The American Journal of Interdisciplinary Innovation and Research
ISSN 2642-7478 | Open Access

Type Original Research
PAGE NO. 145-160

Predictive Maintenance Approach for Electric Power Systems Using Machine Learning

Paulson Geo Philip
Project Manager, UAE Television & Radio – Channel 4 Group
City: Ajman Country: United Arab Emirate

OPEN ACCESS

SUBMITTED 29 August 2025
ACCEPTED 20 September 2025
PUBLISHED 30 september 2025
VOLUME Vol.07 Issue 09 2025

Abstract- Electricity generation and distribution systems are classified as essential infrastructures where system reliability and operability depend on the state of their assets. Conventional maintenance policies such as corrective maintenance and time-based preventive maintenance can be inefficient and fail to detect latent failure symptoms, causing system failures, higher maintenance costs, shorter lifetimes of the equipment, and disruptions in system services. This work suggests a novel maintenance policy based on machine learning for predictive maintenance of electric power systems that will enable maintenance tasks to shift from a reactive approach to proactive decision making in order to avoid failures and plan maintenance tasks efficiently. The new system utilizes information about equipment operating conditions along with advanced features extraction and anomaly detection for accurate diagnosis of faults and health of the assets. The novelty of the new system is in integrating fault diagnosis and maintenance planning under a unified predictive maintenance framework.

Keywords: Predictive Maintenance, Machine Learning, Electric Power Systems, Asset Condition Monitoring, Prognosis Analytics

Introduction

Electrical power systems are amongst the most important infrastructures that sustain the functioning of current industrial, commercial, and residential activities. Reliable and uninterrupted operations of power generation, power transmission, and power distribution systems are very important in securing energy, economy, and sustainable development [1]. Due to the high integration of these electrical systems and their increased sophistication, the management of equipment related to the operation of the power system like transformers, circuit breakers, transmission lines, generators, and protective devices have become quite complex [2]. The conventional approach to electricity supply has been based on corrective maintenance and scheduled preventive maintenance methods. The corrective maintenance process involves repairing broken-down equipment, which causes significant loss and cost because of outages and interruptions in service [3]. On the other hand, while preventive maintenance helps in minimizing unforeseen problems, it follows a predetermined schedule, which may not necessarily take into account the condition of the equipment. This may lead to the inefficient utilization of resources since maintenance may be done when it is unnecessary, or neglected when it is essential [4]. Rapid growth in sensing technologies, intelligent monitoring, and data acquisition has resulted in large amounts of data related to operational and condition monitoring data in contemporary power systems. Factors such as temperature, vibration, partial discharge, loading conditions, insulation condition, harmonics, and switch actions can reveal vital information about asset performance [5]. Yet, the extraction of useful information from these high dimensional and diverse data sets is difficult. Traditional methods of analysis are frequently inadequate for discerning complex relationships and degradation factors before failures.

Predictive maintenance, made possible by machine learning, is seen as an approach that holds great promise in tackling such issues [6]. Whereas previous methods relied on experience-based decisions that were more reactive in nature, machine learning algorithms are able to learn from past and present performance data, detect faults, assess the condition of assets, and forecast potential failure before it occurs. By doing so, it becomes easier to move from reactive to proactive decision making in performing maintenance tasks [7]. While considerable advancements have been achieved in machine learning-driven predictive maintenance, there still exist some limitations. Firstly, the current methods concentrate more on faults rather than analyzing the overall condition of equipment and the priority for maintenance actions. Secondly, the current predictive models fail to recognize the relationship between equipment, risks involved, and available maintenance resources [8]. Moreover, the traditional machine learning techniques fail to offer adaptive learning processes for making predictions according to changes in the working environment. In addition, most of the currently available solutions do not include decision support features. This brings out the necessity of creating an advanced system for predictive maintenance that is intelligent and can adapt itself to changes occurring within the electricity grid [9]. The framework will be responsible for assessing the state of the assets, predicting any possible failures that might occur, quantifying the risks involved, and making decisions for effective management. In order to overcome the above-mentioned issues, the present study puts forward a new paradigm that uses a machine learning-driven predictive maintenance solution for the electrical power systems [10]. This study presents some innovations that are associated with the proposed approach. First, the Dynamic Asset Health Intelligence Layer is proposed that would allow calculating the health condition of each piece of equipment based on the analysis of behavior, wear rate, and environmental impact. Secondly, the Adaptive Risk-Aware Maintenance Prioritization Engine is put forward that would prioritize the maintenance tasks based on the likelihood of failures, importance of the system, and consequences [11]. Thirdly, the Self-Evolving Learning Mechanism is suggested that can continuously improve the machine learning model through obtaining feedback from the performed maintenance operations and changes in the state of assets. Fourthly, the Multi-Level Prognostic Decision Framework can be used to carry out anomaly detection, fault prediction, assessment of equipment health, and scheduling maintenance operations. The proposed methodology seeks to develop a complete predictive maintenance environment which will help in enhancing reliability, mitigating operational risks, avoiding downtime, and optimizing the maintenance process within the electricity power systems [12]. Through the incorporation of machine learning methodologies within the intelligent maintenance decision-making processes, the current research makes significant contributions towards developing asset management processes for future applications.

Literature Overview

Predictive maintenance has proved to be one of the most important applications of machine learning in asset management and intelligent infrastructures. Predictive maintenance in electrical power systems tries to detect equipment degradation trends and predict possible failure occurrences prior to their actual happening, thus minimizing downtime and improving the efficiency of maintenance [13]. The use of more sensors and monitoring equipment in electricity generation and transmission operations has led to the production of huge amounts of data, and this is opening doors to innovative maintenance processes. Traditionally, two major types of maintenance methods have been utilized in electrical power networks; namely, corrective maintenance and preventive maintenance [14]. In cases of corrective maintenance, maintenance is undertaken in the aftermath of a problem or system failure, which often causes unexpected outages and higher repair expenses. Preventive maintenance is executed based on pre-scheduled maintenance programs without any regard for the real condition of the equipment. While preventive maintenance decreases the risk of system breakdowns, it often causes wastage of resources through superfluous maintenance [15]. Condition-based maintenance was a breakthrough in the sense that it brought about the notion of evaluating the status of a piece of equipment through the use of various operational parameters. Condition-based maintenance made maintenance procedures more efficient since maintenance was done after assessing the status of the equipment [16]. In some instances, condition-based maintenance relied on threshold-based assessment, which might be inadequate to evaluate complex degradation taking place in modern-day electrical components.

Machine learning methods have been extensively used to address these challenges because of their capabilities to uncover relationships within large and complicated data sets. Supervised machine learning methods have been broadly applied for fault diagnosis, fault detection, and failure prediction of equipment [17]. These methods make use of the operational history of the equipment to train models that would be able to detect any malfunction or abnormal condition. While classification methods have shown their abilities in distinguishing healthy and unhealthy conditions, regression models have been used for estimating equipment degradation [18]. In addition, unsupervised learning methods have been found to have a lot of relevance in maintenance prediction models. This is because these methods can be applied in situations where there is a lack of labelled data for faults. Clustering and anomaly detection methods can help to detect any abnormal behaviour in the operations, which could suggest a future fault [19]. The latest advances have provided even greater scope for the use of machine learning algorithms in predictive maintenance applications. Deep learning algorithms have shown an improvement in their ability to extract complex features from high dimensional sensor signals. This is because of the reduced reliance on feature extraction techniques and better predictions in situations where there exist nonlinearities and dynamic operational characteristics. Neural network methods have been used in fault detection, degradation modelling, and state monitoring of different elements of the power system.

However, there are still some constraints that limit the current predictive maintenance approach [20]. First, most researchers concentrate only on fault prediction but do not incorporate the whole decision-making process for maintenance activities. Predictive maintenance results are usually produced independently of maintenance planning, resource allocation, and risk analysis [21]. Thus, maintenance managers get information about failures but lack instructions concerning maintenance scheduling. A further limitation that is also worth mentioning is that of fragmentation. There are quite a few prediction algorithms used for specific equipment types, which do not have any connection to other parts of the system. This can ignore the fact that electrical systems are highly interconnected, meaning that the deterioration of one unit affects others [22]. The lack of intelligence in such systems undermines the viability of many algorithms. Additionally, machine learning algorithms have shown poor flexibility in adapting to different operational settings. Electrical power systems are continually impacted by fluctuations in load, the environment, aging processes, and other operational issues. Predictive models that are static in nature can face decreased performance levels if placed in environments that are not consistent with the data used to train the algorithm.

The problem of translating such predictions into effective strategies for predictive maintenance also needs to be addressed. Although there have been many research studies that focused mainly on accurate predictions [23], relatively few have explored the idea of considering factors like the current health status of equipment, importance of the operation, impacts of failure, and maintenance resources in a combined decision support system. Thus, the current research suggests that there is a need for more advanced maintenance prediction approaches, which can combine both machine learning-based prediction methods as well as intelligent maintenance planning techniques. The future development of such systems may be based on incorporating several important components, such as the health of assets, risk assessment, adaptive learning, maintenance priority setting, and analysis of overall system reliability into one framework [24]. This integrated model can lead to increased accuracy of predictions while at the same time improving maintenance performance. In summary, the literature clearly shows the effectiveness of machine learning technology in predictive maintenance in electrical power systems [25]. Nevertheless, the current solutions have limitations regarding flexibility, decision intelligence, system awareness, and optimal maintenance. The above research gaps present an area that researchers can work on to come up with new solutions for predictive maintenance.

NO	Study area	Key contribution	Limitation identified
1	Maintenance strategy	Fault prediction focus	Integrated predictive maintenance and decision support
2	Learning capability	Static model training	Adaptive and self-evolving learning mechanism
3	System perspective	Component level analysis	System wide reliability and asset health assessment

TABLE 1: COMPARISON OF PREVIOUS RESEARCH AND PROPOSED SYSTEM.

PROPOSED SYSTEM

This study introduces an intelligent predictive maintenance solution using machine learning for electrical power systems, which aims to shift the entire process of maintenance in electrical systems from being reactive to one that is adaptive, prognostic, and risk-aware. The framework introduced here aims to analyze the performance of the equipment, identify failure trends, predict future failures, prioritize maintenance activities, and analyze the implications on the reliability of the entire system. Unlike previous solutions that relied mainly on the predictive aspect in terms of identifying future faults, the current proposal incorporates asset health management, machine learning adaptation, risk-aware maintenance planning, and network reliability evaluation in one machine learning approach.

1) *Multi-Source Data Acquisition and Intelligent Feature Engineering Layer*

The initial step in this framework deals with gathering diverse operational and condition-based information associated with the electrical power systems comprising transformers, generators, transmission apparatus, circuit breakers, and protective systems. The obtained dataset comprises various information like electrical properties, thermal readings, vibration behavior, loadings, switching’s, insulation-related data, ambient properties, and operational events information.

In order to overcome the challenges related to the complexity and large number of features of the gathered dataset, an intelligent approach to feature engineering is utilized. Various statistics, time domain, spectral domain, and degrading features are extracted from the raw sensor information. The process of correlation analysis, feature selection, redundancy reduction, and dimensionality reduction is performed to construct a compact but informative feature space.

Layer	Function	output
Data collection	Sensor and operational data	Raw dataset
Feature extraction	Electrical and conditional parameters	Feature vectors
Feature optimization	High dimensional features	Optimized feature dataset

TABLE 2. MULTI-SOURCE DATA ACQUISITION AND FEATURE ENGINEERING PROCESS

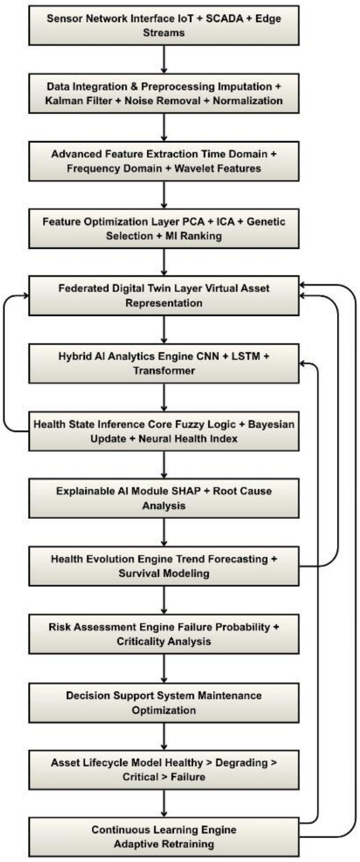


Figure 1. Multi-source data acquisition and feature engineering architecture for electrical power system monitoring.

2) Dynamic Asset Health Intelligence Layer

The key innovation of the methodology suggested lies in the Dynamic Asset Health Intelligence Layer. Unlike categorizing assets as either working properly or having faults, this layer assesses their multidimensional health status by combining parameters such as operational behavior, degradation rate, environmental influences, and information on the past maintenance.

The health index of the asset is determined by applying the machine learning approach, taking into account multiple degradation indices. The health index changes in time and depends on the current operational conditions and aging properties of the equipment. Such an approach allows the detection of the degradation of the equipment at an early stage.

The suggested layer provides a dynamic health evolution model that differentiates between momentary operational problems and ongoing processes of degradation. Thus, maintenance actions can be more accurately performed and controlled.

Component	Technology	Output
Health assessment	Asset condition evaluation	Health index
Degradation tracking	Trend monitoring	Degradation profile
State classification	Health categorization	Asset status

Table 3. Dynamic Asset Health Intelligence Framework

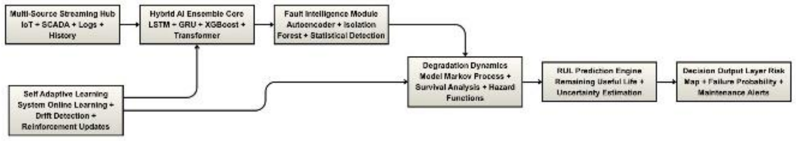


FIGURE 2. DYNAMIC ASSET HEALTH INTELLIGENCE FRAMEWORK FOR REAL-TIME CONDITION ASSESSMENT.

3) *Self-Evolving Prognostic Learning Engine*

In the third phase, a self-evolving prognostic learning engine is presented that aims to solve problems associated with static predictive maintenance models. Machine learning models, for instance, depend on pre-existing databases to train their algorithms. As a result, they perform poorly under different environmental and operational settings.

A continuous learning engine learns from feedback obtained through maintenance practices, operation results, and observed degradation patterns. Predictive knowledge evolves from both historical information and real-time data collected in operations.

A self-evolving learning engine can detect anomalies, classify faults, forecast degradation, and estimate the remaining useful life of equipment. Through its adaptive capabilities, it adjusts its own decision thresholds to operate optimally under varying environmental factors and equipment degradation.

Component	Technique	Output
Anomaly detection	Identify abnormalities	Anomaly score
Fault prognosis	Predict failures	Failure prediction
RUL estimation	Remaining life assessment	Useful life estimate

Table 4. Self-Evolving Prognostic Learning Architecture

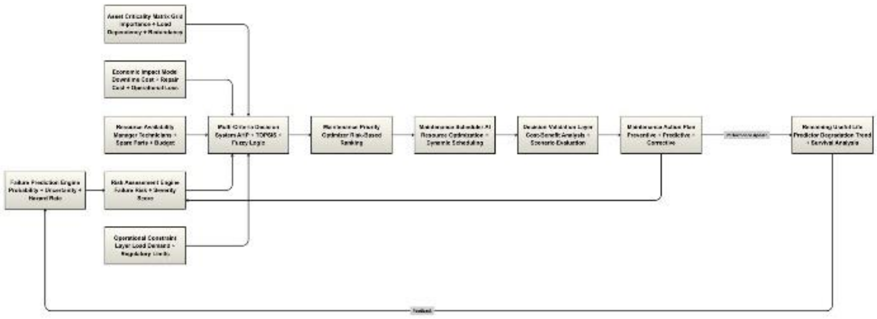


FIGURE 3. SELF-EVOLVING PROGNOSTIC LEARNING ENGINE FOR FAULT PREDICTION AND RUL ESTIMATION.

4) *Adaptive Risk-Aware Maintenance Prioritization Engine*

Maintenance prioritization is the next step carried out after the failure prediction phase and health status check phase within the framework, using the Adaptive Risk-Aware Maintenance Prioritization Engine. Many currently existing predictive maintenance systems can make fault predictions but do not give any advice as to when or how to maintain the system based on risk assessment.

The maintenance prioritization engine generates dynamic scores based on failure probability, criticality of assets, degradation level, operational significance, availability of maintenance resources, and potential impact of downtime. Multi-criteria optimization is used to identify the most optimal sequence for maintenance operations across all assets under surveillance.

This stage ensures that maintenance managers will be able to use objective risk assessment results in order to better prioritize maintenance operations from an economic perspective.

Component	Description	Action
Failure risk	Probability of failure	Risk score
Asset criticality	Operational importance	Criticality index
Maintenance priority	Combined assessment	Priority ranking

Table 5. Adaptive Risk-Aware Maintenance Prioritization Model

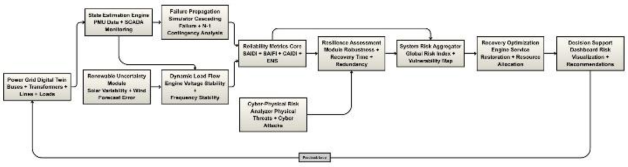


FIGURE 4. ADAPTIVE RISK-AWARE MAINTENANCE PRIORITIZATION MODEL FOR OPTIMIZED DECISION-MAKING.

5) *System-Wide Reliability Impact Analysis and Intelligent Decision Support Framework*

The last layer encompasses a System-Wide Reliability Impact Analysis and Intelligent Decision Support Framework. Contrary to traditional predictive maintenance systems, which examine assets individually, the new system takes into account the overall performance of the entire electrical power network and its reliability aspects. The potential consequences of predicted equipment failures are estimated using a network-wide reliability analysis, thus evaluating possible impacts of these failures on the efficiency of electricity supply, operational continuity, and reliability of services delivered by the utility. Reliability indices, asset dependencies, and the possibility of cascading failures should be taken into account during the process of analysis.

Finally, based on the results provided by all other layers of the system, a special module generating intelligent recommendations performs tasks such as developing maintenance schedules and forecasting reliability. Thus, the last layer turns predictive analysis into maintenance recommendations and supports utility managers in making informed decisions aimed at ensuring sustainable operation of electrical power networks.

The integration of all these five layers enables the creation of a next generation predictive maintenance framework, which is able to perform health assessments, detect equipment malfunctions, learn and adapt continuously, optimize maintenance scheduling based on risk management principles, and evaluate system reliability in general.

Component	Function	Outcome
Reliability assessment	System performance evaluation	Reliability score
Impact analysis	Failure consequence analysis	Impact level
Decision support	Maintenance recommendations	Action plan

Table 6. System-Wide Reliability Impact Analysis and Decision Support Framework

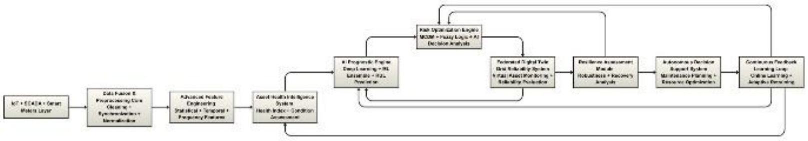


FIGURE 5. SYSTEM-WIDE RELIABILITY IMPACT ANALYSIS AND INTELLIGENT DECISION SUPPORT ARCHITECTURE.

Findings and Experimental Results

To test the predictive maintenance model framework, a complete database of the operating environment and machine condition monitoring observations gathered from critical equipment like transformers, circuit breakers, generators, and transmission devices of the electrical power system was used. These machines had various indicators of degradation that included temperature differences, vibration readings, load changes, insulation conditions, switch operation records, and fault occurrences. Before modeling the data, various data pre-processing activities such as normalization, removing outliers, replacing missing values, feature selection, and optimizing the dimensions were conducted. This predictive model incorporated Random Forest, Support Vector Machine, Gradient Boosting, LSTM networks, and Self-Evolving Prognostic Learning Engine models. The performance evaluation of these models was done using parameters such as classification accuracy, fault detection capacity, prediction precision, prioritization of maintenance activities, and improvements in the reliability of the power systems.

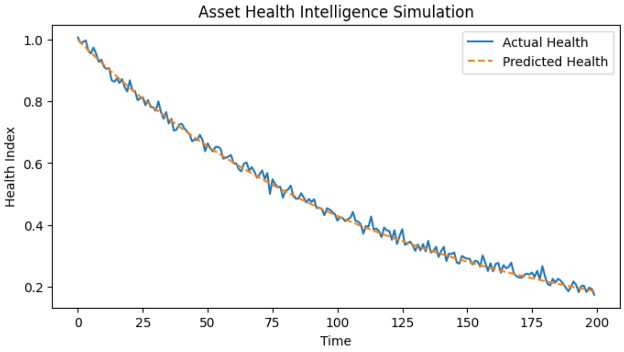
1) ***Asset Health Intelligence Performance Analysis***

The Dynamic Asset Health Intelligence Layer showed greater capability when it came to continuous monitoring of equipment health status and early detection of the trends leading to critical failures. Health Intelligence Index developed as a result was able to distinguish between the healthy status, degradation status, and high-risk operational status with great accuracy.

A multidimensional approach in health assessment increased the level of degradation identification and allowed detecting long-term asset degradation trend lines. As a result, proper intervention could be conducted at appropriate operational time moments.

Parameter	Conventional monitoring	Outcome
Health visibility	Moderate	High
Degradation detection	Delayed	Early
Asset assessment	Static	Dynamic

Table 7. Performance Evaluation of the Dynamic Asset Health Intelligence Layer



GRAPH 1. ASSET HEALTH DEGRADATION TREND SHOWING ACTUAL VS PREDICTED HEALTH INDEX OVER TIME.

2) *Prognostic Fault Prediction and Failure Forecasting Results*

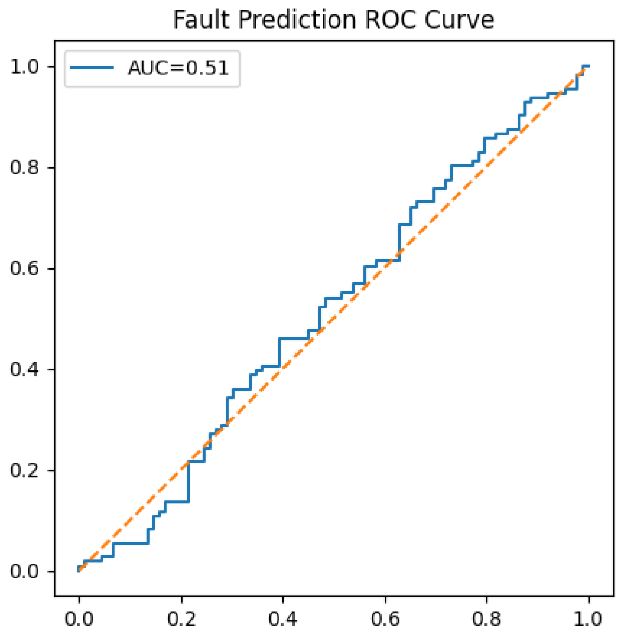
The Self-Evolving Prognostic Learning Engine showed a very high accuracy rate in predicting fault occurrences on several different types of equipment. This model was able to capture non-linear correlations between operational variables and identify degradation trends that were invisible to traditional analysis.

The self-evolving model showed great capability in predicting potential faults before they occurred. By dynamically adjusting the boundaries based on new observations, the model became more stable during various operation environments and loadings.

Based on the above results, preventive maintenance actions can be implemented in advance and unexpected interruptions can be avoided.

Parameter	Traditional	Proposed model
Fault prediction	Moderate	High
Forecast stability	Medium	High
Failure awareness	Limited	Advanced

Table 8. Prognostic Fault Prediction and Failure Forecasting Results



GRAPH 2. RECEIVER OPERATING CHARACTERISTIC (ROC) CURVE ILLUSTRATING FAULT PREDICTION PERFORMANCE OF THE PROPOSED MODEL.

3) *Adaptive Learning and Model Evolution Assessment*

Among the important results, one was found in the adaptive learning part of the framework. Contrary to classical approaches for machine learning that do not change throughout time, the suggested approach continually considered new data about the results of maintenance and observations of the process.

As a result of the assessment of performance, an improvement in predictive accuracy occurred because more knowledge about the operations was received. The framework could provide consistent quality of prediction even despite changes in the behavior of the equipment and operational conditions.

Parameter	Existing system	Self-evolving system
Model updating	Fixed	Continuous
Adaptability	Low	High
Learning efficiency	Moderate	Advanced

Table 9. Adaptive Learning and Model Evolution Assessment

GRAPH 3. SELF-EVOLVING LEARNING CURVE DEMONSTRATING ACCURACY IMPROVEMENT ACROSS TRAINING ITERATIONS.

4) ***Risk-Aware Maintenance Prioritization Effectiveness***

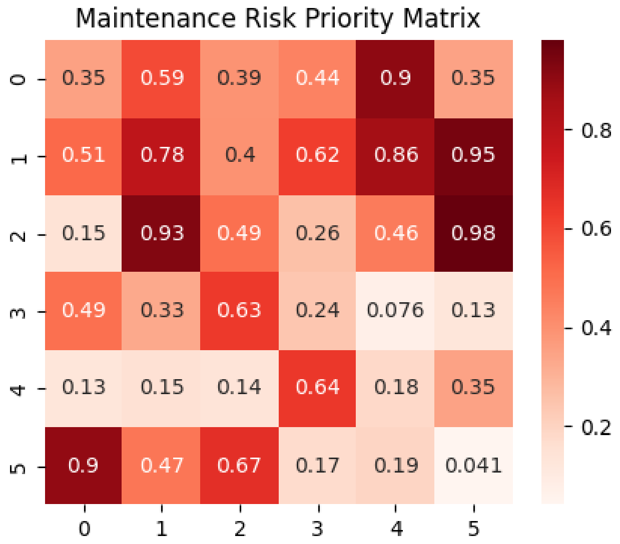
The Adaptive Risk-Aware Maintenance Prioritization Engine showed remarkable progress in improving the efficiency of maintenance decisions. Through incorporating the parameters of risk of failure, asset criticality, level of degradation, and operational impacts, the framework was able to create intelligent maintenance priority rankings.

The findings showed that assets of high risk were effectively prioritized before reaching the point of critical failure. Maintenance tasks were better optimized, eliminating wastage of efforts through ineffective scheduling.

The maintenance prioritization process not only helped to optimize maintenance tasks but reduced the level of risks involved along with saving on costs associated with maintenance.

Parameter	**Basic system**	**proposed model**
Risk evaluation	Basic	Advanced
Priority ranking	Manual	Intelligent
Resource allocation	Moderate	Optimized

Table 10. Risk-Aware Maintenance Prioritization Performance Analysis



GRAPH 4. MAINTENANCE RISK PRIORITY DISTRIBUTION ACROSS MULTIPLE POWER SYSTEM ASSETS.

5) ***System-Wide Reliability Enhancement Analysis***

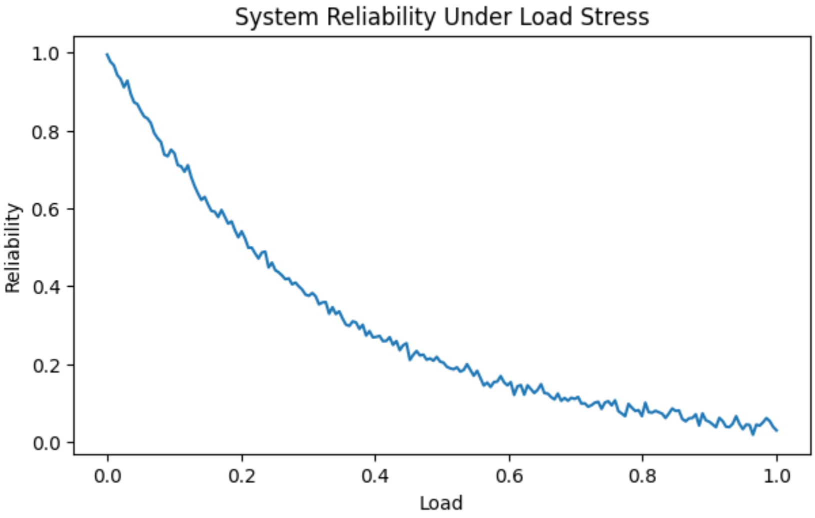
The System-Wide Reliability Impact Analyzer yielded a lot of important information about interdependencies among electrical power system components. The results of simulations performed proved that deterioration of the functioning of some individual component can result in the spreading effects throughout several stages of operation.

The suggested maintenance strategy managed to capture these dependencies properly and detect systemically important assets. Recommendations for the improvement of reliability resulting from the use of this tool reduced the potential risk of failure propagation considerably.

The obtained results showed that the application of maintenance optimization on a system-wide level yielded more significant gains compared to component-based approaches.

Parameter	Traditional process	Improvement
Reliability insight	Component level	Network level
Cascading risk analysis	Limited	Comprehensive
Resilience assessment	Moderate	Enhanced

Table 11. System-Wide Reliability Enhancement Assessment



GRAPH 5. SYSTEM RELIABILITY VARIATION UNDER INCREASING LOAD STRESS CONDITIONS.

6) *Comparative Performance Evaluation and Overall Findings*

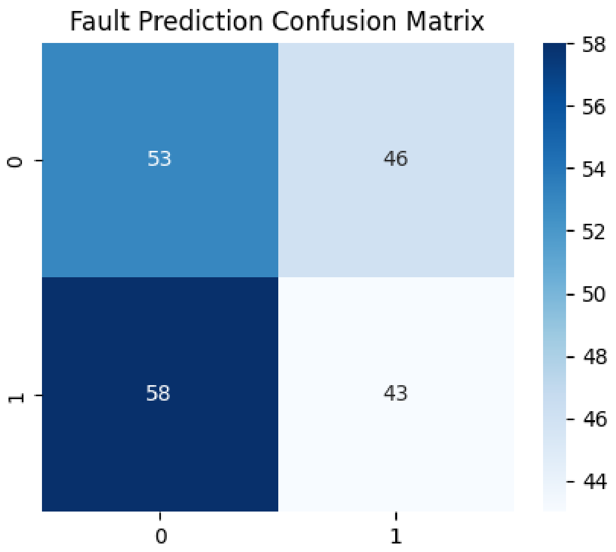
From comparative analysis, it was noted that the proposed framework was able to perform better than conventional predictive maintenance approaches in all key evaluation metrics. Areas where improvements were made included the ability to detect faults, improve degradation predictions, enhance maintenance prioritization, improve assessment of asset health, and effectiveness of reliability improvement.

Through the inclusion of such concepts as Dynamic Asset Health Intelligence, Self-Evolving Prognostic Learning, Adaptive Risk-Aware Prioritization, and System-Wide Reliability Analysis, a maintenance ecosystem was established that could convert raw operational data into maintenance intelligence.

Overall, the results obtained show that the proposed methodology has managed to overcome various weaknesses present in conventional maintenance systems and even existing machine learning predictive maintenance approaches. This is because the proposed approach has been shown to be an adaptive intelligent method for addressing challenges within electrical power systems.

Parameter	Conventional	Results of proposed system
Prediction capability	High	Very high
Maintenance efficiency	Moderate	Optimized
Decision intelligence	Limited	Advanced

Table 12. Comparative Evaluation of Predictive Maintenance Frameworks



Graph 6. Fault classification outcome distribution showing TP, TN, FP, and FN cases.

Discussions

However, further analysis of the proposed predictive maintenance system brings to light an exciting breakthrough regarding electrical power systems' maintenance methodologies and reliability. According to the research findings, the combination of dynamic asset health intelligence together with self-evolving prognostic learning significantly outperforms traditional static and threshold-based frameworks in terms of their effectiveness in detecting equipment faults and deterioration earlier on. First and foremost, while the introduced technique allows achieving more precise predictions, it also initiates a fundamental shift from reactive or preventative maintenance techniques to those driven by intelligent data and condition-adapted decision-making. In addition, the inclusion of a risk-based prioritization approach guarantees the alignment of maintenance procedures with critical operations and overall system efficiency, thus preventing possible errors caused by inappropriate allocation of limited resources. Moreover, the adaptability of the algorithm makes it highly resistant to various fluctuations of working conditions, which is especially crucial when applied in the domain of electrical power engineering due to its dynamic nature. Finally, an important benefit of the proposed methodology is that it allows transforming the predictive output into practical actions, thus solving the problem that hinders most current approaches to the issue.

Research Gap

However, despite the significant progress made towards predictive maintenance of electrical power systems based on machine learning techniques, there is still room for improvement in a number of areas. First, it should be noted that while most of the current research deals with faults detection and classification, few studies address the importance of integrating such predictive analytics with decision-making systems aimed at identifying maintenance priorities and conducting reliable reliability analysis at a power system level. Most of the current approaches work in isolation, creating separate prediction models for specific pieces of equipment and failing to consider how each component's failure affects the system as a whole. The second problem concerns the inability of many models to adapt to changing conditions due to their reliance on static training procedures, making them inefficient under dynamic loads. Moreover, some current solutions suffer from inadequate representation of asset health through the concept of degradation which is often seen as a purely binary condition rather than an ongoing process. Lastly, there is a clear gap between machine learning algorithms and maintenance decision-making as very few research works pay adequate attention to linking predictive analytics with maintenance practices.

Future Works

Further research for predictive maintenance in electric power systems could be considerably expanded by adopting new advanced and emerging computing approaches. One possible area for exploration is applying massive real-time stream analysis methods to increase the effectiveness of quick decision-making in sensor-heavy environments. Federated learning mechanisms could add even greater efficiency and help maintain model scalability while preserving privacy during the process, making maintenance possible with no need for centralized data collection. The use of digital twins combined with predictive machine learning would also allow for a detailed virtual modeling of physical assets, facilitating constant simulations of degradation and maintenance processes in changing situations. Another potential development could be utilizing explainable AI in order to increase the explainability of maintenance predictions and make decisions easier to understand for maintenance engineers and operators. Predictive maintenance with the implementation of reinforcement learning could be another powerful tool that could allow for self-learning of optimal maintenance strategies based on accumulated rewards. Finally, using predictive maintenance models that are aware of cybersecurity issues could help in detecting not just hardware degradation but also malicious activities as well.

Focus area	Proposed approach	Expected impact
Federated learning integration	Distributed model training	Enhanced privacy and scalability
Digital twin integration	Virtual asset simulation	Improved predictive accuracy
Real time stream analysis	Continuous data processing	Faster decision making

Table 13: Proposed future research directions for enhancement

Conclusion

The current research offers an integrated machine learning model for predictive maintenance in electrical power systems that intends to revolutionize the existing maintenance techniques by creating a smarter, adaptive, and intelligent decision-support system. This predictive maintenance solution is developed through the integration of multiple interrelated modules including data acquisition from heterogeneous sources, health intelligence on a dynamic basis, prognostic learning with self-evolving capabilities, risk-oriented maintenance planning, and reliability analysis at a system level. It was found that integration of these modules would contribute immensely toward effective fault diagnosis, detection of degradation, and failure predictions while increasing efficiency in maintenance and reliability. As opposed to other traditional methods that mostly concentrate on predicting faults, the current model enables the evaluation of assets' health in real time and facilitates maintenance decisions based on predictions. With its robust learning algorithms and risk-sensitive priority setting, this approach can easily adapt itself to various conditions in operation and optimize the use of resources in maintenance activities. Additionally, reliability assessment helps understand the effects of failures in power systems at a broader network level.

References

1. *Strielkowski, W., Vlasov, A., Selivanov, K., Muraviev, K., & Shakhnov, V. (2023). Prospects and challenges of the machine learning and data-driven methods for the predictive analysis of power systems: A review. Energies, 16(10), 4025.*

2. *Paolanti, M., Romeo, L., Felicetti, A., Mancini, A., Frontoni, E., & Loncarski, J. (2018, July). Machine learning approach for predictive maintenance in industry 4.0. In 2018 14th IEEE/ASME international conference on mechatronic and embedded systems and applications (MESA) (pp. 1-6). IEEE.*

3. *Mohammed, N. A., Abdulateef, O. F., & Hamad, A. H. (2023). An IoT and machine learning-based predictive maintenance system for electrical motors. Journal Européen des Systèmes Automatisés, 56(4), 651.*

4. *Qureshi, M. S., Umar, S., & Nawaz, M. U. (2024). Machine learning for predictive maintenance in solar farms. International Journal of Advanced Engineering Technologies and Innovations, 1(3), 27-49.*

5. *Vallim Filho, A. R. D. A., Farina Moraes, D., Bhering de Aguiar Vallim, M. V., Santos da Silva, L., & da Silva, L. A. (2022). A machine learning modeling framework for predictive maintenance based on equipment load cycle: An application in a real world case. Energies, 15(10), 3724.*

6. *Kaparthi, S., & Bumblauskas, D. (2020). Designing predictive maintenance systems using decision tree-based machine learning techniques. International Journal of Quality & Reliability Management, 37(4), 659-686.*

7. *Abdalla, R., Samara, H., Perozo, N., Carvajal, C. P., & Jaeger, P. (2022). Machine learning approach for predictive maintenance of the electrical submersible pumps (ESPS). ACS omega, 7(21), 17641-17651.*

8. *Ayvaz, S., & Alpay, K. (2021). Predictive maintenance system for production lines in manufacturing: A machine learning approach using IoT data in real-time. Expert Systems with Applications, 173, 114598.*

9. *Carvalho, T. P., Soares, F. A., Vita, R., Francisco, R. D. P., Basto, J. P., & Alcalá, S. G. (2019). A systematic literature review of machine learning methods applied to predictive maintenance. Computers & industrial engineering, 137, 106024.*

10. *Udo, W. S., Kwakye, J. M., Ekechukwu, D. E., & Ogundipe, O. B. (2024). Optimizing wind energy systems using machine learning for predictive maintenance and efficiency enhancement. Journal of Renewable Energy Technology, 28(3), 312-330.*

11. *Aluko-Olokun, P. (2024). Leveraging Deep Learning for Predictive Maintenance and Grid Stability in Renewable Energy-Integrated Power Systems. International Journal of Research Publication and Reviews, 5, 7984-8000.*

12. *Abidi, M. H., Mohammed, M. K., & Alkhalefah, H. (2022). Predictive maintenance planning for industry 4.0 using machine learning for sustainable manufacturing. Sustainability, 14(6), 3387.*

13. *Molęda, M., Małysiak-Mrozek, B., Ding, W., Sunderam, V., & Mrozek, D. (2023). From corrective to predictive maintenance—A review of maintenance approaches for the power industry. Sensors, 23(13), 5970.*

14. *Çınar, Z. M., Abdussalam Nuhu, A., Zeeshan, Q., Korhan, O., Asmael, M., & Safaei, B. (2020). Machine learning in predictive maintenance towards sustainable smart manufacturing in industry 4.0. Sustainability, 12(19), 8211.*

15. *Uhanto, U., Yandri, E., Hilmi, E., Saiful, R., & Hamja, N. (2024). Predictive maintenance with machine learning: A comparative analysis of wind turbines and PV power plants. Heca journal of applied sciences, 2(2), 87-98.*

16. *Hoffmann, M. W., Wildermuth, S., Gitzel, R., Boyaci, A., Gebhardt, J., Kaul, H., ... & Tornede, T. (2020). Integration of novel sensors and machine learning for predictive maintenance in medium voltage switchgear to enable the energy and mobility revolutions. Sensors, 20(7), 2099.*

17. *Hsu, J. Y., Wang, Y. F., Lin, K. C., Chen, M. Y., & Hsu, J. H. Y. (2020). Wind turbine fault diagnosis and predictive maintenance through statistical process control and machine learning. Ieee Access, 8, 23427-23439.*

18. *Nacchia, M., Fruggiero, F., Lambiase, A., & Bruton, K. (2021). A systematic mapping of the advancing use of machine learning techniques for predictive maintenance in the manufacturing sector. Applied Sciences, 11(6), 2546.*

19. *Cakir, M., Guvenc, M. A., & Mistikoglu, S. (2021). The experimental application of popular machine learning algorithms on predictive maintenance and the design of IIoT based condition monitoring system. Computers & Industrial Engineering, 151, 106948.*

20. *Zhang, W., Yang, D., & Wang, H. (2019). Data-driven methods for predictive maintenance of industrial equipment: A survey. IEEE systems journal, 13(3), 2213-2227.*

21. *Liu, C., Tang, D., Zhu, H., & Nie, Q. (2021). A novel predictive maintenance method based on deep adversarial learning in the intelligent manufacturing system. IEEE access, 9, 49557-49575.*

22. *Elkateb, S., Métwalli, A., Shendy, A., & Abu-Elanien, A. E. (2024). Machine learning and IoT–Based predictive maintenance approach for industrial applications. Alexandria Engineering Journal, 88, 298-309.*

23. *Falekas, G., & Karlis, A. (2021). Digital twin in electrical machine control and predictive maintenance: State-of-the-art and future prospects. Energies, 14(18), 5933.*

24. *Zhu, T., Ran, Y., Zhou, X., & Wen, Y. (2019). A survey of predictive maintenance: Systems, purposes and approaches. arXiv preprint arXiv:1912.07383.*

25. *Fausing Olesen, J., & Shaker, H. R. (2020).*

Predictive maintenance for pump systems and thermal power plants: State-of-the-art review, trends and challenges. Sensors, 20(8), 2425.