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Anti-Islanding Protection in Power Distribution Network Consisting of Multi-DG Units and PHEVs Charging Stations using WPT and PNN

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Abstract

A distribution system is a sensitive part of a power system, and integrating renewable Distributed Generation (DG) system at the distribution level is a hot topic for power system engineers right now. Integration of DG into the distribution network encounters various technical issues, and one of the major issues is unintentional islanding. There are various Islanding Detection Methods (IDMs) for the detection of islanding conditions, which includes active, passive, hybrid, communication system and intelligent classifier-based method. In this research work, the performance of anti-islanding protection system based on Wavelet Packet Transform (WPT), and Probabilistic Neural Network (PNN), which uses transient signals generated during the islanding event for islanding detection is investigated for a power distribution network consisting of multi-DG units and PHEVs Charging Stations. The anti-islanding protection method is based on the point of common coupling (PCC) or Point of connection (PC) voltage measurement and processing of this signal with a WPT to find the Normalized Shannon entropy (NSE) and Normalized Logarithmic Energy Entropy (NLEE) as feature vectors. PNN then makes use of feature vectors for decision-making mechanisms. With this technique, the unintentional islanding operation can be detected within 20 ms. In addition, the Non-Detection Zone (NDZ) is almost zero. The proposed technique is found to be competitive with similar intelligent islanding detection techniques. Also, the proposed technique is computationally simple and fits well into protection scheme of inverter-based DGs which uses Intelligent Electronic Devices (IEDs) for online implementation in the actual system.

Keywords

Electrical Power system, Distributed generation, Unintentional islanding, Anti-islanding protection, Artificial Intelligence, Wavelet Packet Transform, Probabilistic Neural Network

1. Introduction

Distributed generation (DG) has become practicable solution for integrating renewable energy resources into a low-voltage distribution network for mitigating issue relating to global warming. However, integrating DG brings challenges such as a lengthy payback period, sporadic nature of renewables, and glitches in the power system. Moreover, DG integration can also result in unstable voltage and frequency along with power quality problems. Similarly, islanding formation is also one of the major issues in DG integration to main grid. Islanding can be either intentional or unintentional. Unintentional islanding happens when DG is disconnected from the main grid as a result of a circuit breaker trip caused by system failure, imbalanced power, line outage, generator tripping, natural disasters, human mistake, or other disturbances. Failure to notice this issue causes a variety of issues related to power quality (PQ), safety hazards, voltage and frequency instability, and system equipment damage, etc. As a result, DGs must be outfitted with anti-islanding protection relays that can de-energize the DGs in the event of islanding formation.

Further advancement in Electric Vehicles (EVs) and Battery Energy Storage System (BESS) have made huge progress and is becoming affordable in terms of economy and efficiency. Rapid charging is an operation mode of Plug-in Hybrid Electric Vehicles (PHEV) and it necessitates quick battery recharge. This charging mode appears as a low impedance short circuit on the DC side, resulting in power transients on the power grid [1]. Thus, anti-islanding protection scheme should be able to classify the islanding and non-islanding events accurately. According to IEEE Standard 1547[2], DG shall detect the situation for any possible islanding condition and stop energizing the distribution network with in 2 seconds for small variations in voltage and frequency signal. The performance of IDM is evaluated by NDZ and run-on time. The NDZ is the zone in which an anti-islanding technique fails to identify an islanding condition, and the run-on time is the time between when the islanding happens and when it is noticed [3]. In [4, 5, 6, 7] conventional methods for islanding detection and protection are discussed.The conventional methods have a short coming in terms of setting of thresholds, NDZ, power quality and cost. According to IEEE Std.1547, harmonics maintained by the filters,embedded with inverter control systems must be below 5%. The magnitude of the harmonics depends heavily on the grid impedance value, and it will increase in the islanded mode. Thus, using the observation of the voltage and/or current signals in the high frequency components will provide the best solution to detect the islanded condition [8, 9, 10]. To decrease NDZ of the passive methods, advanced signal processing tools such as Duffing oscillations, short- time Fourier transform (STFT) [11] and wavelet transforms (WT) [12, 13, 14, 15, 16], are exploited. Alternatively, WPT has been applied, which divides the whole time-frequency plane, while the WT can only analyze the low-frequency band [17, 18]. In [19], the WPT was employed for the feature extraction(transient high-frequency components) to the d-q-axis component of the 3-phase instantaneous apparent powers. Wavelets have been identified as a highly effective supplementary tool for storing and analyzing problematic power quality waveforms and signals [20].A stationary signal is split into several scales with different levels of resolution in WT analysis by dilating a single prototype function known as the mother wavelet[21].The multi-resolution signal decomposition approach is used in [22] to break down a signal into its features and approximations. For power quality challenges, the most commonly utilized wavelets are Daubechies wavelets of order 4 (db4), db1, db10, db20, Symlet wavelet of order 5 (sym5), "Discrete" Meyer wavelet (DMeyer i.e., dmey), and Coiflet wavelet of order 5 (coif5) [23]. Energy and entropy factors associated with wavelet packet transform are utilized in [24] for automatic signal classification as well as detection of voltage disturbances in electrical signals. The approach described in this work varies from earlier methods in that it employs various wavelet coefficients corresponding to different frequency bands of voltage transients as features rather than complex indices with higher computing demand.

2. Methodology

2.1 Wavelet Packet Transform

One of the well known signal processing tools to examine the non-stationary properties of transient signal is the Wavelet Transform(WT).When investigating transients, WT is more useful than other frequency domain approaches such as windowed Fourier transform [25]. Although the wavelet transform can examine local discontinuities in a signal, it has certain drawbacks, such as batch processing steps, non-uniform frequency sub-bands, less flexibility, and a proclivity to detection failures in noisy situations. In[26] Wavelet Packet Transform (WPT) has been presented as a solution for the aforementioned issues . WPT is the generalization of orthogonal WT.Wavelet packets are used for finer analysis by breaking up detailed (high frequency) space into approximation (A) and detailed spaces (D).

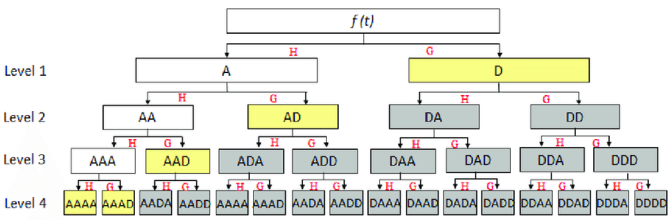

Figure 1: Structure diagram of Four-level WPT decomposition

Figure 1 shows the structure diagram of WPT for four levels of decomposition. As can be observed, both approximation and detail coefficients are divided into two sub-bands, and this process is repeated for further decomposition. As a result, WPT provides a balanced binary tree structure and can provide more precise frequency resolution.The WPT of a signal f(t) is defined mathematically as,

$$f_p^{n,j} = 2^{-j/2} \int_R f(t) \overline{\mu_n \left(2^{-j} t - p\right)} dt \tag{1}$$

Where μ_n is the function wavelet packet,j represents the number of decomposition levels (scale parameters), p represents the position parameter,n is the number of packets due to the decomposition process.The MATLAB function commands wpdec and wpcoef were used for getting wavelet packet decomposition and wavelet packet coefficients of the PCC/PC voltage signals.

2.2 Feature Extraction using NSE and NLEE

Entropy information is usually used to discover abnormal patterns of islanding and non-islanding signals. For the retrieved WPT coefficients, Shannon entropy and logarithmic energy entropy are calculated. The Shannon entropy for each frequency band i and p level is computed using the following equation(2):

$$\text{Entropy}_{\ p,i} = - \sum_{n=1}^{N} \left| Y_{p,k}^{i}(n) \right|^2 \log \left| Y_{p,k}^{i}(n) \right|^2 \tag{2}$$

Where n is the sampling point number, Y is the extracted wavelet packet coefficients at ith frequency band on pth level.

Also, the logarithmic energy entropy is computed using the equation(3):

$$\text{Energy}_{\ p,i} = \sum_{n=1}^{N} \log \left[\left(Y_{p,k}^{i}(n) \right) \right]^2 \tag{3}$$

A feature database which is formed by the aforementioned entropies are then normalized as NSE and NLEE before feeding into the classifiers as input vector,using the following expressions:

$$\text{Entropy}_{\ p} = \frac{\text{Entropy}_{\ p,i}}{\sum_{p=0}^{2^p-1} \text{Entropy}_{\ p,i}} \tag{4}$$

$$\text{Energy}_{\ p} = \frac{\text{Energy}\ y_{p,i}}{\sum_{p=0}^{2^p-1} \text{Energy}_{\ p,i}} \tag{5}$$

2.3 Probabilistic Neural Network

A probabilistic neural network (PNN) is a feed-forward neural network with four layers as input, hidden/pattern, summation and output layer. PNN is mostly used for classification and pattern recognition purpose. Figure 2 shows the structure diagram of the PNN classifier. Each layer's have the following function:

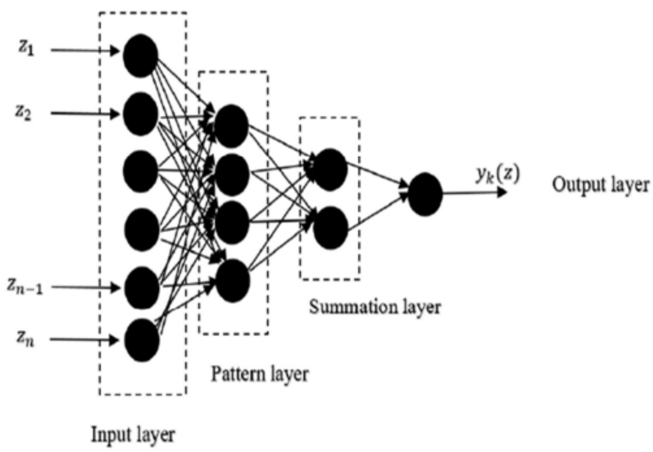

Figure 2: Structure diagram of PNN classifier

- The input layer is a representation of the input vector with a dimension equal to the number of features.
- Each observation in the training data set is represented by a neuron in the pattern/hidden layer. The pattern neuron calculates the Euclidean distance from the center point of the training sample (i.e., the neuron) to the input feature vector and then applies the Radius Basis Function kernel or RBF kernel function to this distance using the spread factor (reasonable range from 0.001 to 0.009 and from 0.01 to 0.09).
- The summation layer is comprised of a neuron that computes the sum of the outputs of the pattern layer neurons for the specific class they represent.
- The output/decision layer detects the class neuron with the highest value in the summation layer, which subsequently reflects the anticipated class for the input vector.

3. Simulation Results and Analysis

Figure 3 is a Micro-grid (MG) test model based on IEEE 14 bus Distribution system that is developed in MATLAB/ Simulink R2021a environment. The MG is coupled to the 69-kV electrical sub-transmission system. This utility grid has a Thevenin equivalent of 100 MVA with an X/R ratio of 10. There are two voltage distribution levels: a primary 13.8-kV voltage level and a secondary 220 V voltage level. Three sub-MGs are shown: AC MG 1 is an area connected at the 220 V level through lines 4, 5 and 6 to the AC MG 2. Circuit Breakers CB4, CB5 and CB6 is considered connected. It operates with 1.5 MW wind power plant powered by a Doubly Fed Induction Generator (DFIG) and supplies energy to four loads. AC MG 2 is another region that works with the 750 kW, PV Array #2, and BESS #2. The frequency of both AC MGs is 60 Hz. The third section is a DC bus-bar that includes the BESS #1, 12.5 kW PV Array #1, and PHEV quick charging station. The BESS system #1 is linked via a boost-buck bidirectional converter, whereas the PV Array #1 is linked via a boost converter to the DC link. The DC bus-bar is connected to the AC MG 2 by two parallel bidirectional converters that can function as rectifiers or inverters and exchange active and reactive power via two transformers. Instead of the two original converters, an equivalent bidirectional converter has been included in the one-line diagram. Details regarding bus parameters and loads of the test model is given in[27].

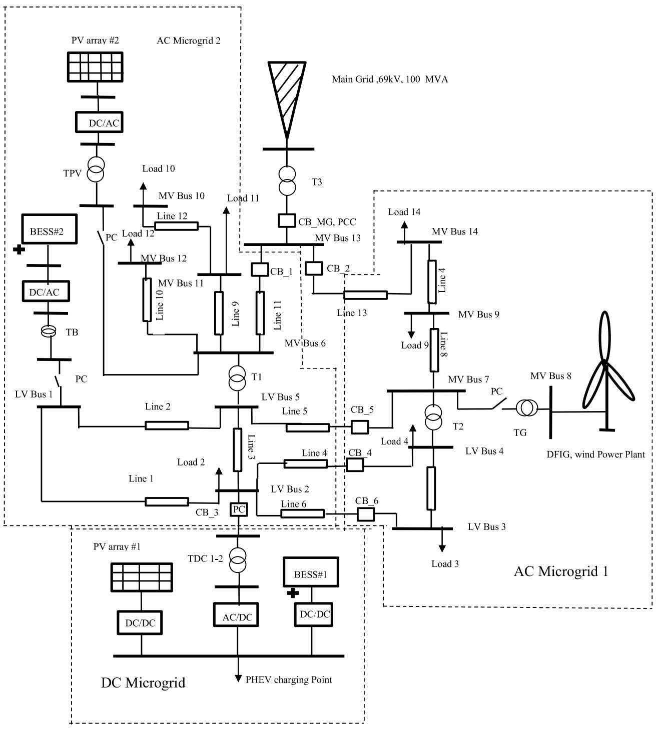

Figure 3: IEEE 14 Bus test system[27]

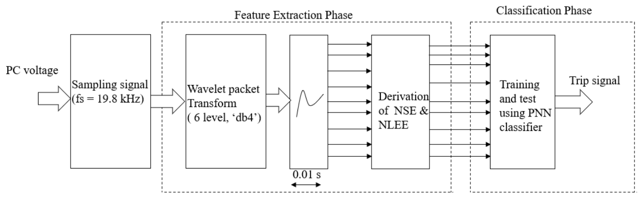

Figure 4: Architecture of IDM

Figure 4, illustrates the architecture of the proposed method. It consists of three modules. The working process of the proposed algorithm is summarized as follows:

- At first, the wavelet packet node matrix is computed using one cycle of the sampled three phase PC voltage signals. The sampling frequency of the three phase PC voltage is 19.8 kHz, with 330 samples per cycle.
- Second, the PC voltage is split into 64 separate bands (level 6) using a multi-resolution wavelet packet with the mother wavelet "db4", and feature values, i.e., NSE and NLEE, are computed for each frequency band using a 0.01 s window.
- Finally, to determine whether or not islanding or faults occur, the command block will be executed so that if islanding or faults cases are detected, the proposed IDM transfers a "trip signal is set to 1" command, whereas non-islanding cases transfer a "trip signal is set to 0" command.

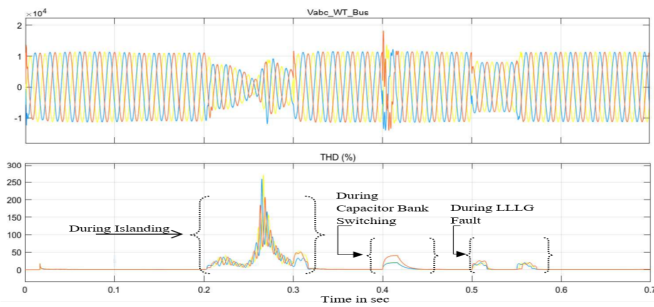

Figure 5: Voltage and THD at PC of Bus 7 during islanding and non-islanding events

Figure 5 shows the wave form of 3-phase Voltage and associated Total Harmonic Distortion (THD) in percentage at

Medium-Voltage (MV) Bus 7. The islanding scenario was created by switching the CB MG at t=0.2 sec until t=0.3 sec. Similarly, the capacitor bank of capacity 1.5 MVAR was Switched on at t=0.4 sec and switched off at t=0.42 sec. Also, from t=0.5 sec until t=0.56 sec LLLG fault was created. It was found that the transient signals associated with islanding, capacitor bank switching and fault events were having unique signatures. Also, the nature of transient during various aforementioned events are similar in both MV bus and Low-voltage (LV) bus in the distribution network. Thus, by capturing the signature of transient signals during various aforementioned events and feeding it to an intelligent classifier, discrimination of islanding events from non-islanding events and protection the system from unintentional islanding is possible without the trouble of nuisance tripping due to misclassification of events. According to IEEE Std 1547, distributed generation systems, such as photovoltaic (PV)inverter output currents, should have minimal distortion levels, with the total current distortion not exceeding 5% of the fundamental current. The principal harmonics of the inverter output current are of the third, fifth, seventh, and ninth orders, and the frequency range of the high frequency components of the PC voltage signal is generally between 160 and 1900 Hz. And, this frequency range can be discovered in WPT for decomposition level 6. Hence, the specified frequency bands are used as the most acceptable decomposition frequency bands to calculate the NSE and NLEE of the PC voltage. Off-line simulations of islanding and non-islanding events are used to infer crucial system behavior aspects. These occurrences are defined by two main sources, which are as follows: First, the operational requirements in IEEE 1547 standards, and then the test techniques recommended by the majority of islanding relay manufacturers.

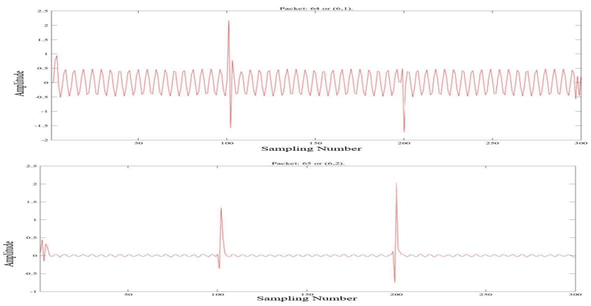

Figure 6: Wavelet Packet 64 and 65 during normal condition

Figure 6 shows the wavelet packet coefficients during normal steady state condition for 6th level decomposition as nodes/Packet 64 and 65, which were utilized as one of the most appropriate decomposition frequency bands in order to obtain feature vectors (NSE+NLEE).

3.1 Case Study 1: Islanding of AC Micro-grid1

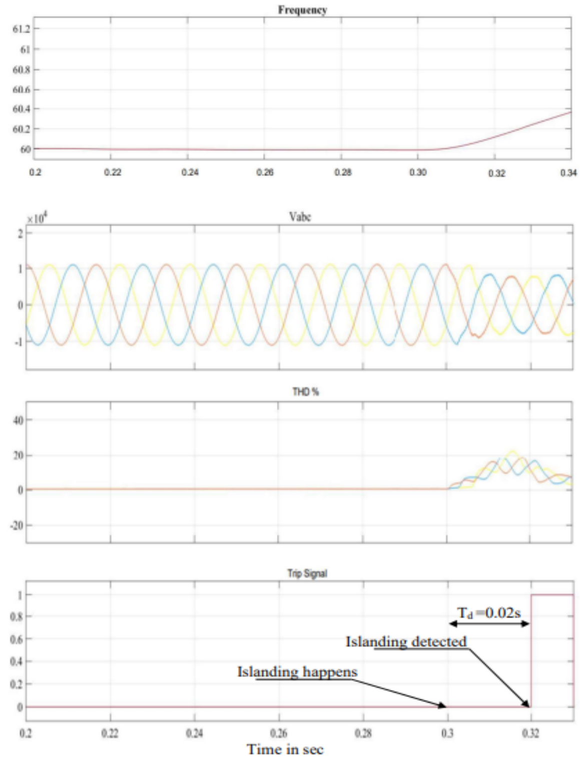

Figure 7: Frequency, Voltage, THD and Trip Signal status during islanding of AC Microgrid1

Figure 7 shows the graph for frequency, 3 phase voltage,% THD, and trip signal status during islanding operation of AC Micro-grid 1. The islanding operation, which was simulated by switching CB2, CB4, CB5, and CB6 at t =0.30 sec with generated active and reactive power, nearly equal to load demand. From figure 7, it can be seen that the rate of change in frequency and voltage right after islanding is very small, thus passive islanding detection techniques based on the Rate of Change of Frequency (ROCOF) and Rate of Change of Voltage (ROCOV) will not be able to detect this islanding condition. But with the intelligent islanding technique based on WPT and PNN the islanding condition is detected within 0.02 sec.

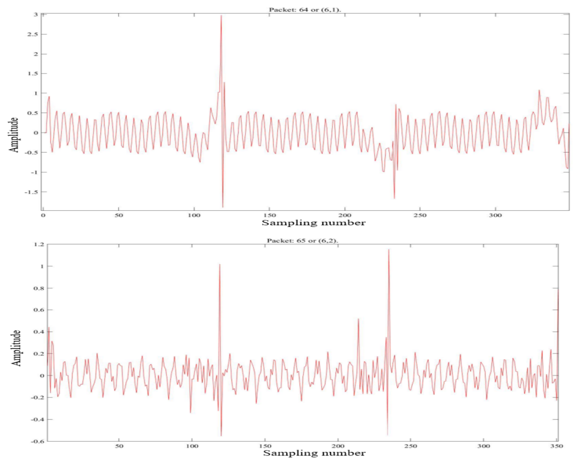

Figure 8: Wavelet Packet 64 and 65 during islanding

Figure 8 shows the wavelet packet coefficient for packet 64 and 65 at PC of Wind Turbine (WT) power plant, i.e, at BUS 7, during the islanding of AC Micro-grid 1, where it can be seen that these wavelet packet coefficients are different from those during normal operation of the system and resembles the transient signal signature during the islanding event.

3.2 Case Study 2: Impact of PHEV fast charging on proposed IDM

Due to the PHEV's low resistance at the charging moment when it is connected to the BESS, constant connection to the LV DN at the rectifier's AC side, and constant connection to the rectifier DC side of the ESS, as shown in figure 3, the PHEV's rapid charging requires a significant amount of power from the charging station. Rapid charging affects the LV DN similarly to high load switching occurring with low inner resistance. So, to mimic this situation a low resistance of 0.01 ohm was connected at the DC side[1].

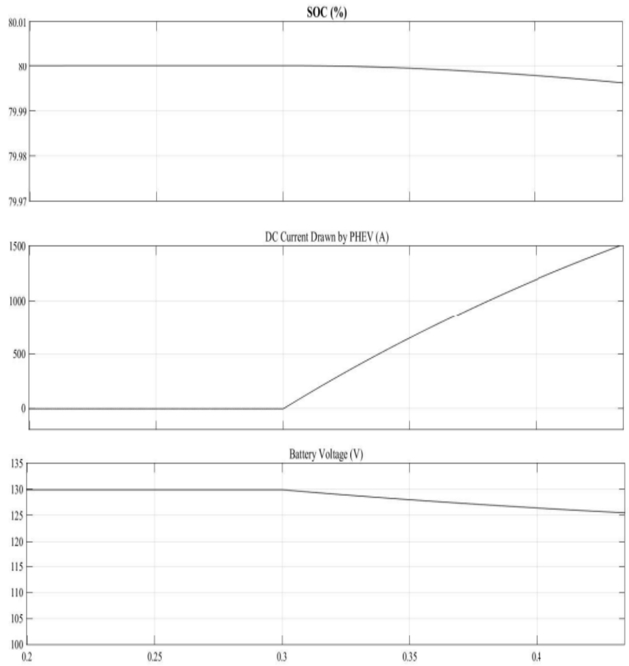

Figure 9: BESS SOC percent, DC current and Voltage during rapid charging of PHEV

The effects of rapid charging are presented on Figure 9. Figure 9, depicts the State of Charge(Soc) of the battery bank in BESS#1 which is at 80% SoC and it will be recharged until the PHEV connects and starts its rapid charging regime. When the PHEV was plugged in for charging at t=0.3 s, it can be seen that the current drawn by the PHEV rapidly rises, and the SoC and voltage of battery of the charging station decrease rapidly.

Figure 10 shows the graph for frequency at Bus 2 where the charging station(BESS#1) along with the PV Array#1 DG is connected. From Figure 10, it can be seen that at t=0.3 s i.e when PHEV rapid charging was initiated , the frequency rose rapidly for short period and then settles down. This short change in frequency could have mimicked an islanding situation. But from Figure 11, it can be verified that the islanding signal was generated only when the islanding was done at t=0.4 s.

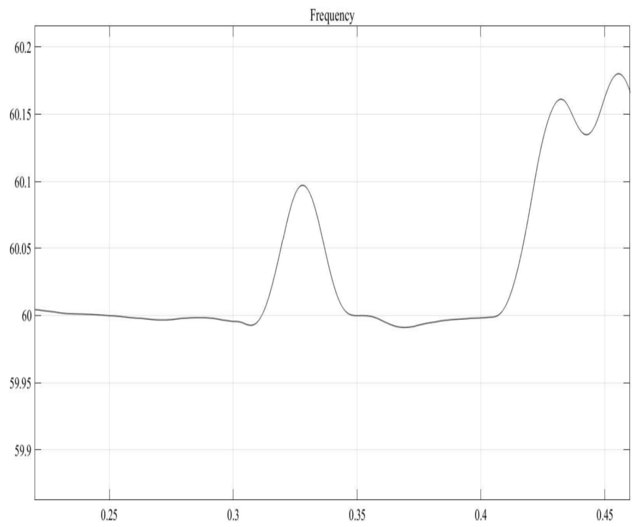

Figure 10: Frequency at PC of PHEV charging station i.e Bus 2

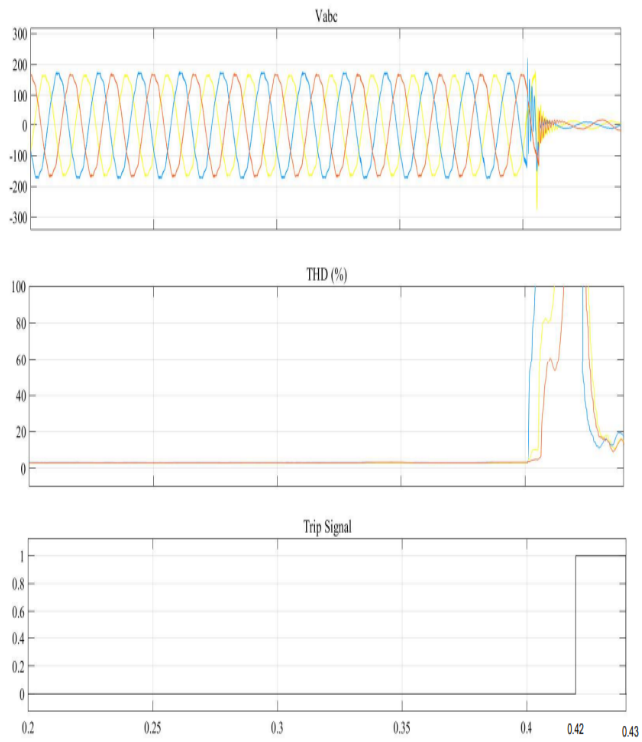

Figure 11: Voltage, THD and Trip signal at Bus 2 during rapid charging of PHEV followed by islanding

3.3 Performance analysis of WPT and PNN based IDM

A total of 300 events, which included 160 islanding and 140 non-islanding events that were generated under the different operating conditions.These events were used for training and testing of the proposed islanding detection. From the experimental simulations results the classification accuracy of almost 98.67% was obtained from the proposed scheme. Table 1 shows the classification results of the proposed WPT and PNN based IDM. Also, table 2 shows the comparison of IDMs in terms of performance indices.

Table 1: Classification accuracy of proposed IDM

	Event	Total cases	Correct detection	Classification accuracy (%)
Training	Islanding	30	30	100
Training	Non-islanding	40	40	100
	Total	70	70	100
Testing	Islanding	160	156	97.34
Testing	Non-Islanding	140	140	100
	Total	300	296	98.67

Table 2: Comparison of IDMs in terms of performance indices

Reference	Technique name	Test system	Detection time (s)	Accuracy (%)	NDZ (%)
[1]	SVM	Only Inverter Based (IB) DG	0.040	100	9.52
[10]	SVM	Only IB DG	0.50	99.49	Zero
[28]	DT	Only IB DG	0.22	100	Almost zero
[29]	RPNN	Only IB DG	0.188	100	Almost Zero
[30]	ANFIS	Two IB DG	0.040	78.71	Almost Zero
[31]	ANFIS	Only IB DG	fast	-	Zero
[32]	DNN	Only IB DG	0.18	98.3	Zero
Proposed	WPT & PNN	Only IB DG	0.020	98.67	Almost Zero

4. Conclusion

The anti-islanding protection capability of intelligent islanding detection technique based on WPT and PNN was investigated in the power distribution network integrated with multi-DG units and PHEVs charging stations. For investigating the performance of the proposed IDM, performance indices parameters like NDZ, detection time and classification accuracy were considered. Also, the discrimination capability of the proposed IDM in discriminating islanding events from non-islanding event such as rapid charging of PHEVs was investigated.The approach was discovered to be capable of detecting islanding occurrences under the worst-case situation, when the DG output power is almost equivalent to the local load consumption, according to modeling and experimental data. The reduction of the NDZ region is therefore close to zero using the proposed strategy.In all cases of study, islanding condition is successfully detected and the detection time is less than 2 sec. i.e., 0.02 sec. Only one input (voltage) signal is required in this technique, and hence the designed algorithm has less computational burden on the Digital Signal Processing (DSP) unit. The summation of NSE & NLEE features, a mother wavelet of db4, the sixth level of decomposition, and a spread factor of 0.001 for PNN were used to achieve a classification accuracy of 98.67 %. Also, the proposed scheme is competitive with similar Intelligent islanding detection techniques.

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