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Advanced in Islanding Detection and Fault Classification for Grid-Connected Distributed Generation using Deep Learning Neural Network

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***Abstract* – Nowadays, the use of renewable energy is increasing, especially distributed power generation (DG) connected to the power grid. There are several problems when DG is connected to the grid. The principal obstacle pertains to the detachment of Distributed Generation (DG) from the grid, a phenomenon well known as islanding. Islanding detection is an important task that should be completed in no more than two seconds. Earlier studies have shown several approaches to islanding detection. The use of an Artificial Neural Network (ANN) based on the learning vector quantization (LVQ) technique is proposed in this paper for fault classification and islanding detection in grid-connected distributed generators. The method consists of discrete wavelet transform (DWT), which extracts some features from the fault signal. Then, LVQ is used to classify the disturbance and detect islanding events. Power, entropy, and total harmonic distortion (THD) are used to obtain the total harmonic value. All features become inputs for LVQ, and system disturbances, lightning, and islanding disturbances are used as LVQ outputs. There are 600 datasets consisting of 200 datasets for each fault as training data. To test the LVQ training results, 120 datasets consisting of 40 datasets for each disturbance are used. The training error is made at 0.1 percent to get good testing results. The test results from 120 datasets showed that the test data achieved 99.10% accuracy. In other words, the test results are very effective because there are only 0.9% errors, and there are 2 test data that do not match the actual situation.**

Keywords: Distributed generation, Learning vector quantitation, power, entropy, total harmonic distortion.

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I. INTRODUCTION

The increasing use of renewable energy has been the main driver behind the recent spike in distributed generation (DG) usage. The Minister of Energy and Mineral Resources of Indonesia, rule number 26 of 2021, which addresses grid-connected rooftop solar PV, is an example of this [1],[2]. In order to generate power from solar energy, this legislation encourages the installation of rooftop solar power generation installations. Even while this cutting-edge technology offers many benefits, incorporating it into the main power system is not without its challenges. One significant area for improvement is identifying islanding situations in which dispersed generation is cut off from the main power grid [3]. Islanding is a condition or situation where part of the power grid or power generation system becomes isolated and still generates its power, separate from the main Grid [4], [5]. In an islanding situation, the part continues to operate autonomously, even when disconnected from the main grid. This can happen when distributed power generation (such as solar panels or wind turbines) is connected to the main grid but isolated due to a fault on the grid. Islanding can be a severe problem as it can cause potential danger to operators and cause damage to equipment if not detected and addressed quickly [6], [7]. Islanding detection is identifying and disconnecting the power supply when this condition occurs.

According to the standard proposed by IEEE, islanding detection should be done in less than two seconds, and the power source should be disconnected [8], [9]. Therefore, various methods have been proposed to detect islanding quickly. These methods can be grouped into two main categories: remote and local. Remote methods include a Power Line Signaling Scheme, Signal Produced by Disconnect, Transfer Trip Scheme, and Impedance Insertion Method. Local methods are grouped into two categories, namely, conventional and modern methods [10]. Implementing remote islanding detection systems comes with a high cost, and using active techniques negatively influences power quality and adds complexity to the system by requiring additional power electronics controllers [11]. Conventional methods consist of active, passive, and hybrid methods [12]. Modern methods consist of Signal Processing and Signal Estimation methods. Among these methods, active, passive, and hybrid methods are most likely to produce an islanding detection time of less than two seconds.

Several previous studies related to islanding detection methods have been published in journals. Among them is the use of active methods in islanding detection, with the main concept in active islanding detection methods being to introduce distortion to the voltage wave pattern in the electrical system [13]. Islanding detection is also carried out using passive methods based on observation and analysis of power network characteristics to detect significant changes [14], [15]. Islanding can also be detected using a hybrid method by identifying islanding events in distributed generation (DG) units that use inverters [16], [17]. It is known that the islanding detection methods that have been used are quite effective for detecting islanding. However, these methods still need to improve, such as expensive devices, potential power degradation, relatively larger NDZ, longer detection time, higher complexity, and the fact that they can only detect islanding conditions in DG systems connected to the grid.

Not just islanding occurs when DG is connected to the grid. Various other disturbances also exist, some of which are internal disturbances and external disturbances (lightning). Disturbance In general, disturbance indicates a condition where something deviates from its intended function [18]. In power systems, disturbances are usually associated with anomalies in the flow of electricity, especially short circuits, which occur when the current goes beyond normal operating conditions. Faults such as short circuits in the power grid system not only lead to significant economic losses but also diminish the overall efficiency of the power system [19]. An electrical fault is an occurrence that stems from malfunctions in machinery, including transformers and rotating machines, as well as human errors and environmental factors.

This paper proposes an Artificial Neural Network (ANN) based on the Learning Vector Quantization (LVQ) method for islanding detection. This method cannot only detect islanding but can also classify other disturbances in the DG system connected to the grid, including internal and external system disturbances. This method also offers a more comprehensive and efficient solution for islanding detection and disturbance classification, overcoming many of the existing methods' shortcomings and significantly improving islanding detection and disturbance management in DG systems.

II. METHOD

A. *Wavelet Transform*

Fault detection methods utilizing machine learning are frequently amalgamated with wavelet transforms to recognize islanding occurrences in power systems. Although these approaches prove effective, concerns emerge regarding extended detection durations and considerable computational requirements, particularly in real-time settings. Therefore, adopting a signal processing-focused approach that can furnish reliable islanding detection without sacrificing processing speed becomes imperative. This is critical in power system contexts, guaranteeing prompt responses to islanding conditions to prevent safety risks and potential damage to equipment [20].

In this formula, 'x' and 'y' denote the scaling and translation constants correspondingly, while '(a)' signifies the wavelet function. The Discrete Wavelet Transform (DWT).

$$WT(f,x,y) = \frac{1}{\sqrt{x_0^m}} \sum f(k) \Psi\left(\frac{n-kx_0^m}{x_0^m}\right) \tag{1}$$

where k, m the are integers, $\frac{1}{\sqrt{x_0^m}}$ is the basis function, and Ψ is the mother wavelet.

$$c_j(n) = \sum_k f(k) \Psi\,(2n-k) \tag{2}$$

$$d_j(n) = \sum_{m=-\infty}^{\infty} x(k) g\,(2n-k) \tag{3}$$

Equations (2) and (3) demonstrate the rough estimation and elaborate coefficients. The Daubichies's mother wavelet, "db4," is employed in this research for islanding detection.

The Wavelet Transform (WT) proves to be a powerful method for breaking down a transient signal into a sequence of wavelets, each representing distinct frequency components within a given time span. Emphasizing specific frequency bands, each wavelet mimics a signal in the time domain, offering a more comprehensive representation than traditional time or frequency analyses. The outcome of the wavelet transform yields valuable insights in the time-frequency domain, facilitating a more profound comprehension of the signal's structure and characteristics [21].

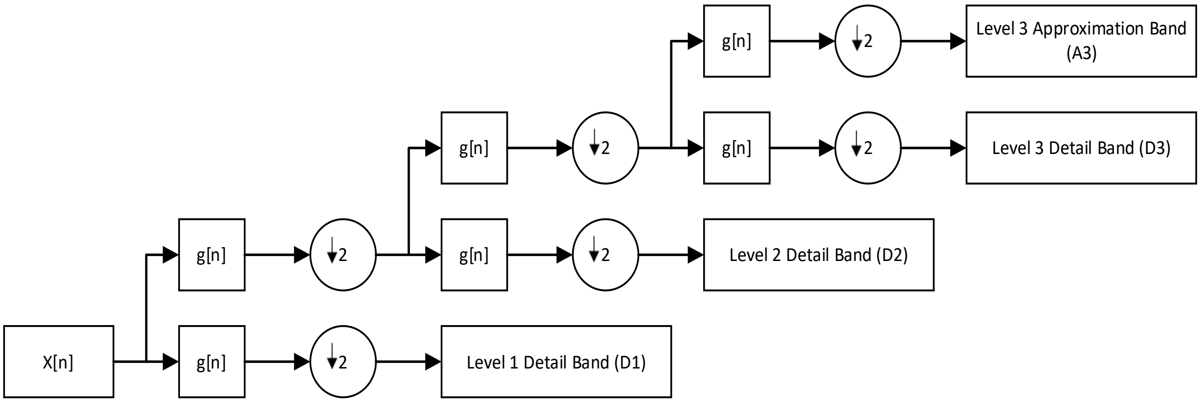


Figure 1. Three-levels decomposition model of Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform (DWT) is a powerful signal processing technique that simultaneously analyzes a signal's frequency and time characteristics [22]. The prevalent use of DWT compared to Continuous Wavelet Transform (CWT) can be attributed to its heightened computational efficiency, effective data compression, simplicity, and absence of redundancy [23]. It accomplishes this by employing high-pass and low-pass filters to extract high-frequency details and low-frequency approximations from the signal. This decomposition process can be iterated to various levels, providing a multi-resolution signal representation. The resulting detail and approximation coefficients allow analysts to explore fine-grained details and broader trends within the signal, making the DWT invaluable for tasks such as denoising, feature extraction, and data compression. The scheme of decomposing signals based on frequency and time can be seen in Figure 1.

B. Learning Vector Quantization (LVQ) Neural Network

Learning Vector Quantization (LVQ) is a training technique for aiding neural networks in pattern recognition and data classification [24], [25]. It imparts supervised learning to the competitive layers within the network, enabling them to autonomously learn the classification of input vectors [26]. Essentially, LVQ enhances the ability of artificial neural networks to identify patterns in data and improves their information processing capabilities [26], [27].

Figure 2 illustrates the LVQ neural network architecture, featuring four units in the input layer and two neurons in the output layer. The input encompasses wavelet power until 5 level, approximation, entropy, and total harmonic distortion (THD). The hidden layer consists of two neurons: X is the learning rate, and W is weighted.

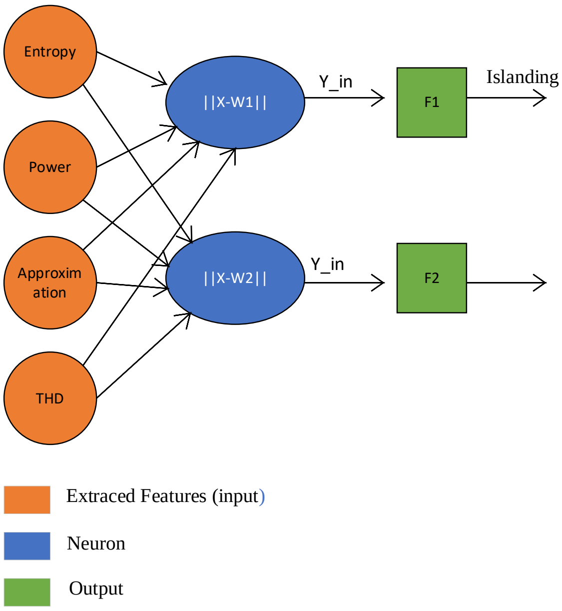


Figure 2. Learning Vector Quantization Architecture

The classification output comprises islanding (F1) and non-islanding (F2), consisting of a system fault and lightning. The input data for this research consists of simulated fault system data, lightning data, and islanding condition data. These fault scenarios were simulated using ATP/EMTP software. ATP/EMTP stands for Alternative Transients Program / Electromagnetic Transients Program [28], [29]. It is a software tool for simulating and analyzing power systems in the time domain. The program was developed by Dr. Scott Meyer and his team in the United States and is distributed by the European EMTP Users Group. The software is widely used for simulating power system transients, including lightning strikes, switching operations, and other disturbances [30]. Figure 3 illustrates the flowchart of the islanding detection and fault classification method. As depicted in Figure 3, when islanding conditions and other faults occur, the corresponding waveforms are captured at the measurement point, in this case, the PCC (Point of Common Coupling). Subsequently, these waveforms are made symmetrical through a symmetrical component transformation operation.

The negative waveform resulting from the balanced component is decomposed using wavelet transformation.

Table 1. LVQ Training Parameters

Parameters	Value
Number of hidden neurons	30
Element vector of typical class percentages	0.5 0.25 0.25
Learning rate	0.001
Learning function	learnlv1
Numbers of Epochs	1000

The training data and targets are utilized to train the LVQ neural network using LVQ parameters as specified in Table 1. Meanwhile, the testing data is employed to evaluate the results of the LVQ training.

Figure 3 illustrates the flowchart of the islanding detection and fault classification method. As depicted in Figure 3, when islanding conditions and other faults occur, the corresponding waveforms are captured at the measurement point, in this case, the PCC (Point of Common Coupling). Subsequently, these waveforms are made symmetrical through a symmetrical component transformation operation. The negative waveform resulting from the balanced component is decomposed using wavelet transformation.

Features, such as energy level and entropy, are extracted from the detail components at a specific level. Other features, such as total harmonic distortion (THD), are also extracted from the disturbance waveform. All data is divided into training and testing sets with an 80 and 20 percent composition, respectively.

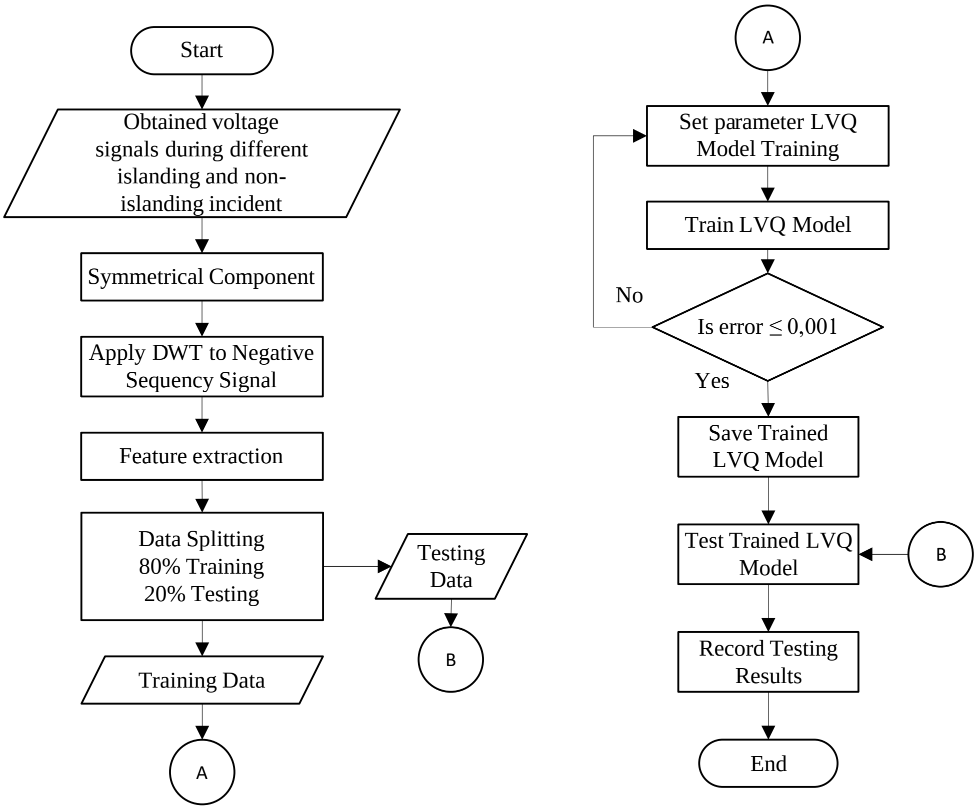


Figure 3. Flowchart of method

III. RESULTS AND DISCUSSION

Figure 4 depicts the simulation circuit of a photovoltage connected to the grid with various system disturbances, lightning, and islanding. The photovoltage has a power of 500 kWp with a local load ranging from 2 kWp to 300 kWp, increasing by two kWp for each change. The grid load is set at 1.5 MVA and 5 MVAr, with the measurement point (PCC) placed after the inverter on the photovoltage side. Simulation results of disturbances and others can be observed in Fig 5(a), 5(b), and 5(c).

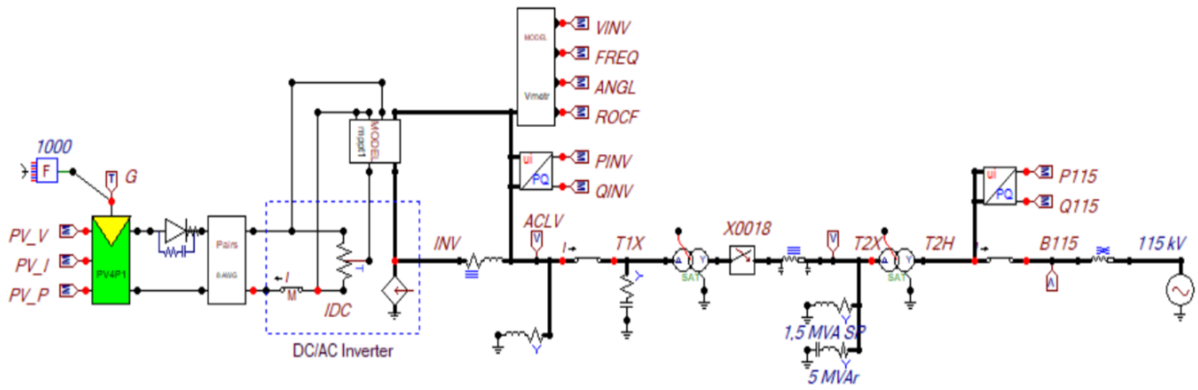
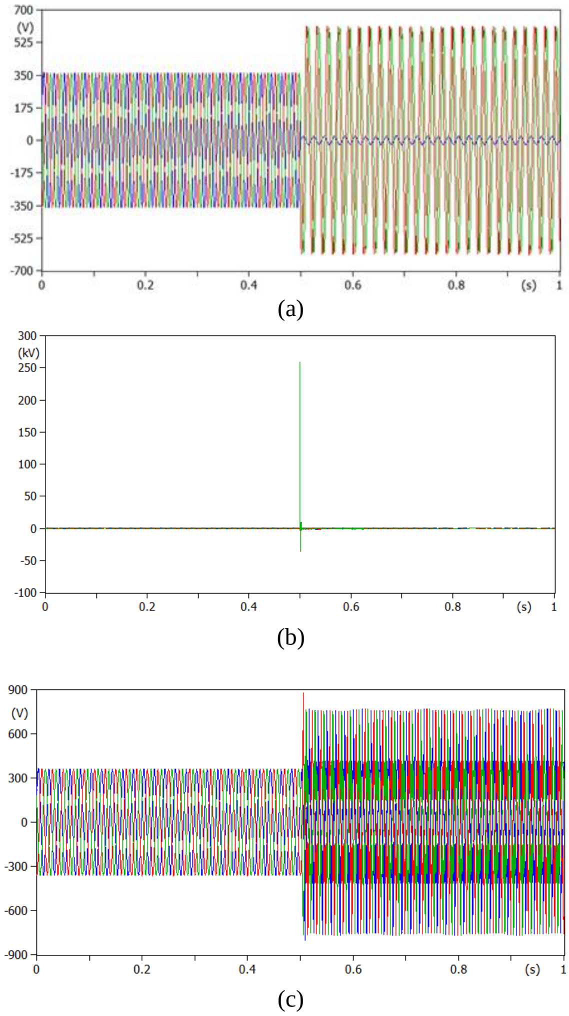


Figure 4. Fault data generated on DG systems connected to the grid

Figure 5 (a) shows the simulation results of a single-phase A-to-ground fault, where the voltage in phase A approaches zero while phases B and C increase almost twice their original values. In Figure 5 (b), the simulation results depict the effect of lightning on the photovoltage connected to the grid. Figure 5 (b) shows that the lightning disturbance generates highly transient voltage, reaching almost 250 kV, 75 times greater than the initial value. Finally, Figure 5 (c) illustrates the simulation results of islanding conditions in the photovoltage system connected to the grid. It can be observed from Figure 5 (c) that the voltage increases after islanding occurs for all three phases: A, B, and C. When islanding occurs (when a photovoltaic system is disconnected from the main power grid), the voltage doesn't always increase; some voltages decrease, while others remain stable. This depends on the local load from the solar panels (PV). It's crucial to ensure that the impact of islanding doesn't exceed 2 seconds to maintain system reliability.

Wavelet energy, entropy, and total harmonic distortion of disturbances were extracted and became input to the LVQ neural network. There were 600 data points involved in this study, of which 480 data points were used to train the LVQ network and another 120 data points to test the trained model. In the context of neural networks, training data (comprising 480 data points) is used to teach the model by adjusting its weights and biases, while testing data (120 data points) evaluates the model's performance. Each type of disturbance contributed 200 data points, of which 160 data points were allocated for training and 40 data points for testing. The test results of the 40 data points are illustrated in Figure 6, which shows that the test data obtained an accuracy of 98.33%, corresponding to the actual data. These results were validated using the confusion matrix, as illustrated in Figure 7. The confusion matrix shows 2 mismatched outputs out of 120 test data points for each fault correctly classified. Overall, these findings demonstrate the effectiveness of LVQ neural networks in detecting islanding and classifying faults in grid-connected DGs with very low error values.



(a)

(b)

(c)

Figure 5. (a) The ATP/EMPT result of phase A to ground fault, (b) The ATP/EMPT result of a lightning fault, and (c) The ATP/EMPT result of the islanding condition

Through successful training, LVQ can accurately classify regular states and different types of disturbances. To achieve precise outcomes, it is necessary to have a training dataset that encompasses diverse electrical system conditions, encompassing standard forms and various kinds of faults condition.

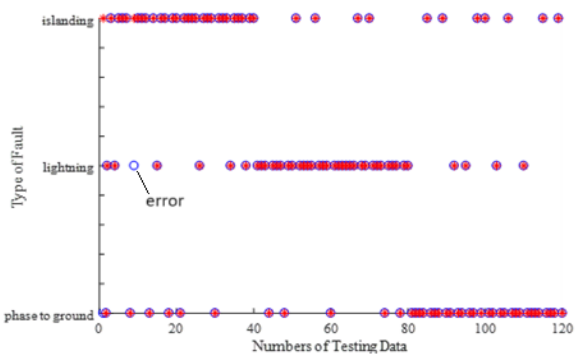


Figure 6. Result of LVQ classification

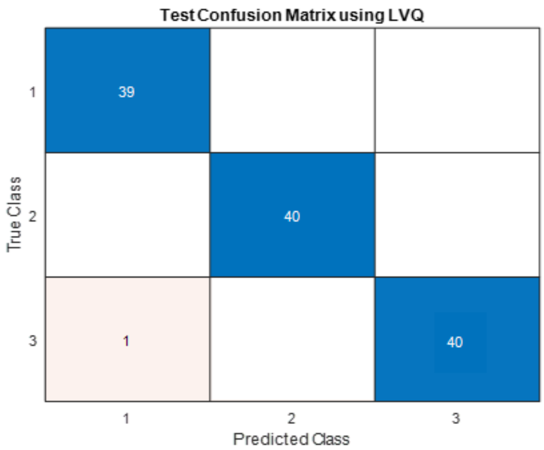


Figure 7. Validation of test results using the Confusion Matrix

Islanding detection and fault classification are critical to ensuring the reliable and safe operation of distributed generation (DG) systems connected to the grid. Islanding refers to the situation where a portion of the DG system continues to generate power independently of the main grid during a grid outage. Detecting islanding events promptly is essential to prevent safety hazards and damage to equipment. Linear Vector Quantization (LVQ) is a machine-learning technique that can be employed for islanding detection and fault classification in DG systems. LVQ is an artificial neural network that learns to classify input patterns based on training examples. This study extracted features such as wavelet energy, entropy, and total harmonic distortion from disturbances in the electrical grid. These features were utilized as inputs for the Linear Vector Quantization (LVQ) neural network. 600 data points were involved in this study, with 480 data points used to train the LVQ network and another 120 data points to test the trained model. Each type of disturbance contributed 200 data points, of which 160 data points were allocated for training and 40 data points for testing. The test results of the 40 data points are illustrated in Figure 6, which shows that all the test data matches the actual data. Remarkably, the LVQ test showed an accuracy of 99.10%. These results were validated using a confusion matrix, as illustrated in Figure 7. The validation confusion matrix shows that there are output classes that do not match, i.e., one data point that do not match. Overall, these findings demonstrate the effectiveness of the LVQ neural network in classifying faults in the power grid very well, with an accuracy of 99.10% compare to previous journal such as [31] with accuracy just 98.9%.

Using a laptop equipped with an AMD Ryzen 7 5800H processor, 16 GB of RAM, and a 64-bit Windows 10 operating system, the time required to complete the training of this method is approximately 605 seconds for all simulation data. Meanwhile, the time needed to perform islanding determination testing using this method is only about 0.82 seconds, which is well below the 2-second limit specified in IEEE 1547.

IV. Conclusion

Islanding is a phenomenon in which dispersed generation is detached from the grid, which can cause danger to equipment and operators at the DG site. detection to determine whether it was true islanding or another disturbance is necessary.

The application of Linear Vector Quantization (LVQ) for islanding detection and fault classification in grid-connected distributed generation systems has proven very effective. This research involves developing and applying LVQ algorithms to analyze grid disturbances and identify islanding events. Simulation results show that the LVQ-based method successfully classifies various fault scenarios, including short circuits, lightning, and islanding faults. This enables timely and accurate responses to mitigate potential risks associated with islanding operations. Islanding detection and fault classifications are essential to ensure the reliable and safe operation of grid-connected distributed generation (DG) systems. LVQ is a machine learning technique that can be used for islanding detection and fault classification in DG systems. LVQ is an artificial neural network that learns to classify input patterns based on training examples. Features extracted from wavelets, such as wavelet energy, entropy, and fast Fourier transform, extract the total harmonic distortion of disturbances in the power grid. These features are used as inputs for the LVQ neural network. LVQ testing showed an accuracy of 99.10%. These results were validated using a confusion matrix. Overall, the findings demonstrate the effectiveness of LVQ neural networks in accurately classifying faults in power grids. The quality of its training significantly influences the effectiveness of LVQ. Including a diverse set of training data covering various fault and islanding conditions enhances the model's capacity to identify complex situations.

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