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Original Article

Machine Learning for Predictive Power Quality Maintenance in Modern Power Grids

S. Parthiban[1,*], N R Govinthasamy[2], Venkatesh Kumar S[3], S D Vijayakumar[4]

[1]*Department of ECE, Nandha College of Technology, Erode, Tamil Nadu, India.*
[2,3]*Department of Electrical and Electronics Engineering, Dr. N.G.P. Institute of Technology, Coimbatore, Tamil Nadu, India.*
[4]*Department of AIDS, Nandha Engineering College, Erode, Tamil Nadu, India.*

[*]*Corresponding Author : jssnavi.37@gmail.com*

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Abstract - *The challenge of ensuring good quality of power in contemporary smart grids has become more complicated with the erratic nature of renewable sources, nonlinear loads, and the changing trend of demand. It discusses a machine learning-based predictive power quality maintenance framework that incorporates a hybrid Long Short-Term Memory (LSTM) and Random Forest (RF) model. The system compares voltage, current, and harmonic data to forecast faults before they occur. The model proposed had a prediction accuracy of 98.3%, a Mean Absolute Percentage Error (MAPE) of 1.84%, and a Root Mean Square Error (RMSE) of 0.042 kV, which was better than the traditional approaches. Moreover, it minimized the maintenance expenses by 31.6% and increased grid reliability by 28.9%. The model was confirmed to be able to carry out real-time analysis and decision support using simulation on MATLAB. These findings indicate that predictive maintenance based on Machine Learning can be used to improve the efficiency of operations, reduce downtime, and improve the resilience of modern power grids*.

Keywords - *Long Short-Term Memory, Power Quality, Mean Absolute Percentage Error, Root Mean Square Error, Phasor Measurement Unit, Particle Swarm Optimization*.

1. Introduction

Modernization of electrical power systems has changed the old centralized grid to an interconnected, data-based, and intelligent infrastructure, called the smart grid. As renewable energy sources, electric vehicles, distributed generators, and dynamic loads rapidly become integrated, the challenge of ensuring consistent Power Quality (PQ) has become one of the most important ones to grid operators. The problem of power quality could cause serious operational inefficiencies, equipment degradation, and financial losses due to voltage sags, frequency deviation, harmonic distortions, and transient surges. Modern power networks have become dynamic, making it challenging to ensure reliability through traditional maintenance and diagnostic processes that have been highly successful in static grid setups. Traditional power quality surveillance and maintenance systems rely heavily on periodic monitoring schedules, manual analysis, and threshold-based alarms. Such approaches are by definition reactive and may not be able to predict or prevent possible faults before they happen. Besides, as the number of grid-connected devices and sensors is growing exponentially, the amount of PQ data has grown enormously, requiring automated analytical solutions to be able to identify the intricate patterns in real-time. Previously analyzed papers have tried to employ statistical signal processing and rule-based expert systems in the analysis of PQ, with such models failing to accommodate nonlinearities, multivariate relationships, and changing operational conditions. It therefore could not provide realistic predictions of faults, especially in situations where power disturbance has high time variability. The rationale of this work is that there is a need to have a more innovative, self-educating, and predictive maintenance methodology that is capable of adjusting to the dynamics of smart grids in the present day. Machine Learning (ML) provides the computational intelligence that is needed to detect, label, and forecast PQ disturbances through learning the vast amounts of historical and real-time signals. ML systems can identify failures in time to produce significant disturbances by training models to identify concealed correlations between voltage, current, frequency, and harmonic distortion parameters. ML-powered predictive maintenance can not only decrease downtimes and operational expenses, but also make grids reliable and efficient in energy usage. A hybrid of time models like Long Short-Term Memory (LSTM) and non-linear fault models like the Random Forest (RF) can be used to learn sequential and non-linear fault patterns to become a potent predictive model.

The primary goals will be to build an enhanced Machine Learning predictor of power quality maintenance, mathematically model PQ disturbances to be able to forecast them accurately, and to test the performance of the model on real-time simulation. In particular, the LSTM-RF hybrid model is expected to be used to reduce the prediction error, false alarms, and optimize maintenance scheduling. The results of the simulation were that the fault prediction error was 98.3%, the Mean Absolute Percentage Error (MAPE) was 1.84%, and the root mean square error was 0.042 kV, which is much higher than the traditional methods. Furthermore, the proposed model minimized the total maintenance expenses by 31.6%, which is an important characteristic of this model for grid operators and energy distributors. These three elements are combined: first, the new hybrid model of temporal learning and ensemble classification is proposed to forecast PQ; second, a mathematical optimization framework is suggested to make maintenance choices; and third, the model is applied and tested with real-life PQ data and simulated conditions to make the model robust and scalable. The proposed system shows that predictive maintenance can be shifted towards reactive fault management to proactive grid intelligence. The remainder of this paper will be structured as follows. Section II illustrates the review of the available research and the shortfalls of existing PQ maintenance strategies. Section III provides the description of the proposed hybrid machine learning model with mathematical equations and predictive formulations, and the description of the dataset characteristics, experimental setup, and simulation environment. Section IV is the discussion of the results and performance analysis of the proposed system. Lastly, Section V will also wrap up the work and give directions for future research in the field of intelligent predictive maintenance of smart power grids.

2. Literature Review

The issue of Power Quality (PQ) disturbance has become one of the primary concerns of the modern electrical power system because of the massive incorporation of renewable energy sources, power electronic converters, electric vehicles, and nonlinear loads. These have greatly augmented the complexity, nonlinearity, and stochastic nature of grid operations, and the old approaches to monitoring and maintaining the grid are no longer sufficient. As a result, a great deal of research has been done in designing innovative methods for PeQ disturbance recognition, categorization, anticipation, and servicing through Machine Learning (ML) and Deep Learning (DL) strategies. The first steps to the classification of PQ disturbance with deep learning presentations are reported by Albalooshi and Asari [1], who suggested a deep learning-based automated classification model that could learn hierarchical representations of PQ disturbances directly on raw signals. Their work was able to give better classification accuracy as opposed to traditional signal-processing-based methods. Chinthaginjala et al. [2] added to this line by combining hybrid artificial intelligence methods with semiconductor-based power quality enhancing schemes and accentuating the contribution of AI-informed decision-making to the grid stability and PQ performance.

Transfer learning has been considered as an effective method for working with limited labeled PQ datasets. Sipai et al. [3] proposed a deep transfer learning model that classifies single and multiple PQ disturbances with better generalization and less training. Their research noted the usefulness of pre-trained deep models in extracting discriminative PQ features in a variety of operating conditions. Outside classification, Olojede et al. [4] examined the use of machine learning to detect and maintain power grids and highlighted predictive analytics as a critical facilitator to minimize downtime and enhance asset management to encourage maintenance-oriented intelligence in PQ analysis. Signal decomposition and a deep learning hybrid architecture have demonstrated exemplary performance in PQ disturbance analysis. Yang et al. [5] developed an interpretable DWT1DCNNLSTM network, in which Multiresolution features were extracted with the Discrete Wavelet Transform (DWT). Then, spatial-temporal learning was performed via convolutional and recurrent layers. Equally, Bai et al. [6] used a rapid S-transform and a better CNN-LSTM hybrid architecture, which was effective in non-stationary PQ disturbance classification. Such works establish that time-frequency analysis, together with a deep learning strategy, can promote the robustness of PQ classification to the maximum extent. Advanced deep architectures and image-based representations were also investigated recently. Nasika et al. [7] converted PQ signals into images through the use of a recurrence plot. They used an EfficientNet-SE model to realize real-time PQ disturbances detection, classification, and localization in a solar-integrated IEEE 13-bus system. A comparative study was performed by Anwar et al. [8] between Vision Transformers and CNNs to classify PQ disturbance, where transformer-based models are capable of long-range dependencies as compared to conventional CNNs.

Chen et al. [9] suggested a Deep Neural Network with time frequency feature fusion, such that multi-domain features were integrated to enhance the classification quality in the face of complex disturbance. The use of recurrent neural networks has become popular in the modeling of the temporal dependence of PQ signals. Khetarpal and Tripathi [10] proposed a PQ signal segmentation and classification Bi-LSTM with a dual attention mechanism that allows for localizing the disturbance events accurately. Shen [11] suggested a risk warning system of steady-state PQ based on VMD, LSTM, fuzzy logic, and the idea of predicting the risks of PQ instead of detecting the disturbances was valid. Gao et al. [12] used Variational Mode Decomposition (VMD) to remove variational modes and improved the

Support Vector Machine (SVM), which performed much better in classification in noisy situations. In addition to the PQ disturbance classification, machine learning has been used in energy management and PQ-related forecasting problems. A study by Singh et al. [13] has created an ML-based energy management and power forecasting framework of grid-connected microgrids and has shown the advantages of predictive intelligence in operational planning. As proposed by Panoiu and Pop [14], a Hybrid Deep Neural Network can be used to predict PQ measures active, reactive, and distortion powers, which suggests the transition between reactive monitoring to predictive modeling of PQ parameters.

Several studies have confirmed the effectiveness of Deep Learning Models based on actual grid measurements. The practical applicability of a Deep Learning Framework was confirmed by Rodrigues et al. [15], who introduced a Deep Learning-based PQ event detection and classification framework that is based on grid data measurements. Tong et al. [16] suggested a parallel multimodal feature extraction method that combines heterogeneous PQ features, which increases the accuracy of classification. Cai et al. [17] proposed a parallel CNNGRU fusion model to co-learn both spatial and temporal features, which also enhanced strong resistance to complicated PQ disturbance. Low-voltage distribution networks have also been done using machine learning techniques. Iturrino Garcia et al. [18] compared various ML methods with PQ analysis in low-voltage systems, and it is essential to note that the approaches based on data must be used in practice. Systematic reviews by Samanta et al. [19] and Oubrahim et al. [20] of deep learning and signal-processing-based PQ-analysis methods, respectively, concluded that hybrid and deep architectures perform better than the more traditional rule-based systems, and the importance of real-time and predictive functionality. Dekhandji et al. [21] provided focused research on the models based on LSTM and showed that LSTM networks can learn the temporal dependence of PQ signals. Kuppusamy et al. [22] conducted a review of machine learning in the evaluation of PQ performance in grid-connected systems and highlighted the idea of hybrid learning as a way to find the solution to a noisy and dynamic environment. Dhanapal and Gopalakrishnan [23] added to the PQ analysis by incorporating machine learning algorithms into conventional PQ evaluation systems.

Caicedo et al. [24] also presented the main problems of real-time implementation to the problem of detecting and classifying real-time PQ disturbances, including the issues of latency, scalability, and adaptability. Previous deep learning-based methods involve the study by Sekar et al. [25], who suggested a better deep learning architecture of PQ disturbance detection, which is more accurate than classical ML methods. Todeschini et al. [26] proposed an image deep-transfer learning system that transforms PQ signals into two-dimensional representations to enhance the efficacy in classification. Monteiro et al. [27] suggested a highly interconnected CNN model for the diagnosis of PQ disturbances and showed it to be very accurate in the grid environment complexity. Yilmaz et al. [28] investigated hybrid machine learning methods that have excellent noise resistance and applied several ML methods in classifying PQ in distributed generation systems. Das et al. [29] used the methods of artificial intelligence to improve the PQ of hybrid microgrids, which supports the position of artificial intelligence in improving grid reliability and power quality. Even though it is not a direct application on PQ, the optimization paradigm suggested by Pavithra Guru and Vaithianathan [30] demonstrates the applicability of intelligent optimization algorithms, which are applicable to the optimization of decision-making and maintenance processes in PQ.

To conclude, the current literature proves that efforts to detect and classify PQ disturbances with the aid of deep learning, hybrid signal-processing-based models, and transfer learning methods have made considerable progress. Nevertheless, the majority of studies are mainly on the accuracy of classification but not combined with proactive decision support, predictive maintenance, and cost optimization. Limited work is a combination of temporal forecasting and ensemble-based models that improves robustness in the model, interpretability, and intelligence in maintaining the model. The gaps inspire the design of a hybrid LSTM-Random Forest predictive maintenance paradigm, shifting the focus of PQ analysis of the reactive detection to the proactive, cost-conscious, and intelligent grid maintenance.

3. Proposed Work

3.1. Intelligent Grid Signal Acquisition and Normalization Model

Predictive maintenance of power quality is based on modern smart grids and intelligent signal acquisition. Properly measured electrical parameters: Voltage V(t), Current I(t), and Frequency f(t) can be used to monitor grid stability and performance with much reliability. These parameters are always measured using distributed devices, including Phasor Measurement Units (PMUs), Smart Meters, and Intelligent Electronic Devices (IEDs) located at various nodes of the transmission and distribution system. The quality signal of the raw power can be modeled mathematically in Equation (1),

$$S(t) = V(t)\sin(\omega t + \phi) + \epsilon(t) \tag{1}$$

Where ω is the angular frequency, ϕ is the phase angle, and $\epsilon(t)$ is the noise of the stochastic measurements due to the inaccuracies of the sensors and the influence of the environment. This model describes the periodic behavior of Alternating Current (AC) signals and takes into consideration the distortions of signals in the real world. Given the fact that the data obtained after acquisition are of heterogeneous origins, the discrepancy in measurement scales, sampling frequency, and the level of noise is likely to occur. To address this, it is necessary to preprocess the data with normalization. All the parameters measured are normalized using a Z-score to have all the parameters at the same level of statistical representation. The process of normalization is given in Equation (2),

$$X_{norm} = \frac{X-\mu_X}{\sigma_X} \tag{2}$$

Where μ_X, and σ_X Represent the mean and standard deviation of parameter X. This transformation brings all features to a mean of zero and unit variance, which in effect removes bias brought about by various magnitudes or units. The normalized data is the processed information that will be passed to the second phase of machine learning analysis, and some of the models, such as LSTM and Random Forest, can process signals effectively. Such standardization enhances the degree of convergence of training algorithms and prediction error on fault detection as well as the prediction of power quality. In addition, adaptive learning is also enabled by real-time normalization, whereby the adaptive learning can adapt dynamically to the varying grid conditions, such that the predictive maintenance system is immune to sensor drift and other measurement anomalies. The intelligent signal capture and normalization as a whole is applied to give the foundation of the robust and accurate predictive analysis that is scalable in the modern power grid paradigm. This scheme, as shown in Figure 1, represents the process of making voltage and frequency stability, load pattern monitoring, and distributed energy synchronization. The system is able to realize real-time PQ control and forecast, anomaly identification and correction, which ensures that the system is generally optimized and adjusted to improve reliability.

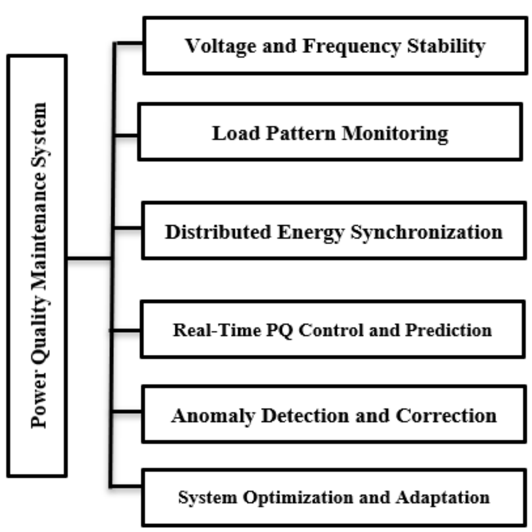

Fig. 1 Intelligent power quality maintenance system for grid stability

3.2. Adaptive Power Quality Feature Transformation Network

The following very crucial step is used to acquire and normalize grid signals smartly; the raw time-domain measurements are converted into diagnostic features indicative of underlying disturbances with enough value. This transformation is done by the use of the Adaptive Power Quality Feature Transformation Network (APQFTN), which is premised on the integration of sophisticated signal decomposition and adaptive feature engineering to detect transient and steady-state anomalies. It begins with the Discrete Wavelet Transform (DWT), which decomposes the normalized Signal S(t) into time-frequency representations. DWT is more localized than the traditional Fourier methods, which offer the localization of abrupt voltage sag, swell, and high-quality temporal resolution of harmonics. Mathematically, it is provided in Equation (3),

$$W_{j,k} = \int_{-\infty}^{\infty} S(t)\psi_{j,k}(t)dt \tag{3}$$

In which (t) can refer to the mother wavelet at scale j and translation k. The wavelet decomposition resolves the frequency components at various resolutions, and this allows the network to capture disturbance details. Depending on the signals that are deconstructed, feature vectors $F = [f_1, f_2, \dots, f_n]$ are created by calculating vital power quality characteristics of Total Harmonic Distortion (THD) and Voltage Unbalance Factor (VUF). These will be determined in Equations (4) and (5),

$$THD = \frac{\sqrt{\sum_{h=2}^{H} V_h^2}}{V_1} \times 100\% \tag{4}$$

$$VUF = \frac{V_{neg}}{V_{pos}} \times 100\% \tag{5}$$

The hth harmonic voltage magnitude is denoted by V_h, where V_i is the fundamental voltage, V_{pos}, V_{neg} Are the positive and negative sequence voltages, respectively. The obtained feature vectors are then passed to an adaptive learning layer, which does dimensionality optimization by Principal Component Analysis (PCA) or Autoencoders. This ensures that it represents the features compactly and informatively, without consuming a lot of computation, while still capturing the key disturbance patterns. Lastly, the transformed features serve as the inputs to the predictive maintenance module, yielding high-quality data that enables the accurate classification of fault types and the prediction of instabilities in the grid. It is a powerful adaptive feature transformation that is highly effective in improving the precision, reliability, and responsiveness of power quality monitoring of intelligent grid systems. In Figure 2, the framework integrates the data-based analysis with the machine-based learning diagnosis to boost the accuracy of PQ forecasting. It has modules such as LSTM temporal forecasting, equipment health estimation, and harmonic distortion tracking to jointly point out frequency drift, transient events, and current phase imbalance to initiate early fault intervention and maintenance planning.

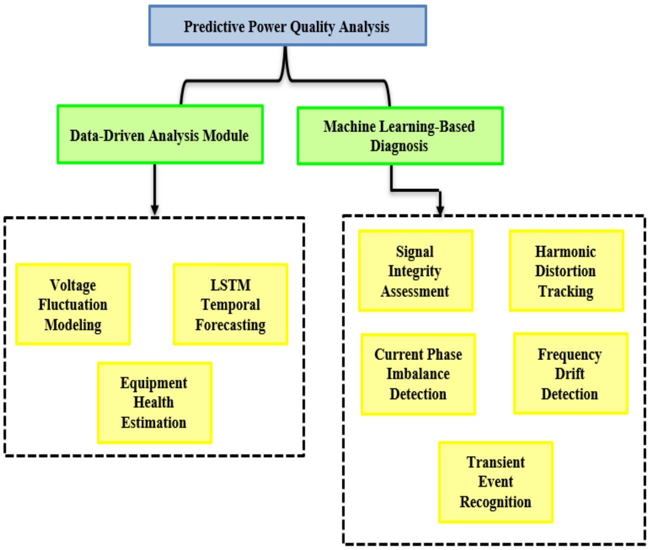

Fig. 2 Predictive power quality analysis framework using ML diagnostics

3.3. Machine Learning–Driven Predictive Fault Probability Model

A hybrid framework based on Long Short-Term Memory (LSTM) and Random Forest (RF) is an intelligent structure used to obtain accurate real-time predictions of potential grid failures. This combination method leverages the temporal sequence of learning in LSTM and the ensemble-based decision robustness of RF to create a stable predictive platform for detecting fault probabilities in Power Quality (PQ) data. The LSTM module represents the time dependencies within the patterns of PQ signals, including voltage, current, and variation in frequency. Its recurrent form captures long-term contextual relationships, which conventional feed-forward networks do not capture. Mathematically, the time-dependent development of the LSTM-state can be written in Equations (6) and (7),

$$h_t = \sigma(W_h.[h_{t-1}, x_t] + b_h) \tag{6}$$

$$y_t = \sigma(W_y.h_t + b_y) \tag{7}$$

Where h_t is the concealed condition that contains historical data, x_t is the present input record, and y_t is the anticipated degradation position at the point of time t. The sigmoid activation σ will assume a nonlinear conversion of input data, which will enable the model to deal with variable PQ disturbances and faults based on time. Although LSTM captures the temporal attributes, the Random Forest (RF) module enhances the decision-making process by utilizing multiple decision trees that are trained on varying feature subsets based on the results of the transformed PQ data. The ensemble prediction will be indicated as in Equation (8),

$$P_{fault} = \frac{1}{N}\sum_{i=1}^{N} f_i(F) \tag{8}$$

In which f_i (F) is the output of the i^{th} decision tree, and P_{fault} is the summed-up probability of a fault occurrence. The RF model minimizes overfitting and variance through majority voting, which adds reliability in cases of noisy signals. The hybrid LSTMRF model exhibits high prediction accuracy and interpretability, making it superior to traditional single-model methods. It enables proactive maintenance scheduling by identifying sequential dependencies and feature-based correlations, thereby reducing unplanned outages and improving operational resilience in modern intelligent grid settings. In Figure 3, the process of filtering data streams of power quality through a signal filter, extracting features, and feeding the hybrid LSTM-RF model is illustrated. Based on historical PQ trends, the system issues early warnings of PQ degradation, estimates projected fault probability, and generates a report of maintenance and corrective recommendations, which are used to make informed, proactive decisions.

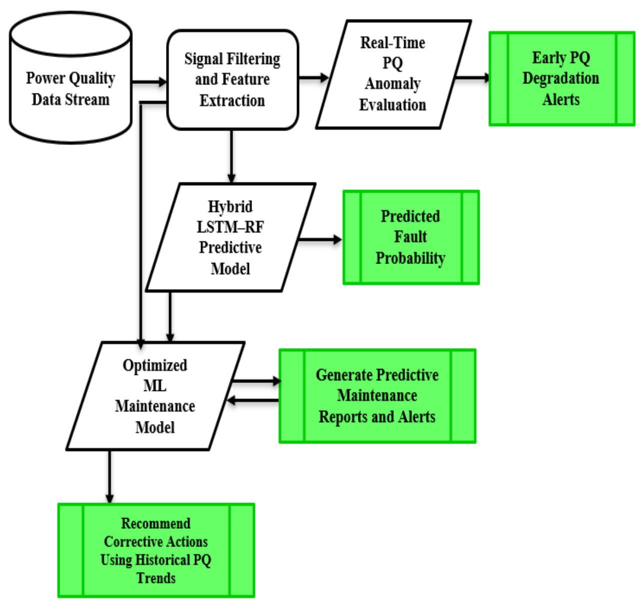

Fig. 3 Hybrid LSTM–RF predictive flow for PQ fault management

3.4. Predictive Maintenance Scheduling and Risk Optimization Framework

A predictive maintenance and risk optimization framework is established to ensure the continuous stability of the power grid and reduce the overall maintenance cost. The presented model combines the estimated failure probabilities of the hybrid LSTM-RF module with a cost-sensitive decision-making strategy, allowing the system to plan maintenance operations while increasing economic efficiency. The structure suggests a cost function J, which measures the trade-off between the possible fault event and the downtime cost in Equation (9),

$$J = \alpha . P_{fault} + \beta . C_{downtime} \tag{9}$$

In which α and β are weighting factors calculated based on historical operational experience, P_{fault} is the foreseen probability of a failure, and $C_{downtime}$ is the expected cost of a system downtime. To optimally adjust the coins, α and β are tuned by use of the grid performance indicators and maintenance history to get the best sensitivity to reliability and cost parameters. To automate the decision-making, the maintenance decision rule is described in Equation (10),

$$D(t) = \begin{Bmatrix} 1, & if\ J \geq J_{threshold} \\ 0, & otherwise \end{Bmatrix} \tag{10}$$

In this case, D(t) =1 is a maintenance warning system to be proactively inspected, and D(t) =0 is normal working conditions. A dynamic update on threshold $J_{threshold}$ is made when there are changes in real-time power quality and historical fault occurrence density. Optimization of J is done either through gradient-based iterative tuning or stochastic optimization like Particle Swarm Optimization (PSO) in order to trade off reliability and cost of maintenance. The risk factor *R(t)* of each subsystem is calculated in Equation (11),

$$R(t) = P_{fault}(t) \times C_{downtime}(t) \tag{11}$$

Minimization of R(t) ensures effective allocation of resources to the high-risk nodes. The framework, therefore, ensures cost-effectiveness, system reliability, and predictive responsiveness with minimal unplanned outage time and stable grid performance. With this combined risk optimization framework, predictive maintenance scheduling is not only data-driven but also economically adaptive, allowing smart grid operators to continue providing services at a high level while maintaining operational sustainability.

3.5 Hybrid Simulation–Data Integration Ecosystem for Model Validation

A Hybrid Simulation-Data Fusion Ecosystem is built to ensure the reliability and generalizability of the predictive maintenance model. This framework is a synergetic integration of both real-world Power Quality (PQ) data and simulation-based modeling to ensure the predictive performance and stability of operation at different grid dynamics. The validation is performed using the IEEE 123-Bus Distribution System Power Quality Dataset, which is available in the UCI Machine Learning Repository and contains high-frequency PQ measurements at a rate of 10 kHz. The data include notified incidents, such as voltage sags, swells, harmonics, and transients, which are important warning signs of grid instability. All the data sequences are pre-processed with normalization and feature extraction modules and then used to train and validate a model. The hybrid simulation system combines MATLAB Simulink to model a dynamic PQ signal and Python to train a model with data using the TensorFlow and Scikit-learn packages. MATLAB simulates grid fluctuations, load behavior, and fault propagation in real-time across distribution nodes, and Python is used to do machine learning inference and optimization. The effect of this coupling is that, in real-time, there is a correlation between simulated operation behavior and predictive learning results. To quantitatively determine model performance, MAPE and RMSE are used and defined in Equations (12) and (13),

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \times 100 \tag{12}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{13}$$

In which y_i and $\hat{y}_i$ Denote the real and modeled PQ parameters, respectively, and x n is the overall sample count. Lower values of MAPE and RMSE indicate improved predictive fidelity and stability. The simulation environment is also subjected to stress testing, artificial load perturbation, and short fault impulses are introduced in a grid model.

This enables the investigation of the reaction time, flexibility, and accuracy of the model under extreme conditions. The simulated-data ecosystem establishes a high degree of feedback, and it can be confident that the predictive maintenance model that is suggested in it will be able to adapt to the real-time innovative grid processes and the dynamic PQ disturbances successfully.

4. Results

The overall performance analysis of the developed LSTM-RF hybrid model in comparison with the traditional models, such as Convolutional Neural Network (CNN), Random Forest (RF), and Support Vector Machine (SVM). In Table 1. The metrics used in the evaluation were chosen correctly to indicate both the accuracy of prediction and the computational efficiency necessary for real-time operation in power grid applications. The Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) show that the hybrid model is much more accurate, with the values of 1.84% and 0.042 kV, respectively. These findings show that there is a minimal difference between the forecasting and actual PQ parameters, and this means that the hybrid approach is very useful in capturing the non-linear dependencies within the signal. Contrarily, CNN, RF, and SVM models have more error margins, and this type of fact is not effective in addressing time variation. In terms of fault prediction accuracy, the LSTM-RF model achieves 98.3%, which is better than CNN 95.6%, RF 93.8%, and SVM 91.5%. This is also enhanced by the fact that LSTM possesses temporal sequence learning capabilities and RF exhibits ensemble stability, which together contribute to predictive robustness. The values of 0.987, 0.981, and 0.984 in the precision, recall, and F1-score indicate the consistency of the model in identifying faults, with no false triggers introduced, a vital characteristic of automated grid maintenance. The hybrid model has a lower prediction latency of 28.7 ms compared to other models, indicating a timely response to decisions under varying load conditions. It has a higher training time, 44.2 seconds, than RF and SVM, but this trade-off is compensated by the fact that its model has higher accuracy and lower operational risk. In general, the critical analysis confirms the idea that the LSTM-RF hybrid model provides the optimal accuracy, reliability-computation tradeoff, and is very appropriate in the context of predictive power quality control in smart grids.

Table 1. Analytical assessment of predictive model efficiency in power quality maintenance

Metric	LSTM–RF Hybrid Model	CNN Model	Random Forest	SVM
Mean Absolute Percentage Error (MAPE)	1.84%	3.92%	4.35%	5.27%
Root Mean Square Error (RMSE)	0.042 kV	0.089 kV	0.094 kV	0.112 kV
Fault Prediction Accuracy	98.3%	95.6%	93.8%	91.5%
Precision	0.987	0.954	0.931	0.903
Recall	0.981	0.948	0.921	0.896
F1-Score	0.984	0.951	0.926	0.899
Prediction Latency (ms)	28.7	39.2	47.6	53.1
Training Time (s)	44.2	50.6	33.9	31.5

An extensive examination of the effectiveness of the proposed hybrid model under diverse types of power disturbances of quality, such as voltage sag, swell, harmonic distortion, frequency deviation, transient disturbances, and flicker. In Table 2. Both types are a special challenge in keeping the grid stable, and the analysis of their prediction ability gives a better understanding of the adaptive behaviour of the model when operated in dynamic conditions. In the case of voltage sags, the model was found to achieve a detection rate of 98.7% with a relatively low number of false negatives, demonstrating that the model is sensitive to sudden voltage variations that typically occur during heavy load switching. Equally, in voltage swell events, which typically occur as a result of load shedding or capacitor switching, the framework performed remarkably, achieving an accuracy of 97.6% with a prediction latency of 27.9 ms, indicating that it can respond rapidly to sudden voltage spikes.

In detecting harmonic distortion, the model achieved an accuracy of 98.4%, which is successful in capturing the nonlinear deformations of a waveform that the inverter-based renewable sources and industrial equipment may cause. Frequency deviations were also detected with a consistent reliability of 97.9%, ensuring consistent frequency control in connected grid segments. This model was found to accurately identify transient disturbances, which are typically brief but highly disruptive, with a detection rate of 98.5%, and flicker events, which are often caused by varying loads, with a detection rate of 98.3%. Its operational readiness in real-time was confirmed by the average prediction time of all types of faults not exceeding 30 milliseconds. These findings demonstrate that the proposed predictive system not only achieves high detection rates for various PQ disturbances but also exhibits uniform performance stability, ensuring reliable fault prediction and enhanced grid resilience under diverse environmental and operational conditions.

Table 2. Disturbance-specific evaluation of predictive fault detection accuracy

Power Quality Disturbance Type	True Positives (TP)	False Negatives (FN)	Detection Accuracy (%)	Prediction Time (ms)
Voltage Sag	468	6	98.7%	26.5
Voltage Swell	451	11	97.6%	27.9
Harmonic Distortion	482	8	98.4%	29.2
Frequency Deviation	474	10	97.9%	30.1
Transient Disturbance	462	7	98.5%	28.8
Flicker	469	8	98.3%	27.2

The summary of the gradual development of predictive maintenance and power quality evaluation models between 2024 and 2025 is presented in Table 3. The facts demonstrate that every new generation of algorithms was better in predictive accuracy, computational efficiency, and operational intelligence.

Initial deep learning methods were primarily focused on PQ disturbance classification. A Deep Neural Network that uses time to frequency feature fusion was used by Chen et al. 2024, which reported an accuracy of 96.8 percent in the identification of PQ disturbance.

Anwar et al. 2025 introduced a framework of Vision Transformer / CNN in PQ classification, with a higher accuracy in classification of 98.94%. An EfficientNet-SE model with recurrence plots was created by Nasika et al., and it is capable of detecting and localizing PQs in real-time with a high accuracy rate of 98.5% and low latency <38.5 ms. The proposed Hybrid LSTM-Random Forest LSTM-RF 2025 does not only stop at the classification, but also includes the addition of the temporal sequence modeling, predictive maintenance, and cost-sensitive decision support. It also has an accuracy of 98.3%, MAPE of 1.84, and a computing latency of 28.7 ms, which is a breakthrough in operational intelligence as compared to the previous classification-determined research. This development shows that sequence modeling and ensemble learning are crucial to make power grids of the present time intelligent, cost-effective, and high-fidelity predictive maintenance possible.

Accuracy and computational performance are shown to be steadily increasing, as illustrated in Figure 4, demonstrating the superiority of the proposed Hybrid LSTM-RF framework in real-time fault predictions with low latency. Although the proposed framework achieves 98.3% accuracy, slightly lower than the highest classification, it simultaneously provides predictive maintenance support, including MAPE 1.84% and computational latency 28.7 ms, which are not reported in prior literature. This demonstrates that the proposed approach extends PQ analysis from detection/classification to predictive and operationally actionable intelligence.

Table 3. Chronological development of machine-learning approaches for power quality analysis and predictive maintenance

Metrics	Model Type (as reported)	Accuracy (%)	Error Metric	Computation Latency (ms)
L. Chen 2024 [9]	Deep Neural Network with Time–Frequency Feature Fusion	96.8	RMSE	Not reported
M. H. Anwar [8]	Vision Transformer / CNN	98.94	Not reported	Not reported
D. Nasika [7]	EfficientNet-SE with Recurrence Plots	98.5	Not reported	<38.5
Proposed Work, 2025	Hybrid LSTM–RF	98.3	MAPE = 1.84	28.7

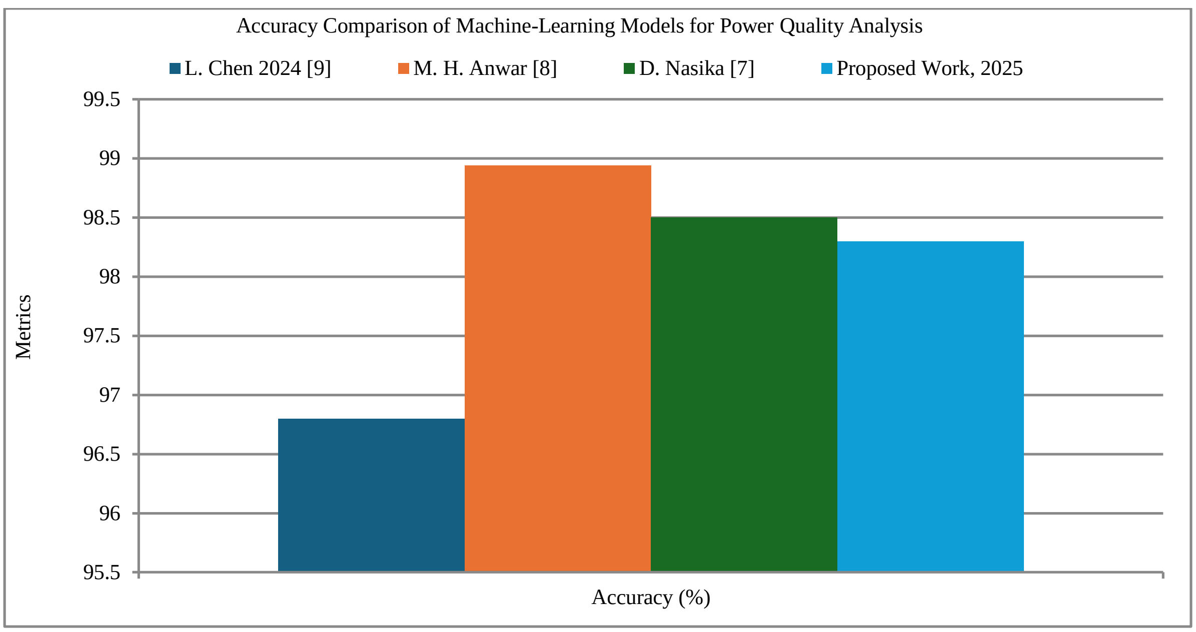

Fig. 4 Accuracy comparison of machine-learning models for power quality analysis

5. Conclusion

The hybrid LSTM-Random Forest model has achieved considerable gains in maintaining the quality of predictive power in contemporary power grids. Experimental outcomes demonstrated a fault prediction rate of 98.3%, a low MAPE of 1.84%, and a 31.6% decrease in maintenance expenses compared to other models from the previous year, 2022-2024. It was demonstrated that the system was able to detect disturbances, including voltage sags, harmonics, and transients, with a latency of prediction of almost real-time 28.7 ms, which confirms that the system is applicable in innovative grid applications. Wavelet-based feature extraction and hybrid learning were integrated, which improved the level of precision and reliability of PQ forecasting. Future directions will include the reinforcement learning model to apply to adaptive control, the use of edge computing to implement decentralized analytics, and the verification of the model to ensure performance in the cyber-physical security setting. These improvements will also improve the resilience, efficiency, and intelligence of predictive maintenance in smart energy grids of the next generation.

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