Power Quality Disturbance Monitoring in PV Integrated Power System with Mode Decomposition and Ensemble Extreme Learning Machine

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ABSTRACT: Power quality disturbance (PQD) monitoring has become an important issue in modern power system due to integration of several renewable energy sources such as photovoltaic (PV), wind energy system (WES), Fuel cells etc. This research presents a mode decomposed based ensemble extreme learning machine (EELM) to recognise and classify the PQD events with higher accuracy in terms of rapid learning speed and smaller computational burden in a complete PV based power system, The PQD signals are decomposed using a variational mode decomposition (VMD) to obtain effective band limited intrinsic mode functions (BIIMF) which leads to compute robust features and improves classification accuracy. For Power Quality Disturbances detection and classification, an ensemble extreme learning machine is suggested since an ensemble outperforms any single contributing model in terms of performance and prediction. The proposed VMD-EELM approach is validated in a modified IEEE 13 Bus system integrating PV with eleven types of PQDs. The proposed research having 100% classification accuracy for no noise and 99.88%, 99.94% 99.94% for 20dB, 30dB and 40dB noises respectively. It is being demonstrated that the suggested method can reliably identify and track PQD occurrences both with and without noise.

KEYWORDS: Power quality; Ensemble Extreme learning machine; PV integration; Variational Mode Decomposition

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I. INTRODUCTION

In past few years, large-scale renewable energy systems have been installed all over the world due to the requirement of clean energy and reduction of harmful emissions as well as being less dependent on the utilization of fossil fuels. With a goal of 100% by 2050, the European Union Renewable Energy Regulation established a target of producing more than 32% of all power from renewable sources by 2030. Among a range of different renewable resources, wind and solar are the two that are most promising for producing considerable amounts of electrical energy. The primary factor driving interest in producing large amounts of electrical energy from renewable sources is global warming. Solar photovoltaics (PV) is one of the most promising renewable energy sources for large-scale power generation because of advancements in solar cell production and converter technology. Photovoltaic (PV) is one of the most promising renewable energy sources for large-scale power generation because of advancements in solar cell production and converter technology. PV electricity would modify various components of the power system and could affect the stability of the system if the current commissioning rate is maintained (Shah *et al*, 2015). Grid-integrated renewable energy (RE) sources have become increasingly prevalent to a large extent in low and medium voltage utility systems in order to satisfy the energy needs of consumers (Chawda et al, 2020). A greater extent of RE penetration has a major effect on the power quality.

Power quality disturbances such as noise, harmonics, notch, sag, swell, voltage fluctuations etc. are considered to be the primary factor that has led to a decline in power quality (Chawda et al, 2020). As the world has grown more industrialised, so has the use of complicated electronic equipment, solid-state switching devices, nonlinear loads, power electronic converters, and relaying/protective devices. The effects of PQ disruptions on the economy are extensive and diverse. In some circumstances, the effects of the PQ disturbances are readily evident because of equipment damage and/or operational loss (Elphick et al ,2015). Social and economic effects encompass uncomfortable building conditions that could harm efficiency, health, or safety, injury to oneself or dread, if industrial safety fails as a result of power quality issues, surrounding buildings may need to be evacuated may occur due to power quality disturbances (Elphick et al ,2015). Thus, it is crucial to regularly monitor these interruptions. The increasing demand for renewable energy needs continuous monitoring. Since PQ issues directly affect the overall viability of the electric transmission and distribution network, electric power systems (EPSs) must now be constantly monitored (Mishra, 2019). For analysing power quality Disturbances (PQD)signal processing techniques are used.

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The fundamental techniques for studying PQD include Fourier transforms (FT), discrete Fourier transforms (DFT), short time Fourier transforms (STFT), fast Fourier transforms (FFT), and wavelet transforms (WT). The stationary PQ signals have been examined by the FT. Due to its fixed window size, STFT is an extension of DFT, which is inadequate for the analysis of a non-stationary signal. Wavelet transform has been used to address the STFT's shortcomings. The nonstationary PQ signals cannot be analysed using families of FT, and DFT has some limitations, such as spectrum leakage and resolution. Because STFT cannot use long window sizes at low frequencies and short window sizes at high frequencies, this is its fundamental flaw (Liu et al, 2018). An inventive technique for time series analysis and signal processing is the singular spectrum analysis. A signal has been subjected to amplitude and phase modulation via SSA. One of SSA's objectives is to break down a time series signal into the sum of a few understandable signals (Liu et al, 2018). Several signal processing algorithms have been presented for PQD feature extraction. The deconstructed signals can be utilised for feature extraction, pre-processing, missing data-point interruption, filtering, and detection. Numerous industries, including food production, weather forecasting, chemical processing, wind prediction, and ECG, have employed singular spectrum analysis (SSA) (Liu et al, 2019). The retrieved features are utilized directly as an input to a classifier, which is rather challenging to handle due to the features' enormous dimensionality. Power quality study must include the classification of PQDs.To increase the classification accuracy of the PQD signal, an automatic classifier must be put into effect. Many classifiers have been developed, including the fuzzy logic, support vector machines, decision trees, maximum likelihood, artificial neural networks, and probabilistic neural networks (PNN). For the categorization of single and multiple combined PQDs, deep neural networks (DNN) are proposed (Liu et al, 2019). The development of in-depth evaluations on the use of signal processing, AI, and optimization strategies in the detection and classification of PQD is done in (He, S., Li, K., and Zhang, M. 2013). Advantages and comparison of different techniques for proper classification and detection are implemented in (Granados-Lieberman, D,et al, 2011) Artificial Neural Networks (ANNs) are particularly good in data clustering, function approximation, pattern matching and classification, and optimisation. The back-propagation method is the most widely used algorithm for training multi-layered feedforward networks. One ANN design that is often used for data classification is the multi-layer perceptron (MLP) (Granados-Lieberman, D,et al, 2011). Here in this research work in a 13 bus PV integrated system variational mode decomposition (VMD)is implemented for feature extraction and ensemble extreme learning machine is utilized for better accuracy.

In the recent past mode decomposition techniques such as Hilbert hung transform (HHT), Empirical mode decomposition (EMD) and Variational mode decomposition (VMD) are used by researchers for extracting features of PQD signals. Cross Hilbert-Hung transform (CHHT) is used to extract features for multiple PQD signals (Dalai et al, 2013). However, EMD which is a part of HHT does not have a strict mathematical basis and is subject to noise and sampling restrictions. Empirical wavelet transforms (EWT) based PQD detection technique is presented in (Thirumala, K., Umarikar, A. C.,and Jain, T,2014), the EWT overcomes the problem of WT but it does not overcome the demerits of EMD .However VMD is proposed recently in year 2014 for mode decomposition and feature extraction in PQD detection in classification in grid integrated distributed generation (Achlerkar, P. D., Samantaray, S. R., and Manikandan, M. S,2016). The alternate direction method of multipliers ADMM, Wiener filtering, and Hilbert transform work together to give a more accurate and superior decomposition result when using the VMD approach. Because of this, any signal may be precisely decomposed into sets of VMFs using the VMD approach, all while retaining important information from the original signals. In this article, the PQD signals are broken down using VMD in order to extract features. Because of this, any signal may be precisely decomposed into sets of VMFs using the VMD approach, all while retaining important information from the original signals. In this article, the PQD signals are broken down using VMD in order to extract features.

Recently machine learning techniques such as ANN, Support vector machine (SVM), Decision tree (DT), Extreme learning machine (ELM) etc.are tried by researchers for PQDs detection and classification's is proposed in (Lin, W. M., Wu, C. H., Lin, C. H., and Cheng, F. S., 2008) to classify PQDs. It has limited effectiveness with large datasets and become computationally expensive when dealing with large datasets. SVMs are highly sensitive to noisy or overlapping data, which can result in overfitting or underfitting. The multi-layer perceptron (MLP) is an ANN design frequently used for data classification. In (Chen, C., Li, W and Su, H.,2014) Kernel extreme learning machine (KELM) is proposed for image classification, though ELM and KELM outperforms it has some limitations which is taken care by ensemble extreme learning machine (EELM) reported in (Chen, Z., Jiang, C., and Xie, L. (2018). EELM combines multiple ELM models to improve accuracy. The combination of multiple models can help to reduce bias and variance, resulting in more accurate predictions. ELM is more robust to noise and outliers in the data because it is based on the principle of combining multiple models. This means that the predictions of the ensemble are less likely to be affected by noise in the data. In this proposed work EELM is used for PQD detection and classification and noise robust VMD is utilised for signal decomposition and feature extraction. A 13 bus PV integrated power system is modelled for verification of proposed technique.

II. THEORETICAL ANALYSIS

A. Variational Mode Decomposition

VMD was introduced by Konstantinos Dragomiretskiy and Dominique Zosso in 2014, as an improvement to the empirical mode decomposition (EMD) method. the output of the VMD algorithm is a set of K modes, each of which represents a distinct oscillatory component of the signal. The modes are ordered by their frequency content, with the lowest frequency mode being the first mode. The modes can be added together to reconstruct the original signal. VMD has been shown to outperform EMD and other signal decomposition methods in various applications, including image denoising, audio processing, and biomedical signal analysis (Liu, W., Liu, Y., Li, S., and Chen, Y. 2023).

When reiterating the input, the true rated input signal y is split up into a finite number of sub-signals, or modes, u_k, each of which has its own distinct sparsity properties. Around a centre frequency ω_k, which will be identified along with the breakdown, each mode is relatively compact. The following plan is suggested to evaluate a mode's bandwidth:

- Obtain a unilateral frequency spectrum, compute the related analytic signal for each mode using the Hilbert transform.
- Each mode's frequency spectrum can be shifted into "baseband" by combining it with an exponential tuned to the appropriate projected centre frequency.

The bandwidth is now estimated using the squared-norm of the gradient, or the Gaussian smoothness of the demodulated signal. Variational Mode Decomposition is required to solve a constrained variational problem, which is represented by the following equation:

$$min_{\{u_k\}\{w_k\}} \left\{\sum_{k=1}^{K} \left\| \partial_t \left[\left(\partial(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-jw_k t} \right\| \right\} \quad (1)$$

$$\text{s.t} \qquad \sum_{k=1}^{K} u_k = y(t)$$

Additionally, $y(t)$ is the original time-domain signal subjected to decomposition

$u_k(t)$ is the kth Intrinsic Mode Function (IMF) also called Variational Mode Function where k = 1, 2, 3, …., K is the total number of IMFs

$w_k = w_1 \dots\dots\dots w_K$ are simplified expression for all the center frequencies

To address the reconstruction constraint in Variational Mode Decomposition (VMD), a quadratic penalty term and Lagrange multipliers are used to make the problem unconstrained. Lagrangian multipliers are also used to strictly enforce constraints.

$$L(\{U_k\},\{w_k\},\Upsilon) = \alpha \sum_{k=1}^{K} \left\| \partial_t \left[\left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right] e^{-jw_k t} \right\| + \|y(t) - \sum_{k=1}^{K} u_k(t)\|_2^2 + \langle \gamma(t), y(t) - \sum_{k=1}^{K} u_k t \rangle \quad (2)$$

Where γ is the Lagrangian multiplier, α the penalty parameter that influences the smoothness of the mode decomposition. $\langle \cdot,\cdot \rangle$ denotes the inner product..

After a series of repeated sub-optimizations known as the alternate direction method of multipliers, the saddle point of the augmented Lagrangian is discovered to be the solution to the initial minimization problem.

I. *Ensemble Extreme Learning Machine*

Ensemble extreme learning machine is a machine learning algorithm that makes effort to combine multiple base learners for enhancing the accuracy of predictions and raise the performance (Chen, Z., Jiang, C., and Xie, L. ,2018). This algorithm was introduced by Huang, Liang and Siew in 2006 for solving classification and regression problems. It helps in stabilizing the result and reduces the risk of being trapped in local optimums(Chen, Z., Jiang, C., and Xie, L. ,2018).The main aim of using Ensemble Extreme Learning Machine(EELM) is to combine the outputs of several ELMs to make a final prediction which is initiated by training different ELM models with different sets of input weights and biases and functions combining their outputs using a weight level average and the difference in the results gets reduced (Stefenon et al.,2019)In this research work ensemble machine learning approach is used for power quality disturbance monitoring for enhancing the accuracy of predication as well as the robustness of the monitoring system respectively .Eventually it helps to uplift the interpretability of the results by implementing a more explainable and transparent model(Stefenon et al.,2019).

A single layer feed forward neural network with $\tilde{n}$ hidden neurons and considering n distinct samples (x_k, yR_k) where x_k is defined below:

Where $x_k = [x_1, x_2, \dots\dots\dots\dots, x_n]$ can be patterned as the model described as shown in fig.1below as under:

$$yR_k = \sum_{j=1}^{\tilde{n}} \lambda_j g(\omega_j . x_j + b_j), \text{k} = 1 \dots\dots\dots \text{n} \quad (3)$$

Where, K=1,2, ----n; λ_i is the jth neuron output, ω_j is the input weight, b_j is the hidden layer bias, $G(.)$ is the activation function.

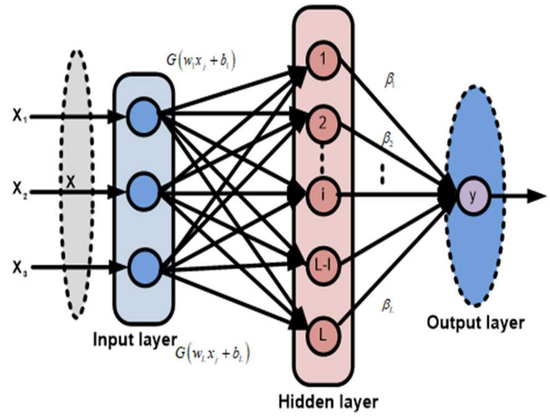

Fig.1 Extreme learning machine

The output is calculated as follows

$$R_k[yR\_k, yR\_k\ 2, \dots\dots\dots\dots\dots\dots yR\_k\ M]^T \epsilon R^M \quad (4)$$
)

The compressed form of equation (1) can be written as follows

$$H\lambda = Y_R \quad (5)$$

$$H = \begin{pmatrix} \omega_1 \dots\dots\dots\dots \omega_n \\ b_1 \dots\dots\dots\dots b_{\tilde{n}} \\ x_1 \dots\dots\dots\dots x_n \end{pmatrix} = \begin{bmatrix} G(\omega_1 x_1 + b_1) \dots\dots.. \\ G(\omega_{\tilde{n}} x_1 + b_{\tilde{n}}) \dots\dots.. \\ \vdots \\ G(\omega_1 x_n + b_{\tilde{n}}) \dots\dots\dots \\ G(\omega_{\tilde{n}} x_n + b_{\tilde{n}}) \dots\dots\dots \end{bmatrix}_{n*\tilde{n}} \quad (6)$$

$$\lambda = \begin{bmatrix} \lambda_1^T \\ \vdots \\ \lambda_n^T \end{bmatrix}_{n*M} \quad , Y_R = \begin{bmatrix} yR_T^1 \\ \vdots \\ yR_n^T \end{bmatrix}_{n*M} \quad (7)$$

By creating an output matrix and using randomly initialised input weights and biases, hidden neurons can simulate these n samples in a single layer feed forward neural network with a variable activation function. The target values can be approximately provided by this t

$$H_{n*n}\lambda_{n*m} - YR_{n*m} \quad (8)$$

Where ε is a small and positive value for solving the linear system and depicted in eqn (4), the result of the smallest norm least square is written as

$$\tilde{\lambda} = H^T Y_R \quad (9)$$

Where $\tilde{\lambda}$ is one of the solutions of least squares

H^T Symbolises the Moore Penrose generalized revere of matrix H

The activation function is described as

$$G_{TAF}(\mu) = \frac{\tau}{1+e^{\frac{v-\delta}{\mu}+\beta}} \quad (10)$$

τ is the mapping factor

$$v = \sum_{j=1}^{n} \omega_j x_j + b_j \quad (11)$$

If the parameters are chosen, $\beta = \delta = 0, \tau = \mu = 1$

Assumption of the second activation function is done

$$G_{lin}(v) = vk_{lin} \quad (12)$$

Once the EELM model is trained with the VMD decomposed signal features, the performance of the classifier is decided on the basis of a performance index called Accuracy. It simply indicates the number of accurately detected events with respect to the total number of events as follows,

$$CA_z(\%) = \frac{Total\ number\ of\ correctly\ classified\ cases\ of\ the\ even\ 'z'}{Total\ number\ of\ cases\ of\ the\ event\ 'z'} \times 100 \quad (13)$$

III. SYSTEM UNDER STUDY AND FEATURE EXTRACTION

A. System Under Study

PV integrated modified IEEE-13 Bus test system is modelled in MATLAB/Simulink as shown in fig.2 (Kersting, W. H., 1991). Solar PV generation of 1mw is connected at bus 652 with 10 km of transmission line, transformer through AC/DC converter arrangement. The loads are connected to the different buses as mentioned in IEEE 13 BUS system (Eristi, B. and Eristi, H.,2022). The different distributed loads are star and delta connected, also the load includes constant KW, KVAR, constant impedance and constant current load. The voltage regulators used in the model are single phase star connected,

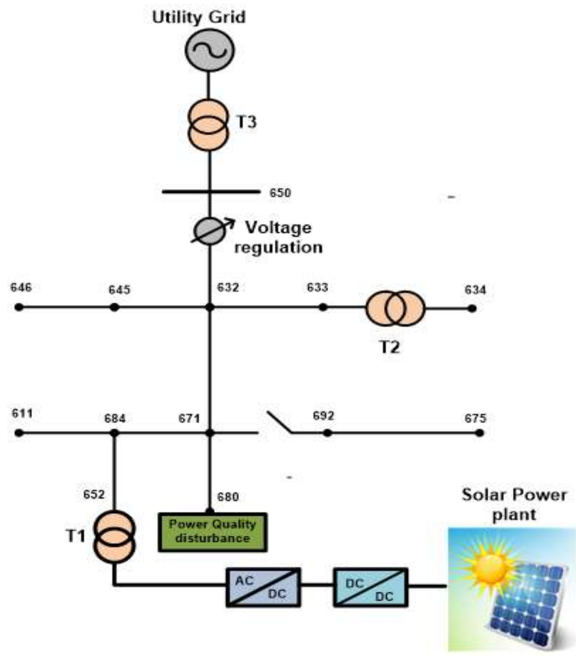

Fig.2.Model Under Study

Adaptive VMDs are used for producing different features from the band selected of limited IMF for prediction of different power quality disturbances along with faults and Islanding challenges. In comparison to VMD-based methods, simple features are required by VMD-based strategies for faster classification of disturbances.

B. Feature Extraction

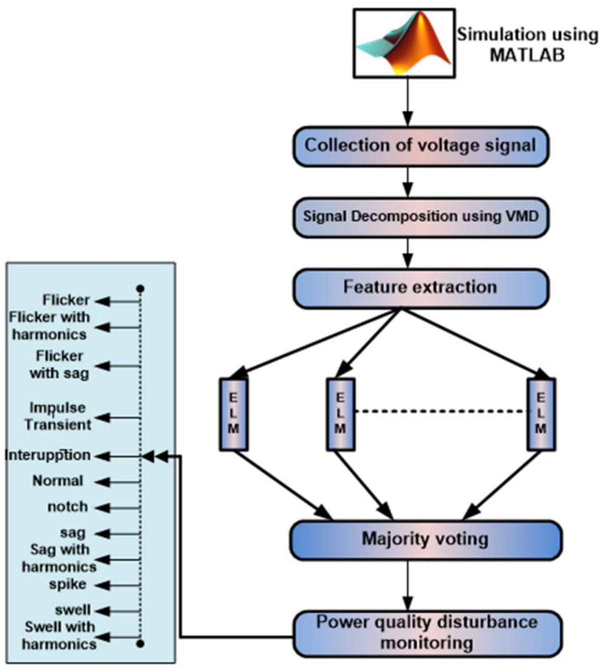

Fig.3 Flow diagram of Power Quality Disturbance Monitoring using VMD and Ensemble Extreme Learning Machine

The target features obtained are expressed as follows:
For a signal z(t), with samples for n=1,2, 3…N
Signal Energy (y_1)

$$y_1 = \sum_{n=1}^{N} z_n^2 \tag{14}$$

Standard Deviation (y_2): Mathematically it can be depicted as:

$$y_2 = \sqrt{\frac{1}{N}\sum_{n=1}^{N}\left(z_n - \tilde{z}_\mu\right)^2} \tag{15}$$

Mean value of the signal: The mean value is represented as:

$$\tilde{z}_\mu = \frac{1}{N}\sum_{n=1}^{M} z_n \tag{16}$$

Total harmonic distortion (THD)

$$THD = \frac{\sqrt{\sum_{m=2}^{\infty} z_{m\_RMS}^2}}{z_{fund\_RMS}} \tag{17}$$

Where Z_{funf_RMS}=harmonic RMS Voltage and Z_{fund_RMS} = fundamental RMS voltage. Feature y_4 is taken as the maximum value of total harmonic distortion. The proposed VMD apply kurtosis index criteria to select the most suitable BLIMF from the different decomposed BLIMFS. The BLIMF with maximum kurtosis index is chosen for computing various relevant features.

IV. RESULTS AND DISCUSSION

Due to PV-generation integration it injects harmonics and noise to the power system which degrades the power quality. Flow diagram of Power Quality Disturbance Monitoring using VMD and Ensemble Extreme Learning Machine is shown in fig.3. The three major steps in the proposed study are modelling of the test system, data extraction, data processing and design of the ensemble classifier. The modelling of the test system is implemented using MATLAB2018a. In the data processing stage, the raw signals are decomposed using VMD and an ensemble extreme learning machine is designed to classify events. Designing an ensemble extreme learning machine (ELM) for event classification involves several key steps: design of base ELM model, splitting the dataset into training and testing sets and initializing multiple ELM models with random input weights and biases. Each ELM is trained on subsets of the training data, with output weights calculated using the Moore-Penrose generalized inverse. The ensemble strategy of bagging combines the outputs of individual ELMs using majority voting,

In this section the efficacy of proposed VMD-EELM is verified with different prominent features. As discussed, the VMD is used to decompose the signal into different band limited intrinsic mode functions (BLIMF) and helps in extracting accurate features for improved accuracy. First the efficacy of the VMD is tested for a synthetic voltage sag signal without noise ,20dB noise and 40dB noise. Significant modes are shown in fig.4, fig.5 and fig.6 respectively. In fig.4 it is observed that the proposed VMD is able to extract noises from original voltage sag with different noises and BLIMF-1 having highest kurtosis index as compared to other modes so BLIMF-1 is selected for feature extraction. In the similar manner fig.5 and fig.6 clearly depicts the decomposition of sag with noises and separation of noises apart from that the decomposition of Sag with harmonic signal is shown in fig.7 and it is proved that VMD is able to separate noises from PQD disturbance signal. The four prominent features as discussed in section- III named as signal energy, standard deviation, Mean value and THD are computed from BLIMF-1.

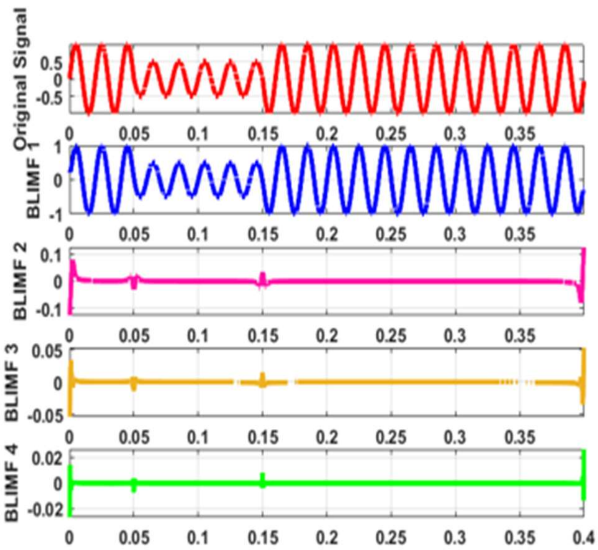

Fig.4. Decomposition of PQD disturbances SAG generated from PV-integrated model with VMD

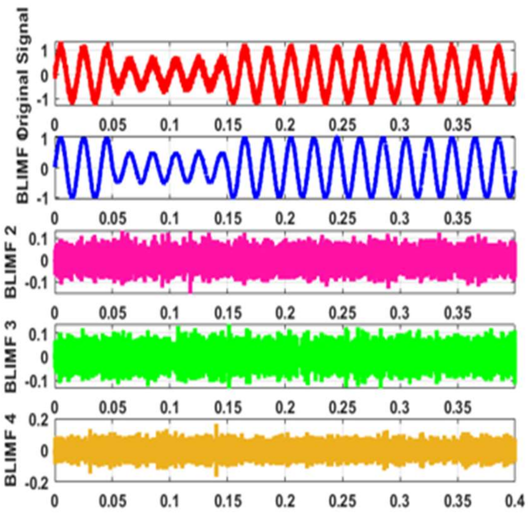

Fig.5. Decomposition of PQD disturbances SAG with 20dB noise using VMD

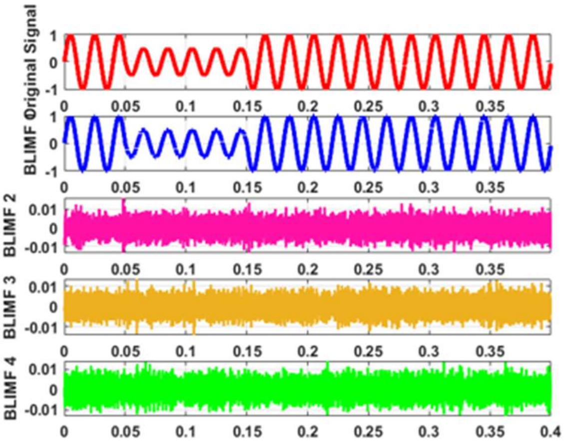

Fig.6. Decomposition of PQD disturbances SAG with 40dB noise using VMD

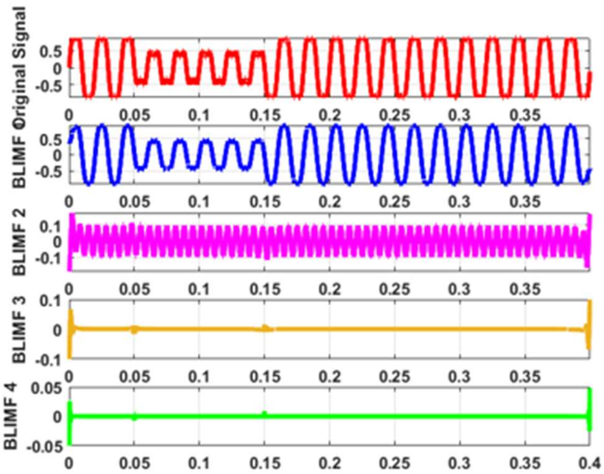

Fig.7. Decomposition of PQD disturbances SAG with 3rd harmonic using VMD

Different real time PQDs test cases are simulated to evaluate the performance of proposed EELM.The number of PQDs events and normal test signals are simulated using the modified IEEE-13bus system integrated with solar power plant as shown in the fig.3. Noisy and simultaneous occurring PQDs are considered to make the analysis more realistic and practical oriented. The 20dB ,30dB and 40dB white gaussian noise is added to the PQD signals. The classification accuracy is studied under both noisy and normal conditions.

For the VMD-EELM, the Power Quality Disturbance Classification Accuracy (CA) is calculated as a performance index. The CA for an individual event 'z' can be calculated using the formula in Equation (12). The suggested scheme's detail performance is displayed in the confusion matrix (CM), where the diagonal represents the correctly classified PQD occurrences.

In the proposed study, 11 number of PQDs are examined such as Flicker (D1), Flicker with Harmonics (D2), Flicker with Sag (D3), Impulse Transient (D4), Interruption (D5), Notch (D6), Sag (D7), Sag with Harmonics (D8), Spike (D9), Swell (D10) and Swell with Harmonics (D11) along with one Normal scenario termed as ‘N’. Therefore, a total number of 12 events are considered for the classification tasks with each class containing 150 set of collected samples, with overall dataset dimension of 150*12=1800.

Table 1. Performance of VMD-EELM with and without noise

PQD disturbance	Symbol of PQD	Training testing ratio	Accuracy (%)			
			Data set 1	Data set 2		
			Noiseless	20dB	30dB	40dB
Flicker	D1	70:30	100	100	100	100
Flicker with Harmonics	D2	70:30	100	100	100	100
Flicker with Sag	D3	70:30	100	100	100	100
Impulse transient	D4	70:30	100	100	100	100
Interruption	D5	70:30	100	99.33	100	100
Normal	N	70:30	100	100	100	100
Notch	D6	70:30	100	100	100	100
Sag	D7	70:30	100	100	100	100
Sag with harmonics	D8	70:30	100	99.33	99.33	100
Spike	D9	70:30	100	100	100	100
Swell	D10	70:30	100	100	100	100
Swell with harmonics	D11	70:30	100	100	100	99.33
Average accuracy			100	99.88	99.94	99.94

The PQDs data sets is divided into 70%and 30% for training and testing respectively. First the training data set is applied for proposed algorithm and the training confusion matrix is shown in fig.8. It is clear from training confusion matrix that accuracy is 100% for all classes. In similar manner the testing data and all data set is applied to proposed EELM algorithm the confusion matrix for testing and all confusion matrix are shown in fig.9 and fig.10 respectively. It is observed from the all-confusion matrix that all disturbance classes are correctly classified with 100 % accuracy in noise free condition. In the next stage 20dB, 30dB and 40dB. noises are added to the data set to access the performance of proposed EELM in noisy condition. The resulting total confusion matrix for 20dB, 30 dB and 40dB noises are shown in fig.11, fig.12 and fig.13 respectively. All the results are tabulated in Table-1

Table 2. Comparison with recent state of art techniques

Sl. No	Techniques used	Number of disturbances	Accuracy without noise	Accuracy under noise condition (%)		
				20dB	30dB	40 dB
01	DCNN (Liu, H *et al*, 2018)	9	100	99.99	-	-
		22	99.52	99.20	-	-
02	DNN (Liu, H., *et al*, 2019)	15	99.56	99.32	99.55	-
03	DCNN (Wang, S., andChen, H. 2019)	16	99.96	98.13	99.66	99.95
04	GOA-SVM (Motlagh, S. Z., and Foroud, A. A 2021)	23	99.56	97.13	98.91	99.17
05	Proposed EELM	10	100	99.88	99.94	99.94

To justify the efficacy of proposed technique, it is compared with currently reported state-of -the -art techniques. The comparison of performances is shown in Table-2. In reference (Liu, H.,*et al* 2018), PQD signals are decomposed using singular spectrum analysis (SSA)and curvlet transform (CT), the PQD classification is carried out using Deep Convolutional neural networks (DCNN)and obtained accuracy of 100%for 9 no's of single PQD disturbances whereas obtained accuracy of 99.52 for 22 PQ disturbances. In ref (Liu, H.,*et al*2019) signal processing and deep learning is used for 15 PQD signals and obtained an accuracy of 99.56%. Deep convolutional neural network (Wang, S.,and Chen, H. 2019) is proposed for classifying 16 PQD signals and the achieved success rate is 99.96 whereas the success rate is 98.13,99.66, and 99.95 for 20dB ,30dB and 40 dB noise respectively. In (Motlagh, S. Z., and Foroud, A. A. 2021) author proposed a Grasshopper Algorithm (GOA) optimise support vector machine (SVM) classifier where the average accuracy is 99.56 without noise and 97.13,98.91,99.17% accuracy for 20dB ,30dB and 40dB noise. The proposed research having 100% classification accuracy for no noise and 99.88%,99.94%,99.94% for 20,30 and 40dB noises respectively which is found better than previous research. For noisy environments the proposed technique is performing well as compared to other techniques.

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In the current study, comparing the computational burden with DCNN and DNN which are claimed to be current state of art techniques. The difference in computational burden arises primarily due to the complexities in their architectures and training processes. the computational burden of a Deep Convolutional Neural Network (DCNN) is generally higher than that of an Ensemble Extreme Learning Machine (EELM). This is because ELM involves only a single feedforward pass followed by a simple least-squares solution for the output weights. This makes ELM highly efficient, especially for large datasets. Experimental studies have shown that they can produce acceptable predictive performance in various tasks, and at a much lower training cost, as compared to networks that are trained by backpropagation (Huang, *et al* 2015). DCNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers, each with numerous parameters to optimize. The training process involves backpropagation and gradient descent, which are computationally intensive. In our proposed study total 1800 data samples are used as input to EELM, considering 10 ELMs with 10 hidden nodes, needs 1,080,000 operations whereas assuming the CNN has 3 convolutional layers with 32 filters of size 3×3 needs 156,638,131,200 operations, The CNN requires significantly more computational resources compared to the ensemble of ELMs. Therefore, the proposed EELM approach is computationally efficient as well as suitable for detection and classification of PQD signals.

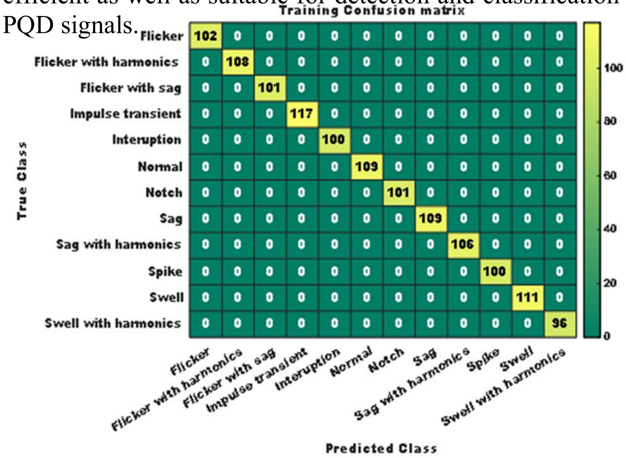

Fig.8.The training Confusion matrix of VMD-EELM in grid tied mode

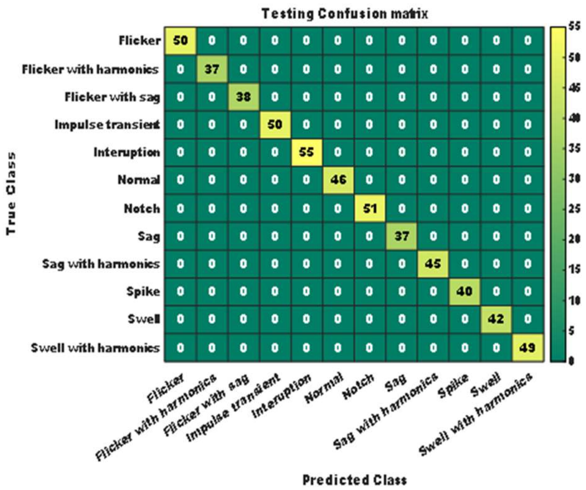

Fig.9.The testing Confusion matrix of VMD-EELM in grid tied mode

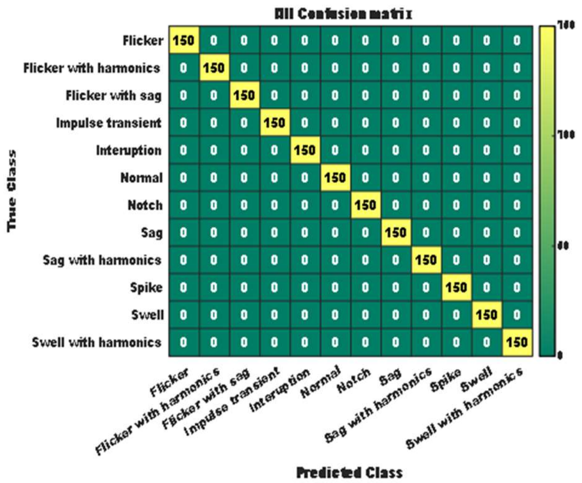

Fig.10.The All-Confusion matrix of VMD-EELM in grid tied mode

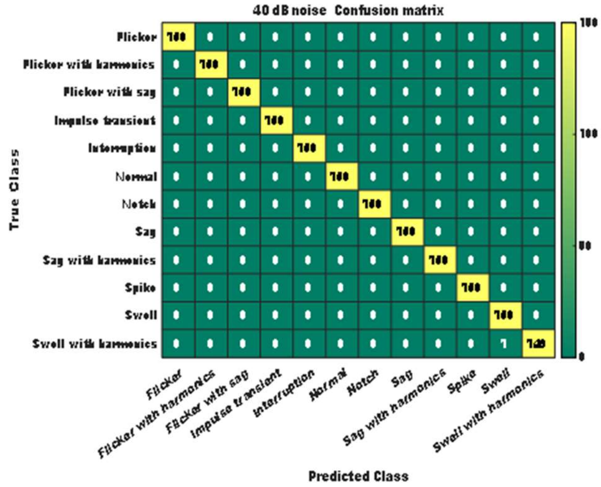

Fig.13.The All-Confusion matrix of VMD-EELM with 40dB noise in grid tied mode

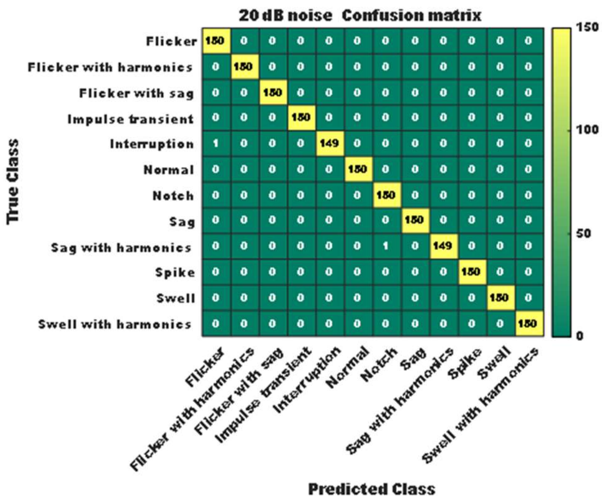

Fig.11.The All-Confusion matrix of VMD-EELM with 20dB noise in grid tied mode

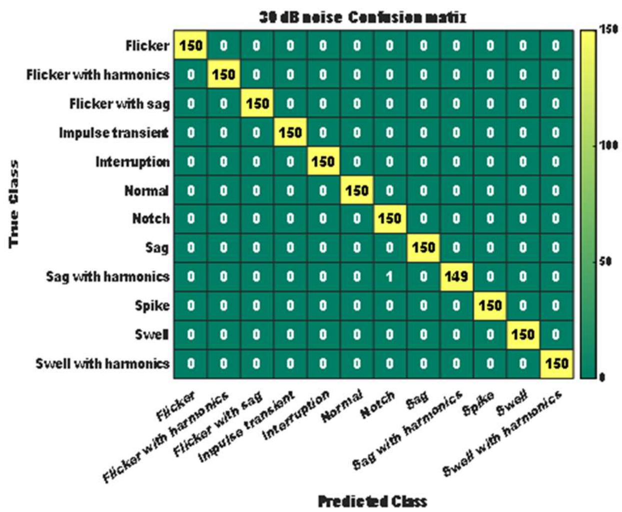

Fig.12.The All-Confusion matrix of VMD-EELM with 30dB noise in grid tied mode

V. CONCLUSION

To detect power quality issues, an unique VMD-EELM data-driven classifier is presented in the current research by integrating different PQ disturbance signals from a PV power system. The study and classification consider various power system signals. The proposed VMD applies the kurtosis index criteria to select the most suitable BLIMF from the different decomposed BLIMFs. The BLIMF with the maximum kurtosis index is chosen for computing various relevant features used for classification. These feature matrices are given as inputs to the VMD-EELM classifier for event identification. The proposed VMD-EELM is verified with MATLAB-generated data for 12 classes. Higher classification accuracy and average classification accuracy are obtained for identifying various disturbances, even in the presence of different SNRs. The proposed research demonstrates superior performance in classifying PQD signals, achieving 100% accuracy in noiseless environments and 99.88%, 99.94%, and 99.94% accuracy under 20 dB, 30 dB, and 40 dB noise conditions, respectively. These results surpass the accuracy of previously reported methods. The proposed technique shows robust performance in noisy environments, making it suitable for detecting and classifying PQD signals. Comparative analysis with recent techniques confirms the efficacy of the VMD-EELM approach, particularly for PV-integrated power systems.

AUTHOR CONTRIBUTIONS

Conceptualization, **R. K. Mallick;** methodology, **R. K. Mallick** and **A. R. Choudhury**; software **R. Agrawal** and **A. R. Choudhury**; validation **R. Agrawal** and **P. Nayak**; formal analysis, **P. Nayak**; data curation, **R. K. Mallick** and **A. R. Choudhury**; writing—original draft preparation, **A. R. Choudhury**; writing—review and editing, **R. Agrawal** and **P. Nayak**.; visualization, **A. R. Choudhury**; supervision, **R. K. Mallick** and R.A; funding acquisition **A. R. Choudhury**. All

authors have read and agreed to the published version of the manuscript.

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