytics approaches. The objective is to establish a structured model explaining how data-driven techniques can improve the reliability performance of electric grid components.

The methodology integrates five major analytical stages:

1. Data acquisition and monitoring
2. Data preprocessing and feature extraction
3. Predictive reliability modeling
4. Risk-based reliability assessment
5. Maintenance decision optimization

The framework is designed around the principle that reliability improvement requires continuous interaction between operational data, analytical models, engineering knowledge, and maintenance strategies.

3.2 Data Acquisition and Condition Monitoring Framework

The first stage involves collecting information representing the operational condition of electric grid components. Modern grid infrastructure generates large volumes of structured and unstructured data through monitoring devices, inspection records, and maintenance documentation.

Structured data may include:

- Electrical measurements
- Temperature variations
- Load profiles
- Equipment operating hours
- Fault events
- Environmental conditions

Unstructured data may include:

- Maintenance reports
- Inspection notes
- Failure descriptions
- Operator observations

3.3 Data Preprocessing and Feature Engineering

The effectiveness of advanced analytics models depends significantly on the quality and relevance of input data. Electric grid monitoring systems generate heterogeneous datasets collected from different sensors, operational databases, and maintenance management platforms. These datasets frequently contain missing observations, measurement noise, inconsistent formats, and irregular sampling intervals. Therefore, preprocessing is a critical methodological stage for transforming raw information into reliable analytical inputs.

The preprocessing stage includes data cleaning, normalization, missing-value management, anomaly filtering, and synchronization of multiple data sources. For example, sensor measurements from transformers or transmission equipment may contain temporary abnormalities caused by communication failures rather than actual equipment degradation. Without appropriate preprocessing, machine learning models may incorrectly interpret these events as failure indicators.

Carbery et al. (2019) demonstrated that preprocessing frameworks significantly influence the quality of insights generated from complex engineering systems. Their findings support the argument that reliability analytics should prioritize data preparation before applying predictive algorithms. In electric grid applications, effective preprocessing improves model stability and reduces false alarms that may lead to unnecessary maintenance activities.

Feature engineering represents another important methodological component. Instead of using raw measurements directly, analytical models require meaningful reliability indicators extracted from operational data. Examples of engineered features include:

- Rate of temperature increase in electrical equipment.
- Frequency of abnormal operating conditions.
- Historical fault occurrence patterns.
- Load stress indicators.
- Degradation-related statistical characteristics.

These features allow machine learning models to identify relationships between operational behavior and potential failure conditions.

Because electric grid components operate under varying environmental and electrical stresses, feature selection must consider both statistical relevance and engineering significance. The integration of engineering knowledge prevents models from identifying mathematically

significant but physically meaningless relationships.

3.4 Machine Learning-Based Reliability Prediction Model

The central analytical component of the proposed framework is a machine learning-based reliability prediction model. The purpose of this model is to estimate equipment health conditions, detect abnormal behavior, and predict possible future failures.

Different machine learning approaches can be applied depending on data characteristics and reliability objectives. Classification algorithms can categorize equipment states into healthy, degraded, and critical conditions. Regression-based models can estimate remaining useful life or failure probability. Unsupervised learning methods can identify unknown degradation patterns when failure labels are unavailable.

The general predictive model can be represented as:

$$R(t)=f(X_t,H_t,E_t)R(t)=f(X_t, H_t, E_t)R(t)=f(X_t,H_t,E_t)$$

where:

- $R(t)$ represents predicted reliability condition at time t ,
- X_t represents real-time operational measurements,
- H_t represents historical equipment information,
- E_t represents environmental and operational influences.

This formulation recognizes that equipment reliability is influenced by multiple interacting variables rather than a single failure indicator.

Xu and Saleh (2021) emphasized that machine learning provides opportunities for reliability engineering by discovering complex patterns that traditional statistical approaches may not capture. However, they also highlighted that reliability applications require careful validation because incorrect predictions can influence safety-critical decisions.

For electric grid applications, prediction models should therefore be evaluated not only by accuracy but also by reliability, interpretability, and operational usefulness.

3.5 Integration of Physics-Informed Analytics

A major limitation of conventional machine learning models is their dependence on large quantities of representative data. Electric grid failures are relatively rare events, creating challenges for model training. To address this issue, the proposed methodology incorporates physics-informed machine learning principles.

Physics-informed models combine operational data with established engineering relationships. Instead of allowing algorithms to learn only from historical patterns, physical constraints guide the learning process.

For example, transformer aging models may incorporate relationships between thermal stress and insulation degradation. Transmission equipment reliability models may include mechanical stress, environmental exposure, and operational loading conditions.

Xu et al. (2023) identified physics-informed machine learning as an emerging approach for improving reliability and safety applications. Such models are particularly valuable when data availability is limited because physical knowledge provides additional information for improving prediction robustness.

The integration of physics-based constraints also improves explainability. Engineers can evaluate whether model predictions correspond with known degradation mechanisms, increasing confidence in analytical recommendations.

3.6 Reliability Risk Assessment Framework

Prediction of failure probability alone does not provide sufficient information for maintenance decision-making. Reliability management requires evaluation of risk based on both failure likelihood and consequence severity.

The proposed framework incorporates a risk assessment model:

$$\text{Risk} = \text{Probability(Failure)} \times \text{Consequence(Failure)}$$

This approach enables utilities to prioritize maintenance activities according to asset criticality.

For example, two transformers may have similar degradation indicators, but their maintenance priorities may differ because one supplies a critical industrial area while another supports a less sensitive network segment. Therefore, reliability analytics must consider operational consequences alongside equipment health.

Suzuki and Yokogawa (2020) emphasized that reliability engineering requires multiple viewpoints, including design, operation, and management perspectives. This principle supports the integration of risk analysis into predictive maintenance frameworks.

3.7 Decision Support and Maintenance Optimization

The final stage of the methodology converts analytical

outputs into maintenance decisions. A decision-support system provides recommendations regarding inspection scheduling, repair requirements, component replacement, and resource allocation.

Arena et al. (2022) demonstrated that predictive maintenance systems achieve greater value when prediction models are connected with decision-support mechanisms. The objective is not simply identifying failures but improving maintenance strategy effectiveness.

A reliability-oriented decision system may consider:

- Predicted failure probability.
- Equipment importance.
- Maintenance cost.
- Availability of replacement components.
- Operational constraints.
- Safety requirements.

The integration of these factors enables dynamic maintenance planning rather than fixed periodic scheduling.

RESULTS

The analytical framework developed in this research indicates that advanced analytics can significantly enhance reliability management for electric grid components by enabling continuous monitoring, predictive assessment, and optimized maintenance decisions. The findings demonstrate that reliability improvement is achieved not through a single analytical technique but through integration of multiple capabilities, including data preprocessing, machine learning, physics-informed modeling, and risk-based decision support.

The literature synthesis reveals that machine learning-based predictive maintenance provides substantial benefits compared with traditional preventive approaches. Predictive models can identify degradation trends before critical failures occur, allowing utilities to perform targeted interventions. Philip (2025) demonstrated that machine learning approaches applied to electric power systems can support early fault identification and improved maintenance planning.

A key finding is that data quality represents one of the most influential factors affecting analytical reliability. The effectiveness of predictive models depends strongly on preprocessing methods, feature selection, and the availability of representative operational information. Studies examining industrial analytics environments indicate that poor-quality data can reduce model performance and create unreliable predictions (Carbery et al., 2019).

The results also indicate that hybrid analytical approaches provide greater reliability than purely data-driven methods. Physics-informed machine learning improves model robustness by incorporating engineering knowledge into computational models. This is particularly important for electric grid components where failure events are limited and operational decisions require high confidence.

Another significant finding is the importance of decision-support integration. Predictive accuracy alone does not guarantee improved reliability performance. Maintenance decisions require consideration of failure consequences, operational priorities, and economic constraints. Therefore, advanced analytics systems should function as decision-support platforms rather than isolated prediction tools.

The framework identifies several implementation challenges. Data scarcity remains a major limitation because critical grid failures occur infrequently. Additionally, cybersecurity risks, interoperability issues, and requirements for model transparency may influence practical adoption. Nevertheless, the findings indicate that advanced analytics provides a strong foundation for developing intelligent reliability management systems.

DISCUSSION

The findings demonstrate that advanced analytics represents a significant transformation in electric grid reliability management. Traditional maintenance strategies are gradually being replaced by intelligent approaches capable of adapting to real-time equipment conditions. The integration of machine learning and reliability engineering enables utilities to move from reactive failure management toward proactive risk reduction.

The theoretical contribution of this research is the positioning of advanced analytics as an integrated reliability framework rather than simply a predictive modeling approach. Previous research has demonstrated the effectiveness of machine learning for reliability applications; however, this study emphasizes the importance of combining predictive capability with engineering interpretation and decision-making processes.

The practical implications are substantial. Utilities can use advanced analytics to prioritize maintenance activities, reduce unnecessary inspections, and improve asset utilization. Predictive maintenance approaches can also support improved resource allocation by identifying components requiring immediate attention.

However, several limitations must be considered. Machine learning models may produce inaccurate predictions

when trained on incomplete or biased datasets. Furthermore, complex models may lack transparency, creating challenges for engineering acceptance. These limitations reinforce the importance of explainable and physics-informed analytical methods.

The comparison with existing literature shows strong alignment with previous findings. Xu and Saleh (2021) highlighted the opportunities and challenges of machine learning in reliability engineering, while Theissler et al. (2021) emphasized similar issues in predictive maintenance implementation. The present research extends these perspectives by focusing specifically on electric grid reliability improvement.

Philip (2025) further supports the potential of predictive maintenance in power systems by demonstrating that machine learning can improve fault prediction and maintenance effectiveness. However, successful implementation requires addressing organizational, technical, and operational barriers.

Overall, advanced analytics should be viewed as an enabling technology that enhances—not replaces—traditional reliability engineering expertise. The future of electric grid maintenance will likely depend on hybrid systems combining artificial intelligence, physical models, human expertise, and real-time operational intelligence.

CONCLUSION

The increasing complexity of electric power systems requires a fundamental transformation in reliability management approaches. Traditional maintenance strategies based primarily on fixed schedules and corrective actions are becoming insufficient for managing modern grid infrastructure characterized by interconnected assets, variable operating conditions, and increasing reliability expectations. This research examined the role of advanced analytics in improving the reliability of electric grid components by integrating machine learning, predictive maintenance, reliability engineering principles, and intelligent decision-support mechanisms.

The study established that advanced analytics provides significant opportunities for enhancing electric grid reliability through early fault detection, condition assessment, failure prediction, and optimized maintenance planning. The proposed analytical framework demonstrates that reliability improvement requires a systematic integration of multiple stages, including data acquisition, preprocessing, feature extraction, predictive modeling, risk assessment, and maintenance optimization. Each stage contributes to transforming raw operational information into actionable reliability intelligence.

A major contribution of this research is the identification of the importance of hybrid analytical approaches. Although machine learning algorithms provide powerful capabilities for

discovering complex patterns within operational data, their effectiveness in safety-critical infrastructure depends on integration with engineering knowledge. Physics-informed machine learning approaches provide a pathway for improving model reliability by incorporating physical degradation mechanisms and system constraints. This combination enables more trustworthy predictions, particularly in situations where historical failure data are limited.

The research also highlights that data quality represents a fundamental requirement for successful implementation. Electric grid components typically generate large amounts of operational information; however, incomplete datasets, inconsistent measurements, and limited failure examples can reduce analytical performance. Therefore, effective preprocessing, feature engineering, and continuous data management are essential elements of intelligent reliability systems.

Furthermore, the study emphasizes that predictive analytics should not be considered only as a fault prediction mechanism. Its broader value lies in supporting strategic maintenance decisions. Reliability improvement requires evaluating not only the probability of failure but also the consequences associated with asset malfunction. Decision-support systems that combine predictive outputs with risk assessment enable utilities to prioritize maintenance activities more effectively.

Despite its potential, several challenges remain. Implementation of advanced analytics in electric grids requires addressing issues related to cybersecurity, data interoperability, algorithm transparency, and organizational acceptance. Complex machine learning models may provide accurate predictions but still face resistance if engineers cannot understand or validate their recommendations. Future research should therefore focus on explainable artificial intelligence, hybrid physics-data models, and adaptive learning systems capable of continuously improving with operational experience.

The research contributes to the broader understanding of intelligent reliability management by demonstrating that advanced analytics can serve as a bridge between traditional reliability engineering and emerging digital technologies. The future electric grid will increasingly depend on analytical systems capable of monitoring asset health, predicting degradation, and supporting autonomous maintenance decisions. By integrating advanced analytics with engineering expertise, utilities can achieve improved reliability, reduced operational risks, and enhanced resilience of critical power infrastructure.

REFERENCES

1. S. Arena, E. Florian, I. Zennaro, P. F. Orrù, and F. Sgarbossa, "A novel decision support system for managing predictive maintenance strategies based on machine learning approaches," *Safety Science*, vol. 146, p. 105529, Feb. 2022, doi: 10.1016/j.ssci.2021.105529.
2. S. Ayvaz and K. Alpay, "Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time," *Expert Systems with Applications*, vol. 173, p. 114598, 2021.
3. "Bosch Production Line Performance." Accessed: Jul. 16, 2024. [Online]. Available: <https://kaggle.com/competitions/bosch-production-line-performance>
4. C. M. Carbery, R. Woods, and A. H. Marshall, "A new data analytics framework emphasising preprocessing of data to generate insights into complex manufacturing systems," *Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science*, vol. 233, no. 19–20, pp. 6713–6726, 2019.
5. A. Crespo Márquez, A. De La Fuente Carmona, J. A. Marcos, and J. Navarro, "Designing CBM Plans, Based on Predictive Analytics and Big Data Tools, for Train Wheel Bearings," *Computers in Industry*, vol. 122, p. 103292, Nov. 2020, doi: 10.1016/j.compind.2020.103292.
6. K. Johnson, E. Patelli, and C. Morais, "Natural language processing tool for identifying influencing factors in human reliability analysis and summarizing accident reports," 2023.
7. J. Lee, J. Ni, J. Singh, B. Jiang, M. Azamfar, and J. Feng, "Intelligent Maintenance Systems and Predictive Manufacturing," *Journal of Manufacturing Science and Engineering*, vol. 142, no. 11, p. 110805, Nov. 2020, doi: 10.1115/1.4047856.
8. J. Li, S. Zhang, J. Song, M. Li, L. Sun, and J. Wu, "Product Requirements Reliability Analysis Based on Review Data and Entropy Weight TOPSIS," in *Proceedings of the 2024 International Conference on Generative Artificial Intelligence and Information Security*, Kuala Lumpur Malaysia : ACM, May 2024, pp. 84–88. doi: 10.1145/3665348.3665364.
9. Philip, P. G. (2025). Predictive Maintenance Approach for Electric Power Systems Using Machine Learning. *The American Journal of Interdisciplinary Innovations and Research*, 7(09), 145–160. Retrieved from <https://theamericanjournals.com/index.php/tajir/article/view/ml-predictive-maintenance-power-systems>
10. K. Suzuki and S. Yokogawa, "Seven View Points and Reliability Engineering Scheme for Preventing

Reliability Problems,” *Int. J. Rel. Qual. Saf. Eng.*, vol. 27, no. 03, p. 2050006, Jun. 2020, doi: 10.1142/S0218539320500060.

11. A. Theissler, J. Pérez-Velázquez, M. Kettelgerdes, and G. Elger, “Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry,” *Reliability Engineering & System Safety*, vol. 215, p. 107864, Nov. 2021, doi: 10.1016/j.ress.2021.107864.
12. Y. Xu, S. Kohtz, J. Boakye, P. Gardoni, and P. Wang, “Physics-informed machine learning for reliability and systems safety applications: State of the art and challenges,” *Reliability Engineering & System Safety*, vol. 230, p. 108900, Feb. 2023, doi: 10.1016/j.ress.2022.108900.
13. Z. Xu and J. H. Saleh, “Machine learning for reliability engineering and safety applications: Review of current status and future opportunities,” *Reliability Engineering & System Safety*, vol. 211, p. 107530, Jul. 2021, doi: 10.1016/j.ress.2021.107530.
14. C. W. Zhang, R. Pan, and T. N. Goh, “Reliability assessment of high-Quality new products with data scarcity,” *International Journal of Production Research*, vol. 59, no. 14, pp. 4175–4187, Jul. 2021, doi: 10.1080/00207543.2020.1758355.