Power Quality Disturbance Detection and Monitoring of Solar Integrated Micro-Grid

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Abstract: - Due to the popularity of microgrids and power quality disturbances (PQD) induced by renewable energies, monitoring in microgrids has risen in popularity in recent years. For monitoring the PQD, many strategies based on artificial intelligence have been proposed. However, when the electrical parameters change, the need to retrain the Artificial neural network (ANN) becomes a significant issue. This paper presents a new approach to the power quality disturbance detection and monitoring of integrated solar microgrids. The power quality event detection is accomplished by analyzing the frequency signal with Wavelet transformation (WT). The classification of power quality disturbance is achieved based on the features. For the classification of PQDs, the retrieved features are fed into a Convolutional neural network (CNN) classifier.

Keywords: - Power Quality Disturbances, Artificial Neural Network, Wavelet Transformation, Convolutional Neural Network, Micro Grid, Renewable Energy Sources, GoogLeNet neural network.

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1 Introduction

The present advancement in technology necessitates an uninterrupted power supply. The uninterrupted power supply impedes because of the limitation of the grid due to numerous reasons. Micro-grid with natural resources integration plays a vital role in accomplishing this need. The integration of renewable resources causes the power quality issue to disturbance and instability. Due to power electronics devices and inverters connected to renewable energy (RE) sources, the grid incorporation of large-scale RE sources, particularly solar and wind energy, induces voltage and current harmonics. One of the major issues today is ensuring acceptable harmonics in the line currents of RE integrated power systems [1]. As the penetration capacity of the PV system increases, a greater level of harmonic distortion is injected into the grid. Therefore the PV system should only be integrated up to the network's full capacity. When a PV system is integrated beyond this maximum penetration level, it produces considerable harmonic distortion, which has a negative impact on the system's performance [2]. As the use of renewable energy grows, it has an adverse effect on the distribution system, generating overvoltage, voltage fluctuations, and reverse power flow to the grid. Maintaining the voltage and current sinusoidal waves at the rated frequency and magnitude is referred to as power quality. Any departure leads to a loss of power system efficiency, jeopardizing the power system's economy by putting undue strain on consumers and suppliers. Practical obstacles such as voltage control, flicker, harmonic distortion, stability, and other power quality issues occur when wind and solar energy are integrated into existing power systems [3]. Circuit breakers, switches, converters, and non-linear loads are all being used more and more these days. The electrical network's power quality disruptions (PQ) are a common cause. To avoid the network and its connected equipment from being disrupted, it is important to identify and classify the various PQ disturbances (single and mixed) [4]. This compels the microgrid's rapid and effective power quality detection and classification. Monitoring the power quality disturbance in order to take corrective action has become a hot topic, particularly in renewable energy source integrated micro-grid systems. The principal source of PQDs in today's distribution networks is rapid industrialization, the use of sensitive electrical equipment on a large scale, massive non-linear loads, and significant usage of power electronics devices. Due to the move from conventional distributed systems to smart distributed systems, the integration of non-conventional based distributed generators (DGs), energy storage systems (ESSs), power electronics converters, and electric car charging stations exacerbates this issue. PQ degradation leads to voltage sag, swell, impulse, oscillatory transients, and other operational difficulties in real-time circumstances. Power quality (PQ) issues in real-time systems can cause various control and protection devices to malfunction or fail, affecting the system's overall performance [4]. The signals of these PQDs are non-stationary and statistically time-varying in nature. Signal processing techniques are widely used to examine non-stationary signals in various power system challenges, including fault identification, islanding detection, differential protection, and the detection of PQEs. Fourier transforms (FT), discrete Fourier transform (DFT), and fast Fourier transform (FFT) were used in the early stages of signal processing applications for PQ analysis (FFT), short-time Fourier transform (STFT), Curvelet transform, Hilbert transform, Empirical mode decomposition (EMD), and variational mode decomposition (VMD) are gaining popularity as a computational approach for extracting spectra for stationary signals at various frequencies [5-13]. The power quality classification is equally essential in PQE monitoring. With minimal human intervention, automatic classification is critical in modern power quality classification. There are several techniques have been employed for the classification of PQEs. One of the most effective ANN approaches is ELM, frequently used to resolve classification difficulties [14-16]. Several other techniques, such as probabilistic neural networks and support vector machines, gained popularity for PQE classification [17-22]. Due to numerous advantages over other renewable energy sources, solar energy proved to be the optimum energy source among all existing renewable resources. The PV systems are a gift to modern society. Numerous power quality challenges develop when connecting an extensive PV system with the grid. Poor or insufficient power quality could lead to financial losses and end-user disturbance. The power system components become overheated and behave unfavorably due to the low power quality issue, resulting in substantial damage [23].

An increasing issue of power quality disturbances due to integration of renewable energy sources like solar and wind to micro-grids may have greater impact on the operation of end user equipments. For mitigation of PQDs, an efficient monitoring system is much needed. The monitoring system is mainly consists of the process of detection and classification of PQDs. Different signal processing techniques like FFT, ST, WT, EMD, and VMD are used for the feature extraction process and different machine learning techniques like ELM, PNN, SVM, DT, FL have been used for establishment of an efficient monitoring system. However, a better monitoring system is always a need for the conditions of real-time, non-stationary, noisy, robust, faster computation, and cost effectiveness. Here, the hybrid approach of CWT and CNN shows better results in many of the above mntioned conditions.

Power quality is the measure of correctness of the power signal without any deviation from the specified range for amplitude, frequency, and phase. Different power quality disturbances are voltage sag, swell, interruption, flicker, transients, and harmonics etc. There is a possibility of simultaneous happening of multiple PQDs. The impact of these PQDs on consumer electronic appliances, power electronics and control instruments based on micro-controllers is severe. To mitigate these disturbances, there is an urgent need of detection, classification, and monitoring of PQDs. Several research work have been done on this issue and this study is an alternative method to answer this issue. The proposed hybrid method is a novel technique consisting of CWT and CNN shows faster computation and better accuracy in comparison to contemporary methods.

The micro-grid uses the environment friendly energy sources to reduce transmission loss, manage the power supply and demand, improve the operation and stability, and to provide dynamic responsiveness. However, the use of power electronics instruments and devices is one of the major reason of PQDs. To mitigate the PQDs, a robust monitoring system is required and for which detection, classification, and monitoring of PQDs are very much necessary. Here, the suggested method is a meaningful approach for the above processes to build a robust monitoring system for mitigation of PQDs.

This article presents the PQD event detection and classification using wavelet transform (WT) and Convolutional neural network (CNN). WT is utilized to extract the prominent features, and CNN is used to classify PQ events. The proposed methodology is validated in a physical real-time PV integrated microgrid.

From decades and over, research work is going on the detection, classification, and monitoring for the mitigation of power quality disturbances efficiently. Here, in this study a hybrid approach consisting of Wavelet transform and CNN is considered for the above work due to the following reasons: (i) faster computation (ii) dealing a large data set (iii) for better classification accuracy (iv) to work on real-time environment and noisy conditions.

The background theory of the WT is presented in the next section. Section 3 describes CNN-based event classification. An experimental setup is presented in section 4. The result analysis is presented in Section 5, and the conclusion is given in the final section.

2 Back Ground Theory of Wavelet Transform

The wavelet transform could provide both the frequency and the time associated with signals, making it extremely helpful in a variety of applications. It gives an STFT generalization. Like DFT and STFT in signal theory, wavelet transformation can be thought of as the projection of a signal into a series of essential functions called wavelets. In the frequency domain, these basis functions provide localization.

2.1 Wavelet Transform

The ability of Wavelet transform (WT) to analyze the local discontinuities of the signals can be best used for steady-state analysis and the analysis of signals in various fields having non-stationary characteristics. The power quality events (PQEs) of the power system have non-stationary features; hence the WT is preferred as a suitable tool to apply for the PQEs detection. The continuous signal *u(t)* in the continuous Wavelet transform (CWT) form can be mathematically expressed with the wavelet function $\psi_c(t)$ as:

$$\mathrm{CWT}(a,b) = \frac{1}{\sqrt{a}}\int_{-\infty}^{\infty} \mathrm{u(t)}\, \psi_c\left(\frac{t-b}{a}\right) dt \quad a, b \in R,\ a \neq 0 \qquad (1)$$

In Eq. (1) the scale and translation parameters are represented by the constants a and b, respectively. The oscillatory frequency and wavelet length are provided by the scale parameter a. The shifting position is well represented by b, the translation parameter. Each scale has a series of wavelet coefficients at each scale which are the output and hence represent the comprehensive PQ signal. The superfluous information in practical applications of CWT makes it unsuitable for signal analysis. The discrete wavelet transform (DWT) is found more appropriate for analysis of the PQEs and can be expressed as in Eq. (2):

$$DWT(m,n) = \frac{1}{\sqrt{a_0^m}} \sum_k u(k)\psi\left(\frac{n-kb_0a_0^m}{a_0^m}\right) \qquad (2)$$

where a_0^m and $kb_0a_0^m$ Represent the scaling parameter and the translation parameter, respectively. The discrete point sequences represented by $u(k)$ are the discrete form of the continuous-time signal *u(t)*. Depending on the type of data used in WT applications, the type of mother wavelet selection has a significant role in analyzing the signal. Among different types of mother wavelets, the Daubechies mother wavelet at scale 4 (db4) has a substantial role in feature extraction and is widely used for various applications.

3 Classification using CNN

CNN, a sub-class of artificial neural networks currently being extensively prominent in various computational vision processing, is increasing interest among researchers across different research areas comprising power systems. CNN is automatically and adaptively adjusted to hierarchical spatial features using backpropagation techniques implementing multiple building blocks, involving various stratified blocks as convolution layers, pooling layers, and fully connected layers. CNN is a sub-program of deep learning models for the computation of information employing a grid pattern as pictures, which can be correlated to the topology of the animal pictorial cortex and formulated to adjust to hierarchical spatial features automatically and adaptively from low- to high-level patterns. CNN is usually made up of three types of layers such as convolution, pooling layer, and fully connected layers. The feature extraction process is involved in the first two layers of CNN topology, whereas in the third layer, the features are mapped into the latest output. The first layer is a significant block in CNN, and It is made up of a series of mathematical processes involving convolution, a type of linear operation technique. If a square neuron layer of size $N \times N$ is followed by a convolutional layer, then the size of the output of the convolutional layer will be $(N-m+1) \times (N-m+1)$, where $m \times m$ is the size of the filter ω. The pre-nonlinearity input can be calculated as $x_{ij}^{l} = \sum_{a=0}^{m-1} \sum_{b=0}^{m-1} \omega_{ab}\, y_{(i+a)(j+b)}^{l-1}$, where x_{ij}^{l} is a unit of the layers and $\sum_{a=0}^{m-1} \sum_{b=0}^{m-1} \omega_{ab}\, y_{(i+a)(j+b)}^{l-1}$ is the sum of contributions by weighted filter components. In digital images, pixel data is assimilated in a 2D grid, i.e., a number array (Fig. 2), and a parameter of a small grid referred to as kernel, which is a feature extractor that can be optimized accordingly to requirements, which is used at every image position, which renders CNNs as being significantly effective in image processing, since a feature may arise at any stage in the image. As one layer relays the output data into the next layer, there can be a progressive complexity with increasing hierarchy being observed in extracted features. The process of optimizing parameters involved in kernel data arrangement is called training. It is the process of minimizing the difference between outputs and ground truth labels by employing optimization techniques such as backpropagation and gradient descent, among others.

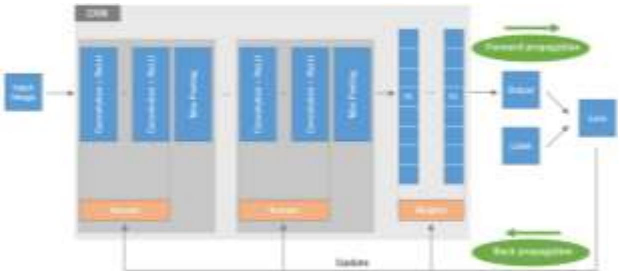


Fig. 1: CNN architecture and its training process.

The performance characteristics of a learning model under specific kernel models and weights are computed using a loss function and a forward propagation technique applied to a training dataset, with parameters, such as kernels and weights, that are updated based on the loss value via backpropagation using the gradient descent optimization algorithm ReLU, rectified linear unit.

3.1 Building Blocks of CNN Architecture

The CNN topology comprises several building blocks such as convolutional, pooling, and fully connected layers. A typical CNN topology entails a stack of convolutional layer and pooling layers that repeats, followed by one or more fully connected layers. The phase in which the input data is processed into the output data by these layers is called forward-ing propagation. This section describes the convolution and pooling procedures configured for 2D-CNNs, but similar operations can be applied for 3D-CNNs.

3.2 Training a Network

Network training includes calculating kernel data for convolutional layers and weights for fully connected layers to minimize differences between training dataset output predictions and specific ground truth labels. Backpropagation algorithms are commonly used in neural network training, where loss function and gradient descent optimizati-on techniques are essential.The model's perfor-mance characteristics under a given kernel and weights are estimated using the training dataset and the forward propagation loss function of the trainable parameters. The kernel and weights are calculated and updated with loss values by optimization techniques such as backpropa-gation and gradient descent.

The available data is generally divided into three sets: training, validation, and testing, but there are several variations on the following sets, such as cross-validation. It then trains the network using the training set, calculates the loss value using the forward propagation technique, and updates the parameters that backpropagation can learn. Validation sets are used to evaluate models, fine-tune hyperparameters, and apply model selection during the training phase. Ideally, the test set should be used only in the last stage of the project, and the training set and validation set should be used to evaluate the performance of the fini-shed model improved and selected during the training phase.

Model training inevitably necessitates fine-tuning hyperparameters and model selection tasks, necessitating several validations and test sets. This method is calculated depending on the validation set's performance, so some info about this validation set is reflected in the model. The model is not directly trained on trainable parameters but overfitting to the validation set. This ensures that a model with hyperparameters fine-tuned in a validation set will work appropriately in a similar validation set. Therefore, control datasets should be used to properly evaluate the performance of the model. The model performance of the new random data is essential and requires a separate test set.

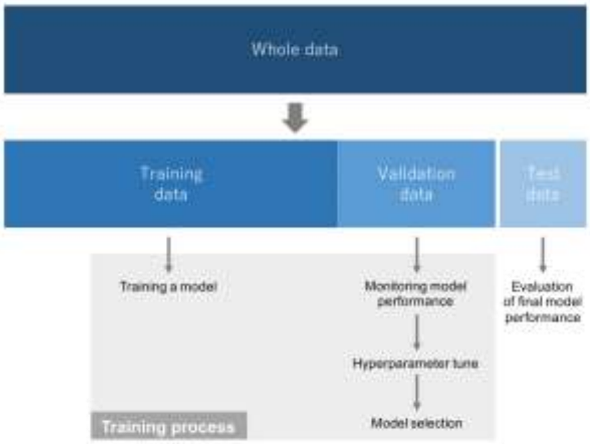


Fig. 2: Available data are typically split into three sets: training, validation, and a test set

Training sets train the network, calculate loss values with forwarding propagation techniques, and update trainable parameters with backpropagation techniques. Validation sets are used to monitor model performance during the ongoing training phase, fine-tune hyperparameters, and perform model selection. Ideally, the test set should be used only once at the end of the project to evaluate the performance of the finished model with a finely tuned and selected strategy after the training process with the training set and validation set. The available data is generally divided into three sets: training, validation, and testing. In the training the training process the training data and validation data are used to train the network. According to the training accuracy of the network, the selection and tuning of the parameters is done by selecting the optimized parameters of the network for enhanced performance. So, in the last phase of the process, the test set is used to find the accuracy of the CNN network.

4 Experimental Setup

Figure 3 shows the complete experimental setup for the proposed work. It consists of 550kwatt of rooftop solar PV array and 2200 PV cells, each 250watt. A REFUsol three-phase inverter. A changer to switch between grid and solar power in case of insufficient solar power. Connection with the main grid. Three-phase loads. Three single phases step down transformer. National Instrument (NI) USB data acquisition card (DAQ). A personal computer with LabVIEW and MATLAB software.

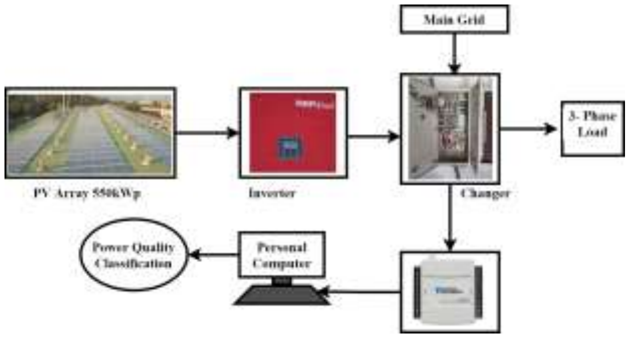


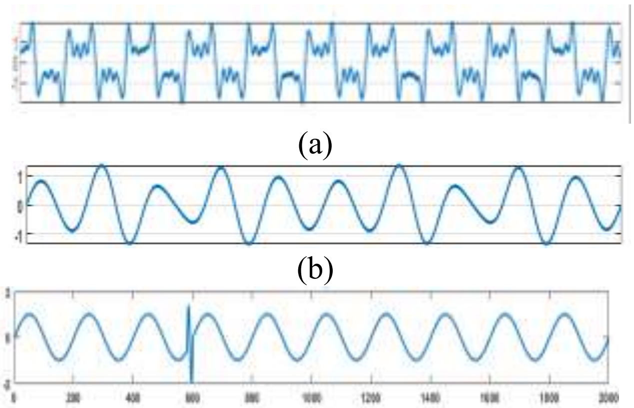
Fig. 3: Experimental setup

Maximum power, voltage at maximum power, open-circuit voltage, maximum current, and short circuit current for each solar cell is 250Wp, 30.72V, 37.05V, 8.15A, and 8.58A, respectively. The solar panels are connected in series and connected at the input terminal of the three-phase inverter. And the output of the inverter is connected to the loads through the changer switch. The role of the changer switch is to switch the load between inverter output and grid connections. By default, the loads are connected with inverter output utilizing solar power. The solar power is less than the load requirement due to clouds covering the panel or in the rainy season. The changer will switch the loads to grid mode. The three-phase voltage and current signals are captured by NI USB DAQ and continuously monitored. The NI USB DAQ is connected to the computer to analyze the power quality event using machine learning technique. NI LabVIEW is used to take the voltage signal through the NI USB DAQ to the computer. The machine learning algorithm is implemented in MATLAB. The data transfer between LabVIEW and MATLAB occurs using TCP/IP protocol.

5 Result Analysis and Discussion

5.1 Time-Frequency Representations

The experiment was performed on the PQE signals obtained from the MATLAB simulation environment and the real-time signal obtained from the experimental setup. The time-frequency representation of a PQE signal is called a scalogram and represents the absolute value of the signal's CWT coefficient. Pre-calculation of the CWT filter bank is required to create the scalogram data**.** The re-calculation of the CWT filter bank is preferabley selected to to acquire the CWTs of multiple signals using the same parameters. The filter bank is used to get the CWT of the first 1000 samples of the signal, and the scalogram of the coefficients is taken.



(a)

(b)

(c)

Fig. 4: (a) Harmonic signal (b) Flicker signal (c) Impulsive transient signal

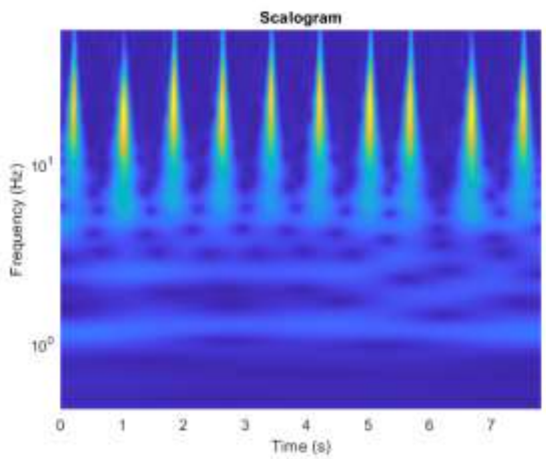


Fig. 5: Scalogram

5.2 Division of Data Into Training and Validation

The scalogram image data is loaded into the program routine as saved image data. Image data store allows programs to store extensive image data, including data that cannot be allocated in memory space, and efficiently read batches of images during the ongoing training phase of the CNN. The images are then categorized and randomly divided into two separate groups. One is for the training dataset, and the other is for the validation dataset. 80% of the images will be used for CNN training, and the rest will be used for validation.

5.3 GoogLeNet

The pre-trained GoogLeNet neural network is loaded. The layer graph is extracted and displayed from the network.

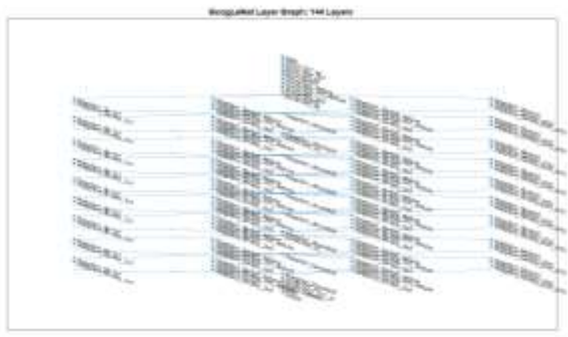


Fig. 6: GoogLeNet Layer Graph

Evaluation of GoogLeNet Accuracy

The network is then evaluated using the network data.

GoogLeNet Accuracy: 100%

Table 1. Initialization of input data normalization (GoogLeNet)

**See the Table 1 at the Annex section*

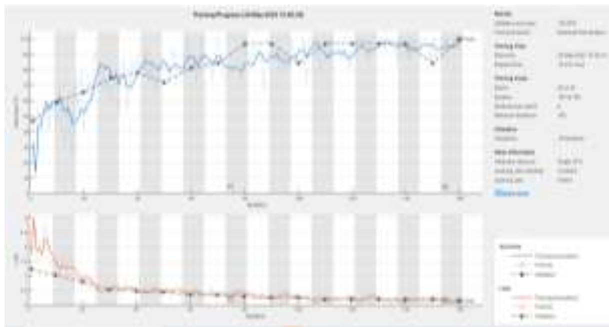


Fig. 7: Training progress (GoogLeNet)

It can be seen that the numbers obtained here are the same as the validation accuracy observed in the training visualization. Next, scale grams were divided into training and validation categories. Both category scalograms were used in GoogLeNet training. The ideal way to evaluate the results obtained after training is that the network is responsible for classifying data that has never been observed before. The calculated validation accuracy is referred to here as network accuracy because not enough data is needed for training, validation, and testing subroutines. The network accuracy is found out by using the data which the network never seen before, and it is done after training the network. The network accuracy found out in this method can be considered as the validation accuracy.

5.4 SqueezeNet

SqueezeNet is a type of deep CNN whose architecture supports image sizes 227x227x3 pixels in size. GoogLeNet has different image dimensions but doesn't need to generate a new image in RGB format according to SqueezeNet's dimensional specifications. It can use the original RGB image.

Loading

The pre-trained Squeeze Net neural network is then loaded.

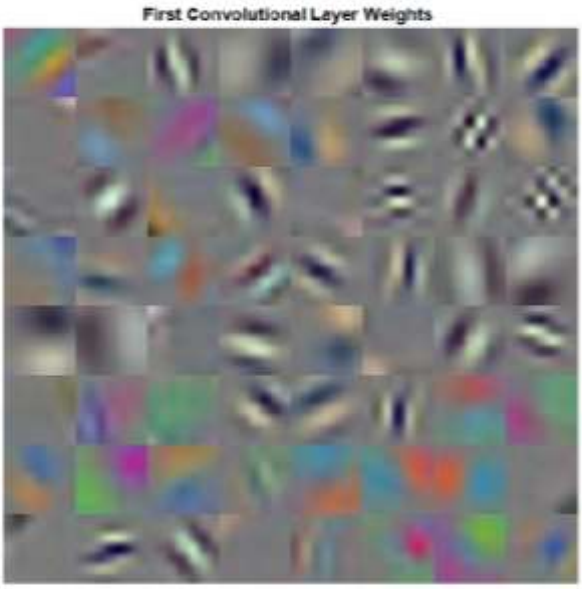


Fig. 8: First Convolutional Layer Weights

5.5 Preparation of RGB Data for Squeeze Net

RGB images have a size suitable for the GoogLeNet architecture. Next, the extended image data is created, and the existing RGB image resized for the Squeeze-Net architecture data is automatically saved.

The setting of Training Options and Training Squeeze Net

Next, new training options will be created for use with SqueezeNet. Then the random seed value is set to the default value, and the network is trained. The training process typically takes 1-5 minutes on a well-designed desktop CPU.

Next, the network's last layer is inspected to see if the classification output layer contains three classes.

During the training process 80% of the data (image) are used for training the SqueezeNet. For the reproduceable purpose the random seed value is set to the default value. The neural network training process is an iterative process which minimizes the loss function. In iteration the used gradient descent alogorithm evaluates the loss function and updates its own weights.

Squeeze Net Accuracy: 93.75%

Table 2. Initialization of input data normalization (Squeeze Net)

**See the Table 1 at the Annex section*

Evaluation of Squeeze Net Accuracy

The network is then to be evaluated using network data.

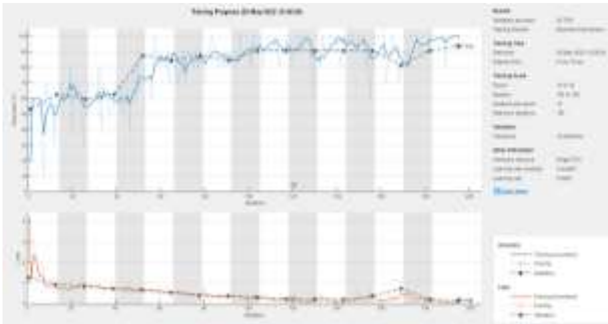


Fig. 9: Training Progress(Squeeze Net)

5.6 Discusion

The suggested method is a hybrid method of CWT and CNN. The scalogram obtained from the wavelet coefficients are fed to the GoogLeNet and SqueezeNet for classification of PQDs. The GoogLeNet and SqueezeNet are pretrained CNN, which are trained with 1000 different kinds of images. The classification accuracy for GoogLeNet is 100% and for SqueezeNet is 93.75%. This classification accuracy is found for a solar integrated micro-grid in real-time environment. This proposed method gives a higher classification accuracy and having a faster computational time. A comparison table is given for the comparison of the suggested method with available present day alternative methods. The limitations, suggested improvements, and future scope of this study is highlighted in the conclusion section.

5.7 Comparison of Classification Accuracy

Table 3. Overall Accuracy Comparison Statistics with other Conventional Methods

Classification Methods	Accuracy Percentage
DWT with ANN	94.37
DWT with NFS	96.5
WPT with MSVM	96.8
DWT with RBES	98.7
ST with DT	98.5
ST with RBES	98.2
ST with PNN	97.4
Proposed CWT with CNN (GoogLeNet)	**100**
Proposed CWT with CNN (SqueezeNet)	**93.75**

6 Conclusion

The above studies show the use of transfer learning and continuous wavelet analysis to classify three classes of PQE signals using pre-trained CNNs i.e., GoogLeNet and SqueezeNet. The wavelet-based time-frequency representation of the PQE signal is used to create scalograms. RGB images of scalograms are plotted using a computer. The image is then processed for fine-tuning of both deep CNNs. Various network layer activations were also investigated. The above study also shows a workflow that can be used to classify signals using a pre-trained CNN model. The above studies also show the efficiency of a hybrid model based on CWT and CNN for detecting power quality events in a solar-integrated microgrid environment with 100% and 93.75% accuracy of GoogLeNet and SqueezeNet, respectively. Here, GoogLeNet and SqueezeNet are two deep CNNs pretrained to recognize the images for classification of PQD signals based on time-frequency representation. This network architecture of CNN is reused for the classification of PQD signals based on images obtained from CWT of the time series data.

The limitation of this study is that its SqueezeNet accuracy is only 93.75%. Further research can be done on the use of efficient feature extraction techniques and parameter optimization of CNN to have better efficiency and lesser computational time in a real-time environment. The detection and classification process of PQDs to be done by deep learning alone may be the future direction of research of this study.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

Conceptualization, Indu Sekhar Samanta, Kunjabihari Swain, Debasish Pattnaik; methodology, Debasish Pattnaik, Ritesh Dash and Indu Sekhar Samanta; software, Indu Sekhar Samanta and Debasish Pattnaik; validation, Indu Sekhar Samanta, Ritesh Dash and Kunjabihari Swain; investigation, Sarat Chandra Swain and Indu Sekhar Samanta; resources, Sarat Chandra Swain and Debasish Pattnaik ; data curation, Debasish Pattnaik , Indu Sekhar Samanta and Kunjabihari Swain; writing—original draft preparation,Debasish Pattnaik, Indu Sekhar Samanta and Kunjabihari Swain, supervision, Sarat Chandra Swain; formal analysis, Sarat Chandra Swain; Visualization, Sarat Chandra Swain; figure and table, Kunjabihari Swain and Indusekhar Samanta. All authors have read and agreed to the published version of the manuscript.

Annex

Table 1. Initialization of input data normalization (GoogLeNet)

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss
1	1	00:00:21	33.33%	46.88%	1.7424	1.2343
2	10	00:01:27	46.67%	59.38%	1.3216	1.0275
3	20	00:02:38	40.00%	65.62%	1.0883	0.7985
4	30	00:03:45	60.00%	75.00%	0.6761	0.5229
5	40	00:04:51	86.67%	78.12%	0.2971	0.4800
7	50	00:05:57	86.67%	71.88%	0.3501	0.4566
8	60	00:07:05	80.00%	81.25%	0.2811	0.3469
9	70	00:08:10	100.00%	84.38%	0.2021	0.3480
10	80	00:09:13	100.00%	96.88%	0.1737	0.2811
12	90	00:10:10	93.33%	96.88%	0.3201	0.2464
13	100	00:10:58	93.33%	84.38%	0.1404	0.2614
14	110	00:11:47	86.67%	96.88%	0.2538	0.1880
15	120	00:12:35	93.33%	96.88%	0.2127	0.1942
17	130	00:13:22	100.00%	96.88%	0.0712	0.1986
18	140	00:14:10	93.33%	96.88%	0.1597	0.2011
19	150	00:14:57	100.00%	84.38%	0.0674	0.2103
20	160	00:15:45	100.00%	100.00%	0.0546	0.1405

Here the base learning rate in all cases of input data normalization is taken to be 1.0000e-04

Table 2. Initialization of input data normalization (Squeeze Net)

Epoch number	Itera-tion	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Validation Accuracy	Mini-batch Loss	Validation Loss
t	1	00:00:07	20.00%	53.12%	4.2032	1.2722
1	13	00:00:27	60.00%	62.50%	0.9195	0.9299
2	26	00:00:48	60.00%	59.38%	0.7726	0.8316
3	39	00:01:09	60.00%	62.50%	0.7032	0.7386
4	50	00:01:26	90.00%		0.7458	
4	52	00:01:30	70.00%	87.50%	0.5993	0.6630
5	65	00:01:51	90.00%	84.38%	0.4828	0.5314
6	78	00:02:12	90.00%	87.50%	0.3731	0.3828
7	91	00:02:33	90.00%	84.38%	0.2220	0.3695
8	100	00:02:47	90.00%		0.3257	
8|	104	00:02:54	90.00%	90.62%	0.2096	0.3013
9	117	00:03:15	100.00%	90.62%	0.0694	0.2194
10	130	00:03:36	90.00%	90.62%	0.2280	0.1890
11	143	00:03:57	100.00%	90.62%	0.0280	0.1959
12	150	00:04:07	100.00%		0.1082	
12	156	00:04:18	90.00%	90.62%	0.1536	0.3638
13	169	00:04:39	80.00%	81.25%	0.7354	0.7383
14	182	00:04:59	100.00%	90.62%	0.0744	0.2016
15	195	00:05:20	100.00%	93.75%	0.0211	0.1672

Here the base learning rate in all the cases is taken to be of the value of 0.0003