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Islanding Detection for PV system using Artificial Intelligence Techniques

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ABSTRACT

The rapid proliferation of photovoltaic (PV) systems in the power grid has underscored the critical importance of effective islanding detection mechanisms to ensure safety, reliability, and compliance with grid standards. Islanding occurs when a portion of the grid operates in isolation from the main power supply, potentially posing risks to equipment and personnel. Traditional detection methods often struggle with detection speed and accuracy, particularly under non-ideal conditions.A hybrid model combining the strengths of machine learning algorithms and signal processing techniques to enhance the sensitivity and specificity of islanding detection. The model employs a two-stage process: the initial stage uses signal characteristics extracted from the PV system's output to generate preliminary detection signals. These signals are then analyzed by a deep learning algorithm, specifically a convolutional neural network (CNN), trained on a comprehensive dataset representing a wide range of islanding and non-islanding scenarios, including various load and generation balances, to make the final determination. This study introduces a novel approach to islanding detection in PV systems, leveraging the capabilities of artificial intelligence (AI) techniques, analyzed and validated using MATLAB software.

KEYWORDS: Islanding Detection, Photovoltaic Systems, Artificial Intelligence, Machine Learning, Deep Learning, MATLAB, Grid Safety, Renewable Energy Integration.

1. INTRODUCTION

Islanding detection is one of the most critical issues considered in any distributed energy resource (DER). Islanding occurs when a part of the distribution system becomes isolated from the main supply. If islanding is detected, the DER should be tripped out. Typically, a DER should be disconnected within 0.1-2 seconds after the loss of the main supply [1-3]. If the islanding is failed to detect, the islanding may lead to power inequality issues and safety issues for machines and humans. Different techniques are presented in the literature for these purposes. These techniques can be broadly divided into remote and local techniques. Remote techniques are associated with islanding detection on the supply side and the local on the DER side. In remote techniques, communication is needed to send a trip signal to the DER when the islanding is detected. Furthermore, Local algorithms divide into passive, active, and hybrid methods.

The main philosophy of the local techniques is based on monitoring the output of the DER and detecting the status of the main supply. This monitoring may base on output power, voltage, frequency, current, etc. If the external source (auxiliary) injects current, power, harmonic…. to the system, in parallel with the monitoring, the technique is called active techniques, otherwise it is called passive technique.

Some of the remote detection techniques presented in the literate are based on the transfer scheme trip and power line signaling scheme. The concept of the transfer trip scheme is based on monitoring all breaker status and sent a trip signal to the DER if the islanding is detected. Supervisory control and data acquisition (SCADA) [4], or wide-area monitoring system (WAMS) [5-6] are used as remote IDM. The signal is continuously generated at the transmission side in the signaling technique, and the DER has a receiver to detect this signal. In these techniques, the islanding status is proved if the DER does not receive any signal [7-9]. A high-frequency impedance estimation-based technique is an example of active detection techniques [10]. In [10], the potential failure mechanism of the f-Q (frequency-reactive power) drifting is analyzed. Then, the researchers proposed a high-frequency transient injection-based islanding detection method. From the results of this paper, the high-frequency temporary injection method is better than the traditional injection method. Another researcher presents a detection method as an example of passive techniques in [11]. In [11], researchers using the Forced Helmholtz Oscillator to the signal at the point of common coupling. The dynamic characteristics of the synchronous generator and signal processing technique are presented in [12]. This paper proposes a hybrid islanding detection method for distribution systems containing synchronous distributed generation (SDG) based on two active and reactive power control loops and a signal processing technique.

Other techniques based on artificial neural network are presented in [13-15]. In [13], the proposed artificial neural network (ANN) employs minimal features of the power system. The performance comparison between stand-alone ANN, ANN- evolutionary programming, and ANN- particle swarm optimization in the form of regression value is performed. In [14], a new composite approach based on wavelet-transform and ANN for islanding detection of distributed generation is presented. The wavelet transform is used to detect events, and then the artificial neural network (ANN) is used to classify islanding and non-islanding events. In [15], the S- transform is used to obtain the frequency spectrum at the terminals of the DER; then, the ANN is used to identify whether the event is islanding. Like other protection functions [16-18], WAMS and machine learning can be used to detect the islanding in the system and send a protection signal to the remote protective relays to prevent any mis operation. Still, it is expensive to apply and need a good communication infrastructure.

2. ISLANDING DETECTION PRINCIPLES AND METHODS

2.1. Islanding Operation in Distribution Grids

Nowadays, there are three types of distribution grids: passive, active, and microgrid. **Figure 1** displays part of the passive, 10 kV distribution grid. The direction of electric energy flow is from the transmission grid (where power plants are connected) through the distribution grid to consumers. Assume that a fault has occurred on the 10 kV transmission line connecting busbars W1 and W0 (the location of the fault is represented by the lightning symbol in **Figure 1**). Then, the protective device will activate the CB6 switch, and the faulted line will be switched off. Simultaneously, the local load (see **Figure 1**) will be disconnected and left without electricity until the faulted line is repaired. In passive grids, the occurrence of islanding operation is not possible.

If the DGs (i.e., a photovoltaic PV and a synchronous generator GEN) are connected to bus W0, the passive grid becomes active—Figure 2. Bus W0 is now a point of common coupling (PCC) between the DGs and the distribution grid. Let us assume the same event as in the case of Figure 1, i.e., line fault and its disconnection. Even though the faulted line is disconnected from the rest of the distribution network (via CB6), the DGs can still supply the part of the network connected to the PCC and the faulted line. The protection schemes and devices need to be updated to ensure the disconnection of the faulted line (CB 7 needs to be installed and connected to the protection device). Such a situation is an example of an islanding operation (or islanding), and in this case, islanding is unplanned and dangerous since the faulted line is energized; workers who want to repair the line may get hurt. Many scientific papers deal with protection coordination in distribution grids with DGs; some examples are [8,9]. However, when the faulted line is disconnected, part of the grid connected to PCC (see red circle in Figure 2) is still an unplanned island. To ensure the sustainability of the islanding operation within the grid island, the balance of active and reactive power between generation and consumption needs to be maintained, which requires regulation and flexibility of the DGs. Since the flexibility of some types of DG (i.e., PV and wind) is limited, it can lead to voltage (magnitude and angle) and frequency distortions [5]. Therefore, such an unplanned grid island must be quickly detected and eliminated (by shutting down all DGs in the grid island), which imposes the need for fast and efficient IDM.

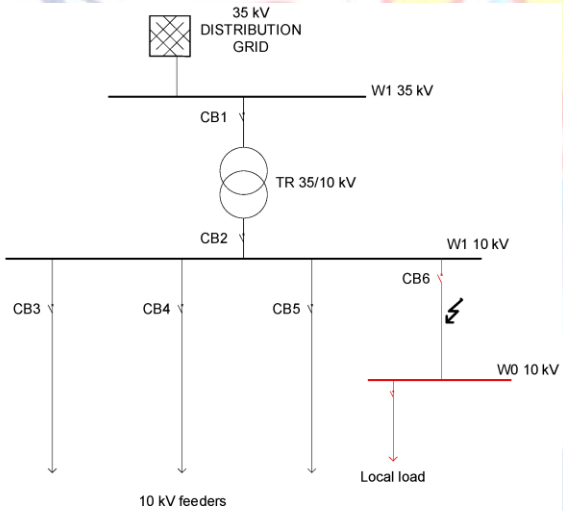


Figure 1. Passive distribution grid

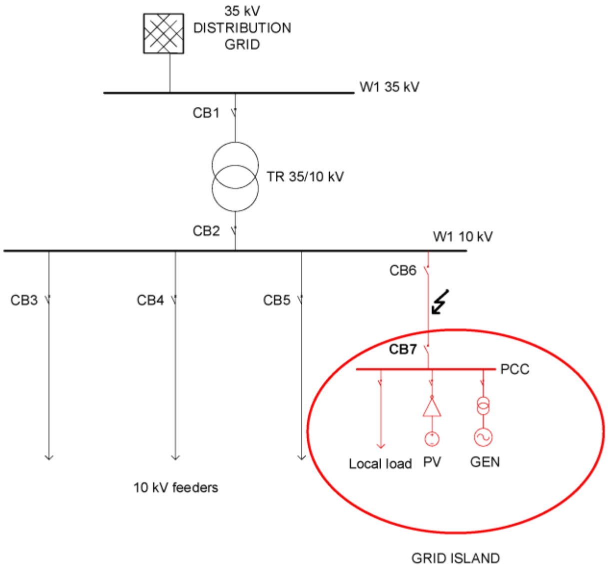


Figure 2. Active distribution grid

The possibility of the planned islanding operation is part of the microgrid definition, so an additional device, such as an energy storage system, is needed (see Figure 3). When planned islanding operation in a microgrid is present, local load needs to be supplied in a reliable manner by the energy produced by DGs or by the energy stored in the energy storage system. Although microgrids can operate in both grid-connected and island mode, they mainly work in grid mode due to high costs. If an unplanned islanding operation of the microgrid occurs (i.e., due to the faults), it needs to be detected quickly, so effective IDM is also inevitable in the microgrid.

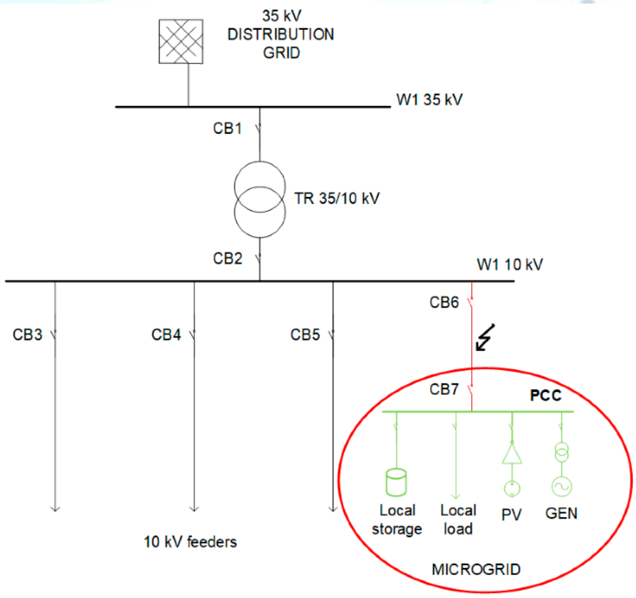


Figure 3. An example of a microgrid.

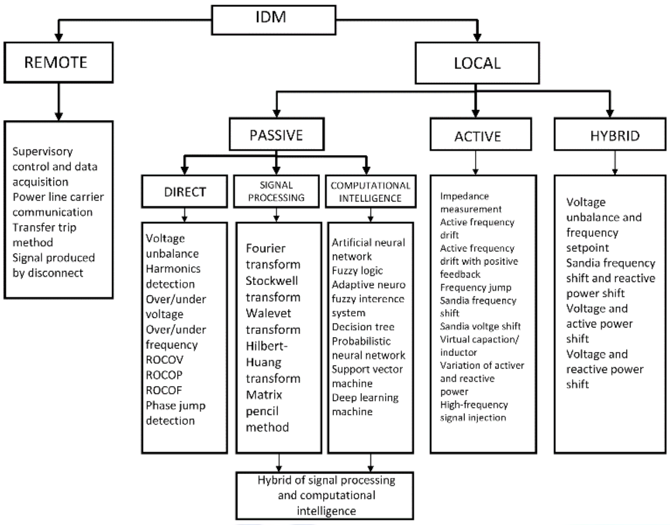


Figure 4. Islanding detection method classification

On the other hand, local methods detect islanding operations based on locally available devices and their measurements. In most cases, they do not require additional equipment cost, but their disadvantage is lower accuracy than remote methods. Local IDMs are further divided into three main groups: passive, active, and hybrid methods (**Figure 4**).

3. ANN AND LEARNING TECHNIQUES

Feed-Forward ANN structure ANN is a learning technique used in different areas for different purposes. The very widely used applications of ANN are classification applications. The main structure of the ANN is shown in Figure 1.

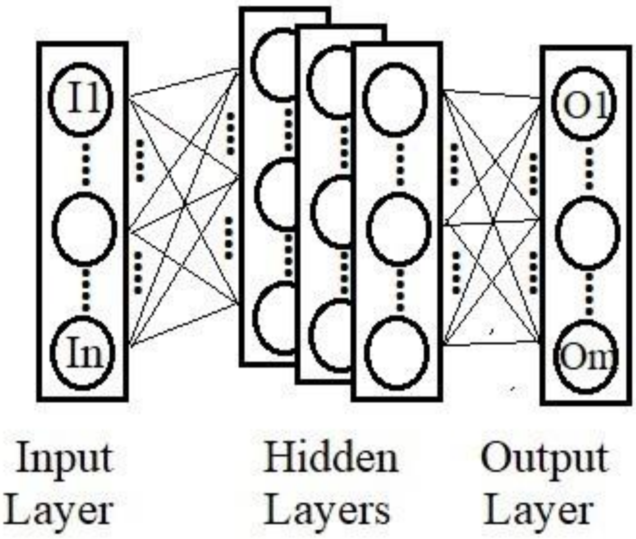


Fig 5: General feedforward ANN structure

In general, ANN has three types of layers: an input layer has n neurons, hidden layer(s), and the output layer has m neurons. Where n and m are the number of inputs and outputs, respectively. The number of hidden layers and the neurons in each hidden layer is adjustable. The optimal number of layers needs more information about the problem to identify. For this study, the number of layers and neurons are selected based on experience; then, general formula to determine the number of neurons in each layer is proposed. Each neuron has an activation function, so the neurons' output is a function of the sum of the inputs (net). Different activation functions are available to use. These activation functions may be divided into step, linear, and nonlinear functions in general. Other nonlinear functions are presented in the literature include sigmoid function, hyperbolic tangent function, rectified linear unit function, leaky rectified linear unit function, soft-max function, and switch function. Each of these functions has advantages and disadvantages. The selection of the activation function is based on the application. The sigmoid function is the most common. Each neuron in layer (i) connects with each neuron in layer (i+1) via a weight. The arrows in Figure 1 refer to the weights.

The weights in the structure are defined by the learning technique based on the inputs/outputs samples. The training samples should represent the overall behavior. The output samples are called targets, where the outputs of the neural network are called outputs. The learning techniques are mainly optimization techniques. The cost function of the methods is to minimize the sum of the absolute (square) error between the output and the target. Once the outputs and the targets are very close together, the learning is done. The backpropagation learning technique is very commonly used in this context. The main disadvantage of this algorithm is the highest probability of sticking to a local solution. Based on this concept, any optimization algorithm (hard or soft computational techniques) can be used to solve this optimization problem. In this paper, two soft computational methods: Genetic algorithm (GA) and cuckoo algorithm (CA) and one hard computational technique (backpropagation), are used and then compared

Genetic Algorithm.

Genetic algorithm (GA) is one of the very widely used techniques in optimization problems. This algorithm is based on the concept of human gene behavior. Firstly, a considerable population generated randomly has a specific number of randomly proposed solutions. Each solution is called a gene. The behavior of these genes is getting from the cost function (the value of the cost function at a specific solution 'chromosome'). If the problem is to maximize, the chromosomes with the highest values have the best performance and vice versa. From the first iteration, the chromosome which has better performance is selected, then these chromosomes will be mated to get a new population. The mating is similar to human mating, but for variable cross-over, so the latest population performs better than the old one. This procedure will repeat more and more to get the specific cost function. The mutation idea is created to prevent any predicted local solution. In the mutation process, the genes in the chromosomes are changed randomly. This simple step is used to add noise to the signal, which will help the algorithm to go over any local solution.

Proposed ANN Structure.

In this paper, three different systems are designed: Power-based system, voltage-based system, and current-based system. Five different sampling rates are tested: 400 Hz, 800 Hz, 1600 Hz, 3200 Hz, and 6400 Hz (8, 16, 32, and 64 per cycle). A complete cycle is considered as a data window. So, in a 400 Hz sampling, the system has eight inputs and a single output.

The number of layers in each system (400, 800, 1600, 3200, 6400) is selected due to Equation (1). The number of neurons in each hidden layer is defined by Equation (2). These equations are based on experience in the classification application. These equations may be used in other classification applications to identify the optimal number of the layers and neurons

$$N_{Hidden\ layer} = \log_2 \frac{N_{input}}{N_{output}} - 1 \quad (1)$$

$$N_i = \frac{N_{input}}{N_{output} 2^i} \quad (2)$$

Where, Ni: number of neurons in hidden layer number i. Two biases are added to the structure: input and output biases (independent neurons have constant output '1'). Figure 2 shows the design of the 800 Hz system. Based on previous equations, the number of hidden layers for 16 inputs and one output equals 3. The numbers of neurons are (8, 4, 2) per each layer, respectively. In this example, the number of weights (size of the optimization techniques) = 51. Generally, the number of weights (Nw) is given by Equation (3), where Nh is the number of the hidden layer.

$$N_w = \left(\frac{N_{input}}{N_{output}}\right)^2 * \sum_{i=1}^{i=N_h} \left(\frac{1}{2 * 4^i}\right) + \frac{N_{input}}{2} + N_{output} \quad (3)$$

The sigmoid function is selected as an activation function of all neurons in this paper. In Figure 2, the green cycles refer to inputs, grey cycles refer to the neurons in hidden layers, red cycles refer to the output neuron, and white cycles refer to biases. Each simulation cycle is used as a sample in the training phase, either with the islanding status or non-islanding status. For each data rate, there is a specific number of inputs. In the simulation phase, the algorithm uses several cycles to decide either the system is islanding or not. The number of cycles depends on the sample rates used. The higher the sample rate, the better the accuracy.

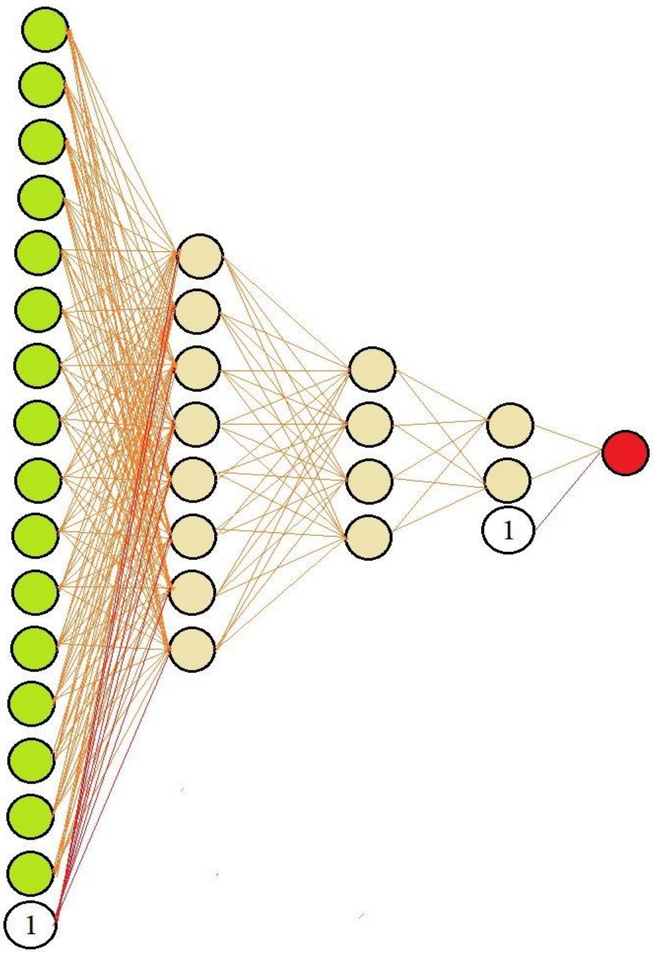


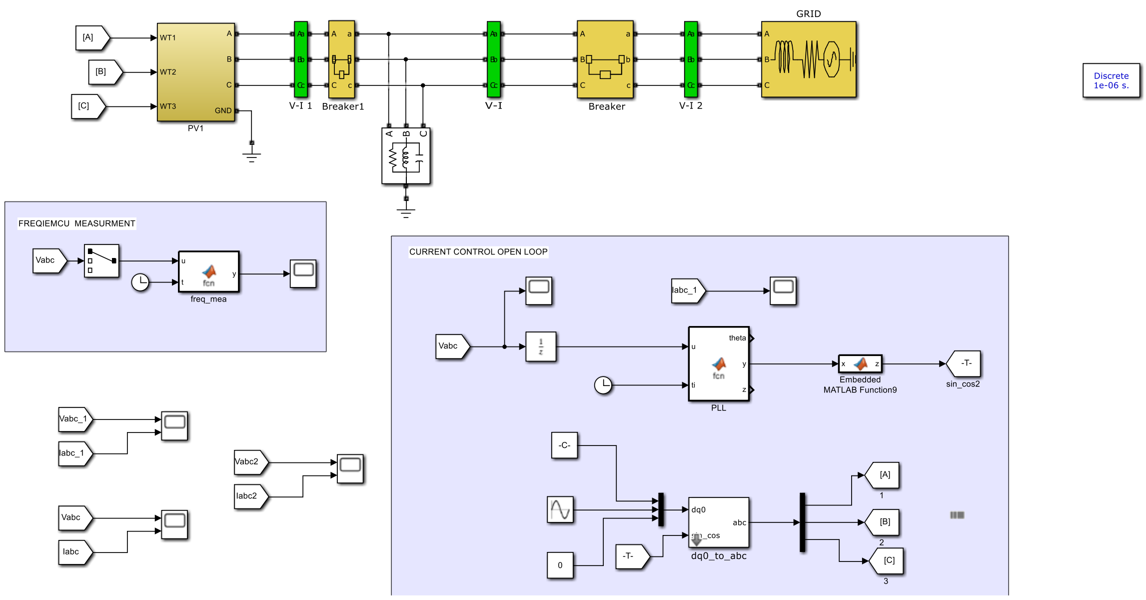
Fig 6: ANN structure, for an example of sample rate equal to 800 Hz

System Understudy.

Different sample rates are considered in this section: 0.4, 0.8, 1.6, and 3.2 KHz. Figure 3 shows the simulation system. Three scenarios are covered here: increase the load to its double value, decrease load to its half value, and trip main supply. Ten cycles are covered for each scenario (five cycles before the event and five cycles after the event). So for each load level, 30 samples are generated (10 samples for load up event, 10 samples for load down event and 10 for the islanding event). Two data sets are generated at different load levels: test data used in training systems and validation data used in simulation systems. Different load levels are covered from 0.2 Pu to 2 Pu stepped by 0.1 Pu for the training data set and from 0.25 to 1.95 stepped by 0.1 for the validation data set. The size of the test data for the 0.8 kHz system is 600×16. Figure 4 shows the sampling technique. Then these inputs are normalized. Figure 5 shows the Simulink model for the system.

4. SIMULATION RESULTS:

Fig. 5 depicts the single-line diagram of a utility grid rated 120 kV at 60 Hz, which has a 120 kV transmission line connected to 120–25 kV, 47MVA transformer to feed 25 kV distribution feeders with a length of 19 km. A 100-kW solar photovoltaic (PV) array is connected to the system at the PCC through a 100 kVA, 0.26 kV/25 kV three-phase transformer and a circuit breaker. The 100-kW PV array, the threephase transformer, and the 100kVA three phase load form a microgrid as shown in Fig. 5. Fig. 6 depicts the model of the system in MATLAB-SIMSCAPE. The figure shows the detailed model of the 100kW Grid-Connected PV Array (R-DER), which consists of 100 kW photovoltaic (PV) array, a dc-dc boost converter, a Voltage Source Converter (VSC), and the Maximum Power Point Tracking (MPPT) controller. The PV array consists of 330 SunPower modules, where 66 strings of 5 series-connected modules are connected in parallel to deliver a maximum power of 100.7 kW (66 strings × 5 modules × 305.2 W/module) and 273.5 V (5 modules × 54.7 V/module) at a standard test conditions (STC) of 1000W/m2 solar irradiance, 25 ◦C PV module temperature. Table 1 lists a summary of the PV system characteristics at the STC. The 5-kHz dc-dc boost converter is used at the output of the PV array to boost dc voltage to 500 V. The MPPT is implemented in the boost converter using a MPPT variant subsystem DC-DC MPPT Boost Control that automatically varies and optimizes the switching duty cycle to generate the required voltage to extract the maximum power using the State flow implementations of the incremental conductance algorithms [36]. A 1.98 kHz three-level three-phase VSC as shown in Fig. 7, converts the 500VDC to 260VACand maintains unity power factor. A filter that contains the 25 μH inductor (L) and the 10kVAr capacitor bank (C) is used to filter the



Simulink blocks of the system under study

Islanding detection for Photovoltaic (PV) systems is a critical safety mechanism. It refers to the ability of the system to detect when the grid has become disconnected. An "island" occurs when a portion of the grid continues to power itself even though it is no longer connected to the wider power system. This can pose serious safety risks, as utility workers may not be aware that a line is still energized, and it can also lead to equipment damage.

Traditional islanding detection methods rely on monitoring certain parameters, such as frequency, voltage, or phase within the PV system, and comparing them to the expected grid conditions. When these parameters deviate beyond a certain threshold, it is assumed that islanding has occurred.

Artificial Intelligence (AI) techniques can enhance islanding detection by allowing the system to learn from a variety of conditions and potentially detect islanding more quickly and reliably.

In the simulation scenario, an AI-driven Islanding Detection System (IDS) is integrated into a grid-tied Photovoltaic (PV) system to ensure rapid and accurate identification of islanding events. At the 5-second mark, the PV system experiences an islanding condition due to a sudden disconnection from the main power grid. The AI module, utilizing a combination of supervised machine learning algorithms and real-time data analytics, begins to analyze the deviations in electrical parameters such as frequency, voltage, and phase angle. The system is trained with a vast dataset that includes normal operation, various fault conditions, and previous islanding occurrences to distinguish between legitimate grid fluctuations and actual islanding events.

During the simulation, the IDS's neural network processes the incoming data streams, detecting anomalies that match the learned islanding signatures. The AI's pattern recognition capability allows for a swift response, and within milliseconds, it confidently classifies the event as an islanding situation. The system then executes a series of predetermined actions, such as sending alerts to the grid operators and initiating protective measures like shutting down the PV inverters to prevent feeding power into an isolated segment of the grid, ensuring the safety of the maintenance personnel and preventing damage to the electrical infrastructure. This rapid detection and response highlight the effectiveness of AI techniques in enhancing the resilience and safety of PV systems within the smart grid environment.

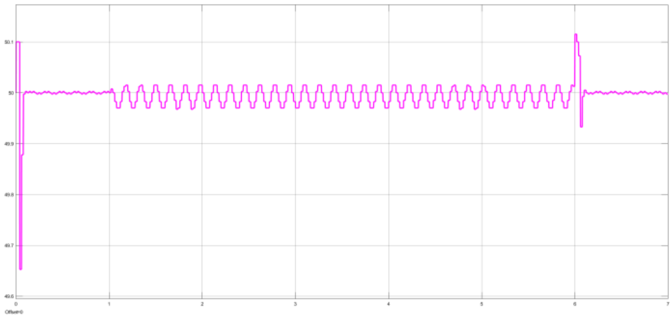


Fig : Frequency of the system

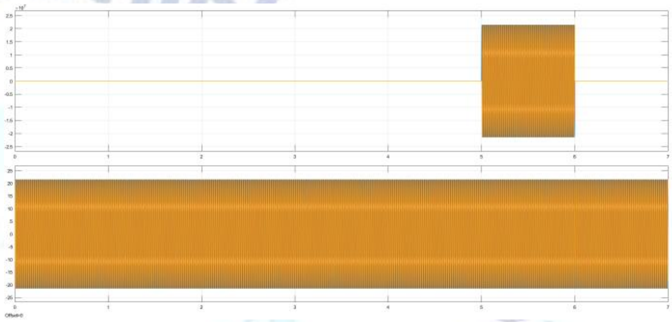


Fig: Voltage and current at the PV side

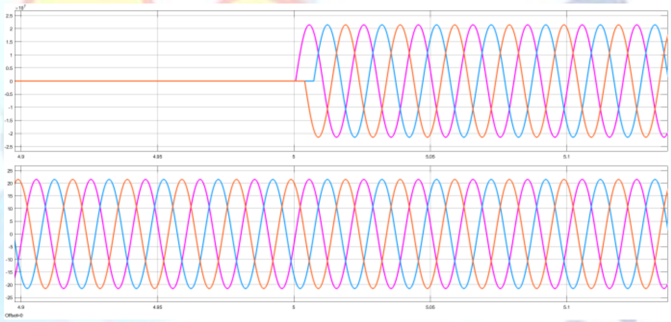


Fig: Voltage and current when the PV system is islanded from the grid

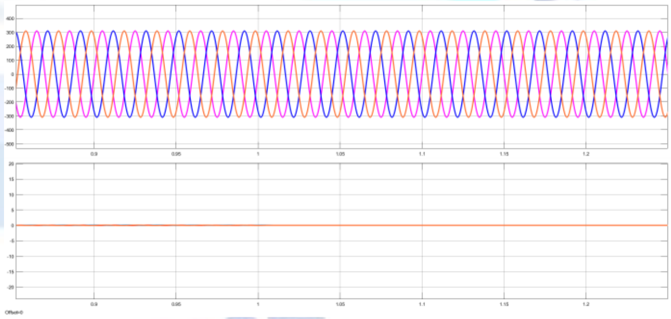


Fig: Voltage and current at the Grid side

5. CONCLUSION

In this paper, the ANN-based technique in the islanding detection application is studied. Doubly fed induction generator wind turbine is selected as distributed generators. Different ANN systems are simulated based on various inputs: Phase voltage/current, neutral voltage/current, and three-phase power, different sample rates are considered: 8, 16, 32, and 64 sample/cycle for each system, and three learning algorithms are simulated using MATLAB 2020a: Backpropagation, Genetic Algorithm, and Cuckoo optimization technique.

From the results, the ANN is a very effective method to detect the islanding in the micro- grid. Different inputs may be used to feed the trained ANN system: Power, phase voltage, and phase current, where the neutral quantities (voltage, current) are not able to use in this application. The accuracy of the system depends on the sample rate. The higher the sampling, the better the performance. 16 sample/cycle is enough to detect the islanding within four cycles in the case of power-based input data.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

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