IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 1 February 2024, accepted 15 March 2024, date of publication 25 March 2024, date of current version 4 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3381621

RESEARCH ARTICLE

Real Time Intelligent Detection of PQ Disturbances With Variational Mode Energy Features and Hybrid Optimized Light GBM Classifier

SAIRAM MISHRA[1], (Graduate Student Member, IEEE), RANJAN KUMAR MALLICK[2], DEBADATTA AMARESH GADANAYAK[2], (Member, IEEE), PRAVATI NAYAK[1], RENU SHARMA[1], (Senior Member, IEEE), GAYADHAR PANDA[3], (Senior Member, IEEE), MOHAMMED S. AL-NUMAY[4], (Senior Member, IEEE), AND PIERLUIGI SIANO[5], (Senior Member, IEEE)

[1]Department of Electrical Engineering, Siksha 'O' Anushandhan (Deemed to be University), Bhubaneswar, Odisha 751030, India
[2]Department of Electrical and Electronics Engineering, Siksha 'O' Anushandhan (Deemed to be University), Bhubaneswar, Odisha 751030, India
[3]National Institute of Technology Meghalaya, Laitumkhrah, Shillong, Meghalaya 793003, India
[4]Electrical Engineering Department, College of Engineering, King Saud University, Riyadh 11421, Saudi Arabia
[5]Department of Management and Innovation Systems, University of Salerno, 84084 Salerno, Italy

Corresponding author: Pierluigi Siano (psiano@unisa.it)

The work of Mohammed S. Al-Numay and Pierluigi Siano was supported by the Researchers Supporting Project, King Saud University, Riyadh, Saudi Arabia, under Grant RSP2023R150.

ABSTRACT The modern era power system is constantly undergoing constructive changes and implementations both in source and load side. Certainly, the distributed generators, unconventional/nonlinear loads, charging stations etc are mostly integrated through power electronics interfaces. As a result, frequent power quality disturbances appear in the system that is to be mitigated at the earliest. Since detection is the prerequisite for mitigation, therefore the article presents a novel intelligent power quality detection scheme to detect and classify the PQ Events. At first, the energy feature of the 5 band limited modes are calculated from variational mode decomposed voltage signals. Then the mode energy features are utilized to train a novel Hybrid Arithmetic Whale Optimized light gradient boosting machine classifier. A total of 15 different PQ events have been investigated and exceptional classification results have obtained with optimum computational complexity, both under noiseless and noisy conditions. Moreover, the accuracy of the proposed PQ classification schemes found to be towering against other related pre-published works. Finally, the ability of the proposed detection scheme is validated in real time though OPAL-RT 4510 and grid simulator hardware in loop setup.

INDEX TERMS Power quality, variational mode decomposition, whale optimization, arithmetic optimization, light gradient boosting machine.

I. INTRODUCTION

The idiom Power Quality simply means the power signal should preserve its sinusoidal characteristics at rated amplitude and frequency [1] and any deviation from these will be treated as Power Quality Disturbance (PQD). The ever-growing energy demand and awareness of green energy have shifted the focus towards distributed generation (DG). These DGs are basically renewable energy source (RES) oriented generation systems. But the power electronics interfacing and the intermittent nature of the RES such as solar, wind have certainly increased the rate of recurrence of PQDs to a higher extend [2]. Along with that, the usability of power electronics in several network equipment's at the grid side as well as in different devices at the industries and end user increased drastically [3]. As a result, numerous types of PQDs are frequently occurring in the power networks such as sag, swell, interruption, flicker, notches transients etc and even a mix of

The associate editor coordinating the review of this manuscript and approving it for publication was Arturo Conde.

few of these. Since, the primary goal of the electricity market participants such as producer, trader and distributer are to deliver power of highest quality. Therefore, it is necessary to continuously monitor the power system and identify the PQDs to take necessary measures at the earliest.

The field of PQD identification have started from the thresholding-based techniques and eventually grown up to intelligent detection techniques (IDTs) [4]. Basically, these IDTs involve two fundamental steps, data processing and development of machine learning (ML) model. In the data processing phase, the hidden features of the power signal are retrieved through some signal processing tool then fed to the second phase to build the ML model. Several signal processing techniques have proposed in literature to address the voltage and current signals having their own uniqueness and limitations [5]. Since PQ signals possess lot of irregularity in terms of amplitude and frequency and often noise contaminated, it is necessary to implement such a signal processor that can act on non-stationary, non-linear and noise prone signals. In this context, mode decomposition techniques like, empirical made decomposition (EMD) [6], ensemble EMD (EEMD) [7], down-sampling EMD (DEMD) [8] are much more useful. But these methods are suffering two major drawbacks such as mode mixing and end effect when the signal nature is very complex. To eradicate the effect of these two limitations Variational mode decomposition (VMD) was introduced [9] which also facilitate low computational complexity while ensuring non-ambiguous outcome of decomposition. In addition to that, VMD has already proven its effectiveness in several PQ studies [10], [11], [12], [13], hence elected as the signal processing tool in this study.

Now, to perform the second step of IDT, it is required to select a ML classifier (MLC) that can well identify the PQ disturbances with utmost accuracy. There are a number of studies reported in literature for detecting PQD through MLCs such as artificial neural network (ANN), decision tree (DT), support vector machine (SVM), extreme learning machine (ELM), kth-Nearest neighbour (KNN) and several variants of these [4], [5]. However, these standalone MLCs are generally search through a number of possible hypotheses to find out the best approximation to the targets. Therefore, they suffer from three major problems those are statistical, computational and representational problems. Since, PQD identification is such a sensitive matter that may lead to catastrophic cascading effect and eventually might end up scenarios like blackout, it should be sincerely addressed with optimum possibility of detection failure. In this regard ensemble MLCs can bring more generalization with uplifted predictability as it combines the prediction of a number of learners [14]. Boosting and bagging are two popular ensemble learning methods. Bagging specifically minimize the variance in the dataset by bootstrapping. A number of bagging techniques have already used for PQD assessment random forest [15], subspace KNN [16] voting-staking based classifier [17] etc. But the key advantage of boosting algorithms over bagging is their ability to produce models with higher accuracy [18]. Moreover, boosting is designed to iteratively improve model performance by focusing on samples that were previously misclassified. This allows boosting to correct errors introduced by previous weak models and ultimately lead to a more accurate final model. A number of boosting methods are found in literature for PQD determination such as adaboost [19], gradient boost [20], XGBoost [21], but it is still in its initial stage of implementation. Another advantage of boosting is its ability to handle imbalanced datasets better than bagging. But the limitation boosting-techniques possess are comparatively slower training process, sensitivity to outliers and difficult to implement in large sized dataset due to sequential building of model. To retain the benefits of boosting and eliminate its drawbacks Light Gradient Boosting Machine (LGBM) has introduced [22], [23]. LGBM is memory efficient, facilitates parallel training, provides speed & accuracy and capable of acting on large dataset. Hence, in this work LGBM is chosen as the MLC. However, LGBM has a number of parameters that can be tuned to enhance its classification ability. Therefore, the study has proposed a novel optimization algorithm hybridizing whale optimization [24] and arithmetic optimization [25] to tune the parameters of LGBM.

Taking into account the unmatched advantages of VMD and LGBM, this paper proposes an intelligent PQD detection scheme having utmost accuracy and minimal computational burden. The contributions of the manuscript are highlighted as follows,

- ✓ Fourteen different Types of Power Quality Disturbance signal assessment is performed in MATLAB Simulink environment. The energy of all the Band Limited Modes (BLMs) obtained from VMD are considered as features for LGBM classifier and thus completely irradicate the worry of selecting most informative BLM as well as identifying different statistical features.
- ✓ Maidan application of proposed Hybrid Arithmetic Whale Optimization Algorithm (AWOA) to optimize the hyper parameters of LGBM so as to bolster its prediction efficiency.
- ✓ The proposed VMD & Hybrid Optimized Light GBM (HOLGBM) based Power Quality Detection Model is validated with different noise contaminated signal to test its effectiveness in real grid conditions and also analysis of comparison is made with related pre-published articles.
- ✓ Real-Time Validation of the HOLGBM PQD detection scheme with OPAL-RT 4510 and grid simulator hardware in loop (HIL) setup is carried out to obtain the detection time which itself a novel attempt in power quality monitoring study.

Further, the paper organization is as follows. The current section covers brief introduction of the research work. Section-II describes the Theoretical aspects of the study. The Section-III is all about the PQ disturbances is to be detected with their mathematical modelling. In section-IV the step wise mythology is discussed along with the proposed detection scheme. The section-V covers the analysis and discussion part of the obtained result. The research work is concluded in the last section.

II. POWER QUALITY EVENTS

In this study a total of 15 different types of PQ events including a healthy signal are taken in to account for analysis. There are 8 single, 4 double and 2 triple PQ disturbances as presented in Table-1. The single events are healthy sinusoidal signal, sag, swell, interruption, flicker, harmonics, notches, oscillatory and impulse transient. The double PQ signals includes independent association of harmonics and oscillatory transient signals along with sag and swell signals receptivity. Further, the triple PQ signals includes the association of both harmonics and oscillatory transient signals independently with sag and swell signals receptivity. The study assumes the reference voltage to be 1p.u. and frequency to be 50 Hz. Therefore, it is required to convert the disturbance signals to per unit before proceeding for any analysis. All the signals are sampled at 10kHz. An integer PQ Index (PQI) of the signals are also mentioned along with their names, which will be useful during real time detection study. Since the work makes use of variational mode decomposition of the signals, Table-1 displays the mathematical modelling along with VMD of all the respective signals. It can be seen that each signal is decomposed to 5 different modes and each mode is placed on the z-axis and the respective mode number is also mentioned.

III. LIGHT GRADIENT BOOSTING MACHINE

Gradient Boosting Machine is an ensemble iterative machine learning algorithm that makes the prediction by aggregating the prediction of a group of weak learners. These learners, often called estimators are generally decision trees. The prime concept of the algorithm is the sequential building of learners, where the current learner is attempting to reduce the error of the previous one. The objective is to optimizing the loss function using gradient descent. GBM can act as both regressor and classifier with different kind of loss function. Generally, the mean square error for regression and log-likelihood for classification in adapted as loss function. Since the concept of the manuscript is demanding classification task, hence here the focus is only limited to classification problem. GBM tries to optimize the loss function $L(t_k, p)$ by finding a prediction value $'p'$ such that the loss function will be minimum. It can be denoted as,

$$f_L = \underbrace{argmin}_{p} \sum\nolimits_{k=1}^{O} L\left(t_k, p\right) \tag{1}$$

The loss function for classification can de defines as,

$$L\left(t_k, p\right) = -\left[\sum\nolimits_{k=1}^{O} t_k \log\left(p\right) + (1-p)\log(1-p)\right] \tag{2}$$

where, t_k is the Target value kth observation of the Training Dataset, $k = 1, 2, 3 \ldots . O$

Next the pseudo residual is evaluated, and the 1st tree is built while taking the residues as the targets. Then the output from the 1st tree is calculated, based on which the next trees are constructed sequentially.

Despite the performance excellence, the efficacy of GBM is affected under big data and high dimensionality of feature set [26]. It is because, the various data points should be scanned to determine an estimate of all feasible tree splits which is time intensive in nature. Therefore, GBM is not scalable for large feature set. To deal with this particular issue Light GBM is introduced. The term "light" signifies the reduction of data and feature dimensionality. First of all, LGBM excludes a considerable part of data with small gradient and keep remaining to evaluate information gain. This is called Gradient based One Sided Sampling (GOSS). Secondly, it only keeps the mutually exclusive features and discard others in a way that is not going to affect the overall accuracy of the predictor. This is called Exclusive Feature Bundle (EFB). These two implementations speed up the training process up to 20 times.

IV. METHODOLOGY

The prime goal of the study is the intelligent identification of PQDs with minimum time and maximum accuracy. In order to achieve this, a three-stage process is followed in this work as shown in Fig.1. These stages are discussed in the succeeding subsections.

A. DATA COLLECTION

Since the work is focusing on data driven solution, a proper data collection process is essential at first. It involves three steps as follows,

1) DATA ACQUISITION

In this stage the voltage signal is sensed from the grid continuously with a sampling frequency of 10 kHz (200 samples/cycle). Since the voltage signals have a periodic characterizes, a 5-cycle snapshot is kept on taking from the continues live data and stacked to data buffer for further data processing. The buffer is having an overlap of 4 cycles, which means every new set of data is collected after a shift of 200 samples from the previous set. It can be clearly seen in the Stage-1 of Fig.1.

2) DATA PROCESSING

The 5-cycle data is further fed to a signal processing stage, to bring edge to the detection process. The signal processing tool (SPT) split the base signal to number of sub signals thereby exposing the disturbance event to be prominent enough. Here the SPT is chosen as VMD due to its advantage of reducing end effect and mode mixing. Most of the studies in this regard trying to select a the most informative sub signal called BLM for feature extraction. But selecting the proper BLM can be another overhead to be solved [27], [28]. Hence in this proposed work the feature extraction is done in a completely different way as discussed in next subsection.

TABLE 1. PQDs with mathematical modelling and variational mode decomposition.

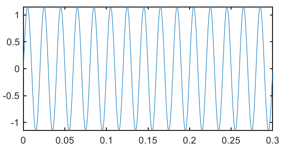
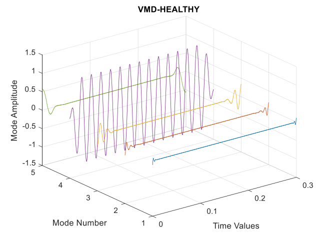
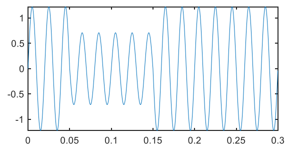
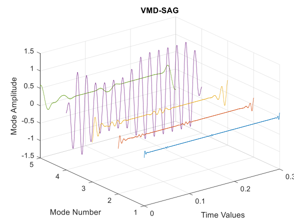
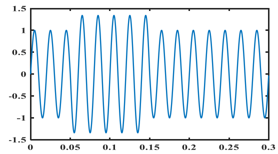
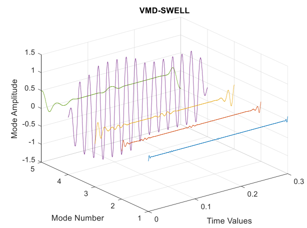
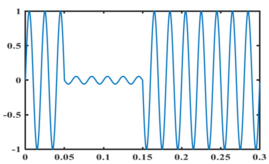
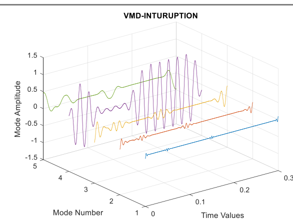
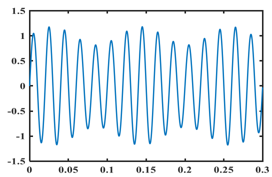
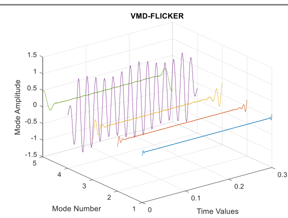
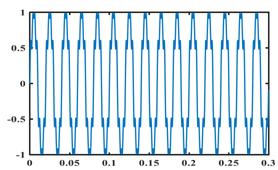
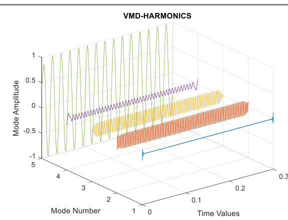
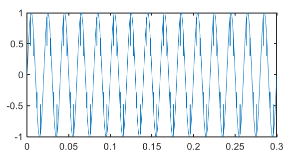
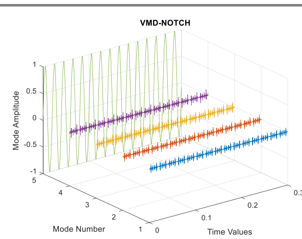
PQD (INDEX)	Mathematical Modelling	Signal	VMD
Healthy (2)	$\sin(\omega t)$ *where*, $\omega = 2 * \pi * 50$		
Sag (1)	$\alpha * \begin{pmatrix} \mathrm{u}(\mathrm{t}-t_1) \\ -\mathrm{u}(\mathrm{t}-t_2) \end{pmatrix} * \sin(\omega t)$ *where*, $0.1 \le \alpha \le 0.9$		
Swell (3)	$\left[1 + \beta * \begin{pmatrix} \mathrm{u}(\mathrm{t}-t_1) \\ -\mathrm{u}(\mathrm{t}-t_2) \end{pmatrix}\right] * \sin(\omega t)$ *where*, $0.1 \le \beta \le 0.8$		
Interruption (0)	$\left[1 - \gamma * \begin{pmatrix} \mathrm{u}(\mathrm{t}-t_1) - \\ \mathrm{u}(\mathrm{t}-t_2) \end{pmatrix}\right] * \sin(\omega t)$ *where*, $0.9 \le \gamma \le 1$		
Flicker (4)	$[1 + \sigma * \sin(2\pi\rho t)] * \sin(\omega t)$ *where*, $0.1 \le \sigma \le 0.2$ *and* $5 \le \rho \le 10$		
Harmonics (5)	$h_1 * \sin(\omega t) + h_3 * \sin(3\omega t) + h_5 * \sin(5\omega t) + h_7 * \sin(7\omega t)$ *where*, $0.05 \le h_{3,5,7} \le 0.15, \sum (h_i)^2 = 1$		
Notches (6)	$\mathrm{Notch}_{\mathrm{Depth}} *$ sample points of $\sin(\omega t)$ $0.1 \le \mathrm{Notch}_{\mathrm{Depth}} \le 0.4$		

TABLE 1. ***(Continued.)*** **PQDs with mathematical modelling and variational mode decomposition.**

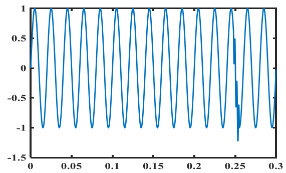
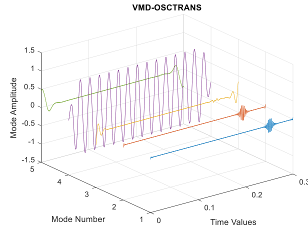
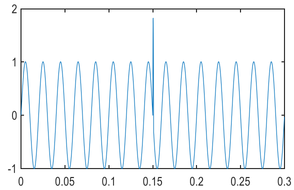
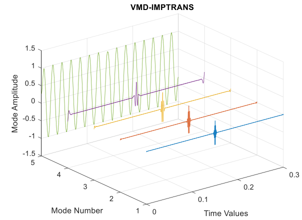
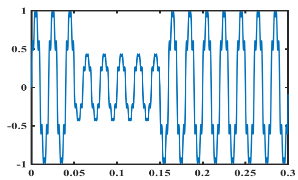
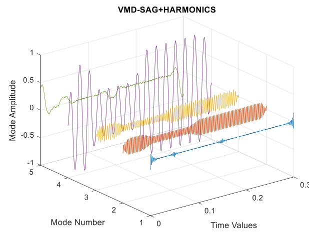
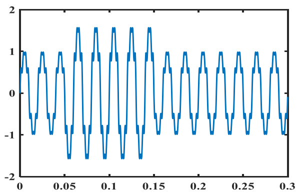
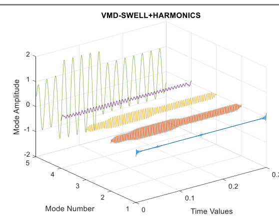
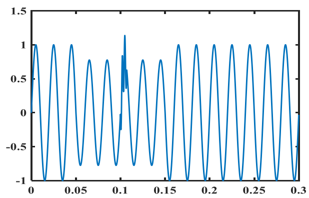
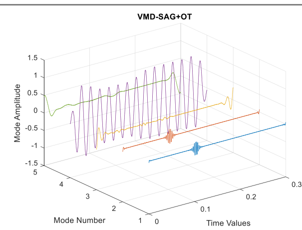
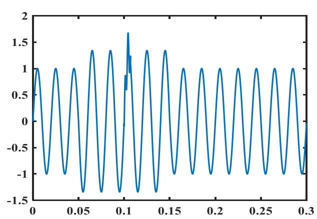
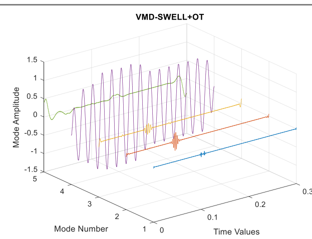
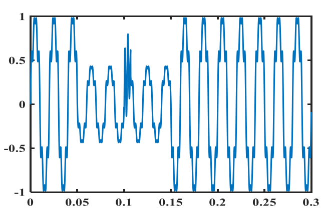
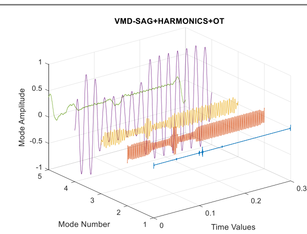
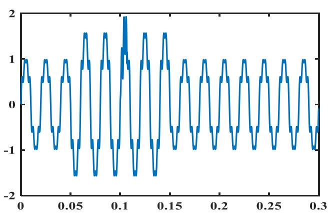
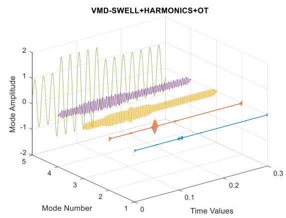
Oscillatory Transient (7)	$\sin(\omega t) + \beta * \sin(\omega_n t) * e^{\frac{-t}{t_y}} * \begin{pmatrix} u(t-t_1) - \\ u(t-t_2) \end{pmatrix}$ *where,* $0.8 \le \beta \le 1,$ $2\pi 300 \le \omega_n \le 2\pi 500,$ $t_y = t_1 + t_2$		
Impulse Transient (8)	$\sin(\omega t) + \beta * \sin(\omega_n t) * e^{\frac{-t}{t_y}} * \begin{pmatrix} u(t-t_1) - \\ u(t-t_2) \end{pmatrix}$ *where,* $4 \le \beta \le 7,$ $2\pi 300 \le \omega_n \le 2\pi 500,$ $t_y = t_1 + t_2$		
Sag+ Harmonics (9)	$\left[1 - \alpha * \begin{pmatrix} u(t-t_1) \\ -u(t-t_2) \end{pmatrix}\right] * [h_1 * \sin(\omega t) + h_3 * \sin(3\omega t) + h_5 * \sin(5\omega t) + h_7 * \sin(7\omega t)]$ *where,* $0.1 \le \alpha \le 0.9,$ $0.05 \le h_{3,5,7} \le 0.15, \sum (h_i)^2 = 1$		
Swell+ Harmonics (10)	$\left[1 + \beta * \begin{pmatrix} u(t-t_1) \\ -u(t-t_2) \end{pmatrix}\right] * [h_1 * \sin(\omega t) + h_3 * \sin(3\omega t) + h_5 * \sin(5\omega t) + h_7 * \sin(7\omega t)]$ *where,* $0.1 \le \beta \le 0.8,$ $0.05 \le h_{3,5,7} \le 0.15, \sum (h_i)^2 = 1$		
Sag+ Oscillatory Transient (11)	$\left[1 - \alpha * \begin{pmatrix} u(t-t_1) \\ -u(t-t_2) \end{pmatrix}\right] * \sin(\omega t) + \beta * \sin(\omega_n t) * e^{\frac{-t}{t_y}} * \begin{pmatrix} u(t-t_3) - \\ u(t-t_4) \end{pmatrix}$ *where,* $0.8 \le \beta \le 1,$ $2\pi 300 \le \omega_n \le 2\pi 500,$ $t_y = t_3 + t_4$		
Swell+ Oscillatory Transient (12)	$\left[1 + \rho * \begin{pmatrix} u(t-t_1) \\ -u(t-t_2) \end{pmatrix}\right] * \sin(\omega t) + \beta * \sin(\omega_n t) * e^{\frac{-t}{t_y}} * \begin{pmatrix} u(t-t_3) - \\ u(t-t_4) \end{pmatrix}$ *where,* *where,* $0.1 \le \rho \le 0.8$ $0.8 \le \beta \le 1,$ $2\pi 300 \le \omega_n \le 2\pi 500,$ $t_y = t_3 + t_4$		
Sag+ Harmonics+ Oscillatory Transient (13)	$\left[1 - \alpha * \begin{pmatrix} u(t-t_1) \\ -u(t-t_2) \end{pmatrix}\right] * [h_1 * \sin(\omega t) + h_3 * \sin(3\omega t) + h_5 * \sin(5\omega t) + h_7 * \sin(7\omega t)] + \beta * \sin(\omega_n t) * e^{\frac{-t}{t_y}} * \begin{pmatrix} u(t-t_3) - \\ u(t-t_4) \end{pmatrix}$ *where,* $0.1 \le \alpha \le 0.9,$ $0.05 \le h_{3,5,7} \le 0.15, \sum (h_i)^2 = 1$ $0.8 \le \beta \le 1, 2\pi 300 \le \omega_n \le 2\pi 500,$ $t_y = t_3 + t_4$		

TABLE 1. ***(Continued.)*** **PQDs with mathematical modelling and variational mode decomposition.**

Swell+ Harmonics+ Oscillatory Transient (14)	$\left[1+\rho*\begin{pmatrix}u(t-t_1)\\-u(t-t_2)\end{pmatrix}\right]*[h_1*\sin(\omega t)+h_3*\sin(3\omega t)+h_5*\sin(5\omega t)+h_7*\sin(7\omega t)]+\beta*\sin(\omega_n t)*e^{\frac{-t}{t_y}}*\begin{pmatrix}u(t-t_3)-\\u(t-t_4)\end{pmatrix}$ *where*, $0.1\le\rho\le 0.8$, $0.05\le h_{3,5,7}\le 0.15, \sum(h_i)^2=1$, $0.8\le\beta\le 1, 2\pi 300\le\omega_n\le 2\pi 500$, $t_y=t_3+t_4$		

3) DATA PREPARATION

The data preparation stage facilitates the extraction of inherent features. These features will be going to act as predictor variables for the machine learning classifier. But it is highly important to make sure the machine learning model should be ready before passing new feature data for prediction. In order to achieve this, a sum total of 30000 synthetic signal data (rows) each of 5 cycles at a sampling frequency of 10khz i.e., 1000 datapoints (columns) are stored to the database initially (30000∗1000 data table dimension). That means 2000 signals from each class considering both noise free and noisy signals are stored in the disturbance database initially. Then the pre stored disturbance data will go through the data processing stage to obtain the BLMs. Next the energy magnitude of all 5 BLMs are considered as features for the MLC. Further the collected feature set is divided in to two parts as Training Data and Testing Data, where 70% is dedicated to training and rest 30% is dedicated to testing.

B. OPTIMIZATION

LGBM is consisting of decision trees, where each tree takes in different subset of features to provide best split. Undoubtedly LGBM has some inherent advantages like parallel learning, speeded up training, least memory utilization and compatibility to handle both small & large dataset [22]. But its performance can be further improvised by optimizing its hyper parameters. There are a number of hyper parameters of LGBM, but the major parameters are being optimized to reach best possible accuracy. Those parameters are estimator count (EC), learning rate (LR), bagging fraction (BAGF), maximum tree depth (MTD), number of leaves (NL) and lambda (L). The NL param is crucial to control the complexity of the model and LR help in weight management in boosting step. The TD and L parameters are optimized to avoid overfitting.

The objective is to identify the optimum set of hyper-parameters $HP_{opt}=\{EC^*, LR^*, BAGF^*, MTD^*, NL^*, L^*\}$ such that the cost function is minimized. For that it is required to define the necessary prerequisites.

First, the dataset with ‘n’ feature-target set is defined as,

$$DS=[(F_1,T_1);(F_2,T_2);---;(F_n,T_n)] \tag{3}$$

where $F_i=\{e_i^{IMF1}, e_i^{IMF2}, e_i^{IMF3}, e_i^{IMF4}, e_i^{IMF5}\}$ is the energy feature vector of all 5 IMFs and T_i is the Target PQD class Index $\in(0,8)$.

Here the energy feature of an IMF can be calculated by,

$$e^{IMF}=\sum\nolimits_{m=1}^{d}(s_m)^2 \tag{4}$$

where s_m is the mth sample of the IMF having length d.

Second, the population (POP) with p candidates is defined as,

$$POP=[HP_1;HP_2;---;HP_p] \tag{5}$$

where $HP_i=\{EC^i, LR^i, BAGF^i, MTD^i, NL^i, L^i\}$ is a set of hyper parameters bearing values in their respective lower and upper range as shown in Table-2.

Third, the cost function of the optimization problem is as follows,

$$HP_{opt}=argmin_{HP\in POP}\left\langle\sum\nolimits_{i=1}^{n}\varphi\left(\check{T}_i,T_i\right)\right\rangle \tag{6}$$

where $\check{T}_i=LGBM(HP_i,F_j)$ is the predicted PQD class index and φ denotes the loss function considered as the objective of the optimization problem.

Fourth is the proposed optimization itself, that combines two different meta-heuristic algorithms. These are Arithmetic Optimization Algorithm (AOA) and Whale Optimization Algorithm (WOA). AOA is a non-gradient based algorithm. It has four main steps: initialization, arithmetic operation, update, and termination. In each iteration, AOA randomly selects two agents and performs one of the four arithmetic operations on them to generate a new agent. Then, the new agent is compared with the worst agent in the population and replaces it if it is better. In contrast, WOA is gradient based. It has three main steps: initialization, encircling prey, and bubble-net attacking.

In each iteration, WOA updates the position of each agent according to a mathematical model that simulates the movement of whales towards the best agent (the prey).

The study proposes a Hybrid Optimization approach where AOA will perform exploration task due to its highly scattering dynamic movement through multiplication and division operation. On the other hand, WOA will involve in exploitation due to its shrinking encircling mechanism to escape from local optima.

The proposed hybrid arithmetic whale optimization algorithm (AWOA) is as follows,

Initialize, POP, UB, LB, ITR$_{max}$, MOA_{max}, MOA_{min}, b, $\mu = 0.5$, $\alpha = 5$, $\varepsilon = 0.000001$
Evaluation of fitness of the candidates Identify the best Search Agent HP_{best}
for1 **$C_{ITR} = 1$: ITR$_{max}$**
  for2 **each HP as k in POP**
    Evaluate, $MOA\,(C_{ITR}) = MOA_{max} + C_{ITR} * \frac{MOA_{max} - MOA_{min}}{ITR_{max}}$
    Take, $r_1 = rand(0, 1)$
    If1 $r_1 > MOA\,(C_{ITR})$
      Take, $r_2 = rand(0, 1)$
      for3 **each variable j in HP**

$$p_{k,j} = \begin{cases} HP_{best}^{j} \div (MOP + \varepsilon) \times \left[(UB_j - LB_j) \times \mu + LB_j\right], r_2 < 0.5 \\ HP_{best}^{j} \times (MOP) \times \left[(UB_j - LB_j) \times \mu + LB_j\right], \text{otherwise} \\ \text{where } MOP = 1 - \left(\frac{C_{ITR}}{ITR_{max}}\right)^{1/\alpha} \end{cases}$$

      endfor3
    else1
      Take, $r_3 = rand(0, 1)$
      for3 **each variable j in HP**
        If2 $r_3 < 0.5$
          Take, $r_{j1} = rand\,(0, 1)$, $r_{j2} = rand(0, 1)$
          Evaluate, $A_j = 2.a.r_{j1} - a$ **and** $C_j = 2.r_{j2}$
          where a linearly decreased from 1 to 0
          Evaluate, $M_j = \left|C_j * HP_{best} - p\right|$
          $p_{k,j} = p - A_j * M_j$
    else2
          Take, $r_4 = rand(-1, 1)$
          Evaluate, $M_j = \left|HP_{best}^{j} - p\right|$
          $p_{k,j} = HP_{best}^{j} + M_j * e^{br_4} * \cos(2\pi r_4)$
        endif2
      endfor3
    endif1
  endfor2
  Check if any candidate exceeds the search space, then bound it
  Revaluate of fitness of the candidates
  Update HP_{best} if better solution found
endfor1

TABLE 2. PQDs with mathematical modelling and variational mode decomposition.

LGBM Parameters	Range		Optimized Value
	Lower	Higher	
Estimator Count (EC)	40	250	79
Learning Rate (LR)	0.01	0.3	0.09
Bagging Fraction (BAGF)	0.01	0.99	0.57
Max Tree Depth (MTD)	1	80	8
Num Leaves (NL)	100	500	127
Lambda (L)	0	1000	221

C. CLASSIFICATION

In stage-3, initially the training procedure is carried out with the optimized hyper parameters of LGBM obtained in stage-2. Here the required training data (feature-target data matrix) is retrieved from stage-1. The training process is performed with a 10-fold cross validation and as a result, the proposed HOLGBM based Power Quality Detection Model (PQDM) is obtained. The very first time the trained model will undergo testing process where the 30% feature data reserved for testing is getting utilized to test its detection accuracy. Then after the proposed PQDM can be utilized for real time detection of power quality events. The real time detection part is marked as GREEN arrow in work flow diagram Fig.1. The steps for real time detection are as follows,

- ✓ The live voltage signal is being constantly sensed and buffered in a batch of 1000 data samples at a sampling frequency of 10khz.
- ✓ Subsequent VMD implementation is made on the collected data samples to obtain 5 BLIMFs.
- ✓ The Energy of all BLIMFs are computed to form the feature vector of 1×5.

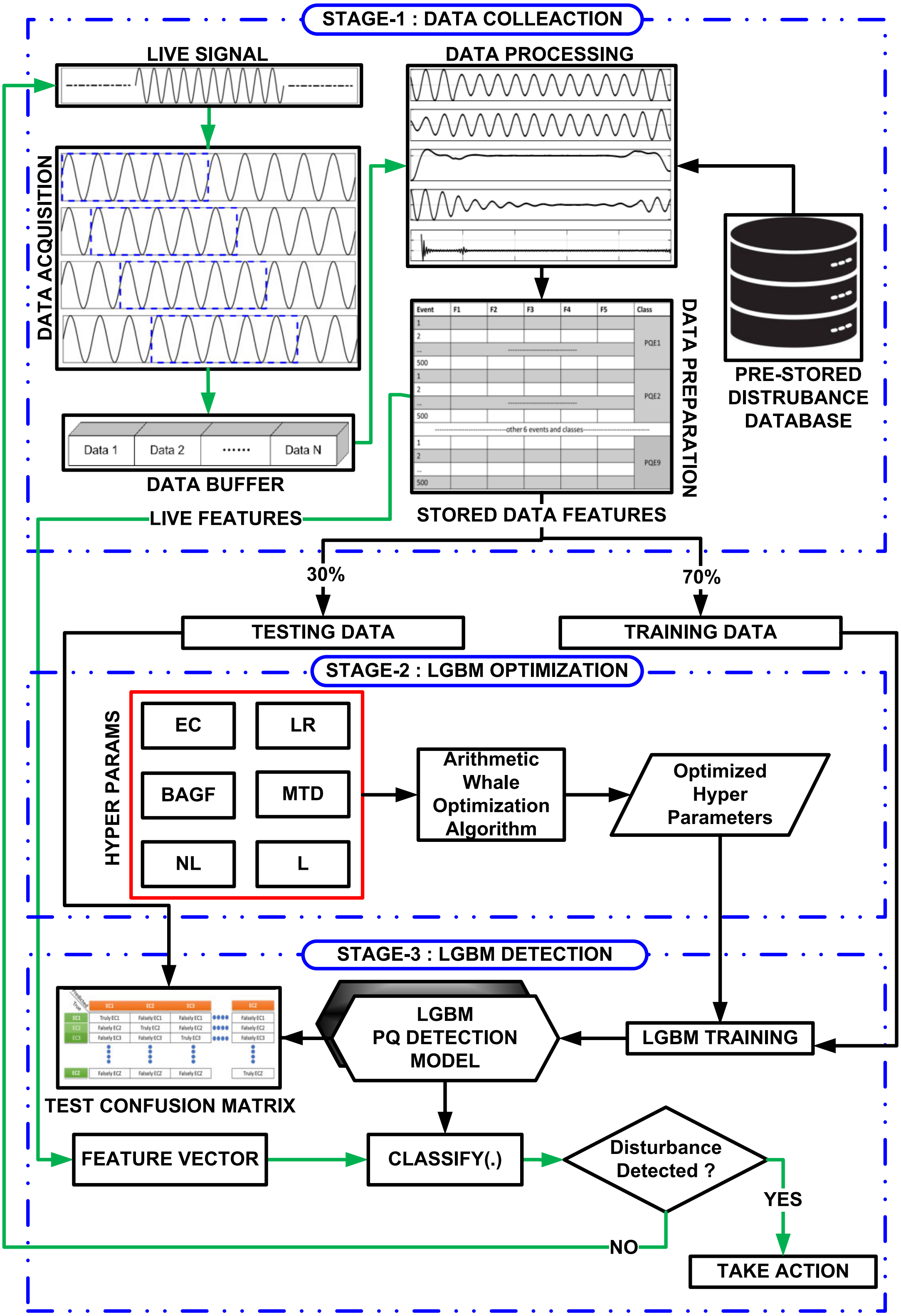


FIGURE 1. Work flow diagram of the proposed HOLGBM.

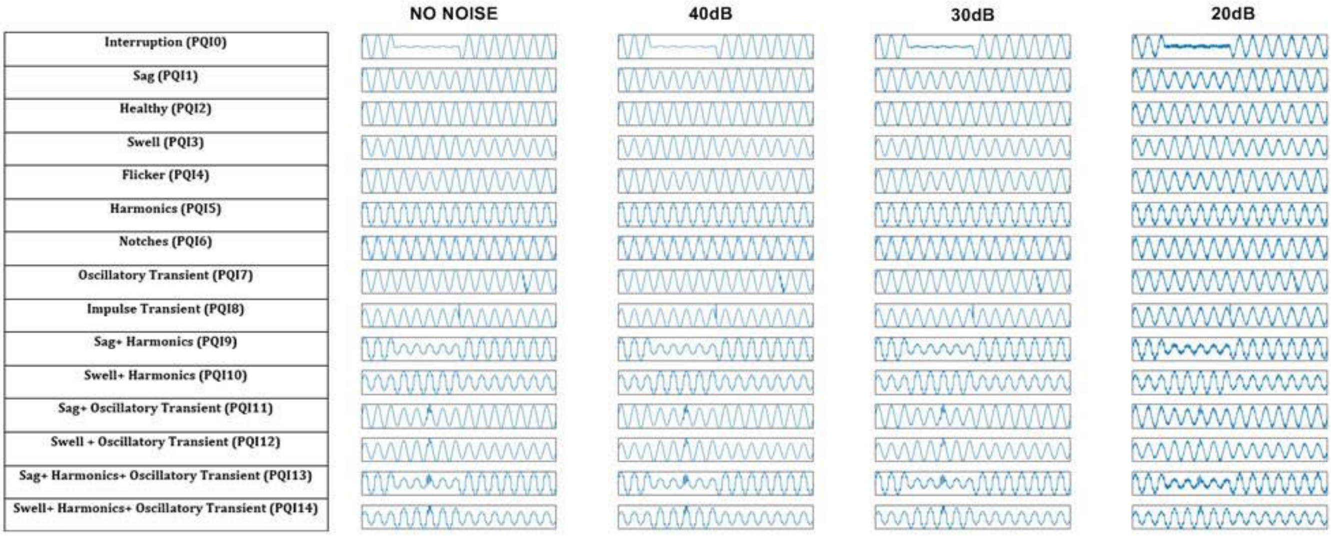


FIGURE 2. Chosen Power Quality Indices (PQIs) and their corresponding wave shapes of all PQ events.

- ✓ The feature vectors are sequentially presented to the proposed VMD and HOLGBM based PQDM for event classification.
- ✓ If disturbance is detected the necessary action is to be taken by the protection system else the loop keeps on continuing.

V. RESULT ANALYSIS & PERFORMANCE EVALUATION

To assess the efficacy of the proposed approach, 14 variations of PQ disturbance signals along with a healthy signal is examined. To create a comprehensive evaluation, 4 different variant datasets are generated namely DS1, DS2, DS3 and DS4 where DS1&2 for single PQ events (PQI0 to PQI8) and DS3&4 for all PQ events (PQI0 to PQI14). DS1 and DS3 is having 500 synthetic samples for each disturbance category with dimension 4500×5 and 7500×5 respectively. While DS2 and DS4 contain 3 subsets of samples possessing signal-to-noise ratios (SNRs) of 20dB, 30dB and 40dB respectively with each dB level having 500 feature sets. That means DS2 and DS4 having dimension 13500×5 and 22500×5 respectivly. A glimpse of all events will every noise level can be seen in Fig.2. It is to be noted that, PQI denotes the respective Power Quality Index as per Table-1. These samples were randomly generated and shuffled. For performance evaluation out of the whole data 70% allocated for training purposes and the remainder for testing with class wise random selection. The modelling stage is executed using MATLAB 18a on a desktop computer equipped with an Intel 2.30 GHz i5-8300 CPU and 8GB RAM.

A. NOISE-FREE PERFORMANCE

Here the DS1 and DS3 datasets are taken into account with 350 samples from each class is dedicated to training and 150 is for testing. Since the performance of a classifier can be well defined through a confusion matrix, therefore the training and testing confusion matrices of the proposed classifier is presented in Fig.3(a) to (d). It is seen that all events are completely detected from the training set with 100% accuracy for both datasets. On the other hand, from the testing set one each from swell, flicker and harmonics are misclassified as interruption, harmonics and flicker respectively in DS1. That means 1347 PQDs truly detected out of 1350 testing event with an accuracy of 99.77%. Similar outcomes can be observed with DS3 test-sets with minimal misclassification and accuracy of 99.56%. It is seen that; few misclassifications are observed between sag + harmonics & sag + harmonics + oscillatory transients as well as swell + harmonics & swell + harmonics + oscillatory transients successively.

B. NOISE-IN PERFORMANCE

Since the power lines in real world often experience electromagnetic interference with communication lines, the measured parameters like voltage or current are usually contaminated with noise. That means it is really necessary to demonstration the performance of the detection scheme under noisy circumstances. In this regard, the DS2 and DS4 datasets are utilized to verify the same where the random sampling of all the three SNR levels are carried out to simulate a varying noise condition then divided in to training and testing in 70:30 ratio. It seems that, accuracy of 98.29% and 96.44% are observed with training and testing for DS2 with only one type of PQ disturbances. The respective confusion matrices are shown in Fig.4(a)&(b). While dealing with complex PQ disturbance dataset, similarities can be observed between many events. Certainly, the training confusion matrix shown in Fig.4(c) is showing accuracy of 98.44% whereas the testing confusion matrix Fig.4(d) is displaying accuracy of 96.77%. This indicates, the performance of the proposed VMD and

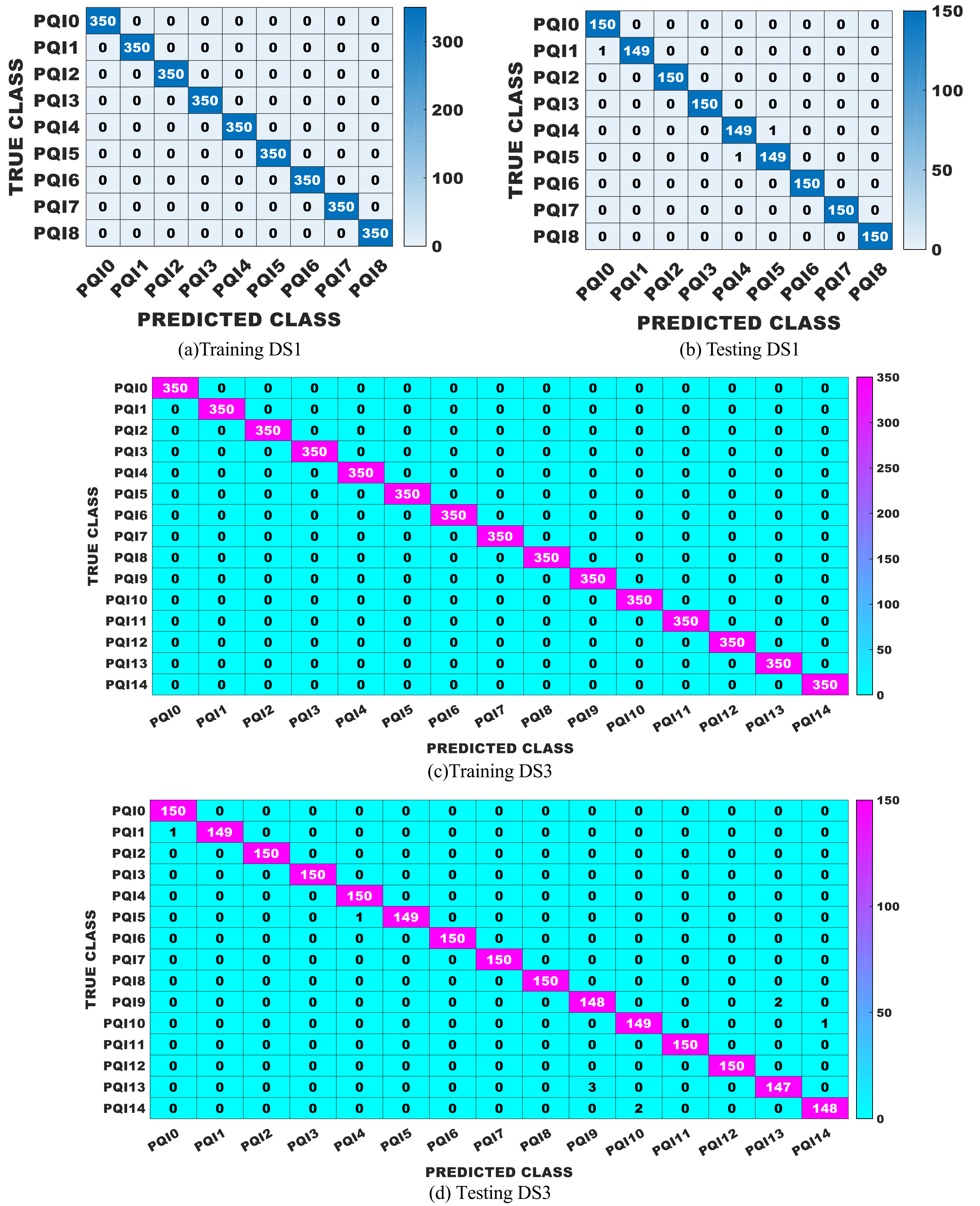


FIGURE 3. **Confusion matrix of noise free dataset DS1 and DS3.**

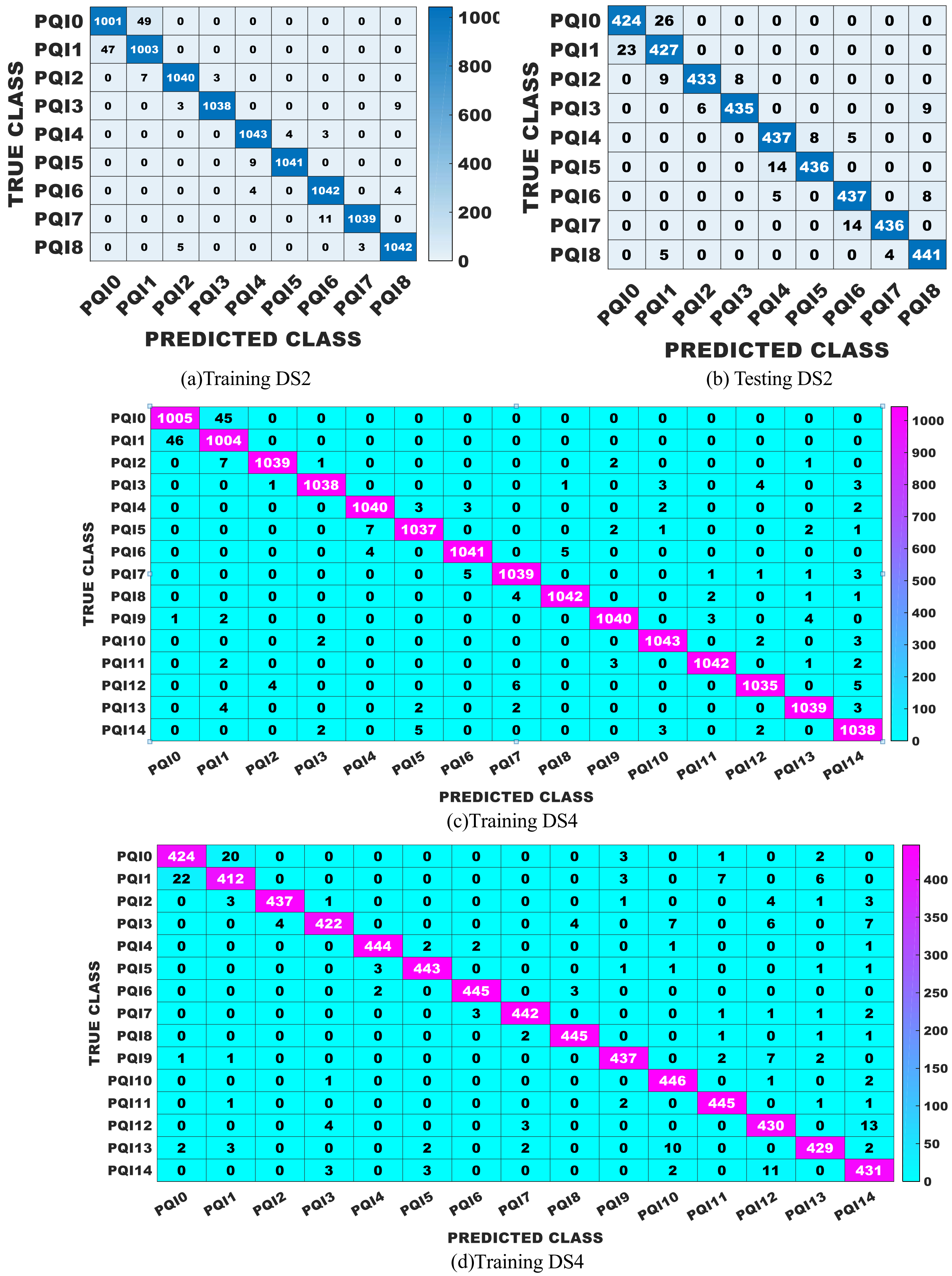


FIGURE 4. Confusion matrix of noise contained dataset DS2 and DS4.

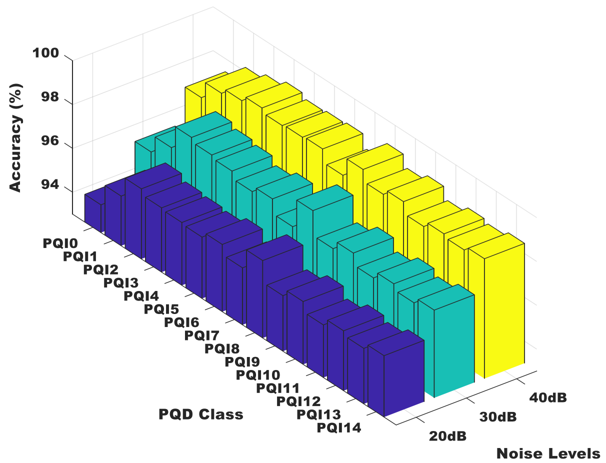


FIGURE 5. **Individual accuracy bar diagram of all disturbance events with 3 SNR levels.**

HOLGBM classifier is neither compromised while detecting complex PQ disturbances nor in case of noise.

Further, the individual accuracy of each PQD class with 3 different noise levels are presented in the bar chart as shown in Fig.4. It is to be noted that this accuracy is calculated on overall data of individual class and not on separately for training and testing data. It is observed that, the maximum accuracy is found to be of impulse transient (PQI8) under 40dB noise whereas minimum accuracy is of 94.26% is found for interruption event (PQI0) at 20dB noise level.

C. REAL TIME VALIDATION

The study carried out a real-time Hardware in Loop simulation to address two crucial aspects. The first one is the performance of the proposed PQDM trained with synthetic + noise contained dataset, against unseen disturbance retrieved from a system that replicating the behaviour of actual grid. The second one is the determination of an average detection time of the classifier. To achieve the same the proposed PQDM is validated through OPAL RT simulator by intentionally creating few of the disturbances in Grid Simulator (GS). Here GS will resemble as a practical grid system, therefore is utilized to apprehend few of the disturbances such as sag, swell and interruption. Moreover, the GS is internally consisting of a front-end converter (FEC) and a load side converter (LSC), where the PWM signal of the LSC is modified to generate the specific disturbances. This PWM is generated at a switching frequency of 5kHz in the host computer and fed to the GS through digital out (D-OUT) of OP5410 by running the real time simulation. Then the measurement points of GS are connected to OP8662 VI sensor and the measurements are fed back to OP4510 through its analog in (A-IN). Finally, the outputs are being displayed by connecting the analog out (A-OUT) of OP4510 to YOKOGAWA Multi Signal Oscilloscope (MSO). The overall validation setup and its flow can be seen in Fig.6.

The MSO is set to display two signals, where the first one is real time PQD signal from GS. The other one is the PQD index which presents the current state of the real time PQD signal detected by the proposed HOLGBM PQ Detection Model. The list of Indices for the PQDs are already given in Table-1. It can be observed from Fig.7 that, a sequence of intentional disturbances are generated from GS for a duration of 15 AC cycles (50Hz) to validate the detection capability of the proposed classifier. In the bottom half figure the index "2" is indicating to PQ label "PQI2" which designates the system is in "Healthy" state. But after the occurrence of SAG event the indicator drops from 2 to 1 indicating to PQ label "PQI1" which designates the system is under "SAG" state. Next the system again gets back to "Healthy" state and indicator changed from 1 to 2 and further steps to 3 indicating to PQ label "PQI3" which designates the system is under "SWELL" state and so on. It is to be noted that the live voltage signal is initially converted to per unit then only further processing is carried out, since the classifier is trained with the per unit signals.

Further the detection time of the proposed classifier is calculated from the real time results. In Fig.8 a sag event is zoomed at 10ms/div to indicate the detection time. It can be clearly seen that the PQ Index changed from 2(healthy) to 1(sag) after certain amount of time delay. This delay is actually the detection time which has two parts as follows,

$$DetectionTime\,(DT) = AcquisionDelay\,(AD) + ProcessDelay(PD) \tag{7}$$

The acquisition delay is because of the way the real time data is collected in the buffer before processing. Since the data collection is made for 5 cycle-window with a 1 cycle gap as shown in data acquisition part of Fig.1, the acquisition delay is fix to 20ms or 200 samples. Further, to calculate the process delay, the PQD Signal and Index samples are saved to the host PC for more than 3000 cycles. From this data, 100 number of PQD observations are taken where the sample difference between the instance of occurrence to the instant of detection are evaluated. It has been observed that the sample difference varies from 341 to 373 as show in Fig.9. That means the process delay varies in between 141 to 173 samples. Therefore, the detection time is evaluated by taking the average of 100 observation which comes to be 358.8 samples (≈35.88ms). Moreover, a confusion matrix is given in Fig.10 of these 100 observations to validate the detection accuracy of the proposed classifier with real time data. It has been observed that, the classifier successfully detected all events without any misclassification i.e., the detection accuracy is found to be 100%.

D. COMPARATIVE STUDY

In this subsection, first the training-testing time and the respective accuracy of the proposed method is compared

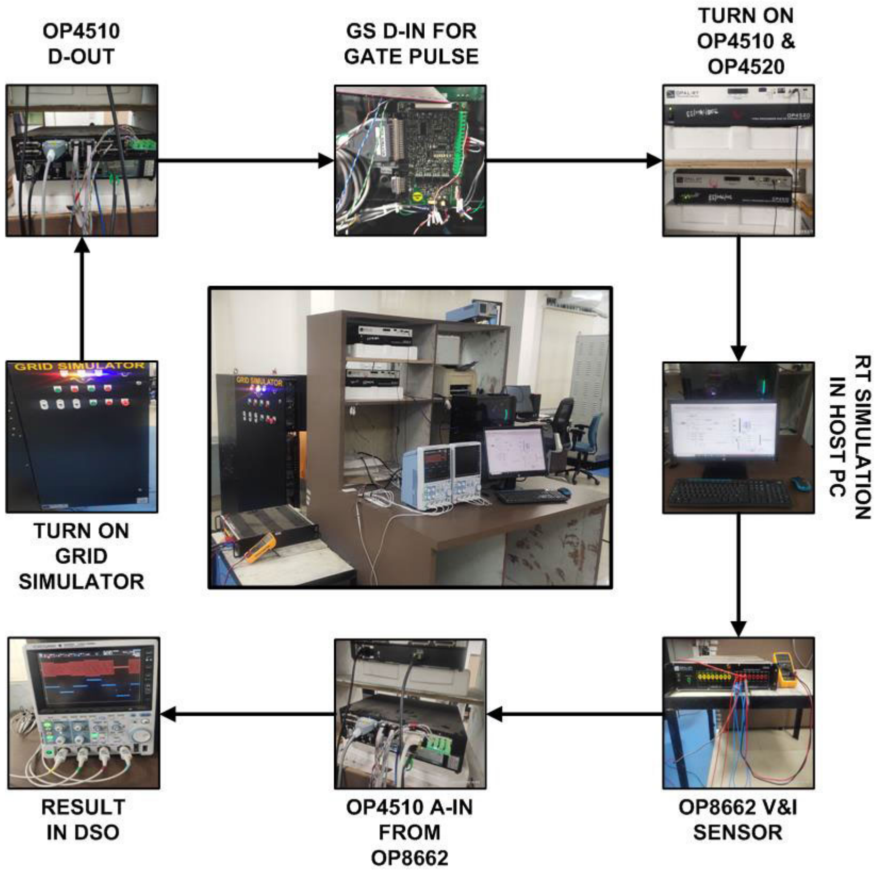


FIGURE 6. Real time setup to validate the proposed PQ detection scheme.

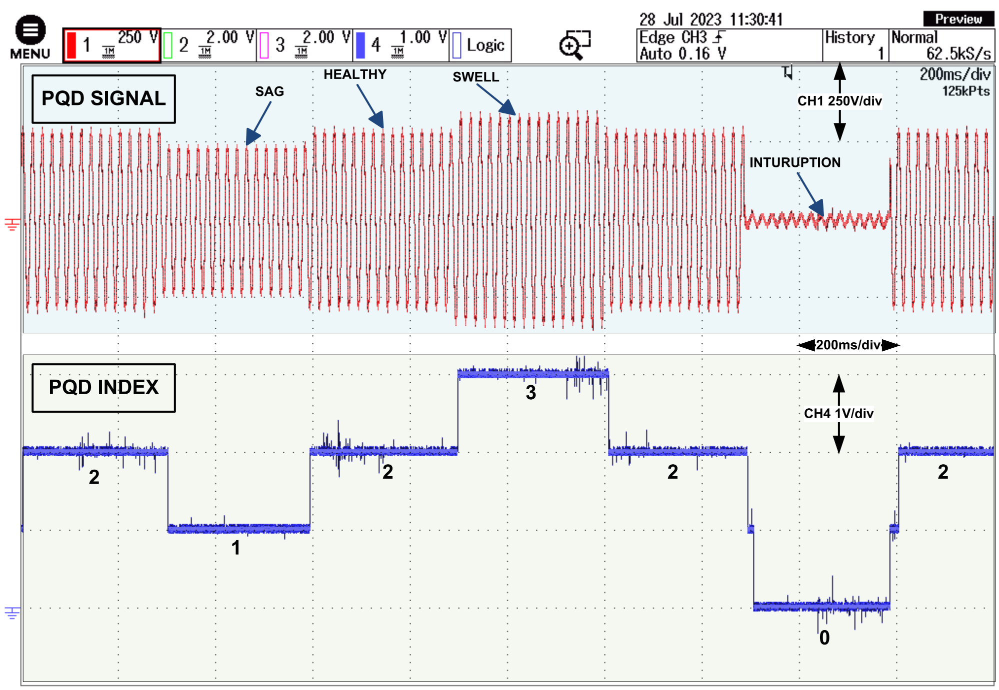


FIGURE 7. Real time voltage and PQD index from MSO.

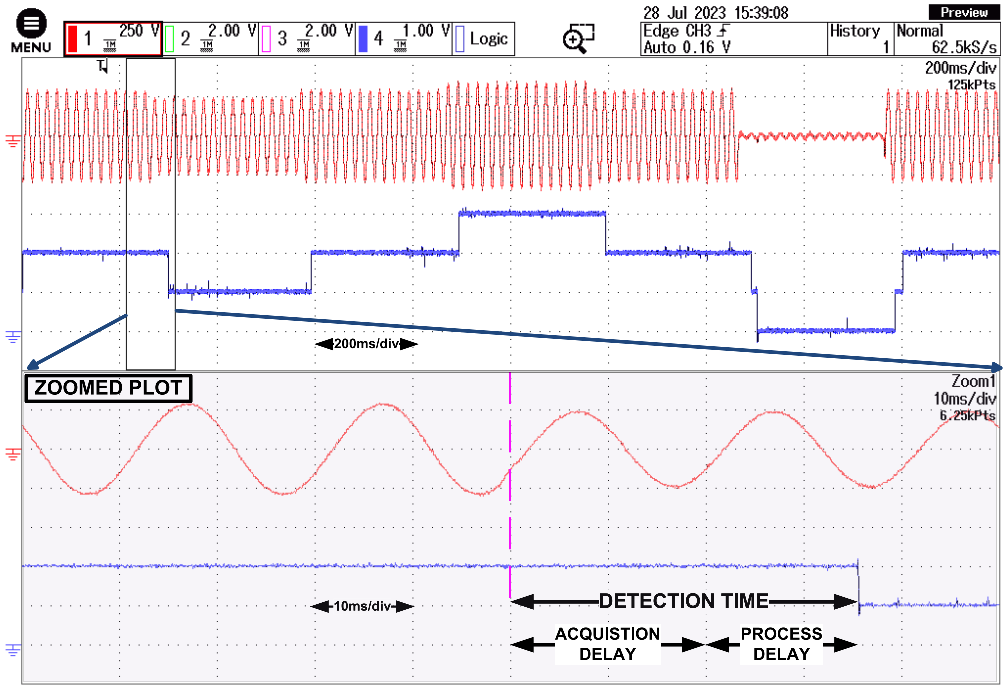


FIGURE 8. Zoomed plot of a sag event for estimating the detection time.

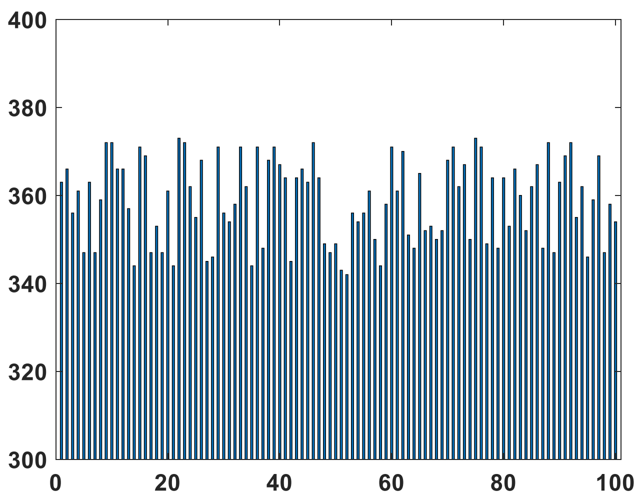


FIGURE 9. Differential sample count between disturbance occurrence and detection instant of 100 real time observations.

TABLE 3. Comparison of GBM and LGBM with proposed HOLGBM along with VMD.

Boosting Techniques	Processing Time (msec)		Detection Accuracy (In %)
	Training	Testing	
VMD+GBM	142.67	11.34	93.2
VMD+LGBM	63.6	11.17	95.1
Proposed VMD+HOLGBM	20.9	10.98	97.21

with plain vanilla Gradient Boosting Machine (GBM) and LGBM. It is to be noted that the dataset taken here is the mix all datasets with dimensions 30000 × 5. Here once again

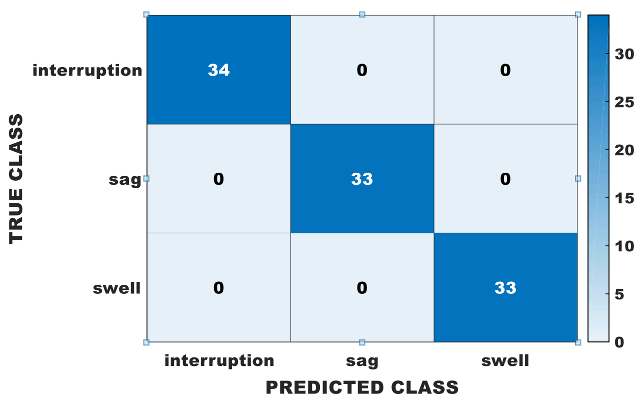


FIGURE 10. Confusion matrix of 100 real time observations.

random sampling in 70:30 ratio is maintained for training and testing respectively. The observation shown in Table-3 revels a significant improvement in training time in the proposed method whereas the testing times are nearly equal to each other. Moreover, the detection accuracy is hitting 97.21% which is also found to be superior among the three.

Further, the proposed PQD detection method is being compared with the similar pre-published methods to study its effectiveness in terms of detection time and accuracy. The outcomes are presented in Table-4 along with the number of test events and sampling frequency. Since, a limited number of research works have been published especially for PQ detection with ensemble tree classifiers, the comparative study is further extended to tally different ensemble tree

TABLE 4. Performance comparison with similar priorly published studies.

SL.	Pre-proposed Works	Event Count	Sampling frequency (In kHz)	Accuracy (In %)			
				Ideal	20dB	30dB	40dB
1	[29], 2016	9	5	99.38	97.77	-	-
2	[30], 2017	10	3.2	99.2	98.5	-	-
3	[31], 2019	7	2	98.61	-	-	-
4	[32], 2019	11	10	99.92	-	-	-
5	[33], 2020	9	3.2	99.78	-	-	-
6	[34], 2020	9	3.2	99.68	-	-	-
7	[35], 2020	16	15.36	99.47	-	97.45	98.37
8	[36], 2022	8	-	-	97.57	98.25	-
9	[37], 2023	8	12.5	99.5	-	-	-
10	Proposed	9	10	99.77	95.72	97.07	98.4
		15		99.56	95.69	97.00	98.39

TABLE 5. Comparison of conceptualization with similar priorly published Studies.

Ref.	Classifier Category	Feature Selection	Dataset Signal Type	Proposed Optimization	Real Time Validation	Detection Time
[38]	Bagging	No	Synthetic + Noise + Experimental	No	No	Not Computed
[19]	Boosting	No	Synthetic + noise + real	No	RTDS	Not Computed
[15]	Bagging	No	Synthetic + Noise + Experimental	No	No	Not Computed
[39]	Bagging	No	Synthetic + Noise + Experimental	No	PQSCADA (non-Realtime)	Not Computed
[40]	Bagging	No	Synthetic + Experimental	No	DSP Based	Not Computed
[7]	Bagging	Yes	Simulated + Noise	IGWO	No	Computed
[41]	Boosting	Auto	Synthetic + Noise	MFFA	No	Not Computed
[42]	Boosting	Auto	Synthetic + Noise + Experimental	No	OPAL-RT	Not Computed
[43]	Boosting	Yes	Synthetic	No	No	Not Computed
Pro-posed	**Boosting**	**Auto**	**Synthetic + Noise + Experimental**	**Hybrid AOA-WOA**	**OPAL-RT and Grid Simulator HIL Setup**	**Computed**

techniques (bagging & boosting) for PQ detection in Table-5. A total of 5 conceptual factors namely, feature selection, dataset type, proposed optimizer, real time validation and detection time are considered. It is found that, most of the studies neither gone for feature selection [15], [19], [38], [39], [40] nor gone for a computation of detection time. As feature selection is a crucial step for classifier performance, it is needed to be taken care of. Unlike other classifiers LGBM [41], [42], [43] automatically take care of feature selection applying its internal GOSS and EFB mechanism, therefore used as base classifier of the proposed study.

Similarly, detection time is also a much crucial performance parameter especially when real-time monitoring is performed and thus calculated in the proposed work. In addition to that, [7] (Memetic Fire Fly Algorithm-MFFA), [41] (Improved Gray Wolf Optimization-IGWO) studies undergone the optimization of classifier parameters but suggested classifier is not validated in real time. Similarly, [39] has tested its PQ detection technique with data extracted from PQSCADA system but no in real-time mode. References [19] and [42] have done real-time simulation through Real Time Digital simulator (RTDS) & OPAL-RT setups respectively whereas [15] proposed Digital Signal Processing (DSP) board-based monitoring system. On the other hand, the proposed study has gone through all the aforementioned conceptual parameters and therefore can be well generalized for real grid applications. Hence, from the overall study and experimentation, it is evident that, the proposed VMD based HOLGBM classifier can well perform the classification task even with practical scenario data.

VI. CONCLUSION

The research work is focusing upon fast and accurate power quality disturbance identification combining the likes of VMD and LGBM. Since most informative signal recognition is a major concern in signal separation techniques like VMD, in this approach all five BLMs are considered to overcome this challenge. Moreover, feature selection is one more key concern in MLC based technique like LGBM, the process is completely simplified by taking the energies of all five BLMs as features. Following the aforesaid information, a feature dataset of 15 PQDs are prepared with dimension of 30000 × 5 combining both ideal and noisy signals where each PQD has 2000 data instances. The dataset is further used to train and test the LGBM where the training time and detection accuracy are found to be 63.6 msec and 95.1% respectively. To improve the performance of the concerned classifier the hyper parameters of LGBM are optimized through a proposed Hybrid Arithmetic Whale Optimization Algorithm. The imposed modification significantly reduced the training time to almost one third i.e. 20.9msec along with elevated the over accuracy to 97.21% with ideal accuracy of 99.56%. Furthermore, the proposed technique is also validated in real time through OPAL-RT and Grid Simulator Hardware in Loop (HIL) setup and three PQ events such as sag, swell and interruption are investigated. A total of 100 real-time signals generated in grid simulator are successfully detected by the proposed VMD & HOLGBM based PQDM with an average detection time of 35.88msec. This setup ensured the integrity and reliability of our experimentation and analysis.

ACKNOWLEDGMENT

Sairam Mishra, Ranjan Kumar Mallick, Debadatta Amaresh Gadanayak, Pravati Nayak, Renu Sharma, and Gayadhar Panda express their gratitude to the Microgrid Research Laboratory, ITER, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, for their invaluable support and resources during the course of this research.

REFERENCES

[1] G. Benysek and M. Pasko, *Power Theories For Improved Power Quality*. Heidelberg, Germany: Springer, 2012.

[2] M. J. Burke and J. C. Stephens, "Political power and renewable energy futures: A critical review," *Energy Res. Social Sci.*, vol. 35, pp. 78–93, Jan. 2018.

[3] Y. Xi, Z. Li, X. Zeng, X. Tang, Q. Liu, and H. Xiao, "Detection of power quality disturbances using an adaptive process noise covariance Kalman filter," *Digit. Signal Process.*, vol. 76, pp. 34–49, May 2018.

[4] M. Mishra, "Power quality disturbance detection and classification using signal processing and soft computing techniques: A comprehensive review," *Int. Trans. Electr. Energy Syst.*, vol. 29, no. 8, Aug. 2019, Art. no. e12008.

[5] O. P. Mahela, A. G. Shaik, and N. Gupta, "A critical review of detection and classification of power quality events," *Renew. Sustain. Energy Rev.*, vol. 41, pp. 495–505, Jan. 2015.

[6] S. Shukla, S. Mishra, and B. Singh, "Empirical-mode decomposition with Hilbert transform for power-quality assessment," *IEEE Trans. Power Del.*, vol. 24, no. 4, pp. 2159–2165, Oct. 2009.

[7] S. Mishra, R. K. Mallick, D. A. Gadanayak, and P. Nayak, "A novel hybrid downsampling and optimized random forest approach for islanding detection and non-islanding power quality events classification in distributed generation integrated system," *IET Renew. Power Gener.*, vol. 15, no. 8, pp. 1662–1677, Jun. 2021.

[8] H. Wang, J. Liu, S. Luo, and X. Xu, "Research on power quality disturbance detection method based on improved ensemble empirical mode decomposition," *Electronics*, vol. 9, no. 4, p. 585, Mar. 2020.

[9] K. Dragomiretskiy and D. Zosso, "Variational mode decomposition," *IEEE Trans. Signal Process.*, vol. 62, no. 3, pp. 531–544, Feb. 2014.

[10] P. D. Achlerkar, S. R. Samantaray, and M. S. Manikandan, "Variational mode decomposition and decision tree based detection and classification of power quality disturbances in grid-connected distributed generation system," *IEEE Trans. Smart Grid*, vol. 9, no. 4, pp. 3122–3132, Jul. 2018.

[11] K. Cai, B. Alalibo, W. Cao, Z. Liu, Z. Wang, and G. Li, "Hybrid approach for detecting and classifying power quality disturbances based on the variational mode decomposition and deep stochastic configuration network," *Energies*, vol. 11, no. 11, p. 3040, Nov. 2018.

[12] M. Sahani, P. K. Dash, and D. Samal, "A real-time power quality events recognition using variational mode decomposition and online-sequential extreme learning machine," *Measurement*, vol. 157, Jun. 2020, Art. no. 107597.

[13] W. Deng, D. Xu, Y. Xu, and M. Li, "Detection and classification of power quality disturbances using variational mode decomposition and convolutional neural networks," in *Proc. IEEE 11th Annu. Comput. Commun. Workshop Conf. (CCWC)*, Jan. 2021, pp. 1514–1518.

[14] M. V. Subbarao, S. K. Terlapu, V. Chakravarthy, and S. C. Satapaty, "Pattern recognition of time-varying signals using ensemble classifiers," in *Microelectronics, Electromagnetics and Telecommunications*. Singapore: Springer, 2021.

[15] M. V. Reddy and R. Sodhi, "A modified S-transform and random forests-based power quality assessment framework," *IEEE Trans. Instrum. Meas.*, vol. 67, no. 1, pp. 78–89, Jan. 2018, doi: 10.1109/TIM.2017.2761239.

[16] S. Karasu and Z. Saraç, "Classification of power quality disturbances by 2D-Riesz transform, multi-objective grey wolf optimizer and machine learning methods," *Digit. Signal Process.*, vol. 101, Jun. 2020, Art. no. 102711.

[17] A. Vinayagam, V. Veerasamy, M. Tariq, and A. Aziz, "Heterogeneous learning method of ensemble classifiers for identification and classification of power quality events and fault transients in wind power integrated microgrid," *Sustain. Energy, Grids Netw.*, vol. 31, Sep. 2022, Art. no. 100752.

[18] R. E. Schapire, "The boosting approach to machine learning: An overview," in *Nonlinear Estimation and Classification* (Lecture Notes in Statistics), vol. 171, D. D. Denison, M. H. Hansen, C. C. Holmes, B. Mallick, and B. Yu, Eds. New York, NY, USA: Springer, 2003. [Online]. Available: https://link.springer.com/chapter/10.1007/978-0-387-21579-2_9#citeas, doi: 10.1007/978-0-387-21579-2_9.

[19] M. V. Reddy and R. Sodhi, "A rule-based S-transform and AdaBoost based approach for power quality assessment," *Electric Power Syst. Res.*, vol. 134, pp. 66–79, May 2016.

[20] L. W. Xu, K. C. Li, and Y. Luo, "Classification of complex power quality disturbances based on incomplete S-transform and gradient boosting decision tree," *Power Syst. Prot. Control*, vol. 47, no. 6, pp. 24–31, 2019.

[21] L. Yang, L. Guo, W. Zhang, and X. Yang, "Classification of multiple power quality disturbances by tunable-Q wavelet transform with parameter selection," *Energies*, vol. 15, no. 9, p. 3428, May 2022.

[22] W. Liang, S. Luo, G. Zhao, and H. Wu, "Predicting hard rock pillar stability using GBDT, XGBoost, and LightGBM algorithms," *Mathematics*, vol. 8, no. 5, p. 765, May 2020.

[23] J. Cai, X. Li, Z. Tan, and S. Peng, "An assembly-level neutronic calculation method based on LightGBM algorithm," *Ann. Nucl. Energy*, vol. 150, Jan. 2021, Art. no. 107871.

[24] S. Mirjalili and A. Lewis, "The whale optimization algorithm," *Adv. Eng. Softw.*, vol. 95, pp. 51–67, Jun. 2016.

[25] L. Abualigah, A. Diabat, S. Mirjalili, M. A. Elaziz, and A. H. Gandomi, "The arithmetic optimization algorithm," *Comput. Methods Appl. Mech. Eng.*, vol. 376, Apr. 2021, Art. no. 113609.

[26] J. Friedman, "Greedy function approximation: A gradient boosting machine," *Ann. Stat.*, vol. 29, pp. 1189–1232, Oct. 2001.

[27] L. Fu, T. Zhu, G. Pan, S. Chen, Q. Zhong, and Y. Wei, "Power quality disturbance recognition using VMD-based feature extraction and heuristic feature selection," *Appl. Sci.*, vol. 9, no. 22, p. 4901, 2019.

[28] H. Li, T. Liu, X. Wu, and Q. Chen, "An optimized VMD method and its applications in bearing fault diagnosis," *Measurement*, vol. 166, Dec. 2020, Art. no. 108185.

[29] J. Li, Z. Teng, Q. Tang, and J. Song, "Detection and classification of power quality disturbances using double resolution S-transform and DAG-SVMs," *IEEE Trans. Instrum. Meas.*, vol. 65, no. 10, pp. 2302–2312, Oct. 2016.

[30] O. P. Mahela and A. G. Shaik, "Recognition of power quality disturbances using S-transform based ruled decision tree and fuzzy C-means clustering classifiers," *Appl. Soft Comput.*, vol. 59, pp. 243–257, Oct. 2017.

[31] X. Shi, H. Yang, Z. Xu, X. Zhang, and M. R. Farahani, "An independent component analysis classification for complex power quality disturbances with sparse auto encoder features," *IEEE Access*, vol. 7, pp. 20961–20966, 2019.

[32] Y. Shen, M. Abubakar, H. Liu, and F. Hussain, "Power quality disturbance monitoring and classification based on improved PCA and convolution neural network for wind-grid distribution systems," *Energies*, vol. 12, no. 7, p. 1280, Apr. 2019.

[33] N. M. Khoa and L. Van Dai, "Detection and classification of power quality disturbances in power system using modified-combination between the stockwell transform and decision tree methods," *Energies*, vol. 13, no. 14, p. 3623, Jul. 2020.

[34] I. S. Samanta, P. K. Rout, and S. Mishra, "Power quality events recognition using S-transform and wild goat optimization-based extreme learning machine," *Arabian J. for Sci. Eng.*, vol. 45, no. 3, pp. 1855–1870, Mar. 2020.

[35] A.-D. Gonzalez-Abreu, M. Delgado-Prieto, R.-A. Osornio-Rios, J.-J. Saucedo-Dorantes, and R.-D.-J. Romero-Troncoso, "A novel deep learning-based diagnosis method applied to power quality disturbances," *Energies*, vol. 14, no. 10, p. 2839, May 2021.

[36] C. Cui, Y. Duan, H. Hu, L. Wang, and Q. Liu, "Detection and classification of multiple power quality disturbances using stockwell transform and deep learning," *IEEE Trans. Instrum. Meas.*, vol. 71, pp. 1–12, 2022.

[37] N. M. Rodrigues, F. M. Janeiro, and P. M. Ramos, "Deep learning for power quality event detection and classification based on measured grid data," *IEEE Trans. Instrum. Meas.*, vol. 72, pp. 1–11, 2023.

[38] S. Upadhyaya, S. Mohanty, and C. N. Bhende, "Hybrid methods for fast detection and characterization of power quality disturbances," *J. Control, Autom. Electr. Syst.*, vol. 26, no. 5, pp. 556–566, Oct. 2015.

[39] J. Liu, H. Song, H. Sun, and H. Zhao, "High-precision identification of power quality disturbances under strong noise environment based on FastICA and random forest," *IEEE Trans. Ind. Informat.*, vol. 17, no. 1, pp. 377–387, Jan. 2021.

[40] M. Sahani, S. Choudhury, S. K. Rout, and D. A. Gadanayak, "DSP based online power quality events detection and classification using Hilbert Huang transform and random forest method," in *Proc. Int. Conf. Comput. Intell. Smart Power Syst. Sustain. Energy (CISPSSE)*, Jul. 2020, pp. 1–6.

[41] R. R. Panigrahi, M. Mishra, J. Nayak, V. Shanmuganathan, B. Naik, and Y.-A. Jung, "A power quality detection and classification algorithm based on FDST and hyper-parameter tuned light-GBM using memetic firefly algorithm," *Measurement*, vol. 187, Jan. 2022, Art. no. 110260.

[42] J. Wu, F. Mei, C. Zhang, H. Miao, K. Li, and J. Zheng, "Classification of complex power quality disturbances based on modified empirical wavelet transform and light gradient boosting machine," *IET Gener., Transmiss. Distribution*, vol. 16, no. 10, pp. 1974–1989, May 2022.

[43] S. Akkaya, E. Yuksek, and H. M. Akgun, "A new comparative approach based on features of subcomponents and machine learning algorithms to detect and classify power quality disturbances," *Electr. Power Compon. Syst.*, vol. 52, pp. 1–24, Sep. 2023. [Online]. Available: https://www.tandfonline.com/doi/abs/10.1080/15325008.2023.2260375?casa_token=rniy3oMzMiQAAAAA:fSWfWXWkRdm5YbRfgEbZSfzfYd9MAJB6yd8ri79VqQWcglNTshcbzcayz9iMrgNUKLCZ2hiB6yqSYPEN

SAIRAM MISHRA (Graduate Student Member, IEEE) received the B.Tech. degree in electrical engineering from Siksha 'O' Anusandhan, Bhubaneswar, Odisha, India, in 2014, and the M.Tech. degree with a specialization in power electronics and drives from the Indira Gandhi Institute of Technology, Sarang, Dhenkanal, Odisha, in 2018. He is currently pursuing the Ph.D. degree with the Department of Electrical Engineering, Siksha 'O' Anusandhan.

RANJAN KUMAR MALLICK was born in India, in 1972. He received the bachelor's degree in electrical engineering from the Institution of Engineers, India, in 1996, the M.E. degree in power system engineering from VSSUT, Burla, Odisha, India, in 2001, and the Ph.D. degree from BPUT, Odisha, in 2013. He is currently working as a Professor with the Department of Electrical and Electronics Engineering, ITER, SOA Deemed to be University, Odisha. He is having 22 years of experience in teaching and research. His research interests include the application of power electronics, optimization techniques in power systems, economic load dispatch, and the design and control of HVDC converters, Load frequency controllers, and optimal harmonic estimation in power systems, stability of power system, power quality along with machine learning, and deep learning applications in power engineering.

DEBADATTA AMARESH GADANAYAK (Member, IEEE) received the bachelor's degree from the Silicon Institute of Technology, Bhubaneswar, India, in 2005, the master's degree from NIT, Rourkela, in 2010, and the Ph.D. degree in electrical engineering from ITER, SOA University, Odisha, India, in 2021. He is currently an Assistant Professor with the Electrical and Electronics Engineering Department, ITER. He has a teaching experience of more than 12 years. His broad area of research interests include microgrids, power systems protection, artificial intelligence, power quality, and power electronics.

PRAVATI NAYAK was born in 1983, India. She received the bachelor's degree in electrical engineering in 2004, the M.Tech. degrees in power electronics and drives in 2010, and the Ph.D. degree from SOA Deemed to be University, Odisha, India, in 2022. She is currently working as an Associate Professor with the Electrical Engineering Department, ITER, SOA Deemed to be University. She has a teaching experience of more than 16 years. Her broad area of research includes microgrids, power systems protection, artificial intelligence, power quality, power electronics, machine learning, and deep learning applications in power systems.

RENU SHARMA (Senior Member, IEEE) is with the Department of Electrical Engineering, Siksha 'O' Anusandhan (Deemed to be University), Bhubaneswar, India. She has around 21 years of leading impactful technical, professional, and educational experience. She has published around 100 journals and conference papers of international repute. She has organized several national and international conferences. Her research areas are smart grids, soft computing, solar photovoltaic systems, power system scheduling, evolutionary algorithms, and wireless sensor networks. She is a Life Member of IE (India), ISTE, and ISSE; a member of IET; and the Past Chair of WIE IEEE Bhubaneswar Sub Section. She has coordinated AICTE sponsored FDP programs. She was one of the Plenary Chairs PEDES 2020. She was the General Chair of IEEE ODICON 2021; flagship conference IEEE WIECON-ECE 2020; and Springer conference GTSCS-2020, IEPCCT-2019, and IEPCCT 2021. She is serving as the Publication Chair for INDISCON-2022. She is a Guest Editor of Special Issue in *International Journal of Power Electronics* (Inderscience) and Special Issue in *International Journal of Innovative Computing and Applications* (Inderscience).

GAYADHAR PANDA (Senior Member, IEEE) received the Ph.D. degree in electrical engineering from Utkal University, in 2007. He is currently a Professor with the Electrical Engineering Department, National Institute of Technology, Meghalaya, India. He has over 24 years of teaching and research experience. He has published more than 120 technical papers in national and international conference proceedings/journals and filed two patents. He has supervised eight Ph.D. students and currently supervising four Ph.D. scholars. He has led several research projects on the integration of renewable energy generation and power quality improvement. He has organized several technical events, such as IEEE conference, symposium, and national workshops. He has delivered several invited talks at various national and international events. His current research interests include automatic generation control, stability improvements using flexible alternating current transmission system devices, power quality, power electronic converters, and distributed power generation. His work involves design, implementation, and operation of ac/dc microgrid with interfacing converters that use digital signal processing, artificial intelligence techniques, and other novel control methods.

He is a fellow of IE and a Life Member of ISTE. He was a recipient of the Power Medal, IE (India) for one of his research papers. He is an Associate Editor of IEEE Access (ITES, Wiley) and also serves on the editorial board for *IJEEPS* (De Gruyter) and the technical/steering committees for several conferences.

MOHAMMED S. AL-NUMAY (Senior Member, IEEE) was born in Riyadh, Saudi Arabia. He received the B.S. degree (Hons.) in electrical engineering from King Saud University, Riyadh, in 1986, the M.S. degree in electrical engineering from Michigan State University, East Lansing, MI, USA, in 1990, and the Ph.D. degree in electrical engineering from Georgia Institute of Technology, Atlanta, GA, USA, in 1997. Since 1998, he has been with the Electrical Engineering Department, College of Engineering, King Saud University, where he is currently a Full Professor. From 2002 to 2006, he was the Dean of admissions and registration with King Saud University. He is a board member of two universities and four private colleges. In January 2018, he became the Vice President of Educational and Academic Affairs, King Saud University. His research interests include the modeling and control of switched mode power supplies, computer science, renewable energy, and the applications of AI.

PIERLUIGI SIANO (Senior Member, IEEE) received the M.Sc. degree in electronic engineering and the Ph.D. degree in information and electrical engineering from the University of Salerno, Salerno, Italy, in 2001 and 2006, respectively.

He is a Full Professor of electrical power systems and the Scientific Director of the Smart Grids and Smart Cities Laboratory, Department of Management and Innovation Systems, University of Salerno. His research activities are centered on demand response, energy management, the integration of distributed energy resources in smart grids, electricity markets, and the planning and management of power systems. In these research fields, he has coauthored more than 700 articles, including more than 410 international journals that received in Scopus more than 20200 citations with an H-index of 68. Since 2019, he has been awarded as a Highly Cited Researcher in Engineering by Web of Science Group.

Dr. Siano has been the Chair of the IES TC on Smart Grids. He is an Editor of the Power and Energy Society Section of IEEE Access, IEEE Transactions on Power Systems, IEEE Transactions on Industrial Informatics, IEEE Transactions on Industrial Electronics, and IEEE Systems.

Open Access funding provided by 'Università degli Studi di Salerno' within the CRUI CARE Agreement