Detection and Classification of Power Quality Disturbances in Large-Scale Industrial Photovoltaic-Rich Distribution Grids Using a Deep Neural Network

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Abstract: **Power quality disturbances (PQDs), including voltage sags, swells, harmonics, and transient fluctuations, pose significant challenges to the stability, reliability, and efficient operation of large-scale industrial distribution grids, particularly with the increasing integration of photovoltaic (PV) systems. This paper presents a deep learning-based approach for the detection and classification of PQDs using real and simulated data from an active industrial distribution network. The distribution grid is modeled and simulated in ETAP 19.0.1, incorporating power load-flow and harmonic analyses to represent the operating conditions of the studied system. A deep neural network (DNN) is trained using a comprehensive dataset to classify the predefined PQD categories. The proposed DNN achieves a training accuracy of approximately 94% and a validation accuracy of approximately 92%, compared with the 85% accuracy reported for the DAG-SVM approach developed by Li et al. [1]. The results demonstrate that the proposed approach can effectively classify PQDs and provide a scalable framework for real-time power quality monitoring. Furthermore, the proposed method enhances the capability of industrial distribution systems to identify and manage disturbances under diverse operating conditions. These findings highlight the potential of deep learning as a practical and scalable solution for PQD classification and monitoring in modern industrial power systems, particularly in PV-integrated environments.**

Keywords: **Active distribution network, Deep learning, Power quality disturbances, Real-time monitoring**

I Introduction

Power quality disturbances represent a critical challenge in maintaining the stability, efficiency, and reliability of large-scale industrial photovoltaic-rich distribution grids, especially with the increasing integration of renewable energy sources such as Photovoltaic (PV) systems. These disturbances, including voltage sags, swells, interruptions, harmonics, and transients, can significantly disrupt industrial operations, leading to financial losses, reduced system reliability, and equipment damage. The detection and classification of PQD are therefore crucial for minimizing these impacts and ensuring seamless industrial operations. Recent advancements in signal processing, artificial intelligence (AI) and machine learning (ML) have opened new pathways to address the complexities of PQD in modern distribution systems. This study provides an overview of state-of-the-art methodologies for power quality (PQ) disturbance detection and classification, with particular emphasis on PV-integrated distribution systems, where the increasing penetration of renewable energy introduces additional challenges for PQ management. Li et al. [1] developed a framework that combines the double-resolution S-transform with directed acyclic graph support vector machines (DAG-SVMs) for the detection and classification of PQ disturbances. Their method achieved high accuracy in distinguishing different PQ events, demonstrating the effectiveness of integrating advanced signal-processing techniques with machine-learning methods. This approach provides a basis for developing detection systems capable of addressing the multifaceted nature of PQ disturbances in real-time industrial environments. Saxena et al. [2] presented an overview of PQ event classification, focusing on fundamental concepts and emphasizing the importance of robust feature-extraction techniques. They also identified several challenges associated with applying these techniques in practical environments, including the requirements for high-speed computation and robustness against noise. Khetarpal and Tripathi [3] conducted a critical review of PQD detection and classification methodologies, highlighting the importance of computational efficiency when processing the large datasets typically encountered in industrial systems. Their study emphasized the need to achieve an appropriate balance between classification accuracy and computational complexity, particularly for large-scale applications. Khaleel et al. [4] investigated AI-based approaches for identifying the underlying causes of power system disturbances. Their findings demonstrated the potential of intelligent methods to improve the reliability and adaptability of power grids while supporting proactive functions be-

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yond disturbance detection, including prediction and prevention. Caicedo et al. [5] presented a systematic review of real-time PQD detection and classification techniques, with particular attention to scalability and adaptability in complex power systems. Their study highlighted the trade-off between computational speed and classification accuracy, which is particularly important in large-scale industrial systems with high PV penetration. Salkuti et al. [6] examined PQ challenges in microgrids and discussed mitigation strategies associated with renewable energy integration. Their findings are relevant to industrial distribution systems incorporating PV generation, where the intermittent nature of solar power can increase the variability and complexity of PQ disturbances. Singh et al. [7] reviewed feature-extraction techniques for PQ disturbance classification in distributed-generation systems and discussed their effectiveness under different system requirements. Similarly, Beniwal et al. [8] critically reviewed methodologies for detecting and classifying PQ events in smart grids, highlighting the growing application of deep learning techniques to address the diverse and dynamic characteristics of modern power systems. Chawda et al. [9] further reviewed PQD detection methods developed for utility grids with high renewable-energy penetration and emphasized the importance of combining conventional and modern computational techniques to address the challenges introduced by renewable energy sources. Ravi and Kannaiah [10] proposed a PQ disturbance classification method based on the Stockwell transform and optimization techniques. Their approach uses advanced signal-processing methods to improve classification accuracy while maintaining computational efficiency. Priyadarshini et al. [11] investigated several signal-processing techniques for PQ analysis, including Fourier, short-time Fourier, and wavelet transforms, and demonstrated the importance of selecting appropriate signal-processing tools for different types of disturbances. Yan et al. [12] reviewed recent trends and methodologies in intelligent PQD detection and classification and identified emerging approaches, including hybrid models that combine conventional techniques with AI-based methods. Mahela et al. [13] provided a comprehensive review of PQ event detection strategies, tracing the development of these techniques and identifying research gaps that remain to be addressed. Jha and Shaik [14] investigated PQ mitigation strategies for PV-integrated systems and discussed practical approaches for improving system reliability and resilience. Oubrahim et al. [15] reviewed signal-processing and pattern-recognition techniques for characterizing PQ disturbances and discussed their applicability to a range of power system scenarios. Mishra [16] examined the application of soft-computing techniques to PQD detection and classification, particularly in the presence of uncertainties inherent in power systems. Oliveira and Bollen [17] investigated recent developments in deep learning for PQ analysis and highlighted its capability to process large and complex datasets with high accuracy. Samanta et al. [18] further reviewed deep-learning applications in PQ analysis, including convolutional neural networks (CNNs) and recurrent neural networks (RNNs), which have demonstrated considerable potential for classification tasks. Ma et al. [19] investigated the application of CNNs to PQ disturbance classification and demonstrated their ability to extract relevant features directly from input data with limited preprocessing. Dekhandji et al. [20] employed long short-term memory (LSTM) networks to analyze the temporal characteristics of PQ disturbances, demonstrating their capability to capture sequential dependencies. Finally, Khetarpal et al. [21] applied deep convolutional autoencoder networks to PQD detection and classification and reported improved classification performance, demonstrating the potential of unsupervised deep-learning techniques for PQ analysis.

Recent studies have further expanded the methodological landscape of PQD detection and classification by incorporating attention mechanisms, recurrent architectures, Transformer-based models, active learning, and hybrid signal-processing frameworks. Chiam et al. [22] developed an LSTM-based approach combined with wavelet decomposition and an attention mechanism to capture both temporal and time-frequency characteristics of PQDs, demonstrating the potential of recurrent architectures for complex disturbance patterns. Eristi et al. [23] investigated PQD classification in solar PV-integrated power systems using continuous wavelet transform and a hybrid CNN-based framework combining AlexNet, GoogLeNet, neighbor component analysis, and support vector machines, highlighting the effectiveness of combining time-frequency representations with deep feature extraction and conventional classifiers. More recently, Yoon and Yoon [24] proposed a Transformer-based deep learning model for real-time power-system disturbance detection, demonstrating the capability of end-to-end attention-based architectures to process voltage and current waveforms without relying exclusively on conventional feature-engineering procedures. In another direction, multi-strategy active learning has been investigated to reduce the dependence on large amounts of labeled data for multiple PQD classification, providing an alternative learning paradigm for practical monitoring applications [25]. Furthermore, recent studies have explored more advanced attention-based architectures, including multi-level convolutional networks combined with Transformer models for PQD classification in microgrids, with particular emphasis on extracting both local temporal features and global dependencies from raw one-dimensional signals [26]. Other recent developments include multi-scale CNNs with attention mechanisms [27], residual networks with channel-attention mechanisms [28], and transformer-based time-frequency feature fusion [29], reflecting a clear shift toward end-to-end and attention-enhanced learning architectures for robust PQD classification.

Despite the considerable progress in signal processing, machine learning, and deep learning for PQD detection and classification, important challenges remain when these methods are considered for large-scale industrial distribution grids with high PV penetration. Recent approaches have demonstrated considerable classification performance using advanced architectures such as CNNs, LSTMs, attention mechanisms, and Transformers; however, many of these methods are evaluated primarily using benchmark or simulated datasets, microgrid test systems, or specifically constructed disturbance signals. Moreover, several approaches rely on additional signal transformations, handcrafted or engineered features, or multi-stage feature-extraction procedures, which may increase computational complexity and limit their direct applicability to practical industrial monitoring environments. In this study, a deep learning-based approach is developed specifically for PQD detection and classification in a large-scale industrial PV-rich distribution grid. The proposed model is trained using a combination of real operational and simulated data, enabling it to learn representative disturbance patterns while accounting for the operating characteristics of an actual industrial distribution network. Furthermore, the integration of power-system simulation with the deep learning framework provides a scalable basis for real-time PQ monitoring. To the best of the authors' knowledge, this study is among the first to investigate PQD classification using real operational data from a large-scale industrial PV-rich distribution grid, thereby addressing an important gap between advanced methodological developments and their practical deployment in active industrial distribution systems.

II PQ Problem Statement In Active Distribution Grids

Power quality (PQ) is a critical aspect of modern power systems, as it directly affects the performance, efficiency, and operational safety of electrical equipment. With the increasing demand for electricity across industrial, commercial, and other sectors, maintaining an acceptable level of power quality has become a major challenge. PQ problems include a wide range of phenomena, such as transient events, short- and long-term voltage variations, voltage and current unbalance, harmonics, interruptions, and sudden changes in voltage magnitude. In active distribution systems, particularly large-scale industrial distribution grids with high photovoltaic (PV) penetration, poor power quality can have significant operational and economic consequences. These consequences include reduced equipment lifetime, increased maintenance costs, production losses, and degradation of product quality. In industrial production lines, for example, electrical interruptions and voltage dips can interrupt manufacturing processes and increase downtime, resulting in substantial financial losses. Accordingly, this study focuses on voltage variations and harmonic distortion in active distribution grids, as these phenomena play a key role in maintaining the reliable and efficient operation of industrial power systems. In particular, voltage dips and swells caused by the starting or disconnection of high-power motors, as well as voltage and current harmonics exceeding the permissible limits specified by relevant standards, must be carefully evaluated to minimize their adverse operational and economic impacts.

A Voltage Dip / Swell

Voltage dips are commonly caused by faults in power systems and may also result from the connection or starting of large loads in industrial applications. They typically occur following significant changes in load conditions or during the starting of large motors. For instance, an induction motor may draw a starting current four to twelve times its rated full-load current. This substantial increase in current causes a voltage drop across the system impedance. During a fault, the resulting increase in current magnitude can lead to a more pronounced reduction in voltage. In contrast, voltage swells may occur following sudden changes in load conditions, such as the disconnection of a large load, including a medium-voltage motor, or variations in reactive power compensation, such as the energization of a capacitor bank [30].

B Harmonics

Electrical devices with nonlinear voltage-current characteristics are major sources of harmonic distortion in power systems. Common sources of harmonics include power electronic converters used as rectifiers in various industrial applications, such as adjustable-speed drives (ASDs), uninterruptible power supplies (UPSs), battery chargers, and static frequency converters. Other significant sources include power converters, arc furnaces, and equipment operating under magnetic saturation. Because nonlinear devices constitute a substantial portion of the total load in industrial electrical distribution systems, harmonic analysis is an essential aspect of their design and operation. Relevant standards specify the permissible levels of harmonic distortion at the point of common coupling (PCC). By modeling power-system impedances as functions of harmonic frequency and representing harmonic sources as injected currents or imposed voltages, harmonic studies can be performed to evaluate the effects of nonlinear loads on the voltage and current characteristics of the system [29].

III Methodology And Approach

A Power Load Flow

Numerical analysis, which involves the simultaneous solution of a set of algebraic equations, is fundamental to the analysis of electrical power systems. In power load-flow studies, these equations are solved computationally to determine the operating conditions of the system. The first step in the load-flow analysis is to construct the bus admittance matrix (Y-bus) using the transmission-line, transformer, and distribution-grid data. The Newton-Raphson method is employed in ETAP 19.0.1 to perform the power load-flow analysis. This iterative method is widely used because of its strong convergence characteristics and its ability to provide reliable solutions for nonlinear power-system equations, including cases in which other conventional methods may encounter convergence difficulties. For each bus, the following equation can be expressed in terms of the Y-bus matrix:

$$I_i = \sum_{j=0}^{n} Y_{ij} V_j \tag{1}$$

where I_i is bus bar current, Y_{ij} is admittance between buses i and j and V_j is bus bar voltage j. Expressing (1) in polar form, the following relationship is obtained:

$$I_i = \sum_{j=1}^{n} \left|Y_{ij}\right| \left|V_j\right| \angle(\theta_{ij} + \delta_j) \tag{2}$$

The complex power on the bus i is:

$$P_i - jQ_j = V_i^* I_i \tag{3}$$

where P_i is active power on the bus i and Q_j is reactive power on the bus i. Substituting I_i from (2) in (3) and separating the real and imaginary part:

$$P_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_j + \delta_j) \tag{4}$$

$$Q_i = \sum_{j=1}^{n} |V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_j + \delta_j) \tag{5}$$

B Harmonic Load Flow

Harmonic release can occur across various domains and frequencies. In power systems, the most common harmonics are the sinusoidal components of a periodic waveform, which can be categorized into several main frequency components. Fourier analysis is the mathematical tool employed for this type of analysis. In a balanced three-phase system under non-sinusoidal conditions, the voltage harmonic order or current is defined as:

$$V_{ah} = \sum_{h\neq 1} V_h (h\omega_0 t - \theta_h) \tag{6}$$

$$V_{bh} = \sum_{h\neq 1} V_h \left(h\omega_0 t - \left(\frac{h\pi}{3}\right) \theta_h \right) \tag{7}$$

$$V_{ch} = \sum_{h\neq 1} V_h \left(h\omega_0 t - \left(\frac{2h\pi}{3}\right) \theta_h \right) \tag{8}$$

Harmonic voltage coefficients and currents are parameters used to measure and analyze harmonics in power systems. These coefficients indicate the proportion of each harmonic (frequencies above the base frequency) in the voltage or current of the system and are important in evaluating the effects of harmonics on the quality and performance of electrical systems. Consequently, the effective voltage and current in the presence of harmonics can be expressed through the following equations:

$$V_{rms} = \sqrt{\sum_{h=1}^{n} V_h^2}, \tag{9}$$

$$I_{rms} = \sqrt{\sum_{h=1}^{n} I_h^2}, \tag{10}$$

$$THD_V = \sqrt{\left(\frac{V_{rms}}{V_{f,rms}}\right)^2 - 1} \tag{11}$$

$$THD_I = \sqrt{\sum_{h=2}^{n} I_{h,rms}^2} = \sqrt{\left(\frac{I_{rms}}{I_{f,rms}}\right)^2 - 1} \tag{12}$$

C Deep Neural Network-Based PDD Classification

A deep feedforward neural network (DNN) is developed in this study for the detection and classification of power quality disturbances (PQDs). The proposed network consists of an input layer, two fully connected hidden layers, and an output layer. Three input features are first normalized using the MinMaxScaler and then fed into the network. The first hidden layer contains 128 neurons with ReLU activation, while the second hidden layer contains 64 neurons with ReLU activation. Finally, a Softmax output layer generates the probability associated with each disturbance class. The overall architecture is therefore defined as 3-128-64-C, where C denotes the number of output classes.

Input data and normalization: The neural network accepts the input data as the initial feature. Within this framework, the following three characteristics are designated as input values: $X = [\text{Voltage}, \text{THD}_i, \text{THD}_i]^T$. To ensure that the data is on a uniform scale and to prevent the model from being disproportionately influenced by features with larger scales, the MinMaxScaler is employed. This technique maps the data to the interval [0,1]. The normalization formula is presented as follows [30]:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \tag{13}$$

where X is original feature value, X_{min} is minimum value of the feature across the dataset, X_{max} is maximum value of the feature across the dataset and X_{norm} is normalized feature value within the [0,1] range.

First layer: In this stage, the inputs pass through a dense layer with 128 neurons and the ReLU activation function. The structure of this layer is described below: (i) the first layer contains 128 neurons, (ii) each neuron computes a linear combination of the inputs and weights; adding a bias term to generate a new output; and, (iii) this linear output is passed through the ReLU activation function. The mathematical representation is as follows:

$$Z_1 = b_1 + XW_1 \tag{14}$$

where X is input matrix (size: $n \times 3$, where n is the number of samples and 3 is the number of features), W_i is weight matrix size: 3×128 as 3 features connect to 128 neurons), b_I is bias vector (size: 1×128 and Z_I is output of the first layer. This linear combination is then passed through the ReLU activation function:

$$A_1 = ReLU(Z_1) \tag{15}$$

The ReLU function operates as follows:

$$ReLU(x) = \max(0, x) \tag{16}$$

The purpose of this function is to introduce nonlinearity into the model.

Second hidden layer: After the first layer, the data is passed to the second layer, which consists of 64 neurons and also uses the ReLU activation function. The second layer has 64 neurons. The outputs from the first layer serve as inputs for this layer. The mathematical representation is similar to the first layer:

$$Z_2 = b_2 + A_1 W_2 \tag{17}$$

where is A_I is output from the first layer (size: $n \times 128$ W_2 is weight matrix size: 128×64 as 128 features connect to 64 neurons), b_2 is bias vector size: 1×64 and Z_2 is output of the second layer. This linear output is then passed through the ReLU activation function:

$$A_2 = ReLU(Z) = \max(0, Z) \tag{18}$$

Output layer: The output layer is responsible for generating the final predictions, expressed as the probability of each class. This involves two steps: a linear combination and the application of the Softmax function. The output layer predicts class probabilities. The number of neurons equals the number of classes (e.g., 3 neurons for a 3-class prediction). The linear output is computed as:

$$Z_3 = b_3 + A_2 W_3 \tag{19}$$

where is A_2 is output from the second layer size: $\mathrm{n} \times 64$ W_3 is weight matrix size: 64×3 as 64 features connect to 3 output classes), b_3 is bias vector size: 1×3 and Z_3 is output of the final layer.

Softmax function: The Softmax function converts the outputs into probabilities:

$$\text{Softmax}(x_i) = \frac{e^{x_i}}{\sum_j e^{x_i}} \tag{20}$$

where is x_i is output of the i neuron in the output layer, C is total number of classes, and e^{x_i} is exponential of x_i. This ensures the probabilities sum to 1, with each value representing the likelihood of the input belonging to a specific class.

Cost function: The cost function evaluates the model's performance. Sparse Categorical Cross entropy is used in this model, ideal for multi-class classification problems. It calculates the difference between the predicted outputs and actual labels:

$$L = -\sum y_i \log(A_{3,i}) \tag{21}$$

where is y_i is output of the i neuron in the output layer, and $A_{3,i}$ is total number of classes.

Optimization: The Adam optimization algorithm is used to train the neural network. This method combines Momentum and RMSProp techniques to adjust the weights and biases, ensuring stable and efficient convergence. Key steps include:

Gradient moments:

$$m_t = \beta_1 m_{t-1} + (1 + \beta_1) g_t \tag{22}$$

$$v_t = \beta_2 v_{t-1} + (1 + \beta_2) g_t^2 \tag{23}$$

Bias correction:

$$\hat{m}_t = \frac{m_t}{1 - b_t^t}, \quad \hat{v}_t = \frac{v_t}{1 - b_t^t} \tag{24}$$

Weight update:

$$\theta_t = \theta_{t-1} - \eta \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon} \tag{25}$$

where m_t is exponential moving average of the gradients, v_t is Squared values for m_t, and $\hat{m}_t$ is correction factor for first bias, $\hat{v}_t$ is correction factor for second bias, θ_t is weight at time, β_1 is gradient averaging rate (default value 0.9), β_2 is gradient variance averaging rate (default value 0.999), g_t is gradient at time, η is learning rate, and ϵ is small constant to prevent division by zero. The real data is part integrates the trained deep learning model, which have been applied in the active power distribution grid. The real data application part of this paper is explained as follows: (i) first step—power load flow analysis: to effectively leverage the foundational data of the active distribution network, a power load distribution analysis is conducted under the condition that all consumers are fully operational. Subsequently, the voltage values, along with the specifications for harmonic voltage and current at each bus, will serve as reference information; (ii) second step—motor starting study: to investigate the occurrence of voltage dips or swells within the distribution system, a study focused on the starting characteristics of the largest medium voltage motors will be conducted. In large-scale industrial distribution active plants, the rotating equipment, like motors and compressors, has an important role. So, the data obtained from this study will facilitate a comparison between the primary findings and established standards; (iii) third step—PV connection to distribution grid: to review and check the harmonic effects in distribution grids, a photovoltaic (PV) plant that will supply power in the event of an outage in one of the incoming supply lines has been simulated. During this phase, variations in voltage, as well as the harmonics of voltage and current, will be analyzed through a harmonic load flow study; and, (iv) fourth step—segmentation collected data: following the completion of the simulation and analysis of the distribution network, all collected data, including voltage, voltage harmonics, and current for each bus, will be systematically categorized into base operating modes, specifically motor starting and PV plant connection. This data will serve as the foundational input for the deep learning system.

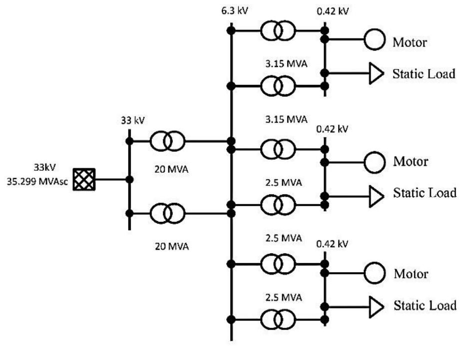

Figure 1. Single line diagram for feeder #1.

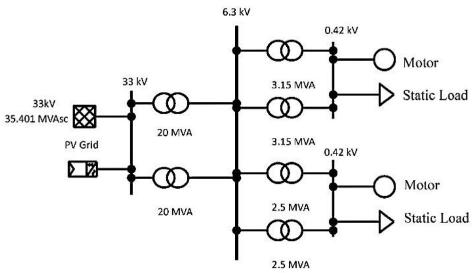

Figure 2. Single line diagram for feeder #2.

IV Simulation And Experimental Result

A Upstream Network and Dataset

The studied large-scale distribution grid is supplied by two 33 kV cable lines originating from an upstream GIS substation. These cables are directly connected to the input terminals of a 33/6.3 kV transformer, providing the entire power demand of this plant. The electrical network specifications of the incoming supply, as received from the upstream substation, including the short-circuit capacities and X/R ratios of the incoming feeders, are summarized in Table I. To develop and train the proposed deep neural network, a comprehensive dataset was constructed by integrating real operational data from the industrial distribution grid with simulated data generated via ETAP 19.0.1. The final dataset comprises a total of 4500 samples. To ensure the model's robustness and practical applicability, the dataset was constructed with a specific contribution ratio: approximately 30% of the data consists of real operational measurements recorded from the actual industrial plant, while the remaining 70% consists of simulated data generated under various loading and fault conditions to expand the diversity of the disturbance patterns. The dataset is categorized into three predefined power quality disturbance classes, reflecting the primary operational scenarios discussed in the methodology. The distribution of samples across these classes is as follows:

- Class 1: Base/normal operating mode (1200 samples): Represents the steady-state operation of the grid under normal load conditions.
- Class 2: Motor starting events (1800 samples): Captures voltage sags, swells, and transient fluctuations caused by the starting of large medium-voltage motors.
- Class 3: PV plant connection (1500 samples): Represents harmonic distortions and voltage variations introduced during the energization and operation of the photovoltaic system.

This structured distribution ensures that the DNN is adequately trained to recognize both normal operating conditions and the specific disturbances associated with large motor starting and PV integration in the active distribution grid.

B Distribution Grid Structure

The configuration of the simulated distribution grid is illustrated in Figs. 1 and 2. This network is supplied by two 33kV cable feeders from a GIS substation. The incoming lines to the main power substation of the complex are connected to four 33/6.3kV power transformers. The technical specifications of the power and distribution transformers employed in the studied industrial distribution network, including rated power, voltage levels, impedance values, grounding methods, and vector groups, are presented in Table II. The total power consumption and system design of the unit is based on process design specifications, which have been derived from the system's process data. In this distribution plant's main substation, two 6kV switchgear panels, fed by parallel transformers, are designated to connect and supply power to medium-voltage electric motors and distribution transformers.

C Simulation and Discussions

Load distribution studies were performed using ETAP 19.0.1 C software based on the single-line diagram of the entire system. All equipment and components simulated in the software, including transformers, motors, cables, solar panels, and fixed loads, were performed by the standards available in the software. The distribution network was simulated based on the following assumptions:

- A GIS substation supplies the input power of this industrial unit with 6x1x300 mm2 cables.
- Motor information is selected based on the specifications available in the software and IEC standards.
- Cable reactance and resistance values are considered based on the specifications of IEC standards.
- The secondary voltage of the power transformers is 6.3 and 0.42 kV, respectively, in the no-load state.
- The capacity of any transformer (power and distribution) should not be less than 120% of the power consumption.

Figure 3 illustrates the variations in the training and validation accuracy of the proposed deep neural network (DNN) over 200 training epochs. The primary objective of the proposed DNN is to detect and classify the predefined power quality disturbance categories using the selected input features. As shown in the figure, the training accuracy increases rapidly during the initial stages of training and exceeds 80% after approximately 20 epochs. The validation accuracy follows a similar trend and gradually stabilizes as training progresses. At the end of the training process, the training accuracy reaches approximately 94%, whereas the validation accuracy stabilizes at approximately 92%. The relatively small difference between the training and validation accuracies indicates satisfactory generalization performance and does not suggest substantial overfitting. The considered disturbances include abnormal voltage conditions, voltage sags, overvoltages, transient fluctuations, and harmonic distortion. The achieved accuracy demonstrates the potential of the RNN model for the rapid and accurate detection of PQDs in active distribution systems, where timely identification of disturbances is essential for maintaining reliable system operation. Overall, the results shown in Fig. 3 indicate that the model achieves stable classification performance under the adopted training configuration and dataset. Figure 4 presents the variations in the training and validation errors of the proposed DNN over 200 training epochs. The error metric represents the difference between the model predictions and the corresponding actual outcomes. As observed in the figure, both training and validation errors decrease substantially during the initial stages of training, indicating that the model progressively learns the underlying patterns in the training data. The error is initially relatively high, at approximately 1.2, but decreases rapidly as the training progresses and falls below 0.4 after approximately 50 epochs. The close correspondence between the training and validation error curves further indicates consistent model performance and limited overfitting. In particular, the simultaneous reduction in both errors suggests that the model learns the general characteristics of the dataset rather than memorizing specific training samples. By the end of the training process, the validation error decreases to approximately 0.25, indicating a high level of classification performance. The minor fluctuations observed in the training error during the final epochs can be attributed to the iterative optimization process as the model approaches a minimum of the objective function. Overall, Fig. 4 demonstrates that the proposed DNN achieves stable training behavior and satisfactory generalization performance, supporting its potential application for PQD detection in industrial distribution systems.

Table 1. Incoming Feeders Electrical Specifications

Incoming Feeders	Maximum		Minimum	
	SCC (kA)	X/R	SCC (kA)	X/R
Feeder #1 3Ph	35.299	13	29.077	13
Feeder #1 1Ph	2.973	13	2.69	13
Feeder #2 3Ph	35.401	13	29.077	13
Feeder #2 1Ph	2.974	13	2.69	13

Table 2. Power and Distribution Transformers Specification

Type	Rated Power (MVA)	Voltage (kV)	%Impedance	Grounding Method
THM01A/B Power	20	33/6.3	10	NGR
THM02A/B Power				
TML01A/B Distribution	2.5	6/0.42	8.5	TN-S
TML02A/B Distribution				
TML03A/B Distribution				
TML05A/B Distribution	3.15		9.5	
TML06A/B Distribution				

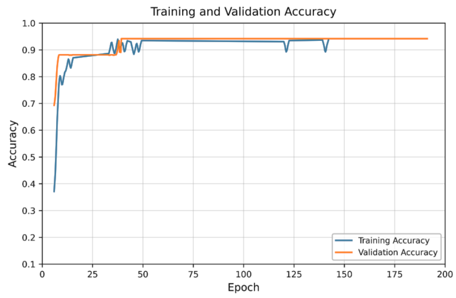

Figure 3. Accuracy and validity diagram of the trained model based on 200 epochs.

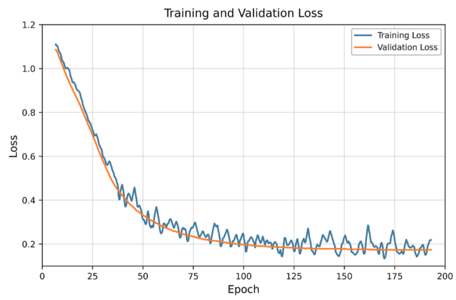

Figure 4. Loss diagram of the trained model based on 200 epochs.

V Conclusion

This study provides a comprehensive investigation of PQDs in active distribution networks and develops a deep learning-based approach for their detection and classification. Active distribution networks, owing to their complex structures and the increasing integration of distributed energy resources, such as photovoltaic (PV) systems and other distributed generation units, are susceptible to various disturbances that can reduce operational efficiency, increase costs, and potentially damage sensitive equipment. A key contribution of this study is the use of real operational data obtained from an industrial distribution network in Iran, which enhances the practical relevance and applicability of the developed approach. The results demonstrate that the proposed deep neural network can accurately identify various PQDs, including voltage sags, harmonics, and transient fluctuations. The models maintain satisfactory classification performance under different operating conditions and variations in the input data, indicating their robustness and generalization capability. Furthermore, the use of real operational data improves the practical effectiveness of the models compared with approaches based solely on simulated data. A comparison with conventional methods further indicates that the proposed deep learning approach has a greater capability to identify complex disturbance patterns. The developed framework also has potential for application in smart distribution systems, where rapid and accurate disturbance detection can support timely system monitoring and corrective actions.

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