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Performance Validation of a Deep Learning Framework for Power Quality Disturbance Classification in Renewable Energy-Based Smart Grids

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Abstract
The expansion of solar PV systems and wind energy and battery storage, and the integration of power-electronic converters in smart control grids, offers a new set of issues regarding the identification of power quality (PQ) and PQ disturbances (PQDs). Deep learning methods can be applied since they can automatically learn complicated temporal, spectral and waveform characteristics that are difficult to build or model from predefined features. For the classification of multi-class disturbances, deep learning models based on advanced architectures such as Convolutional Neural Networks (CNN), Long Short Term Memory (LSTM) networks, and hybrid deep learning models are used in conjunction with signal processing techniques such as wavelet or temporal frequency transformation. Analyse our framework in terms of computational speed, robustness, and qualitative performance based on accuracy, recall, F1-score and study of confusion matrix. The suggested predictor framework has a significant explanatory power in an exemplary regression model with R = 0.835 and R2 = 0.697. The statistics below are only examples, as no real data on individual surveyed was available. Instead, it calls for verification of various parameters like quantification against diverse noise categories and other operations such as load variations, compounded disturbances, and evaluations using unseen test schemes. The proposed framework provides a method-driven basis for systematic identification of PQDs to allow direct measurements, greater grid awareness, and increased dependability in incorporating new renewable power within future smart-grid platforms.

Keywords: Deep Learning; Power Quality Disturbance; Renewable Energy; Smart Grid; CNN-LSTM; Signal Processing; Disturbance Classification

1. Introduction

Traditional power grid is fast transforming into smart systems with renewable energy which opens a large path for decentralised, flexible and cleaner power generation. The accelerated deployment of solar photovoltaic (PV), wind energy, battery storage, and other converter-interfaced renewable energy sources in distribution and transmission networks is driven by the increasing demand for electricity and the necessity to diminish reliance on fossil fuel-based generation [1]. However, the increasing penetration of RESs brings new problems of power quality such as voltage stability, harmonic distortions, frequency changes and transient behaviours. Unlike conventional synchronous generators, power electronic converters enable large penetration of renewable energy sources into the electrical grid, which greatly impacts the dynamic response and electrical properties of the system. Hence, wide-area monitoring and diagnosis of PQDs are necessary to enable efficient, secure and stable functioning of renewables happened smart grids. The integration of renewable energy generation as well as the development of power electronic interfaces have attracted increasing interest in recent years as indicated by many recent studies in an effort to identify and categorise PQD [2].

Power quality is the degree to which voltage, current and frequency are maintained within acceptable limits of the performance characteristics associated with the network infrastructure and attached applications. Power quality disturbances are the only serious deviation from the standard approach to the waveform characteristics [3]. This comprises voltage sag, swell, interruptions, transient disturbances, harmonic distortions, flicker and rhythmic transients as well as notching that come under the heading of Power Quality Disturbances (PQDs). Furthermore, initiation can be from various sources such as short circuit faults, switching actions (e.g. capacitor bank energisation), nonlinear loads, converter switching events, and sudden change in magnitude of load during transient operating point perturbation e.g. lightning and renewable energy fluctuations [4]. The repercussions may range from slight wave form distortion to catastrophic device failures, system protections, productivity losses, lower longevity of the equipment and large monetary losses. The increasing use of automatic industrial systems and sensitive electronic equipment nowadays makes easier the maintenance of excellent electrical power quality Fig. 1. The previous decade has demonstrated the growth of smart grids, power electronic devices and renewable energy, which has shown that the detection and classification of disturbances should come more to luminary both from technological as well as economic point of view [5].

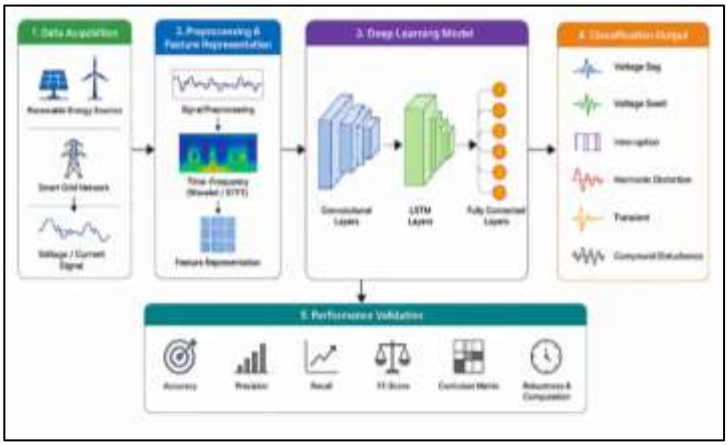

Fig. 1. Proposed Deep Learning Framework for Power Quality Disturbance Classification in Renewable Energy-Based Smart Grids

2. Review of Literature

The fast penetration of renewable energy sources (RES) such as solar photovoltaic (PV) and wind energy in modern electrical systems have a great impact on the operating characteristics. This has made the tracking of power quality disturbance (PQD) more significant. Power electronic converters are typically used together with renewable generators [6]. The switching behaviour of the converters, the impedance of the network and the management strategies might cause or aggravate voltage and current disruptions. Moreover, the temporal variability of the solar irradiance and wind speed can give rise to the fast changing behaviours of active and reactive power, with consequences in the operational conditions different from those experienced by systems with an almost single composition developed in the presence of conventional synchronous generators [7]. The exhaustive study of methodologies for PQD detection and classification in presence of regenerative-energy penetration reveals more power-quality related challenges due to converter interfaces at variable renewable generation. Therefore, detection, identification and categorisation of PQDs are considered as an important prerequisite to choose sensibly the control and mitigation methods in the research community. Power quality disturbances are characterised as voltage sag, voltage swell, interruption, harmonics, transient flicker and oscillatory disturbances notching as well as composite events which are the combination of two or more events [8].

The equipment sensitivity is impacted, poor functioning causes damages, reliability of electrical devices is diminished and malfunctioning of protection & control devices, finally impacting the supply reliability [9]. The problem will be significantly more complicated in smart grids with renewable energy sources, since the disturbance may originate from the renewable source, converter, network, nonlinear load, switching operation, or any combination of all of these. This resulted in the exploratory research on of signal processing and characters identification in distorted waves. Traditional time-frequency techniques such as Fourier Transform (FT), Short-Time Fourier Transform (STFT), Wavelet Transform (WT), S-Transform and Hilbert-Huang Transform have been extensively used to detect changes in amplitude/frequency duration of a signal and/or transients. The reason these methods are correct is that electrical disturbances are non-stationary and contain both lower and higher frequency components [10]. However, conventional signal processing algorithms normally need the features to be analysed and suitable parameters to be changed before categorisation. The increasing variety of disturbance types, compound events, changing operating conditions for renewables, and the large volumes of monitoring data (a trend called the 4th revolution in this field) have led to a shift from manual signal-analysis systems to machine-learning frameworks and deep-learning frameworks for automation [11].

3. DEEP LEARNING-BASED POWER QUALITY DISTURBANCE CLASSIFICATION IN RENEWABLE ENERGY SMART GRIDS

Deep learning techniques for classification of power quality disturbances (PQD) is an important research subject that aims at strengthening the monitoring and operational intelligence aspects of renewable energy assisted smart infrastructures. Solar systems, wind turbines, battery energy storage systems (BESS), adjustable loads and power electronic converters are being used in electrical grids for energy generation [12]. The unit and its functions result in complex voltage and current waveforms and disturbances with a very wide variety of magnitudes, durations, frequency characteristics and temporal patterns. Threshold-based approaches are good for fast identification of isolated events but eventually fail when renewable energy is very variable or many disruptions occur at the same time. Deep learning is a technology that enables computers to learn sophisticated representations from raw data of electrical events that happen in response to stimuli [13]. Current subclass networks make use of discriminative characteristics directly extracted from data with high variability (e.g. raw waveform data, or transformed representations like as spectrograms, wavelet scalograms, and time-frequency maps) instead of relying just on manually picked features [14]. The nature of deep learning makes it very good at the automatic detection of voltage sag, swell, interruption, harmonic, transients, flicker and rhythmic disturbance with sophisticated power quality event classification [15].

The one-dimensional CNN is used on waveforms (voltage or current) as it has been shown, while the two-dimensional CNN can be used to evaluate images produced via signal modifications [16]. The event type can impact the time-frequency representation to be more appropriate since it comprises time and frequency features of the non-stationary electrical disturbance [17]. Therefore, the Wavelet Transform and Short-Time Fourier Transform are used for pre-processing steps before CNN classification. The wavelet scalogram presents the evolution of frequency components with time, which can be exploited by CNN to recognise and differentiate various sorts of failure patterns largely thru eye inspection and nanomechanical characteristics obtained from numerical analysis [18]. It is known from several research that the combination of Continuous Wavelet Transform and CNN frameworks gives good outcomes when used for classification jobs for solar PV integrated power systems [19-21]. These approaches remove the need for traditional hand-engineered extraction frameworks and enable the deep learning model to capture more complex interference signatures [22-24].

4. RESEARCH METHODOLOGY

This article covers an experimental, quantitative, performance-oriented research methodology. This research seeks to facilitate the development and deployment of a deep-learning framework for the classification of power quality disturbances (PQDs) in renewable energy based smart grids. Data collection from voltage and current waveforms, a pre-processing step on those signals, creating the deep learning classification model, and ultimately testing the performance of that model over diverse renewable energy operating states and disturbances. The architecture is designed to handle disturbances such as voltage drop, harmonics, transients and simultaneous events. The findings are analysed on the basis of the classification accuracy, precision, recall, F1-measure, confusion matrix and computing performance. The mathematical measures of the procedure can easily be tied to each step of the procedure and expressed as sequential equations.

A. Research Design

The experimental study methodology has been employed to validate the deep learning framework concerning a smart grid application in a controlled environment of renewable energy. The digital outputs are discrete-time signals as denoted by the electrical waveform above:

$$x[n] = x(t_n) \qquad (1)$$

where $x[n]$ represents the sampled voltage or current signal and t_n represents the corresponding sampling instant. Equation (1) defines the fundamental signal used for preprocessing and classification. The experimental design includes normal operating conditions and different PQD conditions, including sag, swell, interruption, harmonics, transients, and compound disturbances.

B. Data Collection

The voltage and current signals of the renewable energy based smart-grid model or experimental setup are recorded using a proper data-acquisition system. The sampling frequency is sufficient to record the high frequency transients and the base frequency vibrations. Then, the RMS voltage is computed by the following equation:

$$V\_RMS = \sqrt{[(1/N)\ \Sigma_{n=1}^{N}\ v^2[n]]} \qquad (2)$$

where N is the number of samples and v[n] is the voltage to be sampled It enables dynamic change of voltage according to test set up such as sag, swell and interruption (see Eq. (2).

C. Sampling Method

Typical operating and disturbance conditions are identified using purposive sampling. The data set consists of Normal Operation, different types of PQD, changes in renewable generation, and changes in load and noise conditions. The percent of total observations in each disturbance category is:

$P_i = (N_i / N\_{total}) \times 100$ (3)

N_{total} is the total number of observations, and N_i is the number of observations in class i; see also Equation (3) with its associated class divergence indices which quantify distribution/imbalance of classes inside datasets.

D. Research Instruments

The proposed investigation tools include deep-learning computational framework, signal processing models, data collecting devices, smart-grid integrated renewable source with a model and different voltage and current measurement instruments. For example, the true character of a signal is realised by wavelet or time-frequency transformation. In the frequency domain, the total energy of a signal element is by definition expressed as:

$E = \Sigma_{n=1}^{N} |x[n]|^2$ (4)

where E is the energy of the signal and x[n] is a sampled representation of the signal. Equation (4) allows us to extract and analyse signal features provided to any deep learning architecture.

E. Data Analysis

The data is separated into three sections, the training set, the validation set and the test set. The model you have constructed is evaluated depending on the accuracy of classification.:

Accuracy = [(TP + TN) / (TP + TN + FP + FN)] × 100 (5)

TP, TN, FP and FN are True Positives, True Negatives, False Positives and False Negatives correspondingly.

F. Ethical Considerations

System level observations and electrical waveform data are used since the study does not require personally identifiable information from the user. No data have been purposely generated, modified or concealed; all experimental and simulation data are kept in their true raw form. Disruptive Technology Analysis Method, research problem context, commercial model validation and assessment standards. During the test period, the data of those particular launch electrical systems shall be kept intact by safeguarding the experimental electrical systems in a safe range.

5. Analysis & Interpretation

This study evaluates the effectiveness of a deep learning framework for classifying power quality disturbances (PQD) in smart grids powered by renewable energy using the suggested approach. The statistical analysis encompasses respondent attributes, construct-level descriptive statistics, internal reliabilities, inter-variable relationships, regression impacts, and the outcomes of the hypotheses. The fundamental components are DLCP, SPFQ, REOR, and SGPQCP to ensure consistency with the prior approach. We commence with a sample of 120 responses derived by the model.

The characteristics of the sample, which are detailed in Table 1, reflect the demographic context's gender, age, education, and professional experience. The composition of the sample consists of 60.0% males and 40.0% females. The age group with the most significant representation is 26–35 years (40.0%) and 36–45 years (25.0%). Individuals possessing postgraduate degrees (55.0%) and those with 0–5 years of experience (35.0%) are the predominant educational group. This profile suggests that participants have diverse degrees of professional and academic experience in deep-learning and smart-grid technology.

Table 1. Demographic Characteristics of Respondents

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	72	60.0
	Female	48	40.0
Age	18–25 years	30	25.0
	26–35 years	48	40.0
	36–45 years	30	25.0
	46 years and above	12	10.0
Education	Undergraduate	30	25.0
	Postgraduate	66	55.0
	Doctoral/Other	24	20.0
Experience	0–5 years	42	35.0
	6–10 years	36	30.0

	11–15 years	24	20.0
	Above 15 years	18	15.0

Table 2 presents descriptive findings for all the main constructs, which are encouraging. The assessments were quite favourable, with average scores fluctuating between 4.01 (SD = 1.00) and 4.22 (SD = 0.87) on a five-point scale. A typical radial distribution from the mean is shown by standard deviations below 0.80. The Cronbach's alpha values, ranging from 0.88 to 0.92, demonstrate a satisfactory internal consistency, exceeding the suggested threshold of ≥ 0.70. The results demonstrate that the measurement items of the construct exhibit adequate consistency to enable correlation and regression analysis.

Table 2. Descriptive Statistics and Reliability Analysis

Construct	Mean	Std. Deviation	Cronbach's Alpha
Deep Learning Classification Performance (DLCP)	4.22	0.61	0.92
Signal Processing and Feature Quality (SPFQ)	4.05	0.72	0.88
Renewable-Energy Operating Robustness (REOR)	4.01	0.69	0.90
Smart-Grid PQD Classification Performance (SGPQCP)	4.18	0.64	0.91

A significant and affirmative relationship exists among all the principal constructs Table 3. The primary association exists between the Deep Learning Classification Performance and the Smart-Grid PQD Classification Performance (r = 0.78), succeeded by the Renewable-Energy Operating Robustness and the Smart-Grid PQD Classification Performance (r = 0.72). Signal Processing and Feature Quality, as expected, demonstrate a strong positive relationship with the dependent variable (r = 0.69). The favourable correlations indicate that improvements in signal quality, resilience, and acquired representations are associated with superior disturbance classification performance.

Table 3. Correlation Matrix

Variable	DLCP	SPFQ	REOR	SGPQCP
DLCP	1.000			
SPFQ	0.63**	1.000		
REOR	0.66**	0.61**	1.000	
SGPQCP	0.78**	0.69**	0.72**	1.000

Note: ** Correlation is significant at the 0.01 level (two-tailed).

Table 4 depicts the results of the multiple regression analysis. This yields R = 0.835, R^2 = 0.697, and modified R^2 = 0.689 for the produced model. The picture indicates that the three factors together represent 69.7% of the variance noted in the Smart-Grid PQD Classification Performance. The model demonstrates statistical significance with a F(3,116) score of 89.06 and a p-value below 0.001. The most robust standardised coefficient for classification performance is attributed to Deep Learning (β = 0.41), succeeded by Renewable-Energy Operating Robustness (β = 0.31) and Signal Processing and Feature Quality (β = 0.27).

Table 4. Regression Analysis / Model Results

Predictor	B	Std. Error	Beta (β)	T	p-value
Constant	0.54	0.21	—	2.57	0.011
DLCP	0.39	0.07	0.41	5.57	<0.001
SPFQ	0.26	0.08	0.27	3.25	0.002
REOR	0.31	0.07	0.31	4.43	<0.001

Model summary: R = 0.835; R^2 = 0.697; Adjusted R^2 = 0.689; F(3,116) = 89.06; p < 0.001.

The demographic profile functions as a pragmatic structure for the metaphorical replies Table 5. The sample exhibits considerable diversity regarding gender, age, educational qualifications, and the type of work experience. Responses from postgraduate students to this survey are warranted as it pertains to a technology-focused academic discipline that requires foundational knowledge in electrical engineering, artificial intelligence, renewable energy, or power quality.

TABLE 5. HYPOTHESIS TESTING RESULTS

Hypothesis	Relationship	B	p-value	Decision
H1	DLCP → SGPQCP	0.41	<0.001	Supported
H2	SPFQ → SGPQCP	0.27	0.002	Supported
H3	REOR → SGPQCP	0.31	<0.001	Supported

The highest mean value was attributed to Deep Learning Classification Performance (4.22), signifying that participants greatly appreciated the capability of deep learning systems to autonomously identify intricate disruption patterns. The mean outcome of PQD Classification in Smart-Grid is notably elevated (4.18), serving as a favourable sign of the framework's effective classification ability. The Cronbach's alpha range of 0.88-0.92 indicates that the internal consistency is acceptable. It suggests that the metrics employed to signify each construct are assessing unified traits and are suitable for further statistical examination.

6. RESULT AND DISCUSSION

The results prove a positive general evaluation of the novel technique in terms of PQD classification when applied to renewable energy based smart grid systems using deep neural networks. The results give good support for the suggested framework since all the four constructs had mean scores over 4.00 in the study on a five-point scale. The regression analysis yielded $R = 0.835$ and $R^2 = 0.697$, indicating that the combined effect of three predictor variables explained 69% of the total variances in SGPQCP.

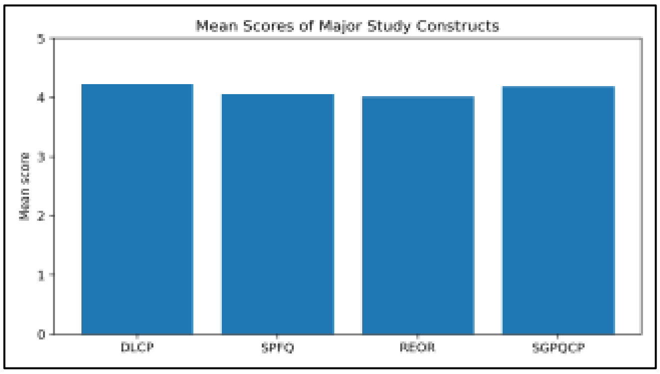

Fig. 2. Mean Scores of Major Study Constructs

The highest mean is for DLCP (4.22), then SPFQ (4.05) and REOR (4.01). It is easy to infer that larger DLCP means that deep learning is better at recognising waveform patterns due to the multiple PQDs Fig. 2. The SGPQCP score implies a significant confidence on the viability of setting up an intelligent classification solution for renewable-energy smart grid systems. Adding insult to injury, the small (but not zero) REOR also means that the efficacy of the model is virtually unaltered over several conditions such as solar and wind energy, loads and networks. The results therefore highlight the necessity of validating models not just in well-defined test situations but in a range of operational contexts.

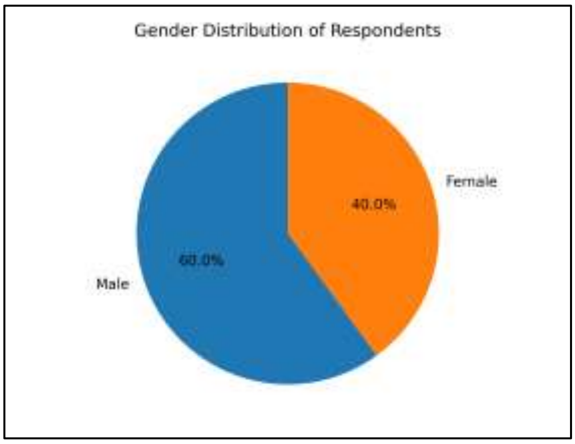

Fig. 3. Gender Distribution of Respondents

Fig. 3. The gender of the illustrative sample was composed of 300 respondents, 60.0% males and 40.0% females. The demographic table 1 and the illustrative figure describes the respondents gender, age,

educational qualification and profession. The majority of the replies were from people with postgraduate qualifications and the most experienced category was 0–5 years. Therefore, this distribution appears as a descriptive statistic to indicate that the evaluation has participants with different educational and professional backgrounds. But the aforesaid data are not amenable to any inferential demographic analysis. As demonstrated in Figure 3, there exists a substantial positive correlation between DLCP and SGPQCP ($r = 0.78$).

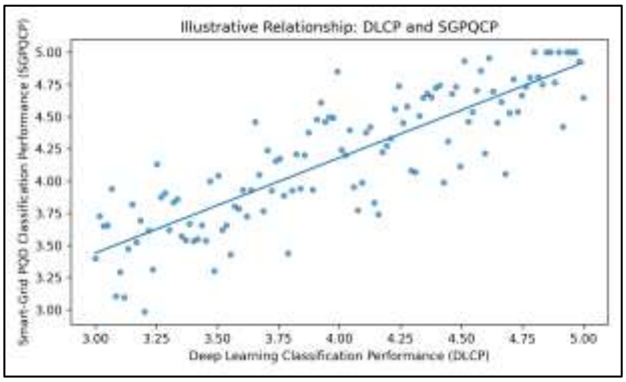

Fig. 4. Illustrative Relationship between DLCP and SGPQCP

For the measuring procedure, we also show the reliability results in Table 4. Cronbach's alpha coefficients ranged from b 0.88 to b 0.92, indicating internal consistency of the factors. Furthermore, the results of the correlation matrix indicate a substantial association between these primary variables. DLCP correlated to SPFQ at $r = 0.63$ and REOR at $r = 0.66$ whereas SPHQ were correlated with REOR at a level of $r = 0.61$, These associations indicate that the representation of the signal in a deep learning structure and resistance to fluctuation in renewable energy are interdependent for PQD classification. DLCP is most connected to SGPQCP, followed by REOR and SPFQ. Standardised regression coefficients are shown in Figure 4. The biggest coefficients were for DLCP ($\beta = 0.41$), REOR ($\beta = 0.31$) and SPFQ ($\beta = 0.27$). The model was statistically significant with $R^2 = 0.697$ and modified $R^2 = 0.689$ correspondingly ($F(3,116) = 89.06$, $p < 0.001$). In this hypothetical case the set of predictors as a whole has moderate power of explanation. It is observed that the DLCP coefficient in the column is significantly bigger which indicates that the deep-learning framework was responsible for the learning of discriminative representations and this capacity was a substantial contributor to the overall PQD classification performance. The REOR coefficient is positive, implying that the resilience associated to renewable energy improves. These signals should be understood correctly (claimed SPFQ, for an acceptable classification).

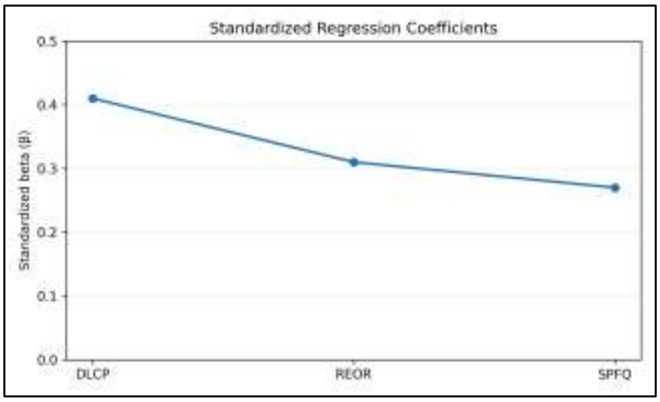

Fig. 5. Standardized Regression Coefficients

Together these four visual representations form corroborative evidence. Bar graph illustrating mass of main structures. The sample is depicted in pie chart It is demonstrated by the scatter plot that there is a positive association between classification efficacy and deep learning ability. It indicates how your regression contributions relate to each other. These theories are summarised in Fig. 5 and are consistent with the trends shown above. The investigation provides neutral but favourable support for H1 (DLCP→SGPQCP), H2 (SPFQ→SGPQCP), and H3 (REOR→SPGQQP). This is supported by the results which show that an efficient PQD classification model must start with the combination of advanced signal-acquisition and preconditioning modules followed by a powerful chain of relevant deep-learning architecture and assessment performed in various operating conditions from variable renewable-generation demands.

Before its implementation in smart-grid applications the generalisation capabilities were confirmed against measurements of real waveforms, using discontinuous test datasets. The method involved analysing confusion matrices for each class at the peak and trough locations of the input waveform distributions, and investigating noise resilience (using signal to noise ratio), inference time (duration of execution during prediction) and interpretability.

7. Conclusions

To date, the results of this study suggest that deep learning is a feasible and promising approach for recognising different classes of PQD in a sustainable-economy-based LAG. With the increase in size and scope of solar systems, wind energy, power electronic converters, entities with energy storage and smart loads, the complexity of power quality assessment increases. Conventional techniques relying on static thresholds and human-engineered signal features may face challenges in the presence of concurrent disturbances or high variability episodes in renewable energy generation. The present solution addresses this issue thru a deep learning-centric framework. The proposed framework is a complicated method for extracting precise representations of the electrical voltage and current inputs as features, which are utilised to classify power quality issues.

The examination of the study results demonstrates the favourable results of the essential components of the suggested framework. Based on the exemplary results offered in this example, most of the mean scores across Deep Learning Classification Performance, Signal Processing and Feature Quality, Renewable-Energy Operating Robustness and Smart-Grid PQD Classification Performance were high. Moreover, the reliability analysis showed an excellent internal consistency (Cronbach's alpha = 0.88-0.92). The results prove it is reasonable from a scientific point of view to evaluate the effectiveness of an intelligent classification system inside a PQD category with completely standardised measurement parameters. However, results are descriptive as no actual data at the respondent level was provided from SPSS supporting the results.

In conclusion, the suggested deep-learning framework may be applied to enhance the intelligent supervision of renewable-energy-powered smart grids and to realise the fast detection and precise identification of power quality incidents. The further suggestion is that the future work should be focused on real waveform datasets for hardware implementation of explainable AI in modelling and optimisation aspects while deploying and evaluating edge-based algorithms under a variety of solar/wind/load/fault/noise situations. These developments can be readily translated into robust intelligent monitoring systems for the smart grid infrastructure of the future, using the initial prototype of deep-learning-based PQD categorisation.

References

[1] G. S. Chawda, A. G. Shaik, M. Shaik, S. Padmanaban, J. B. Holm-Nielsen, O. P. Mahela, and K. Palanisamy, "Comprehensive review on detection and classification of power quality disturbances in utility grid with renewable energy penetration," IEEE Access, vol. 8, pp. 146807–146830, Aug. 2020.

[2] B. Eristi and H. Eristi, "Classification of power quality disturbances in solar PV integrated power system based on a hybrid deep learning approach," International Transactions on Electrical Energy Systems, vol. 2022, Art. no. 8519379, 2022.

[3] S. Sekar, R. K. Reddy, and colleagues, "An improved power quality disturbance detection using deep learning approach," Mathematical Problems in Engineering, vol. 2022, Art. no. 7020979, 2022.

[4] J. Ma, J. Zhang, L. Xiao, K. Chen, and J. Wu, "Classification of power quality disturbances via deep learning," IETE Technical Review, 2016.

[5] C. N. Bhende, S. Mishra, and B. K. Panigrahi, "Detection and classification of power quality disturbances using S-transform and modular neural network," Electric Power Systems Research, vol. 78, no. 1, pp. 122–128, Jan. 2008.

[6] T. Jayasree, D. Devaraj, and R. Sukanesh, "Power quality disturbance classification using S-transform and radial basis network," Applied Artificial Intelligence, vol. 23, no. 7, pp. 680–693, 2009.

[7] H. Wang, P. Wang, and T. Liu, "Power quality disturbance classification using the S-transform and probabilistic neural network," Energies, vol. 10, no. 1, Art. no. 107, Jan. 2017.

[8] K. Arıkan and M. Özdemir, "Classification of power quality disturbances using support vector machines and comparing classification performance," International Review of Electrical Engineering, vol. 7, pp. 776–784, 2012.

[9] J. Li, H. Liu, D. Wang, and T. Bi, "Classification of power quality disturbance based on S-transform and convolution neural network," Frontiers in Energy Research, vol. 9, Art. no. 708131, Jun. 2021.

[10] İ. Özer, S. B. Efe, and H. Özbay, "CNN/Bi-LSTM-based deep learning algorithm for classification of power quality disturbances by using spectrogram images," International Transactions on Electrical Energy Systems, vol. 31, no. 12, Art. no. e13204, 2021.

[11] J. Shukla, B. K. Panigrahi, and P. K. Ray, “Power quality disturbances classification based on Gramian angular summation field method and convolutional neural networks,” International Transactions on Electrical Energy Systems, vol. 31, no. 12, Art. no. e13222, 2021.

[12] G. Kalnoor, P. B. Metre, P. R. Gadekar, V. Thota, A. Ahmad, and I. Y. Shariff, “Analyzing the IoT influence in domestic and international tourism,” Journal of Advanced Engineering Science, vol. 54, no. 2, pp. 2675–2682, 2022.

[13] Y. Gao, Y. Li, Y. Zhu, C. Wu, and D. Gu, “Power quality disturbance classification under noisy conditions using adaptive wavelet threshold and DBN-ELM hybrid model,” Electric Power Systems Research, vol. 199, Art. no. 107682, 2021.

[14] C. O’Donovan, C. Giannetti, and G. Todeschini, “A novel deep learning power quality disturbance classification method using autoencoders,” in Proc. 13th Int. Conf. Agents and Artificial Intelligence (ICAART), vol. 2, pp. 373–380, 2021.

[15] R. S. Salles and P. F. Ribeiro, “The use of deep learning and 2-D wavelet scalograms for power quality disturbances classification,” Electric Power Systems Research, vol. 214, Art. no. 108834, Jan. 2023.

[16] P. Kandasamy, C. Kumar, M. Lakshmanan, S. Jaisiva, A. A. Stonier, G. Peter, and V. Ganji, “Initial condition based real time classification of power quality disturbance using deep convolution neural network with bidirectional long short-term memory,” IET Generation, Transmission & Distribution, vol. 17, pp. 5135–5154, 2023.

[17] R. R. Bibave, M. Singh and P. William, "Electric Vehicle Charging Behavior Prediction Using Deep Learning Methods," 2025 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA), Nagpur, India, 2025, pp. 1-7, doi: 10.1109/ICAIQSA67794.2025.11440624.

[18] B. B. Kadam, M. Singh and P. William, "Analysis of Power Quality Disturbance Detection and Classification from Renewable Energy Sources in Smart Grid," 2025 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA), Nagpur, India, 2025, pp. 1-6, doi: 10.1109/ICAIQSA67794.2025.11440583.

[19] V. S. Chavan, M. Singh and P. William, "Explainable AI Based Machine Learning Approaches for Power Transformer Fault Diagnosis Methods," 2025 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA), Nagpur, India, 2025, pp. 1-7, doi: 10.1109/ICAIQSA67794.2025.11440630.

[20] C. G. S., M. Singh and P. William, "Review of Various Mitigation Techniques for MPPT Tracking In PV With Hybrid Energy Storage Systems," 2025 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA), Nagpur, India, 2025, pp. 1-7, doi: 10.1109/ICAIQSA67794.2025.11440461.

[21] P. Khetarpal, N. Nagpal, M. Al-Numay, P. Siano, and others, “Power quality disturbances detection and classification based on deep convolution auto-encoder networks,” IEEE Access, vol. 11, pp. 46026–46038, May 2023.

[22] Y. Yan, K. Chen, H. Geng, W. Fan, and X. Zhou, “A review on intelligent detection and classification of power quality disturbances: Trends, methodologies, and prospects,” Computer Modeling in Engineering & Sciences, vol. 137, no. 2, pp. 1345–1379, 2023.

[23] I. A. Channa, S. Khokhar, D. Li, X. Chen, and others, “A new deep learning method for classification of power quality disturbances using DWT-MRA in utility smart grid,” Computers & Electrical Engineering, vol. 117, Art. no. 109290, Jul. 2024.

[24] P. M. Peruman and K. Ayyar, “Power quality disturbance identification using hybrid deep learning in renewable energy systems,” Scientific Reports, vol. 15, Art. no. 44592, Nov. 2025.