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Original scientific paper

Embedded Parallel Computing Platform for Real-Time Recognition of Power Quality Disturbance Based on Deep Network

Dewan FENG

Abstract: Systems powered by scattered sustainable power sources are highly susceptible to disturbances in the quality of power. Power Quality Disturbances (PQD) signals can degrade the functionality of grid-powered appliances. The older techniques for recognizing thePQD signals involve feature extraction. Manual analysis needs to set up a digital signal processor platform, which may lead to a time-complex process and errors in accuracy. Real-time PQD (RPQD) recognition techniques have advanced Embedded Parallel Computing Platform(EPCP), various signal processing methods, artificial intelligence, and Deep Network (DN) methodologies to recognize RPQD signals successfully in real-time scenarios using EPCP-RPQD-DN. Initially, the proposed algorithm implements hybridized Deep Belief Network and Long Short-Term Memory (DBN-LSTM) to accurately recognize the real-time PQD signals. Secondly, the DBN module maximizes the input signal features for the generation of PQD in a fixed period by training phase directly from raw PQD input signals and forwards it to the LSTM module. Third, in LSTM, the time series nature of PQD signals is easily analyzed using three layers, allowing it to run on the EPCP model. The PQD sample signals are employed to train the DBN in a central monitoring server. A series of PQD signals generated by the EPCP simulation environment is carried out to validate the effectiveness of the EPCP-RPQD-DN approach. Real-time simulation of electromagnetic fault conditions in the power system by Real Time Digital Simulator (RTDS) hardware. Experimental evaluation shows that DN learning improves accuracy rate, reduces computational overhead, and minimizes error rate compared to existing approaches.

Keywords: deep belief network; embedded parallel computing; long-short term memory; power quality disturbance

1 INTRODUCTION

Power quality is one of the most significant aspects of an electrical power grid. Power quality is affected by voltage sag, swells, waveform distortions, and transients. Non-linear loads and other power load transmission networks are thought to be the primary cause of power quality disturbances. Signal quality and form distortions caused by power quality disturbances reduce total performance. PQD monitoring and analysis are often carried out using specialized measuring instruments, including power monitors, analog-digital converters, graphic cards, etc. To recognize PQD concerns, real-time recognition and categorization of single and complex PQDs from massive data is required. Real-time PQD is primarily related to sophisticated signals, systems platforms, robust artificial intelligence, and deep network techniques to categorize PQDs quickly, and an increased A PQDs maintenance system is being developed using an embedded platform. The emergence of algorithms based on deep learning offers PQD recognition by utilizing raw input signals to characterize PQD signals. Deep Network approaches merge extracting features and categorizing features into a single component, which accommodates the extraction and sorting of features being completely separate from older techniques. However, researchers will increasingly focus on using techniques based on deep learning to detect disturbances.

Real-time PQ measurements can aid in the knowledge of PQD transmission in the power network and allow for more accurate and timely actions regarding PQ concern mitigation. An RTDS is an excellent simulation tool for researching electricity systems. RTDS works perfectly to analyze intermittent electromagnetic incidents that occur in real time. RTDS simulation successfully and reliably captures signal variance and specific dynamic properties.

Conventional PQD recognition methods consist of three stages: extraction of features, image segmentation, and training and exposure. Earlier approaches have limited performance; thus DN model is introduced in [1]. A multi-label classifier and voting techniques are used to implement end-end PQD recognition in the DN model. Even though it produces good accuracy, it seems to have a computational burden by performing pre-training and retraining in the same phase. PQDs can seriously influence the relationship between electricity makers and consumers, resulting in energy inefficiencies, a restricted lifetime of power, failure and damages to sensitive loads, malfunction of control-based industrial operations, and so on [2]. Deep neural networks are prone to extended network training times and lesser computational time for restricted classification accuracy when dealing with massive quantities of power-quality data [3]. Convolution Neural Networks (CNN) based on the deep network were used with an attention methodology to identify the PQDs. All input solution in the attention model is increased by the actual components multiplied by the timestamp duration [4]. It gives good accuracy and reduced error rate, but it fails to focus on the computational complexity of the proposed system in PQD identification. A Field Programmable Gate Array (FPGA)-based PQD is created [5] for real-time diagnosis by combining Wavelet transform (WT) with Decision Tree and Least-Square Support Vector Machine (DT-LSSVM) algorithms. An Internet-based Power Quality Monitoring System (IPQMS) based on FPGA is presented [6] to recognize PQD utilizing real-time software systems and web application programs on the server computer. WT's average efficiency is acceptable in ideal conditions but suffers dramatically in chaotic surroundings.

The recognition rate of multiclass Support Vector Machine (SVM) algorithms is great using mono-frequency components and adaptive PQD signal decomposition method. It also used WT-based signal processing approaches to address the noise issue, which demands significant neural network-based processing and results in computational complexity [7]. Deep CNN and Online based Sequential Random Vector Functional Link

Networks (O-SRVFLN) were merged to improve accuracy. However, the design is fairly sophisticated, making it unsuitable for a real-time device [8]. A Modified ST method (MST) suggested an enhanced window function for optimum power concentration recognition in PQD signals in time-frequency distributions. However, the method focussed more on time, and the frequency-related terms with synthetic PQD signals failed to improve more in real-time recognition [9]. A multivariate and sequential disturbance recognition approach is proposed to identify the real-time detection of PQDs. It has criteria that the training dataset follows a supervised approach needed for each hypothesis test to identify PQD, i.e., for each disturbance type in addition to the 'no disturbance' scenario [10]. For complex PQDs, a three different classification strategy based on TDSFs is used. Adaptive K-Nearest Neighbor with Excluding Outliers (AdaKNNEO) for the learner considers the properties of PQDs and offers high resilience. Sustainable energy production will reach a new level, creating more challenging PQD [11]. A new deep convolutional network structure is presented for PQD recognition and attains good efficiency, a faster convergence rate, and improved generalization capacity. The major downside is that they still cannot recognize certain aspects of disturbance inputs, such as disturbance amplitude [12]. In [13] implementation of the hybrid method, Hilbert and Stockwell Transform (HT&ST) effectively identifies both the single disturbance at a time and multiple disturbances at a time of PQDs. It is achieved by keeping the number of features to a minimum, and it shows degradation in noisy environments. In [14], the Arduino controller is employed to recognize real-time PQD signals, making the proposed Fusion of Time Domain Descriptors (FTDD) approach computational complexity due to its hardware setup. As a result of the introduction, the standard disturbance execution method of different environment, which uses electronic signal analysis in terms of characteristics extracted and Algorithms, has been used to detect irregularities, demonstrating their shortcomings [15]. In [16], the authors proposed Compressed Sensing-Bidirectional Long Short Term Memory (CS-BiLSTM) in solving the challenges of a higher sampling frequency and a large hardware implementation expense of doing PQD signal task; it lacks concentration on the accuracy rate. To resolve the challenges in the abovementioned concepts, the contributions of this work are given as follows:

- To recognize accurate Real-time PQD(RPQD) input samples for DBN training, six PQD classes are categorized based on the disturbance magnitude, frequency, and voltage circumstances with various time series signals.
- Employed hybridized Deep Belief Network and Long Short-Term Memory (DBN-LSTM) to classify real-time PQD signals effectively
- To maximize the input signal features for generating data frame models using various samples of PQD in a fixed period by training phase in a DBN module.
- LSTM is utilized to easily evaluate the time-series data nature of PQD signals by three layers, allowing it to run on the EPCP model.
- The EPCP simulation setup is utilized to reduce the computational complexities of the implementation,
- Finally, the EPCP-RPQD-DN implementation gives a minimal error rate, reduced computational burden, and enhanced recognition accuracy.

The remainder of this work is ordered in the following manner: Section II discusses existing recognition of power quality disturbance methods using a deep network integrated with an embedded parallel computing platform and its performance outcomes and shortcomings, thereby promoting the implementation of the hybridized DBN-LSTM technique for recognizing RPQD in EPCP. Section III presents the implementation procedure for the suggested EPCP-RPQD-DN algorithm. Section IV presents recognized experimental results for different PQ disturbances in RTDS. Finally, conclusions are drawn, and the future scope is given in Section V.

2 LITERATURE REVIEW

PQD is a problem that has been addressed and brought to light in the past. Several strategies for recognizing PQD types have been reviewed using survey studies and contain extensive, thorough information regarding these algorithms to implement the proposed algorithm.

Deng et al. [17] suggested a bidirectional Gated Recurrent Unit (Bi-GRU)-a based sequential model for category recognition and time localization of combined power quality disturbances. The test outcomes indicate that type recognizing is more than 98% accurate, and the sample variance of the starting-ending timestamp position is fewer than 0.469 ms. Sahani et al. [18] proposed Hilbert Huang Transform Weighted Bidirectional Extreme Learning Machine (HHT-WBELM) recognizes individual and several power quality disturbances in real-time. A hardware prototype is constructed using a digital signal processor for testing and validating the proposed model. Hence able to construct a variety of real-world Power Quality Events (PQEs) by varying both linear and non-linear demands. The main advantages include relevant feature extraction, higher learning rate, lower computation complexity, and higher accuracy. Wang et al. [19] suggested a unique full closed-loop technique Deep Convolutional Neural Network (DCNN), to recognize and categorize PQDs. Several modules are layered to select knowledge from huge disturbance data automatically. The results show recognition rate, noise tolerance, and computation time improvements. Le et al. [20] suggested an Adaptive Dual Resolution Stockwell Transform assisted with Short-Term Renyi Entropy estimation (ADRST-STRE) to recognize the individual and combined PQD events in real-time and enhance the Time-Frequency (TF) recognition of PQD waves. It works better only for lower frequency harmonics but needs to be improved for higher values. It could also recognize a higher proportion of disturbance types while requiring few parameters and delivering a better computational complexity and high prediction performance.

Rodriguez et al. [21] proposed a hybrid method that employs the Hilbert-Huang Transform (HHT), LSTM, and Recurrent Neural Networks (RNN) to recognize and categorize PQD. The Ensemble Empirical Decomposition (EEMD) and masking were used to eliminate the existence of the type mixture. Results demonstrate that the EEMD produces a higher overall accuracy of 98.8%. Evaluating various deep learning configurations is critical to enhancing the classification process's effectiveness in real-time events.

Sahani et al. [22] proposed a combined Reduced-Sample Empirical Mode Decomposition (RSEMD), a new signal classification technique that extracts the strongly correlated conventional single mode of cycles in PQD. Hence a Class-Specific Weighted Random Vector Functional Link Network (CSWRVFLN) algorithm is used to distinguish complicated PQDs in real time. The PQD recognition approach is tested and validated using an FPGA-integrated processor. Proposed results show reduced computational burden, improved accuracy rate, and stable anti-noise efficiency.

This section summarizes a comprehensive review of studies on real-time recognition and assessment of PQDs was conducted. The various DN-based algorithms are chosen for analyzing different metrics related to PQD recognition. The existing algorithms reviewed, Bi-GRU, DCNN, and HHT-LSTM-RNN, were taken for comparison since it shows all related metrics relevant to the implementation purpose of the proposed scheme. The other algorithms, like FFT-WBELM, ADRST-STRE, and RSEMD, with their result outcomes and limitations, are related to the time series of PQD signals.

3 PROPOSED WORK

PQDs are voltage or current deformities that exhibit unanticipated intensity fluctuations to reference voltage over time. Typically, rules and recommendations are used to classify and recognize every disturbance. To distinguish the categories of PQD events, relevant parameters (features) from raw PQD signals must be extracted and put into deep network-based algorithms.

The primary objective behind this method is to acquire real signals under actual operational circumstances. Fig. 1 illustrates the proposed scheme diagram for recognizing various PQD signals. Following the capture of PQDs, the source PQDs signal was handled by the DN model, where both are extracting the features and recognition section, implemented as a pre-processing component. It requires the same sophisticated instruments as the simulation environment. It thus needs an EPCP hardware setup for generating signals in which trained DBN-LSTM phases are given as input and signals are recognized. In the final stage, the intelligent classifier's output determines the outcome. The metrics evaluated in this simulation environment are better than the models shown in the result analysis.

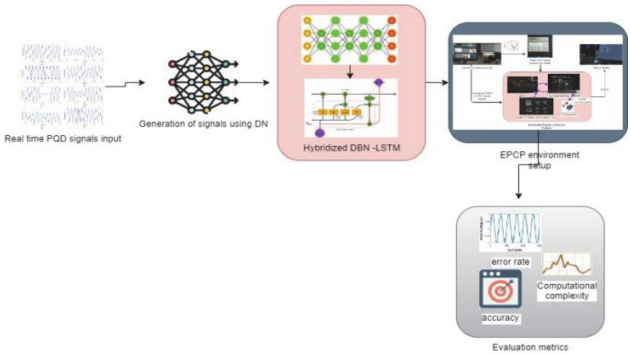


Figure 1 The EPCP-RPQD-DN implementation of PQD signal recognition

3.1 Real-Time PQD Signals Input

Tab. 1 illustrates the Six types of single disturbance included in the power-generated quality signals PQD from standard IEEE reference. They are all types of raw input of Real-time PQD(RPQD) signals like Sag, swell, interruption, harmonics, notching, and oscillatory transient labeled with the number from PQD 1 to 6, respectively. Following its definition, voltage duration range and its reason for occurrences [24]. Each PQD type is depicted in a diagrammatic waveform representation for further proceedings for recognizing the PQD signal.

Table 1 Power quality disturbance signals models in real-time

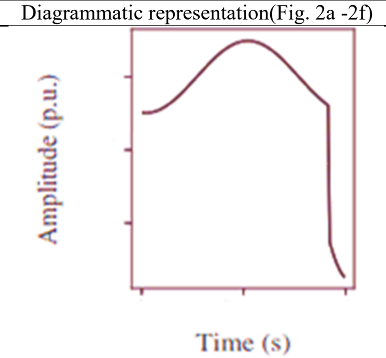
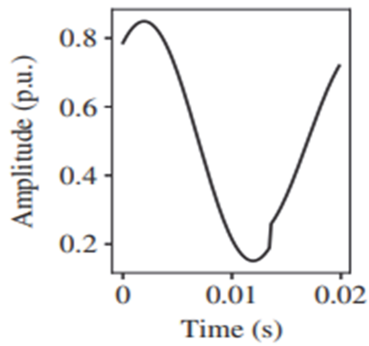
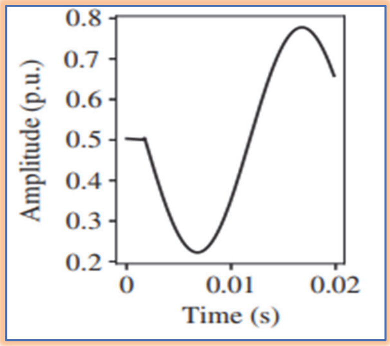
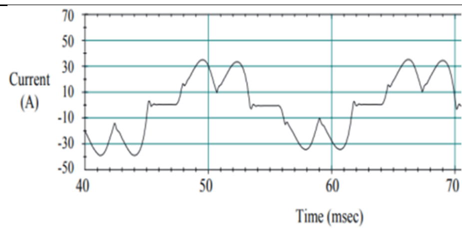
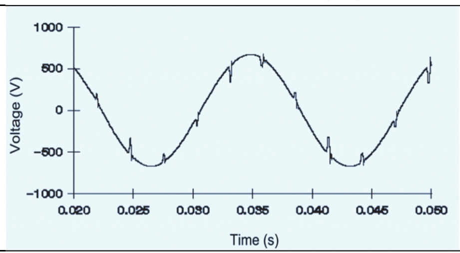
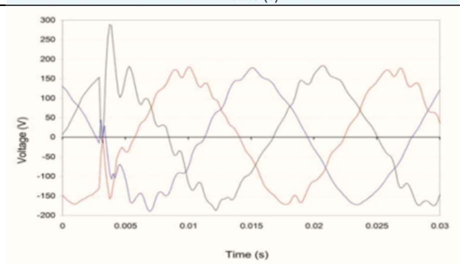
PQD class & type	Description	Diagrammatic representation(Fig. 2a -2f)
Sag-PQD1	decrease in voltage of the altering current magnitude between 0.1 and 0.9 per unit, PQD occurs between half cycle to 1 minute. Cause: short circuit, heavy load	
Swell-PQD2	Highest voltage alternating current magnitude from 1.1 to 1.8 pu, between 0.5 cycles to 30. Cause: Heavy load turns off	

Table 1 Power quality disturbance signals models in real-time (continuation)

PQD class & type	Description	Diagrammatic representation(Fig. 2a -2f)
Interruption-PQD3	Temporary reduction in RMS voltage less than 0.1 pu with the range of 0.9 to 1.0 Causes: machine controller fault,	
Harmonics-PQD4	Disturbances with the power frequency (50 or 60 Hz) Cause: Non-linear power source	
Notching-PQD5	Recurrence, but with a high-frequency content. Cause: Continuous, direct power from three phase	
Oscillatory Transient-PQD6	Primary frequency less than 5 KHz to 500 KHz and duration measured in microseconds (ms), the magnitude of 0.1 pu Cause: Powering capacitor bank	

The mathematical modeling simulation generates consecutive signals. Following the real samples per second of distribution transformers within the power grid, the capturing rate can be adjusted to 3200 Hz. Also, the sample duration of the voltage stability signal is 18 cycles. Flexible yet complicated trigger engines (a mixture of hardware and programming) are utilized to select what data and the amount to be preserved.

3.2 Generation of Signals by DN

Deep network techniques automatically extract features from the source signal. After getting the raw input signals, the sample disturbances need to be generated for more samples. The disturbance signals are created randomly, and the frequency rate is set to 6.4 KHz, resulting in 128 measurements for each cycle. The total number of frames in signals for each kind is 1000, with 800 as a training set and 100 as a testing phase, and the remaining 100 examples for verifying the learned knowledge. Because of six varieties of samples, the sum of all the samples must be generated concerning various magnitudes, amplitude, and frequencies. The types of disturbance signals used for generation are Sag, swell, harmonics, interruption, notching, and Oscillatory transient. The generated PQD signals are fed into the DBN module to recognize power quality disturbances.

3.3 Real-Time Recognition of PQD by Hybridized DBN-LSTM

Deep network approaches features extracted from the source signal automatically. The proposed hybridized combinations of DBN and LSTM give greater recognition accuracy, minimal error rate, and reduced computational complexity. The depth of a DBN and the size of each hidden layer affect classification accuracy and training time. The fundamental advantage of DBN is its high compact and increased non-linear mapping relations. DBN might also handle massive data with self-training capabilities that gradually reduce the source values having a lower correlation with the fitness function. In Fig. 3, the diagram shows the combined module of DBN-LSTM architecture. The original raw PQD signals are utilized as a source for the DBNs input. The number of PQD subtypes determines the output layer. Furthermore, its multi-hidden layer model trains appropriate sampling data for greater accuracy.

3.3.1 Algorithm Flow of Hybridized DBN-LSTM

1. **Input:** Let us consider the input column vector as D with d types. $D = \{ D_0, D_1, \ldots D_d \}$ each type represents the RPQD obtained from the input data source [23]. The following equation should be used to normalize the data frames for pre-processing:

$$PQ(normalize) = \frac{PQ - PQ_{\min}}{PQ_{\max} - PQ_{\min}} \tag{1}$$

where $PQ(normalize)$ represents the normalized value ranges from (0 ,1) in Eq. (1).

3.3.2 Pre-Training

After passing through the input, follow the recognized transitions that are interpolated into the DBN module's hidden layer 1. Consider (w,t) as the weight and threshold or bias values given as input for the hidden layer 1 to the next level. It aims to minimize the PQD of each data frame in the training model to obtain the initial parameters $\text{minimum}(i,td)$ for DBN:

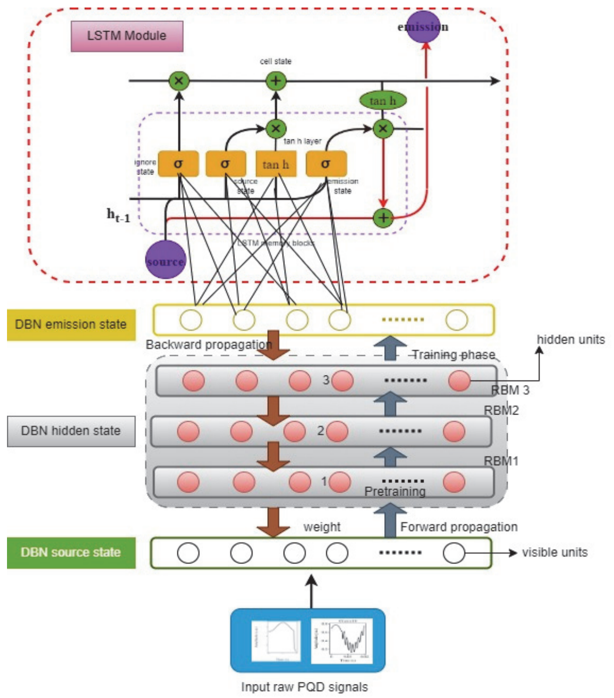


Figure 3 The hybridized DBN-LSTM architecture for PQD signal recognition

3.3.3 Restricted Boltzmann Machine (RBM)

Since it overlaps with different DBN levels, the Restricted Boltzmann Machine(RBM) is the basic building block of a DBN, and efficient learning techniques have been developed to train it. They also limit RBMs to those that lack visible (*visible*) and hidden (*hidden*) layers. Because RBMs' both layers are conditional independent configurations exaggerated in Eq. (2).

$$p\left(\frac{visible}{hidden}\right) = p\left(\frac{visible_i}{h}\right) \text{ and } p\left(\frac{hidden}{visible}\right) = p\left(\frac{hidden_i}{visible}\right) \tag{2}$$

3.3.4 Activation Function

DBN is a stacked layer of RBM interconnections among them, and every layering of RBM interacts with the previous and subsequent layers. Following stages with the activation function f_1 and f_2 for hidden and output layers use the sigmoid function in Eq. (3).

$$\sigma(x) = \frac{1}{1 + e^{-x}} \tag{3}$$

where x is the network input, e is 2.718; the curve ranges from 0 to 1.

3.3.5 Training Phase

Greedy techniques are used to train DBNs. The greedy training process takes a layer-by-layer procedure to generate essential best, dynamic parameters. DBNs do Gibbs sampling on the two top hidden layers. The RBM described by the first two hidden layers is sampled in this stage. RBM training advancement aims to minimize negative log likelihood by accurately predicting well-trained parameters with initial i and training dataset td values. RBMs convert inputs to place in the forward propagation. RBMs integrate each incoming layer with a unique weight and a single added biased layer. The output is sent to the hidden state by the algorithm. Setting network settings is required to achieve improved network performance, with setting the learning rate crucial.

RBMs interpret collection of numbers to generate the reconstructed inputs in the backward pass. The RBM compares its reconstruction to the original input at the visible layer to assess the quality of the output. Hence, one of the primary variables affecting DBN training duration and highest accuracy is the margin of error of input variables in Eq. (4).

$$\log(i,td) = -\sum_{visible/td} \log p(visible, i) \tag{4}$$

where i represents the w and td represents the training dataset. The gradients are calculated using estimates of two variables, the positive and negative phases. It gives the minimal error rate identification of the proposed architecture. It is simple to compute, and the computation burden of the previous layer is enormous. The situation's complexity necessitates using a computational model, which makes the calculation viable (2 m).

3.3.6 Output Layer

Logistic Regression (LR) is built on the RBM recognition system. To obtain the output of prediction models, use the model to learn the DBN-LSTM approach and continually optimize the weighted inputs. LR is a probabilistic logistic classifier with a weight matrix and a bias or threshold vector (w,t) as parameters in Eq. (5). We can tune x to get different y.

$$Prediction\ of\ output(y) = \arg\max(p(Y = i \mid x, w, t) \tag{5}$$

where the output prediction value is represented as y of logistic regression, the stochastic variable of the output layer is given as Y. The input variable x belongs to class i and is given as a probability statement. The output layer of DBN is fed into the LSTM as a source state input feed for PQD signals.

LSTM is a sophisticated neural network that is excellent for analyzing and predicting data with time accuracy. Yet, rising PQD signals input data sets, particularly power systems, it is challenging for LSTM to sustain prediction accuracy solely using a time sequence of previous weight. To face the challenges influencing capacity planning, DBN can resolve them by ensuring the individual factors. The demand characteristics are not observable, so several layers are added via the RBM layer to hierarchically categorize connection inputs and outcomes features. Based on the initial assumptions, the general model developed in this research is as follows: To supplement the two neural network techniques, DBN-LSTM are integrated for identifying predicting approach. These vectors are joined using the concat function to generate an additional layer. Its function is to interconnect. If the entity is an input, add its data items also as the DBN network's input and the output of the DBN as the recognized PQD value from each data input.

The LSTM has three states that assist the infrastructure in reducing long-term data reliance. These are the Ignore State, Source State, and Emission State, with the mathematical representations of states from equations 6-8. The Ignore State deletes unnecessary or redundant data. Finally, the Output power must process data with the cell state after the source state processes the additional data. The core of LSTM is memory condition (m).Whether or not something is ignored, e is governed by three variables in Eqs. (6) to (8).

$$i = sigmoid\left(\sigma\right)\left(w_{is}s + w_{ih}h_{-1} + offset\left(i\right)\right) \tag{6}$$

$$s = \varnothing\left(w_{ss}s + w_{sh}h_{-1} + offset\left(s\right)\right) \tag{7}$$

$$e = sigmoid\left(\sigma\right)\left(w_{es}s + w_{eh}h_{-1} + offset\left(e\right)\right) \tag{8}$$

where ignore or forget state is represented as i. The source and emission gate are represented as *sande* with the intermediate output h. The activation function sigmoid is represented as σ, and tanh represents the $\varnothing$.

Models of PQD data frames are generated to train and optimize the hybridized DBN-LSTM. The EPCP then employs the well-trained DBN-LSTM to recognize PQD in the RTDS.

3.4 EPCP Setup Environment for PQD Signals

Raw and real-life PQD signals are given to identify for evaluating the suggested method further. Fig. 4 illustrates the Nividia TX2 component as an EPCP-based DN platform with a quadcore advanced computing machine CortexA57, 256-core GPU, 8 GB LPDDR4, and 32 GB eMMC. Analog to Digital (AD) sampling frequency was set to 6.4 Hz. AD components sample the analog signals of PQD from the RTDS simulator portion. EPCP recognizes PQD signals in real-time, once the hybridized DBN and LSTM structure trained at the centralized server is delivered to it. The terminal output display gives the outcomes, and the figure depicts the entire embedded simulation environment for recognizing PQD.

The computational time of DN is significantly lesser than the other existing methods due to its parallel computation ability of Nvidia TX components GPU and fusion of three hidden layer steps in hybridized DBN and LSTM technique. Due to the parallel computing characteristic of deep network structure, distributed parallel embedded training and calculation can be realized on a combined module of DN implemented in multiple GPUs with little modification of the code components.

The monitors' interaction with such "real-time" is commonly instrument transformers, such as electricity, and potential translators, such as electricity and voltage. Measurements like velocity, force, and temperature require specific transformers. The production of various detectors typically s powers signal to the original account of the device of the dimension to enable observations to be taken using metric terms.

The power quality monitoring analog-to-digital conversion process generally employs sophisticated phase locked-loop sample selection methods that guarantee that both the initial specimen and Every loop have labeling components, even when supervision is misrepresented, less voltage, and step in the process waveforms. Low-frequency signals are typically at a rate of 128, 256, or 512 samples per cycle. Typically, voltage is measured on rotation, where x is 20 ms or 16.66 ms for 50 Hz or 60 Hz, respectively. This timeframe is typically 200 ms for harmonic measurements. These characteristics have included the power quality components. Since a PQD is unexpected, power quality monitoring should continually record and analyze the data to maximize record time. Despite the expanding availability of low-cost memory, information cannot be retained indefinitely in every phase for every attribute.

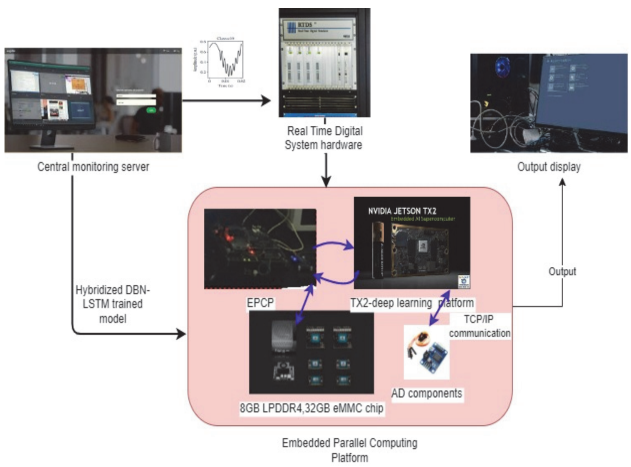


Figure 4 EPCP simulation environment

3.5 Evaluation Metrics

The important performance metrics comprise accuracy rate, computational complexity, error rate, and so on for assessing the quality of a suggested algorithm for recognizing and categorizing PQDs. The performance accuracy is obtained using Eq. (9) to recognize the PQD accurateness recognized for all the original samples.

$$Accuracy = \frac{number\ of\ correct\ PQD\ recognitions}{overall\ number\ of\ samples} \tag{9}$$

One may or may not acquire noisy signals while gathering real-time signals. As a result, noise is added to evaluate all signal types consistently.

The summary of the proposed system gives the best performance accuracy and reduced computational complexity. It is proved that the results mentioned above show that the suggested method using EPCP-RPQD-DN with the implementation of hybridized DBN-LSTM allows for constant power quality disturbance recognition and categorization in real time using EPCP using the deep network. The proposed method can detect and categorize PQD events successfully and effectively, which also provides a way for regular inspection of power quality electric distribution.

4 RESULTS AND DISCUSSION

This section elaborates on the utility of the suggested method for analyzing common power quality aspects in real-time recognition systems. The comparative analysis with existing systems shows the robustness of the proposed system. The power quality disturbance signal has many styles and features.

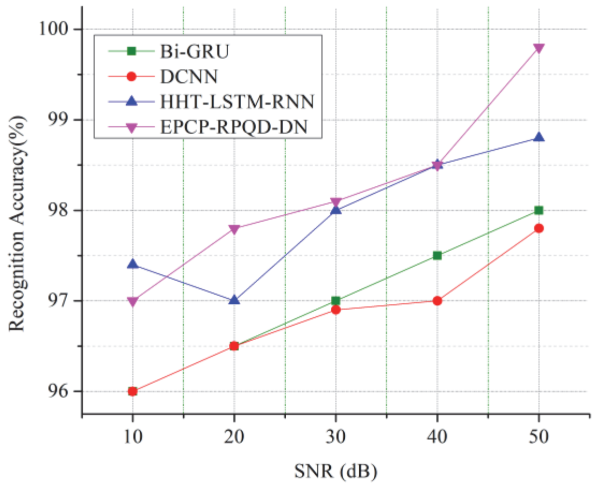


Figure 5 Comparative analysis for recognizing the accuracy of PQD signals

The dataset used in this study was implemented in the EPCP simulation platform, where 80% of this data is adopted for the training and 20% for the testing phases. To recognize the PQD signals in real time are usually categorized in terms of their periodic manner and based on their magnitude. In this work, the mathematical and conditional parameters described on IEEE 1159 standard were taken as a reference [23] from which the sample raw input PQD signals are generated. Tab. 1 gives the PQD class and types with definitions and reasons for disturbances. An account of the parametric signal definition and the parameter range variations and representations reported for each disturbance is identified. The disturbance signal is generated using a different sampling frequency in terms of Hz. The input attributes in this paper include six types, which are Sag, swell, harmonics, interruption, notching, and Oscillatory transient.

The recognition accuracy of PQD signals is compared to various methods, based on the disturbance of Signal-to-Noise Ratios (SNRs) as illustrated in Fig. 5. The proposed EPCP-RPQD-DN algorithm implements hybridized DBN-LSTM for recognizing the PQD accurately; in this paper, the accuracy reaches greater than 99.7% when the noise level reaches a maximum of 50dB SNR in the PQD. The suggested algorithm can easily recognize the disturbances in the signals. Hence the implementation of this algorithm is best compared to Bi-GRU, DCNN, and HHT-LSTM-RNN methods.

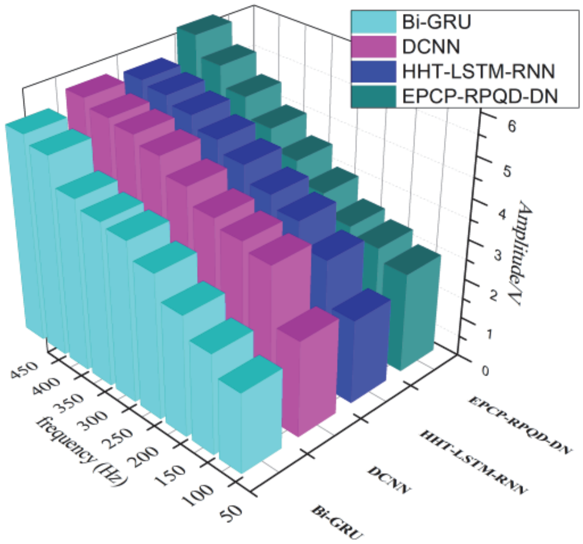


Figure 6 Performance comparison based on amplitude and frequency of PQD

From Fig. 6, the frequency of the above graph ranges from 50 to 450 Hz, and the amplitude ranges from 0 to 6 for the recognition of real-time PQD using the proposed EPCP-RPQD-DN in which the system reaches the maximum throughput. In addition, the power quality that reaches the peak value can also reflect the degradation performance. The peak values calculate the near closer value reaches in the amplitude taken from the data source attributes [23] of PQD signals implemented in the EPCP platform. The signals are also converted using Analog to Digital converter components in the specific TX2 module for enhancing the recognition of PQD.

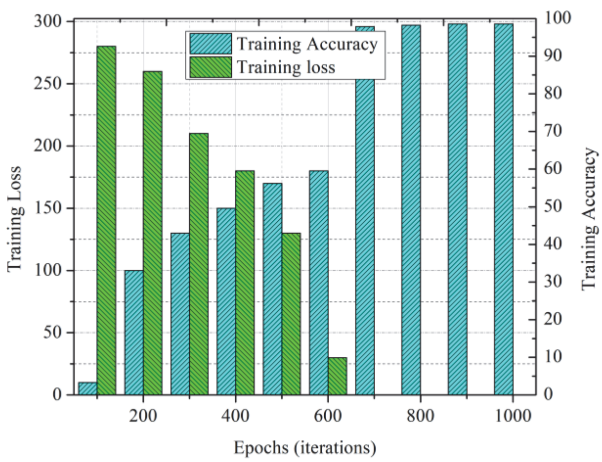


Figure 7 Training loss and accuracy for various epoch sizes

As illustrated in the above Fig. 7, the accuracy of recognizing PQD increases during the early stage of training. The loss value lowers after approximately 600 rounds of iterations during training and testing, resulting in a fast decrease of less than 0.2. From 800 to 1000 epoch steps, the training accuracy reaches its maximum and remains constant for the remaining iterations. Since accuracy reaches a maximum, there is no loss during the epochs. The accuracy rate rises to almost greater than 99% and then stabilizes when training loss is completely zero, suggesting the system mode. Compared to the existing algorithms, the suggested EPCP-RPQD-DN performs better at PQD recognition in all scenarios.

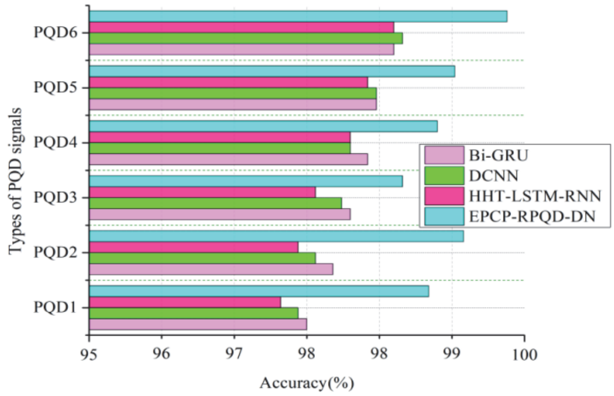


Figure 8 Comparison of different types of PQD signals

From the above Fig. 8, the PQD signal types are recognized by using the proposed EPCP-RPQD-DN with the hybridized DBN-LSTM algorithm where the different types of PQD signals categorized from 1 to 6 represent the sag, swell, interruption, harmonics, notching and oscillatory transient are taken as input attributes from IEEE standard given in [23]. Six types of single disturbances are included in the power-generated quality signals. The recognition accuracy is compared with existing Bi-GRU, DCNN, and HHT-LSTM-RNN. From the result analysis, the proposed scheme has greater accuracy than all PQD types.

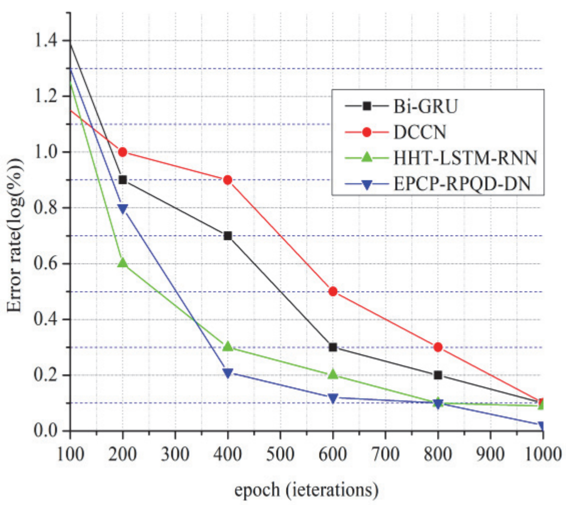


Figure 9 Error rate comparison of PQD recognition using various methods

In Fig. 9, the error rate depiction results show that the proposed EPCP-RPQD-DN scheme for recognizing the PQD signals shows a minimal error rate compared to other existing algorithms Bi-GRU, DCCN, and HHT-LSTM-RNN. It nearly shows that 0.2 is error rate identification during the training phase of the hybridized DBN-LSTM implementation. The input attributes are six types of PQD signals, with each iteration ranging up to 1000 epochs with a duration of 100 batch size of each input signal.

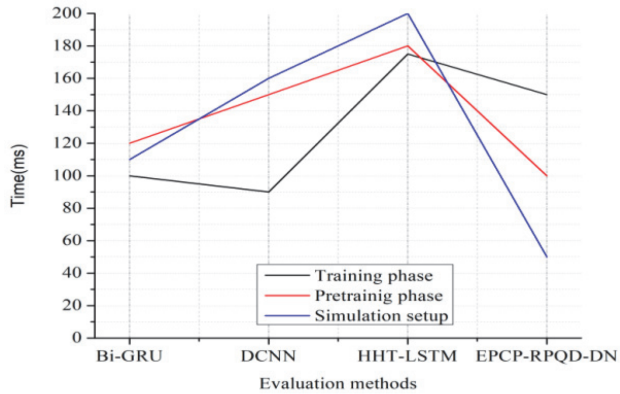


Figure 10 Computational complexity comparison based on different training criteria

In Fig. 10, the computational complexity burden of implemented scheme is compared with existing methods based on the pre-training phase, training (fine-tuning), and simulation environment setup. Based on the graph results, the hybridized DBN-LSTM architecture consists of a parallel computing platform. Thereby computational parameter complexities are reduced for PQD signals in all scenarios. The input attributes are identified from [23] concerning the time complexity of microseconds (ms).

The summary of the results and discussion section shows that the implemented algorithm EPCP-RPQD-DN gives better performance in accuracy, reduced error rate, and computational complexity by EPCP simulation setup for training implementation cases. With the help of hybridized DBN- LSTM, the time series PQD signals are easily recognized and trained for recognition.

5 CONCLUSION

Various studies show that the proposed EPCP-RPQD-DN algorithm is an effective and efficient method for real-time recognizing PQ disturbances under all environments by implementing a hybridized DBN-LSTM model. As a result, the range and complexity of procedures that can be executed in parallel at any given time are limited. Thus, the proposed model achieved higher recognition accuracy, reduced error rate, and lesser computational complexity. The domain of embedded computer devices for parallel computing of more powerful devices helps to reduce the computational complexity of implementation. With the help of DN, there is no need to spend more time in feature extraction, and all the steps are combined in addition to the training phase of the implementation model. Hence, there is an advantage of reduced time complexity with the additional hardware benefits of parallel computing. Even though it has obvious advantages, there is also a limitation in the acquisition of signal processing. There may be a chance of signal decomposition at the early stages when devices have a limited power supply. In the future, this work is to concentrate on the coverage area of PQD signals with the specified location of the disturbance.

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Contact information:

Dewan FENG
(Corresponding author)
Department of Network and Information Security,
Chongqing Vocational Institute of Safety & Technology,
Chongqing, China
E-mail: 1621030517@stu.cpu.edu.cn