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Islanding detection in photovoltaic based DC micro grid using adaptive variational mode decomposition and detrended fluctuation analysis

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Abstract
This study presents a novel approach using adaptive variational mode decomposition with detrended fluctuation analysis to detect the islanding disturbances for photovoltaic based DC micro grid. DC parameters are simple to estimate in comparison to AC profile. Thus DC parameters are recorded under islanding scenario, and processed through proposed adaptive variational mode decomposition which decomposes the signals into intrinsic mode functions. These segregated intrinsic mode functions are further selected optimally by choosing the significant weighted kurtosis index. This optimal selection (maximisation of weighted kurtosis index) is ensured by modified particle swarm optimisation in terms of number of modes (K) and penalty factor (σ). For detection and monitoring (D&M) accurate islanding scenario the significant intrinsic mode functions are subjected to detrended fluctuation analysis, where power exponent (α) values are utilised for correct detection (i.e. distinguishing islanding out of other grid contingencies by two and three dimensional scattering plots). The effectiveness of the proposed D&M for DC micro grid is established in this paper in terms of classification accuracy and relative computational time. The proposed DC side islanding D&M method is less complex (as compared to AC signals) to be implemented. Fastness and accuracy of proposed D&M is established and performed in MATLAB/Simulink platforms.

1 | INTRODUCTION

To increase the power demand and diminish the environmental factors, DC micro grid has been gaining wide attention in recent years. The DC micro grid is used especially for small scale and local load applications, which includes improving the efficiency, power quality and reliability of the system. In DC micro grid islanding detection is most challenging due to lack of standards, and the system extracted parameters are only voltage and current [1]. Islanding occurs when a section of the DC micro grid distribution network gets disconnected from the utility grid. Islanding scenario is a threaten to workers, equipments, line restoration and circuit breaker reclosing. According to IEEE-1547, IEEE 929–2000 and IEC–62116 standards required for detecting the islanding phenomenon within 2 s along with appropriate protective action [2, 3]. The existing methods for AC micro grid islanding detection comprise various approaches that include communication channels based techniques, passive and active islanding technologies. From the literature, AC micro grid islanding detection methods such as rate of change of frequency, voltage unbalance and phase shift techniques are not fitted to the DC micro grid islanding detection because they are related to the parameters of frequency and reactive power thereby makes the islanding detection approach more difficult [4]. According to IEEE 1547 the DG’s are preferred to be disconnected from the rest of the network, which provides no operational scenario for DC micro grid under AC-DC network connection (e.g. AC side utility, hybrid AC-DC micro grid). Thus detection of islanding events by simple DC side parameters (no periodic zero crossing/frequency) are proposed in this paper for an effective detection and monitoring (D&M).
Some of the passive methods used in DC micro grid islanding detection are DC over voltage/under voltage, rate of voltage and current signals at the point of common coupling (PCC) and model current autocorrelation function etc. [5]. These methods work efficiently and are simple to implement as long as a significant difference exists between the power generation and load demand. However, passive methods also result in appreciable non-detection zone (NDZ) which requires some corrective action. On the other hand in active islanding approach, a small disturbance is injected to the DC converter control system to influence the voltage and current signals at the PCC to undergo changes thereby affecting the overall system performance during islanding [5]. Active techniques are having small NDZ but result in huge impact on power
TABLE 1 Specifications for PV based DC micro grid system

| PV System parameters | Circuit components | Isolation circuit breaker | Transformer T1 = 400 kVA, 260 V/25 kV, 60 Hz, T2 = 47 MVA, 120 kV/25 kV, 60 Hz. |
|----------------------|---------------------|---------------------------|----------------------------------------------------------------------------------|
| Sun power            | Transformers        | Point of common coupling  | ICB PCC                                                                           |
| SPR-35E-WHT-D PV     |                      | Line parameters           | R1 = 0.064 Ω, X1 = 2.81 mH.                                                      |
| module               |                      | Converter parameters      | Nominal frequency 60 Hz, 260 V, 400 kW; DC capacitance 120 μF.                   |
| Open circuit voltage | Transformers        | DC-AC                     | BC1, BC2, BC3, BC4, BC5 = 5×106 kW (+8% IEC 6210), 470 V (DC).                   |
| = 64.6 V, short      |                      | DC-DC                     | 250 kW, 500 V                                                                     |
| circuit current = 6.14 A, voltage at  |                      | Load parameters           | 3.725 kW, 500 V                                                                   |
| maximum power point  |                      | Source parameters         | (PV1, PV2, PV3, PV4) 4×100 kW (each) = 400 kW                                    |
| = 54.7 V, current at |                      | PV system                 | 500 V                                                                             |
| maximum power point  |                      | DC bus                    | 1000 kW                                                                           |
| = 5.76 A, maximum    |                      | Battery                   | 120 KV, 2500 MVA                                                                  |
| power = 315.072 W,   |                      | Utility grid              |                                                                                  |
| parallel strings = 64, |
| series strings = 5,  |
| PV active power at 1000 (W m$^{-2}$) = 100 kW. |

FIGURE 4 Islanding study of the proposed system under photovoltaic penetration change. (a) DC current $I_{dc}$ for different penetration levels, (b) intrinsic mode function’s ($M_2$, $M_3$, and $M_4$) for DC current signal under 100% photovoltaic penetration, (c) intrinsic mode function’s ($M_1$, $M_3$, and $M_4$) for DC current signal under 20% photovoltaic penetration, (d) bar graphs of optimised weighted kurtosis index weighted Kurtosis index for significant intrinsic mode function’s.
quality. The methods used in active islanding of DC micro grid include harmonic injection, insertion of controllable loads and positive feedback methods [5, 6]. Apart from active and passive methods communication links are used in the DC micro grid to monitor the circuit breaker status, voltage and the current signals at the PCC thereby initiating the tripping of breakers when the islanding occurs [5]. Although this remote approach is very effective in reducing the NDZ significantly while producing very accurate islanding detection, it results in high cost by using a high speed communication link that becomes ineffective during communication link failures [7, 8].

Thus observing the above mentioned drawbacks of the DC micro grid islanding detection methods, this paper presents a new mode decomposition technique to process the DC current

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**FIGURE 5** Islanding study of the proposed system under DC load change (generation < load) (a) DC current $I_{dc}$ for +10% load variation, (b) intrinsic mode function’s (M1, M2 and M3) for DC current signal under +10% load variation, (c) bar graphs of optimised weighted kurtosis index weighted Kurtosis index for significant intrinsic mode function’s

**FIGURE 6** Islanding study of the proposed system under DC load change (generation > load) (a) DC current $I_{dc}$ for -10% load variation, (b) intrinsic mode function’s (M1, M2 and M3) for DC current signal under -10% load variation, (c) bar graphs of optimised weighted kurtosis index weighted Kurtosis index for significant intrinsic mode function’s

**FIGURE 7** Islanding study of the proposed system under DC load change (load nearly equal to generation) (a) DC current $I_{dc}$, (b) intrinsic mode function’s (M1, M2 and M3) for DC current signal, (c) bar graphs of optimised weighted kurtosis index weighted Kurtosis index for significant intrinsic mode function’s
and voltage signals at the common DC bus and extracting relevant features from them for the detection of DC micro grid islanding disturbances. Empirical mode decomposition and local mean decomposition are used to decompose the non-stationary signals like voltage and current for feature extraction, but these methods suffer from mode mixing problems [9, 10]. A relatively new signal processing technique like variational mode decomposition (VMD) is a user-defined technique, which converts the signal from recursive mode to a non-recursive mode and has less information loss and improved system accuracy [10]. The requirement to cope with existing signal processing techniques is the detection accuracy and reliability, with required fastness in operation for DC micro grid

### TABLE 2

| Events                  | Event name |
|-------------------------|------------|
| Islanding               | C₁         |
| Load change             | C₂         |
| Pole to pole (PP) fault | C₃         |
| Pole to ground (PG) fault | C₄     |

### TABLE 3

| Class type | α value | α low | α mid | α high |
|------------|---------|-------|-------|--------|
| C₁         | 2.025   | 0.614 | 0.324 |
|            | 1.952   | 0.739 | 0.567 |
|            | 1.832   | 0.803 | 0.415 |
|            | 1.805   | 0.633 | 0.284 |
|            | 1.793   | 0.625 | 0.262 |
|            | 1.815   | 0.602 | 0.289 |
| C₂         | 2.425   | 1.582 | 1.286 |
|            | 2.306   | 1.484 | 1.203 |
|            | 2.161   | 1.657 | 1.023 |
| C₃         | 1.153   | 1.791 | 0.877 |
|            | 1.216   | 1.723 | 0.785 |
|            | 1.384   | 1.886 | 0.651 |
| C₄         | 1.551   | 1.376 | 1.965 |
|            | 1.643   | 1.255 | 2.126 |
|            | 1.765   | 1.192 | 2.479 |
FIGURE 9 Pole to Pole (PP) fault study of the proposed system under fault resistance variation. (a) DC current $I_{dc}$ for different fault resistances, (b) intrinsic mode function's (M2, M3 and M5) for DC current signal under high resistance (1 $\Omega$), (c) intrinsic mode function's (M2, M3 and M4) for DC current signal under low resistance (0.1 $\Omega$), (d) bar graphs of optimised weighted kurtosis index weighted Kurtosis index for significant intrinsic mode function's

TABLE 4 RCT comparisons for proposed system with existing methods

| S.no | Method                      | RCT (p.u) |
|------|-----------------------------|-----------|
| 1    | S transform and probabilistic neural network (PNN) [16] | 2.40      |
| 2    | Wavelet transform with neural network [17]         | 2.02      |
| 3    | Rough set based method [24]                       | 1.32      |
| 4    | proposed                                       | 1.00      |

TABLE 5 Classification accuracy for the proposed system

| Type of scenario | No. of randomly taken $\alpha$ values | Correctly classified $\alpha$ values | Classification accuracy (CA) (%) |
|------------------|--------------------------------------|-------------------------------------|---------------------------------|
| Islanding        | 25                                   | 25                                  | 99                              |
| Load change      | 25                                   | 24                                  |                                 |
| PP fault         | 25                                   | 25                                  |                                 |
| PG fault         | 25                                   | 25                                  |                                 |
| Total            | 100                                  | 99                                  |                                 |
application. Thus the signal decomposed intrinsic mode functions (IMFs) are optimally selected in terms of number of modes: $K$, and penalty factor: $\sigma$, by minimisation of objective function (i.e. significant weighted Kurtosis index (KI$_w$)). This adaptive mode selection is presented by a nature inspired meta-heuristic evolutionary modified particle swarm optimisation (MPSO) algorithm, against proposed adaptive VMD (AVMD) operation. This improved AVMD-MPSO based signal processing is quite accurate and fast in operation as presented in Section 5. The recently proposed MPSO [11] provides optimal solution with a fewer generations and is found to be quite efficient and does not suffer from premature convergence like the GA [12] and earlier PSO algorithms [13–15]. After obtaining the pertinent features from the significant IMFs it is required to detect the islanding out of various non-islanding grid operational disturbances.

To classify the islanding and non-islanding events of the DC micro grid widely used classification techniques for the AC micro grid can be applied here [16–20]. These techniques include artificial neural networks, fuzzy systems, support vector machine and extreme learning machines and their variants [16] etc. These methods are fairly complex and involve large execution times and therefore in this paper a simple but efficient detrended fluctuation analysis (DFA) has been used to detect and classify various islanding and non-islanding disturbances in DC micro grid [21]. DFA is useful for detecting the long correlation range of a non-stationary time series under noise by removing the fluctuation in the signals. Also it is related to the random walk by modifying its root mean square analysis and has been used earlier in several application areas like medical data classification, DNA study, weather records, geology, ethnology and solid state physics, financial time series etc. [21, 22]. The DFA based classifiers are utilising distinguishable power exponent ($\alpha$) values to detect any event. The window length

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**Figure 10** Pole to ground (PG) fault study of the proposed system under fault resistance variation. (a) DC current $I_{dc}$ for different fault resistances, (b) intrinsic mode function’s (M1, M2 and M6) for DC current signal under high resistance (1 $\Omega$), (c) intrinsic mode function’s (M1, M3 and M5) for DC current signal under low resistance (0.1 $\Omega$), (d) bar graphs of optimised weighted kurtosis index weighted Kurtosis index for significant intrinsic mode function’s

**Figure 11** Comparison of islanding and different grid contingencies in logarithmic graph through detrended fluctuation analysis analysis
(W) is considered as regulating parameter to obtain dissimilar $\alpha$, to detect accurate DC side islanding out of various grid contingencies.

The DC side variations are utilised for islanding (especially unintentional) detection by AVMD-MPSO based optimal IMFs selection, and DFA based fast, accurate event classification in this paper. These islanding D&M method for DC micro grid will be useful for DC side power balancing, management under unintentional islanding events. This work is considered as future scope of this paper.

The organisation of the present work is described in section wise. In Section I introduction has been discussed. The description for the photovoltaic (PV) based DC micro grid system has been explained in section II. Section III describes AVMD, where adaptiveness is ensured by $K_I$ parameter selection by MPSO algorithm in terms of $K$ and $\sigma$. In section IV complete details about the DFA analysis classifier has been introduced. In section V and VI performance and effectiveness of the proposed technique for the DC micro grid are discussed and compared with existing methods have been explained.

2 CONSIDERED PHOTOVOLTAIC BASED DC MICROGRID CONNECTED THROUGH AC UTILITY

In the proposed system PV based DC micro grid are connected with utility grid through a voltage source converter (VSC) as shown in Figure 1. The output voltage from the PV is increased with the help of DC-DC converter which is connected to the DC bus. A lamp load and DC motor load are connected at the DC bus, which is rated as 500 V as shown in Figure 1. A battery with DC-DC converter also connected at the DC bus. The obtained AC output voltage from the VSC is stepped up by the transformers which are connected to the utility through PCC. According to the UL1741 standards the proposed model is taken for islanding detection method for worst case scenario. In the present study isolation circuit breaker opens under disturbance conditions so that the utility is disconnect from the PV based DC micro grid network. During this state there is a change in system parameters and studies are conducted using a switching time of 1.2 s. In this study the sampling time is considered as 50 $\mu$s. The proposed system model parameters are depicted in Table 1.

3 ADAPTIVE VARIATIONAL MODE DECOMPOSITION BASED ISLANDING DETECTION

To detect islanding phenomena with DC side variations an AVMD is proposed in this paper where optimal IMFs selection is presented with MPSO based minimisation problem. To understand the whole operation initially the classical VMD is explained.

3.1 Variational mode decomposition

VMD is a novel adaptive signal decomposition technique that decomposes a non-stationary signal into modes ($\alpha_i$) or sub signals with particular properties. Every mode has been linked with a central frequency ($\omega_i$) and by using the $l^2$ norm, and its gradient estimates the bandwidth.
As a result the VMD process can be taken as a constrained optimisation problem, which can be described in Equation (1).

\[
\min_{\{\omega_k\}} \left\{ \sum_k \left\| \delta(t) \left( \frac{j}{\Pi t} \right) \star \omega_k(t) \right\|_2^2 \right\},
\]

subjected to \( \sum_k \omega_k = f \).

where \( \delta(t) \) indicates dirac distribution and \( \star \) represents convolution operator. The lagrangian multiplier \( \lambda \) and quadratic penalty term are provided in the variational unconstrained problem.

In case if a Gaussian noise is present in the signal, a penalty term \( \sigma \) is incorporated to provide accuracy. Equation (1) is represented in the following form using lagrange multiplier as

\[
L(\{\omega_k\}, \{w_k\}, \lambda) = \sigma \sum_k \left\| \delta(t) \left( \frac{j}{\Pi t} \right) \star \omega_k(t) \right\|_2^2 + \left\| f(t) - \sum_k \omega_k(t) \right\|_2^2 + \left\langle \lambda(t), f(t) - \sum_k \omega_k(t) \right\rangle.
\]

Further by using the alternate direction method of multipliers a saddle point for Equation (2) is obtained. Prior to that decomposition mode number \( (k) \), frequency mode domain \( \gamma_k^1 \), central frequency \( w_k^1 \) and lagrangian multiplier \( \lambda^1 \) are initiated. Consequently, from Equations (3) and (4) upgraded the modes \( \hat{\gamma}_k \) and \( w_k \) are obtained as:

\[
\hat{\gamma}_{k+1}^1(w) \leftarrow \frac{\int_0^\infty w | \hat{\gamma}_k^{1+1}(w) - \sum_{k \geq k} \hat{\gamma}_k^1(w) + \frac{\lambda^1_k}{2} |^2 dw}{\int_0^\infty | \hat{\gamma}_k^{1+1}(w) |^2 dw},
\]

\[
w_{k+1}^1 \leftarrow \frac{\int_0^\infty \left| \hat{\gamma}_k^{1+1}(w) \right|^2 dw}{\int_0^\infty \left| \hat{\gamma}_k^1(w) \right|^2 dw}.
\]

The centre frequencies and modes along with Lagrange multiplier are obtained for every updating process as

\[
\lambda_{k+1}(w) \leftarrow \lambda_k^1(w) + \tau \left( \hat{f}(w) - \sum_k \hat{\gamma}_k^{1+1}(w) \right).
\]

where \( \tau \) is the noise tolerance. The above process is continued till convergence, which can be shown in Equation (6).

\[
\sum_k \left\| \frac{\omega_k^{k+1} - \omega_k^k}{2} \right\|_2^2 < \varepsilon.
\]

Here \( \varepsilon \) is the convergence criterion; \( \tau \) and \( \varepsilon \) are chosen to be small and they impact the decomposition outcomes. In VMD mode decomposition number \( k \) (final value \( k = K \) plays an important role by filtering the noise present in the non-stationary signal. If the \( k \) value is chosen to be small then it becomes mode mixing and also the larger \( k \) value gives excessive decomposition. Therefore an optimum mode number is determined which will reduce overall execution time and will produce most relevant features for the detection of islanding and non-islanding events for a DC micro grid.

### 3.2 Weighted kurtosis index estimation

In VMD method the non-stationary signal can be decomposed into number of IMFs. For selection of a number of useful IMFs, KL\(_w\) is used as a significant measurement parameter.

\[
KL_w = K_s \times |CC|.
\]

Where \( K_s \) is the kurtosis index of the signal \( A(n) \), \( N \) is the signal length, \( CC \) is the correlation coefficient between the signal \( A(n) \) and \( B(n) \).

\[
K_s = \frac{1}{N} \sum_{n=0}^{N-1} A^4(n),
\]

\[
CC = \frac{E \left[ (A - \bar{A})(B - \bar{B}) \right]}{E \left[ (A - \bar{A})^2 \right] E \left[ (B - \bar{B})^2 \right]}.
\]

### 3.3 Optimal intrinsic mode functions’ selection from significant weighted Kurtosis index by modified particle swarm optimisation

PSO is a metaheuristic method which is introduced by the Kennedy and Eberhart [11] where the current position of the particle \( i \) is represented as \( y_{i(k)} \) where \( k \) is the iteration number. Further each particle’s current local best position is \( y_{p(i,k)} \) and its global best position obtained by this algorithm is \( y_{G(k)} \). The velocity of particle \( v_{i(k)} \) is referred to the current
location change with each iteration $k$. The velocity and position of accelerated particles towards their local best and global best outcomes $p^{(i,k)}$ and $y^{(i,k)}$ are both updated iteratively and these are expressed in Equations (10) and (11), respectively.

$$p^{(i,k+1)} = p^{(i,k)} + g_1 w_1^{(k)} (y_p^{(i,k)} - y^{(i,k)}) + g_2 w_2^{(k)} (g^{(i,k)} - y^{(i,k)}), \quad \text{(10)}$$

$$y^{(i,k+1)} = y^{(i,k)} + p^{(i,k+1)}; \quad i = 1 \text{ to } N. \quad \text{(11)}$$

where $g_1$ and $g_2$ are perception and general parameters, respectively, which are inclusively called as acceleration coefficients; $w_1^{(k)}$ and $w_2^{(k)}$ are the random vector numbers which lie between 0 ≤ $w$ ≤ 1; $N$ is the swarm size. The updated equations are represented as follows:

$$y^{(i,k)} = \begin{cases} y^{(i,k)}, & \text{if } f(y^{(i,k)}) < f(y_p^{(i,k)}) \\ y_p^{(i,k)}, & \text{if } f(y^{(i,k)}) \geq f(y_p^{(i,k)}) \end{cases}, \quad \text{(12)}$$

$$y^{(i,k)} = \begin{cases} y^{(i,k)}, & \text{if } f(y^{(i,k)}) < f(g^{(i,k)}) \\ y_p^{(i,k)}, & \text{if } f(y^{(i,k)}) \geq f(g^{(i,k)}) \end{cases}. \quad \text{(13)}$$

To obtain better local and global search positions of the particles, a damped inertia weight term is used to update particle velocity as

$$y^{(i,k)} = w_i y^{(i,k)} + g_1 w_1^{(k)} (y_p^{(i,k)} - y^{(i,k)}) + g_2 w_2^{(k)} (g^{(i,k)} - y^{(i,k)}); \quad i = 1 \text{ to } N. \quad \text{(14)}$$

where $w_i$ is the damped inertia term, which impacts the momentum parameter. The global search is improved by the larger value of the damped inertia term and local search is enhanced by the smaller value of the damped inertia term. The performance of the inertia weight of PSO has been improved when the range lies between 0.9 and 1.2. The linearly decreasing inertia weight equation has been depicted as follows:

$$w_i^{(k)} = \left( \frac{w_{i_{\max}} - w_{i_{\min}}}{\max_k} \times (\max_k - k) \right) + w_{i_{\min}}. \quad \text{(15)}$$

where $w_{i_{\min}}$ the minimum inertia is weight and $w_{i_{\max}}$ is the maximum inertia weight. The present iteration value is considered as $k$ and maximum value of iteration as $\max_k$, according to these $w_i^{(k)}$ reduces from $w_{i_{\max}}$ to $w_{i_{\min}}$. In addition to above mentioned methods other improved adoption method has been introduced namely, chaotic inertia weight which is described as follows:

$$w_i^{(k)} = \left( \frac{w_{i_{\max}} - w_{i_{\min}}}{\max_k} \times (\max_k - k) \right) + w_{i_{\min}} \times a^k. \quad \text{(16)}$$

where $a$ is the chaotic parameter. The value of $\gamma$ lies between 3.75 and 4 then the inertia weight acts chaotically. The chaotic parameter increases the swarm particle diversity and improves the randomness of the swarm. The addition of chaotic term improves the convergence speed and the convergence accuracy.

The minimum weighted kurtosis index (MKI$_w$) is chosen as the objective function or fitness for the proposed system as

$$(K, \sigma) = \min \{ \frac{1}{MKI_w} \}. \quad \text{(18)}$$

where $K$ and $\sigma$ are the optimal parameters and MKI$_w$ is defined in Equation (7). The flow chart of the proposed technique as shown in Figure 2 and described in step wise as follows:

**Step 1:** Initially, set the parameter initiation for the MPSO, which are population size, maximum number of iterations ($S$) and moving velocity of the particles ($v_\max, v_\min$). In this regard maximum number of iterations is taken as 25, lower boundary of ($K, \sigma$) is taken as (1, 1000) and upper boundary of ($K, \sigma$) is taken as (10, 10,000).

**Step 2:** In this step the KL$_w$ from the IMFs by processing the non-stationary current signals using AVMD.

**Step 3:** If the KL$_w$ fitness value has been low compared with the best fitness recorded value such as MKI$_w$, then the current position and velocity of the whole particles in population are updated.

**Step 4:** Ultimately, if the $k$ value is greater than equal to $S$, then the iteration process is terminated and the optimal values such as MKI$_w$, $\sigma$ and $K$ are obtained as the output.

After getting the optimal values from the MKI$_w$ using the proposed algorithm a threshold value of kurtosis index (KL$_w$) is chosen to be greater than 1 for choosing the number of important modes. The optimal values of mode number ($K$) and penalty factor ($\sigma$) have been obtained from the algorithm after the convergence to the minimum value of the objective function is reached.

The PSO algorithm is implemented by choosing population size as 20, $\gamma = 3.9$, $w_{i_{\max}}$ as 1.1, $w_{i_{\min}}$ as 0.6, $g_1$ and $g_2$ are chosen as 2. Here the optimal values of $K$ and $\sigma$ are found as 3 (total number of modes $\approx 6$, three modes with KL$_w > 1$). The adaptive selection of IMFs by KL$_w$ threshold is evidenced in result analysis (Section 6) part, where depending on signal profile under various operational contingencies (e.g. islanding, load change and irradiation change for PV generation) the IMFs are also selected adaptively.
4 | FAST AND ACCURATE DETRENDED FLUCTUATION ANALYSIS BASED ISLANDING DETECTION

The selective IMFs by AVMD-MPSO is processed further through DFA to estimated power exponent ($\alpha$) values depending on window size regulation. This scheme provides distinguishable $\alpha$ for different contingencies. This section is describing the islanding detection (two and three dimensional scatter plot) in terms of accuracy (i.e. classification accuracy (CA)) and fastness (relative computational time (RCT)).

4.1 | Detrended fluctuation analysis

DFA technique is used for classifying the islanding events in a system. In case of complex and non-stationary signals DFA technique is applied to quantifying the signals which are having correlation properties. In the proposed system DFA method is used to classifying the islanding and non-islanding (such as grid connected mode, pole to pole ((PP)) fault and pole to ground (PG) fault) events. In the proposed system extracted non-stationary signal presents DC offsets, which can be removed by subtracting the average of the non-stationary signal from the original signal then obtained signal can be written as:

$$Z(p) = \sum_{k=1}^{P} X(k) - \bar{X}(k).$$

$$W = P/n.$$  

where $X(k)$ is DFA applied in which signal, $\bar{X}(k)$ is the average of the $X(k)$ during the period of $k = 1$ to $P$ and $P$ be the number of samples for the original signal. The integrated signal $Z(p)$ is decomposed in to $W$ windows, in which sampling points are of same size. So the window length or size can be represented in Equation (20).

In each window DFA helps to finding the fluctuation of the signal. After identification of the signal for each window is build up with local trends and formulated by using fitting curve polynomial with the least square method. In these trends for each window the order has taken as one. The integrated signal can be represented for each window as $Z(k)$ and the trend signal can be $Z_t(k)$:

$$Z_t(k) = \sum_{j=1}^{b} \beta_i t^i.$$  

The difference between $Z(k)$ and $Z_t(k)$ can be treated as detrended signal for the specific window length. This can be formulated as:

$$E_x(k) = Z(K) - Z_t(k).$$

where $E_x(k)$ as detrended signal. DFA analysis can be useful for small data into large number of data samples this has been termed as window length. In case of the detrended signal window length is small then this comes under high fluctuation study and the window length has been taken as high this comes under low fluctuation study. The detrended signal gives better outcomes according to the window length. The rms value of the detrended difference signal for a specific window defined as

$$F(n) = \sqrt{\frac{1}{P} \sum_{k=1}^{P} (E_x(k))^2}. \quad (23)$$

There exists a power relationship between $F(n)$ and $n$ called as power exponent ($\alpha$) which can be represented in Equations (24) and (25), in which $\alpha$ is power exponent. This is vital to initiating the fluctuation for the mode function. To execute the proposed method under various disturbances DC current signals are captured with the help of model and these signals are processed as shown in Figure 3.

$$F(n) \approx n^\alpha. \quad (24)$$

$$\lg (F(n)) = \alpha \lg n. \quad (25)$$

5 | PERFORMANCE EVALUATION

To evaluate the performance of the proposed AVMD-PSO the considered PV generation based DC micro grid (Figure 1) has been simulated in the MATLAB/simulink platform. The details of modelling parameters are provided as in Table 1. Proposed AVMD-MPSO method is used to decompose the non-stationary signal into IMFs (Section 3). DFA is used to classify the events like islanding and non-islanding (grid connected mode DC load variation, PP fault and PG fault) disturbances etc. During any grid uncertainty operation (including islanding), DC voltage and current signals at the DC bus are being affected. These signals are easy to estimate as DC profile is independent of phase and frequency (periodic). Thus D&M at DC side is quite simpler as compared with AC side measurements. In the proposed system scenario DC current disturbance conditions are mainly used for detection and classification of islanding. The performance efficacy of the proposed D&M for DC side islanding detection is validated in MATLAB platform and calculated with CA and RCT as shown in Equations (26) and (27).

$$\text{RCT} = \frac{\text{Computational time for a particular method}}{\text{Minimum computational time for all techniques}}. \quad (26)$$

$$\text{CA} = \frac{\text{Number of correctly classified } \alpha \text{ values}}{\text{Randomly taken } \alpha \text{ values from total } \alpha \text{ values}}. \quad (27)$$

6 | RESULT ANALYSIS

To test the islanding detection method for the proposed system, various islanding and non-islanding conditions (load change, PP,
and PG faults) [5] have been considered. During the islanding condition, the real power mismatch between generation and load is done by varying PV penetration and DC load. As a result, deviations occur in the DC parameters (DC voltage and DC current). The deviations in the parameters are also observed during the grid-connected mode when load changes and fault resistances are varied in load change and fault cases. Under every condition, the deviated signals are retrieved which are further used for detecting and classifying the islanding and non-islanding disturbances.

Further during islanding of the DC micro grid, load-generation mismatch can occur in the system. This mismatch can be influenced by various reasons such as PV penetration and load changes. During PV penetration and load change, generation can either be less than load or generation can be greater than load or load nearly equal to generation. Due to this reason, authors considered these variations to validate the proposed islanding detection method [5] during such conditions. In the proposed photo voltaic (PV) based DC micro grid system, DC current signals are taken into consideration to detect and classify the islanding and non-islanding disturbances. Islanding event is subjected for the considered DC micro grid system at AC side when PCC (Figure 1) is disconnected from utility. The islanding event can be discussed under different scenario along with various types of other grid as well as DG contingencies (e.g. load change, PP fault and PG fault etc.) are studied to avoid false detection (Table 2). The various types of simultaneous events (i.e. no loading (100% PV penetration) and PV penetration change) conditions have been simulated under islanded system which can be shown in Figure 4(a), that represents DC current signals under islanding switching time at 1.2 s. Similarly during switching time DC current oscillates for a few cycles and after subjecting the DC current to the AVMD-MPSO technique and the obtained IMF’s are shown in Figures 5(c), 6(c), 7(c), respectively. The simulated DC current signals are processed through the DFA for classifying the islanding and non-islanding disturbances.

In DFA method window size is vital to tracking the disturbance signals. To differentiate these signals accurately, three alpha values having with different window sizes have been considered, where \( \alpha_{\text{low}} \) is the shorter window frequency, \( \alpha_{\text{mid}} \) is the medium window frequency and \( \alpha_{\text{high}} \) is the higher window frequency. In the proposed system \( \alpha_{\text{low}} \) is between 4 to 504 samples (100% PV penetration) are: 2.025, 0.614 and 0.324 for three different fault variations as shown in Figure 9(a). The IMF’s are obtained under high fault resistance, medium fault resistance and low fault resistance as shown in Figure 9(b),(c). The optimised IMF’s are calculated by KLw as shown in Figure 9(d). PG fault is initiated from 1.2 to 1.4 s under different fault resistances like low, medium and high as shown in Figure 10(a). The significant IMF’s of low resistance and high resistance are shown in Figure 10(b),(c). The KLw thresholds are used to select the IMF’s which are represented in bar graph in Figure 10(d). The selected IMF’s are processed through the D&M for classifying the islanding disturbances.

The proposed D&M takes computation time of 45 ms (without communication, CB’s switching delay) when other existing techniques take large detection time (e.g. S-Transform: 98 ms, Wavelet:75 ms). The \( \alpha_{\text{low}}, \alpha_{\text{mid}}, \alpha_{\text{high}} \) are obtained for this proposed scheme as: 1.832, 0.803, 0.415 for 20% penetration; 1.952, 0.739, 0.567 for 80% penetration level, respectively (Table 3). The proposed islanding detection scheme is recorded as superior in terms of computation time (36 and 42 ms for 20% and 80% penetration change, respectively) as compared with existing techniques (S-Transform: 97.5 ms, 105 ms and wavelet: 72 ms, 76 ms, respectively). In addition to this, the DC load variations during islanding condition, the \( \alpha_{\text{low}}, \alpha_{\text{mid}}, \alpha_{\text{high}} \) values are calculated as 1.805, 0.633 and 0.284 for \(+10\%\) load variation (load > generation); 1.815, 0.602 and 0.289 for \(-10\%\) load variation (load < generation); 1.793, 0.625 and 0.262 for load nearly equal to generation, respectively. In the proposed islanding detection technique the computational time is recorded as 32 ms, 30 and 26 ms for \(+10\%\), \(-10\%\) and load nearly equal to generation variations, respectively, when compared to those of
S-transform: 107, 97 and 85 ms, and wavelet transform: 88, 75 and 68 ms, respectively.

The $\alpha_{\text{low}}$, $\alpha_{\text{mid}}$, $\alpha_{\text{high}}$ are obtained load change scenario as: 2.425, 1.582, 1.286; for higher loading, and 2.161, 1.657, 1.023 for lower loading conditions of DC load change, respectively. In case of PP fault the $\alpha_{\text{low}}$, $\alpha_{\text{mid}}$, $\alpha_{\text{high}}$ are 1.153, 1.791, 0.877; obtained for high fault resistance and for low fault resistance $\alpha_{\text{low}}$, $\alpha_{\text{mid}}$, $\alpha_{\text{high}}$ are 1.384, 1.886 and 0.651. In PG Fault under high fault resistance the $\alpha_{\text{low}}$, $\alpha_{\text{mid}}$, $\alpha_{\text{high}}$ obtained as 1.551, 1.376, 1.965; and for low resistance these values are recorded as 1.765, 1.192 and 2.479.

The detection and classification of accurate islanding are obtained by 2 dimensional (2D) and 3 dimensional (3D) scatter plots [21]. The scatter plots are utilised for identifying the correlation of behavioural fluctuation for distinct frequency ranges. The $\alpha$ values for different events (e.g. islanding, load change, fault condition etc. as in Table 2) are recorded in Table 3 and displayed in terms of 2D and 3D scatter plots in Figures 12 and 13, respectively. The islanding event is distinctly visible while plotted across $\alpha_{\text{low}}$ versus $\alpha_{\text{high}}$, (Figure 12(a) and $\alpha_{\text{low}}$ versus $\alpha_{\text{mid}}$ (Figure 12(b), as compared with other events (i.e. 99 $\alpha$ values out of 100 randomly selected from total $\alpha$ values are inside the cluster). Also for load nearly equal to generation, islanding condition can be established effectively as shown in Figure 12(a) green marker cluster, in Figure 12(b) blue marker cluster and Figure 13 sky blue marker cluster.

RCT is obtained from computation time of individual events as depicted in this section above and the formulation is obtained as in Equation (26). CA is estimated after thorough case study (i.e. different disturbances) and the formulation is as expressed in Equation (27). The proposed islanding D&M for DC micro grid is showing efficacy over conventional techniques in terms of RCT and CA as shown in Tables 4 and 5.

7 | CONCLUSION

This paper presents a novel approach towards DC side islanding detection technique for multiple DG (PV based) integrated micro grid. IEEE 1547 standard cannot be fully applicable to DC systems because the load reactive component is not present in the DC systems [1]. DC micro grid islanding detection is challenging since the only measurable parameters are DC voltage and DC current. To overcome the present standard limitation a new DC parameter variations based DC islanding detection method is presented in this paper. The DC current (majorly) variations are used for getting the IMFs based on a new AVMD technique. This adaptive operation is ensured by MPSO based optimal $K_{Iw}$ selection of significant IMFs. This step is providing a reduced computational signal processing solution as all IMFs are not utilised for islanding detection. The selective IMFs are further processed through DFA based detection algorithm where different power exponents ($\alpha_{\text{low}}$, $\alpha_{\text{mid}}$, $\alpha_{\text{high}}$) are computed. These values are recorded in terms of 2D and 3D scattered plots for accurate islanding detection. The CA and RCT are the two parameters by virtue of which the superiority of proposed D&M is established. The islanding events have been simulated with PV penetration change and DC load variations (generation > load, generation < load and load nearly equal to generation). The islanding condition is distinguished effectively as compared with other grid contingencies (e.g. loading change, faults etc.).

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