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PASSIVE DETECTION OF ISLANDING EVENTS IN MICROGRIDS USING MACHINE LEARNING

Ali Majeed Mohammed ALYASIRI

Master Thesis

Supervisor

Prof. Dr. Osman N. UÇAN

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Ali Majeed Mohammed ALYASIRI

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This is to certify that I have read this thesis and that in my opinion it is fully adequate, in scope and quality, as a thesis for the degree of Master of Science.

Prof. Dr. Osman Nuri UÇAN

Supervisor

Examining Committee Members (first name belongs to the chairperson of the jury and the second name belongs to supervisor)

Academic Title Name SURNAME	Faculty, University	____________________
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I certify that this thesis satisfies all the requirements as a thesis for the degree of Master of Science.

Asst. Prof. Dr. Çağatay AYDIN

Head of Department

Assoc. Prof. Dr. Oğuz BAYAT

Director

Approval Date of Graduate School of

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Ali Majeed Mohammed ALYASIRI

DEDICATION

To my parents and my family and every one help me to complete this thesis**.**

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ABSTRACT

PASSIVE DETECTION OF ISLANDING EVENTS IN MICROGRIDS USING MACHINE LEARNING

Ali Majeed Mohammed ALYASIRI,

M.Sc., Electrical and Computer Engineering, Altınbaş University

Supervisor: Prof. Dr. Osman N. UÇAN

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The recent emphasis on using renewable energy instead of the traditional power generation techniques, which are badly affecting the environment, has introduced the use of Distributed Generation (DG) power grids. In these grids, smaller energy sources are distributed over the entire grid, instead of using larger centralized power units as usual. This type of grids imposes new challenges in operating and protecting the power generation units, as well as the quality and availability of the power flowing through the grid. One of the most important challenges faced by using the DG power grids is islanding detection, where a specific part of the DG grid, which is known as a microgrid becomes energized by the power sources in that part, but not connected to the main power grid. Such situation must be detected in order to disconnect DG power sources from the distribution grid, to protect the DG distribution systems from the negative influence of such situation on the management, protection and operation of these distribution systems. The IEEE standard for distributed generation power grids recommends detecting islanding events in DG grids within an interval of two seconds. Several methods have been proposed to detect islanding events. These methods can be divided into three main categories that are active, passive and communication-based methods. Passive islanding detection methods are the least expensive and do not degrade the quality of the energy provided on the network. Machine learning techniques are widely employed in such techniques, according to their ability to detect complex features. In this study, an islanding detection system is proposed based on the predictions provided by artificial neural networks. Three types of neural networks are evaluated in this thesis, the Convolutional Neural Network (CNN), simple Recurrent

Neural Network (RNN) and a Long- Short-Term Memory (LSTM) neural network. According to the ability of these neural networks of detecting features in multi-dimensional inputs, the proposed method collects the phases' voltages from the grid and use them to predict the state of any events occur on the network. The use of instantaneous values allows faster detection, as the changes in these values are detected immediately. The proposed system has been able to outperform the existing methods using the LSTM neural network, with 99.77% predictions accuracy, 100% Dependability Index (DI) and 99.31% Security Index (SI)

Keywords: Distributed Generation; Islanding Detection; Machine Learning; Artificial Neural Networks.

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LIST OF ABBREVIATIONS

DG	: Distributed Generation
EU	: European Union
NDZ	: None-Detection Zone
CNN	: Convolutional Neural Network
RNN	: Recurrent Neural Network
SFS	: Sandia Frequency-Shift
ROCOF	: Rate of Change of Frequency
ROCPAD	: Rate of Change of Power Angle Deviation
THD	: Total Harmonic Distortion
SVM	: Support Vector Machine
LSTM	: Long- Short-Term Memory
DI	: Dependability Index
SI	: Security Index
PV	: Photovoltaics
PU	: Per Unit

1. INTRODUCTION

The interest in distributed generation (DG) has grown rapidly in recent years, especially after the increased usage of renewable energy. For example, the members of the European Union (EU) have planned to cover a minimum of 20% of total thermal and electrical demand using this kind of energy, [1]. The use of new technologies poses new challenges in the planning, implementation and integration of these new technologies with the existing methods being used. One of the most important challenges faced by the integration of DG with the existing power grids is the detection of islanding events from the main grid [2].

Islanding is the state where a certain part of a power grid becomes energized by the power sources in that part of the grid, isolated from the remaining power grid. The standards proposed by the IEEE state that an islanding event should be detected and power sources are disconnected within less than two seconds. Thus, many techniques are proposed to detect an islanding event with the least possible time. These techniques may be categorized into three main categories that are Active, Passive and Communication-based [3].

The main theory behind active islanding detection methods is by adding some distortion to the waveform of the power system voltage. The larger the power system, the less the effect of this distortion, as the larger rotating power units are providing pure sine wave to the grid. Then, when an islanding event occurs, the waveform becomes more affected as the size of the power grid becomes smaller, and the ratio of the power provided by the source to the total power in the grid becomes larger.

These methods are mainly used with inverters, as it is easier to distort the output current by manipulating the input current of the control circuit. Then, the distortion of the waveform at the terminal of the inverter is measured, in order to be able to decide whether the local grid is connected to the main grid or it is in islanding mode. Islanding detection using active methods is accurate and fast enough to detect the islanding events within the suggested limits by the IEEE standard. These methods also have a very narrow non-detection zone (NDZ), compared to the other methods. The main disadvantages of these methods are the need for relatively expensive equipment and the degradation of the power, provided to the grid, because of the distortion added in the inverter unit.

Islanding detection using passive methods is based on monitoring the variables of the power grid closely, in order to detect any changes in these variables, so that when a change exceeds the preset threshold, the grid is considered to be in an islanding state. Islanding detection, in these techniques, may rely on one or more variables in order to make a decision about the state of the grid. The threshold values may be set manually by studying the system to conclude the most affected variable when an islanding event occurs, or by collecting data from the system and use machine learning techniques, such as data mining, in order to find the most effective variables, and the appropriate threshold values for these variables.

The use of passive islanding detection methods is very inexpensive, as it requires no additional equipment to be added to the power system. But the existing techniques that rely on passive detection suffer from relatively larger NDZ, when compared to the other two islanding detection methods, and the higher detection time. The time is not only consumed by the detection process itself, but the variables used by these methods are also not instantaneous values. Thus, these values also require some time to measure the value and sense the change in it, where some techniques rely on the rate of change of a variable. Decision trees are very popular in passive islanding detection, where variables are compared to their thresholds in a tree-like distribution. When a decision cannot be made depending on a specific variable, the path to the next level is selected depending on the value of that variable.

Detecting the islanding of a DG power grid can be achieved using communication among different locations on the grid. Then, by collecting these data, it is possible to decide whether the grid is in islanding state in the meantime or not. These methods are of the most reliable methods in islanding detection, but they require intensive communications in order to interchange information from one point to another. Transfer trip and power line carrier are two widely used communication-based islanding detection techniques. These methods have very high accuracy in detecting islanding events, but as they rely on communication systems to interchange information about different parts on the DG grid, they require expensive infrastructure, and the detection cannot be achieved in case of failure in the communication system. These methods are also stated to be complex, when the feeder of the DG grid reconfigurable, [3].

Extracting rules that rely on raw data by computers, whether these rules are noticeable by humans or not, is known as machine learning. Machine learning is a part of artificial intelligence, where machines attempt to learn from data, then apply this knowledge in different applications. Many applications are based on machine learning nowadays because of the high performance in prediction and decision making in real-time with very accurate results. The advantage of machine learning is that the extracted knowledge can be applied to new data that is not included in the data used by the machines to extract the knowledge.

There are many branches of machine learning. Neural networks in one of the highly-performing branches, which simulates the way neurons are connected in the human brain. It consists of units called neurons, distributed in multiple layers. The relations between neurons in one level and neurons in the next are updated during the knowledge extraction process. The last layer of the neural network is known as the output layer, which carries out the output computed in the network to the external world. There are different types of the neural networks, depending on the distribution of the neurons in that network and the number of implemented layers.

The Convolutional Neural Network (CNN) is one of the widely used neural network techniques. This method extracts relation from adjacent features in a multidimensional space in order to find further relations, in the next layer, among features detected locally in each layer of the network. Then, these networks are connected to fully connected layers, so that features detected in the last convolutional layer trigger neurons in the fully connected layer. Techniques using convolutional neural networks have shown extraordinary performance in image classification, as features in images are detected in a specific region, then these features are combined together in the next layers to create more complex shapes.

Recurrent Neural Network (RNN) is another type of artificial neural networks, where the positioning of the value has effect on the features detected by the neural network. Such detection is achieved by including the output of the neuron from the previous computations in the computations of the current one. Thus, this neural network also has the ability of handling two-dimensional inputs, where the timing of the values is used to arrange the inputs in one of the axes, while the other axis depends on the number of features per each input. Different approaches are proposed to control the flow of the data in the neural network, hence, controlling the effect of previous values on the computation at the current time instance.

1.1. PROBLEM DEFINITION

Passive islanding detection methods are very easy to use and integrate with a DG power system, in contrast to the communication-based methods, as it requires no communications between devices in the power grid and proposes no quality degradation of the power provided in the grid as the active detection methods do. Moreover, the passive islanding detection methods, proposed earlier in the literature, do not rely on instantaneous values, which leads to a delay in the measurement process, and a delay in the changes sensing as these values summarize a range of instantaneous values. The use of such values leads to larger NDZs and longer detection time.

1.2. AIM OF THE THESIS

The aim of this thesis is to propose a passive islanding detection method that relies on the usage of the instantaneous values of the DG power grid voltages. The use of such values allows passive detection methods to provide faster and more accurate decisions about the state of the local power grid operation state. According to the capabilities of certain types of neural networks, in detecting local and distributed features in a multidimensional space, the instantaneous values are fed to these neural networks in a way similar to the way images are fed to the neural networks.

1.3. THESIS LAYOUT

The remainder of this study is constructed as follows:

- Chapter two: reviews the literature related to the subject of this study.
- Chapter three: explains the use of the different types of neural networks to detect islanding events in microgrids.
- Chapter four: demonstrated the results of the experiments conducted in order to measure the performance of each method.

- Chapter five: discusses the results of the experiments and illustrates the performance of each method in islanding detection.
- Chapter six: shows the conclusions acquired from this study.

2. LITERATURE REVIEW

The maximum time recommended, by the IEEE 1547 standard [4], to detect and act in case of unintentional islanding of a distributed generation system is limited to 2 seconds. Thus, many techniques are proposed to detect the islanding events within the minimum possible time, resources and data. These techniques may be classified, according to the way they interact with the power system, into three main categories that are active, passive and communication-based techniques [5]. Active techniques rely on perturbing the power grid and monitor the response of the grid to the injected perturbation. In case of an islanding event exists, the effect of the perturbation injection is much higher than it is in normal operation. Thus, methods based on such techniques, such as [6-10], have a narrower non-detection zone (NDZ), but they cause power quality degradation according to the injected noise, and require expensive equipment for that injection [7, 11].

2.1. ACTIVE ISLANDING DETECTION

The studies that presented active islanding detection methods rely on many detection schemes. For example, [6, 8, 10] use Sandia frequency-shift (SFS) to detect islanding events. These methods are mainly proposed for grids that have inverters in their distributed generation, as the frequency shifting, which is shown in figure 2.1, is easier to achieve in inverters than other mechanical rotating generation units. In normal operation conditions, this deformation of the waveform is unnoticeable as it is connected to relatively huge generation units that are generating pure sine waves. While, the deformation of the waveform becomes more sensible, when that area becomes in an islanding state. Thus, it is possible to detect islanding events by measuring the effect of the SFS to the waveform of the grid [12].

Another anti-islanding approach is used in [7], which is a positive feedback based scheme. This scheme relies on amplifying the disturbance in the transient that occurs at the islanding event, so that the voltage/frequency relay may sense that disturbance and trigger. Thus, it is called positive feedback, as it positively feeds the same transient data back to the system in order to amplify it. Such systems may be implemented based on the system voltages or its frequency [13].

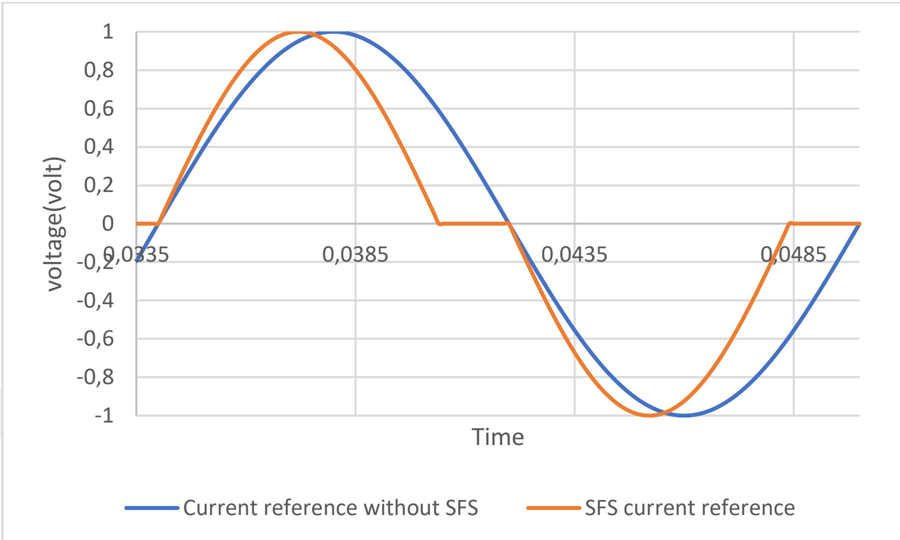

Figure 2.1: Sandia frequency-shift.

Moreover, the active anti-islanding method proposed in [9] is based on using the frequency drift scheme, which introduces a small deviation in the frequency of the inverter's current, so that, by measuring the deviation of the terminal voltage of the inverter indicates an islanding event. This deviation is achieved by injecting a distortion current to the inverter's reference current. Thus, when the grid is operating normally, the terminal voltage of the inverter is synchronized to the grid, while when an islanding event occurs, the frequency deviates according to the distortion current injected to the reference waveform. This enables the detection of islanding with narrower non-detection zones.

2.2. PASSIVE ISLANDING DETECTION

The other category of islanding detection techniques that are used in the anti-islanding systems are the passive techniques. These techniques rely on measurements of variables that are measured locally, so that no remote measurements are required, which enables these techniques to detect the islanding events without any communications, [14, 15]. These variables are, usually, the frequency, voltage, distortion of the harmonics, etc., measured at the distributed generation side of the grid, where a huge difference occurs in these values when an islanding event occurs. These techniques, compared to the active techniques, require less detection time and has no influence on the distribution system, but may mal-operate, unlike the active techniques where mal-operation is almost impossible, [16].

The rate of change of frequency (ROCOF) is one of the widely used variables in the passive islanding detection methods, where preset limits are programmed into the relay, so that, when the ROCOF exceeds the preset limit for the preset period of time, the relay triggers indicating that an islanding event is detected. The ROCOF is inversely proportional to the size of the power grid, where the smaller the grid, in terms of generation and consumed load, the easier it is to change the frequency, [17]. Thus, it is used to detect the islanding events in the distributed grid, as the loss of the main grid results in a relatively small islanded power system, where the frequency can be easily affected by any change in the power flow. In these methods, sometimes it is difficult to distinguish the difference between an islanding event, and some other events that may occur during operation, such as, loss of a generation unit, sudden load change and some other events that do not cause islanding, [18].

Another approach is presented in [19], which measures the rate of change of power angle deviation (ROCPAD) in order to detect islanding events. The estimation of the phasor is based on the measurement of three parameters, which are the phase angle, amplitude and frequency. By predicting the instantaneous values of the voltage and the current of the DG system accurately, using a phasor, which is synchronous transformation based, it becomes possible to detect any abnormal behavior and eventually detect the islanding event, [19]. This method requires a maximum of one full cycle in order to detect the islanding event, which is less than the time requires by the ROCOF based methods. The reason behind the faster performance of this method is that it uses the instantaneous values of the measured variables, which reduces both the time required to measure the variable, and the time required to process the measured values to produce the required results. Although the results of conducted experiments are relatively good, the performance if the proposed method is not tested under switching of high capacitive load, which generates a burst in the instantaneous values of the voltage and the current of the local DG grid, [20].

Some other studies propose passive islanding detection methods based on monitoring more than one variable simultaneously. For example, the method proposed in [21] relies on monitoring the rate of change of the voltage and the rate of change of the power angle. The main idea behind using this combination is to enable the system of detecting islanding events in DG grids, where the local load is similar to the power generated locally. These variables are derived using the instantaneous values of the voltage and current of the system.

The method proposed in [22] also uses a combination of variables in order to detect an islanding event. The variables selected for this method are the voltage unbalance and the Total Harmonic Distortion (THD) of the current. The use of the current's THD variable improved the accuracy of the islanding detection when tested using events that included non-islanding events, such as load variation and switching. The selection of the variables used in the passive islanding detection, in such methods, is based on studying the system where anti-islanding is required in order to figure out the variable, or more, that is highly affected by the islanding events, to propose an accurate islanding detection system.

2.2.1. Machine Learning Employment in Passive Islanding Detection

Data mining techniques are used to evaluate the effect of islanding events on every measurable value. These techniques are also capable of detecting relations between more than one feature and islanding events. Thus, using these techniques enables better islanding detection techniques, by directly using these techniques to classify the events according to the measured values, or by evaluating the contribution of each feature in the classification process, so that, it is possible to select the feature, or a combination of features, with the highest contribution in the classification, of an event to be an islanding event or not, in order to achieve best possible detection, [23].

Data mining is the process of extracting knowledge from a huge dataset. This knowledge represents the patterns in the dataset and relations among features in it. These patterns and relation may not be noticeable to the human, because it may include many features or the dataset is so huge that makes it difficult to be examined by the humans, [24]. Data mining techniques may be divided into two categories, which are supervised and non-supervised techniques. The non-supervised techniques, such as clustering, require no prior training and data are split into homogenous groups, where tuples in a certain group are more similar to tuples in that group than tuples in other groups, [25]. Supervised techniques, such as classification, require pre-labeled dataset in order to allow the techniques to extract the related knowledge. Thus, the extracted knowledge can be used to predict the class of a new unlabeled tuple, which enables the prediction of the behavior of that tuple and action required to interact with such tuples depending on the characteristics of the corresponding class, [26].

The classification results are only predictions, which means that evaluating these techniques must be done by comparing the predicted behavior of the tuple with the actual behavior it is going to have in the future. Such evaluation is not very much useful, as any method needs to be evaluated prior to applying it in the runtime or real-life data, in order to select the classifier with the best performance. Thus, the labeled data is split into two parts, one for training and one for testing. As the behavior of the labeled data is known, the extracted knowledge from the training part of the data set is applied to the test part. Then, the predicted classes of the tuples are compared to the actual classes, or labels, of each tuple, [27]. One of the widely used classification evaluation metrics is the accuracy, where the ratio of the correctly classified tuples is used as an indication of the classification performance of the classifier. The higher the accuracy, the better is the performance of the classifier, [28].

The threshold settings of the islanding detection relays are very critical, and they represent the margin between a good and a bad detection system. The approaches proposed in [29-31] use data mining techniques to extract the optimal values that may be used in the relays to distinguish an islanding event from other non-islanding events that may occur during normal operation of the DG power system. In this method, the extracted values are distributed in a decision tree, where features and threshold values are distributed in an upside-down tree-like presentation. The new values are examined against the concluded tree, where the value of each feature is compared to the threshold value, and the result if this comparison leads to a specific branch in the next level, which may be a class of another comparison, [32]. An illustration of a sample decision tree is shown in figure 2.2, where F is the feature, T is the threshold value and C is the predicted class.

The approach proposed in [33] uses Support Vector Machine (SVM) data mining technique to find the best placement of the plane that splits the tuples into two classes, islanding and non-islanding events. This is achieved by distributing the tuples according to the values of the features into a multi-dimensional space in order to optimize the equation of the plane that represents the boundaries of the spaces of each class. Later on, when a new tuple is required to be predicted, it is compared to this plane to conclude the side that the new tuple falls into, which represents the predicted class for that new tuple.

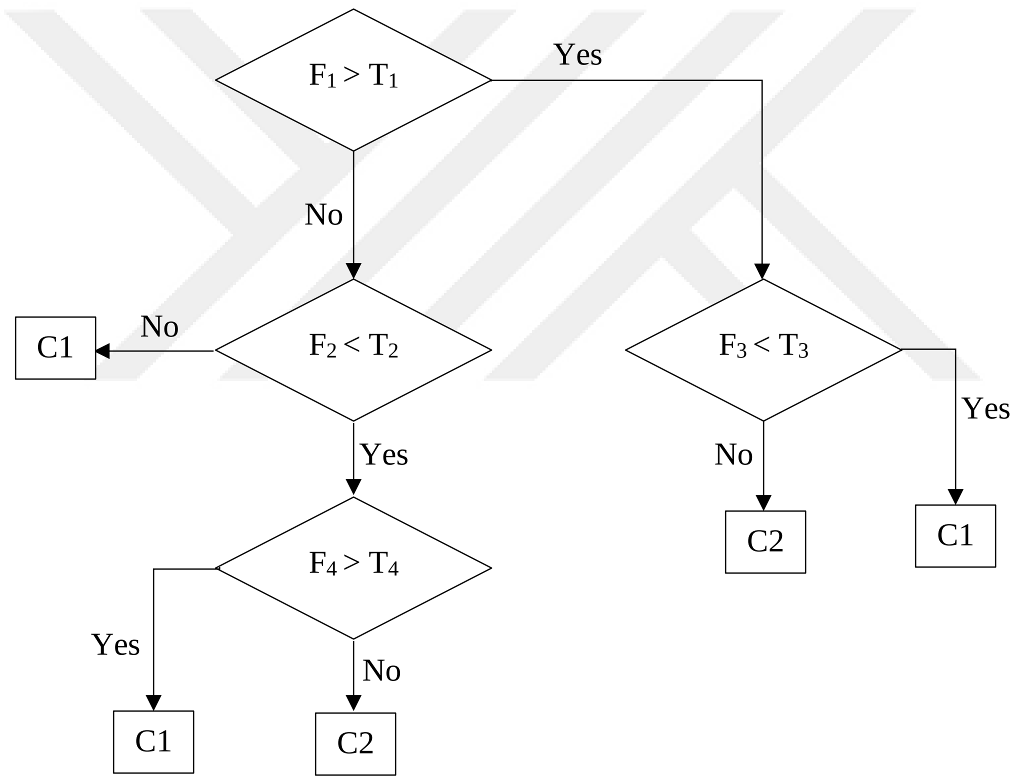

Figure 2.2: Sample decision tree.

Features selection is another important data mining technique, which is used for detecting features that have higher contributions to the actual classification. The features that have less importance, which is also known as rank, are neglected to reduce the complexity of the computations. For example, the dataset shown in Table 2.1 has four features, and the tuples are classified into two classes. It is obvious that the feature “F1” has the highest rank, as it is possible to predict the class that each tuple belongs to by simply knowing its value in that feature, while the feature “F2” has absolutely no contribution in the actual classification, so that it is possible to neglect that from any further data processing. The features “F3” and “F4” also have very low rankings, but the use of features with such values may be useful in some classifiers like the decision tree, where a combination of two or more features may be used to predict a class for the tuple. The technique proposed in [5] uses a feature selection algorithm to select the features that have the highest contribution in the actual classification in order to create a random forest, which is a group of decision trees, where each tree is trained using a random sample of the labeled dataset. The use of features selection, in the study, reduces the execution time of the random forest classifier, which leads to a faster islanding detection.

Table 2.1: Features contribution in the actual classification.

F1	F2	F3	F4	Class
X	A	M	J	C1
X	A	N	K	C1
Y	A	M	K	C2
Y	A	N	J	C2

2.3. COMMUNICATION-BASED ISLANDING DETECTION

Communication-based anti-islanding methods detect islanding events mainly using power line signaling or transfer trip. Such methods are expensive as the required communication system is extensive, which is usually quite expensive, but they have relatively smaller NDZ than the active and passive method and cause no degradation of the power quality, [34]. The communication-based islanding detection method proposed in [35] monitors some variables, such as the power, voltages, currents and frequency, at different parts of the DG power system in order to detect the islanding events. The time required by the system to detect an event is approximately one to two cycles, and the NDZ of this method is very small. Thus, the only drawback of this method may be limited to the need of a high-cost infrastructure for the communication system, and the system malfunctions in case of loss of communication, which affects the reliability of the system.

There are some proposed methods that used a combination of more than one islanding detection method for anti-islanding systems. These methods, such as [36-40], may use any of the detection methods together in order to come up with systems that share the benefits of the used techniques, but may also suffer from their drawbacks. For example, the hybrid method proposed in [37] monitors the ROCOF in the passive part, but injects SFS to the system in the active part of the method. Although this method is accurate and has very small NDZ, the power quality is still degraded by the noise injected by the SFS.

2.4. ARTIFICIAL NEURAL NETWORKS

Recently, neural networks have received a lot of attention according to the high performance and accurate results it is providing. Deep learning is a computer learning method, which basically uses a multi-layer neural network that is updated using the training dataset, so that it can be used in classifying any unclassified new data [41-43]. There are different neural network techniques that are widely used in different applications. Convolutional Neural Network (CNN) is one of the widely used techniques of the neural networks, basically for image classification, [44]. This technique is based on the actual way that living creatures use to classify, which is presented by [45] as the image received by the eye may be split into units, where a feature detected in one unit may or may not be related to another feature that is detected in another unit. This kind of vision provides better comprehension of the images, hence better classification of the objects in the image.

Similarly, the CNN creates filters, where each filter is responsible for detecting one feature, which is mostly an edge. Then this filter is passed over the entire image to locate the positions where this feature is located. These locations are then combined together to detect any objects in the image, or to classify that image. Face detection is one of the applications where CNNs are usually used, [46-49]. The first convolutional layer detects the different type of edges in the image, then, the second layer detects the position of the eyes, mouth and nose. If placed properly, then the third layer detects the region as a face. Moreover, studies like [50-52] use CNN to classify animals in images by combining the detection of multiple features and the location of each one, so that results depend on specific shapes, such as the shape of the nose, ears, mouth and so on. These networks have proven to have very good performance, and has the ability to detect a wide range of features in order to result in a high accuracy classification.

Convolutional Neural Networks are based on the way that living creatures see the surrounding, by dividing the received image in the eye into units, where filters are used to extract features from that unit. Then, same, or other, filters are applied to the results of these filters in order to find relation among features detected in the previous convolutional network, whether it is in the same unit or not. For example, CNNs have the ability to classify animals depending on the shape of their ears, so that one convolutional layer detects edges, then the next layer detects the position of the ears, while another layer combines the shapes and positions of the ears to classify the animal detected in the image [53].

In order to achieve that, filters of certain shaped features that are built by the neural network itself in a preset size during the training process, are placed over an equal size area of the image in order to detect how identical that part of the image to that filter. These filters are then used to scan the existence of matching features in the input and pass the results to the next convolutional network. The main aim of this procedure is to identify the local features in a certain area of the image, because the use of traditional neural networks cannot detect adjacent pixels in more than one dimension in the input data. The next convolutional layer, then, combines the existence and location of each feature and move it forward to another convolutional layer, or a fully connected layer.

As these filters have a specific width, there are two main techniques to scan an input of a certain size. The movement of the filter in a certain dimension ends by the end of that dimension in the input, which is known as valid padding. Or, by adding padding to the input so that the scan ends when the filter scans the entire pixels in that dimension in all possible positions of the filter, which is known as same padding, [54]. In islanding detection, and as it is very important to retrieve information about the newest instantaneous values added to the matrix, to ensure faster detection, the ‘Same’ padding method is selected.

Each filter is moved through the entire input, with a step size known as strides. Where the strides hold the number of pixels that filters in a certain convolutional layer move in each direction. The larger steps mean faster scans, but it is possible to miss some matches in the scanned area or detect a weak match, especially when the filters include a very narrow feature to detect, [55]. Thus, and because of the narrow distribution of values in the matrix, the strides values are set, so that each filter moves one pixel in each iteration through the matrix.

To provide non-linearity to the output of each neuron in the neural network, which aims to provide more accurate classification by using non-linear margins to split items in the multi-dimensional space of the input [56, 57]. Three popular activation functions are widely used with neural networks, which are the Sigmoid, TanH and ReLU functions. The output of the Sigmoid function varies from zero to one, depending on the input value of the activation function, where smaller values cause the output to be close to zero, while larger values cause the output to approach one. On the other hand, the TanH activation function outputs values that vary from minus one to one, in a rate of change similar to the output of the Sigmoid function, where the rate of change in the value around zero is higher than the rate of change when values move away from zero, in both directions. While ReLU activation function passes the input value as it is when that value is larger than zero, otherwise, outputs zero. The output of each activation function, with respect to the input values, is shown in Figure 2.3. The ReLU activation function has an overall better performance than the other activation functions, especially when used with the convolutional neural networks, [58]. Thus, the ReLU activation function is used in the neural network built to test the performance of such methods in detecting islanding events.

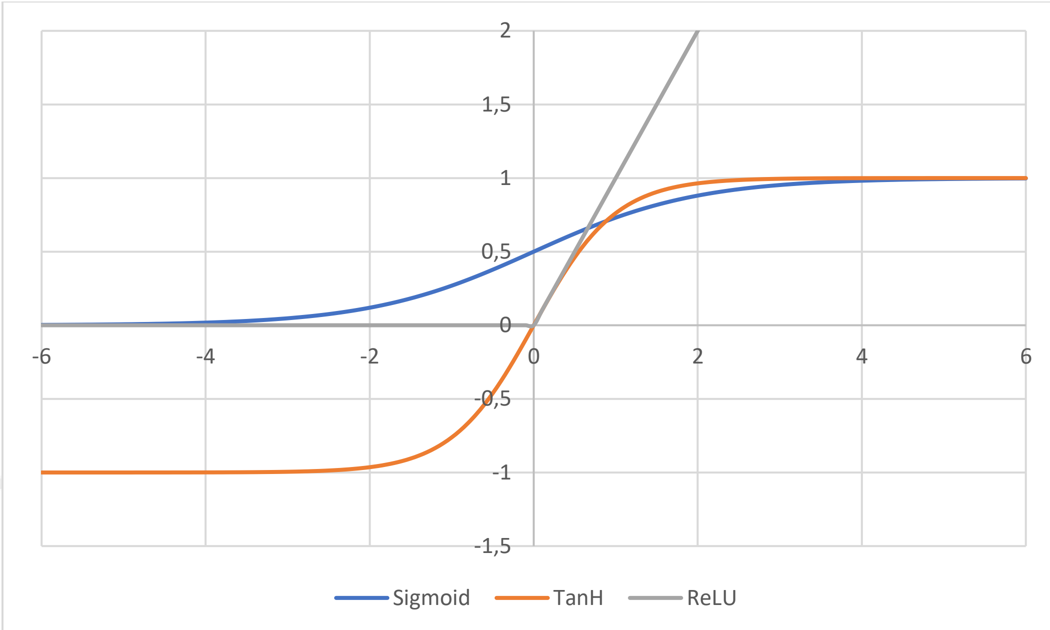

Figure 2.3: Neurons activation functions.

Another type of artificial neural networks that also has the ability to handle two-dimensional inputs is the Recurrent Neural Network (RNN). According to the existence of a feedback from the output of a neuron to its inputs, after being weighted, the output of that neuron at time instance *t+1* is affected by its output at time instance *t*, Thus, this type of neural networks has shown good performance in detecting features in time-sensitive data, i.e. time series, according to the time relativity among these values. In simple RNNs, shown in Figure 2.4, the output of the neuron is considered exactly like one of its inputs, i.e. multiplied by its weight and included in the summation. The detection of complex features in time series using these simple RNNs can suffer from the vanishing or exploding weights problem. This problem occurs according to the intense update of the weights' values during the backpropagation and the complex nature of the features in the inputs [59].

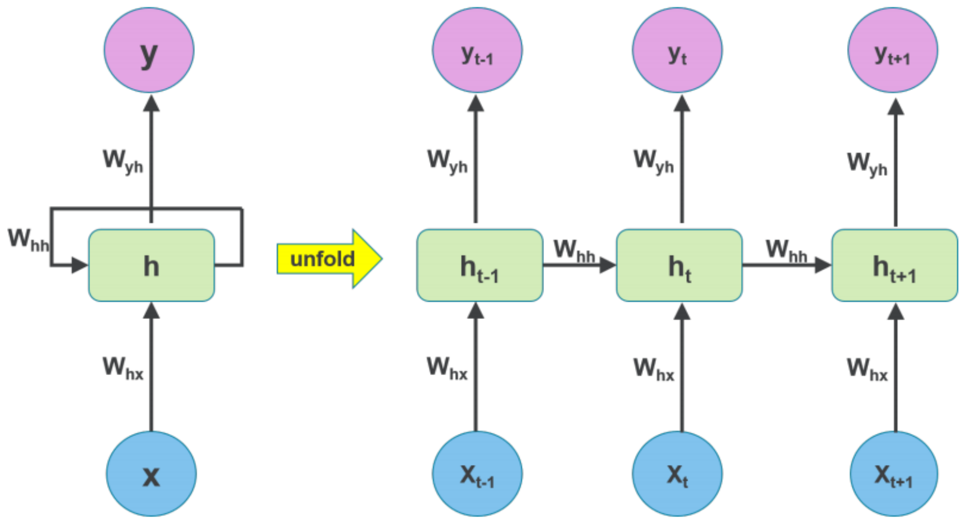

Figure 2.4: Structure of an RNN [59].

Thus, another type of RNNs is proposed that uses gates to control the flow of the values in the neural network, so that, the effect of the values is in the computations is weighted according to their importance rather than their position [60]. Hence, this type of RNN is known Long- Short-Term Memory (LSTM). As shown in Figure 2.5, such control of the data flow is achieved using a set of gates, where each gate is responsible for controlling the flow from a certain part of the data. The forget gate f_t uses sigmoid function to control whether to allow the output from the previous step to go through the computation or not, using Equation 2.1.

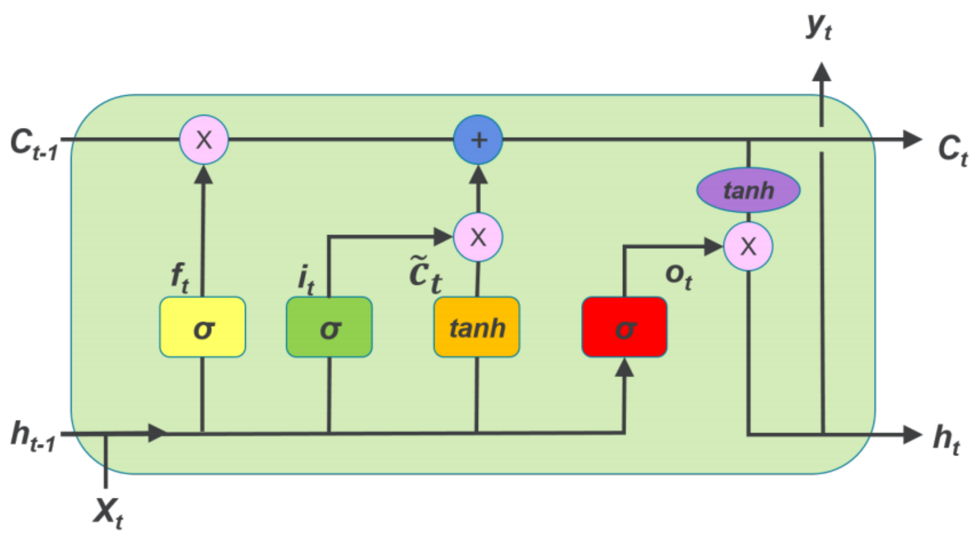

Figure 2.5: Structure of the memory block in an LSTM neural network [59].

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f) \quad (2.1)$$

Then, the input gate layer, which uses sigmoid function as well, controls the inputs that are required to go through with the values acquired from the output of the previous time instance, using the Hyperbolic Tangent (tanh) function, as shown in Equation (2.2) and (2.3).

$$i_t = \sigma(W_i.[h_{t-1}, x_t] + b_i) \quad (2.2)$$

$$\tilde{C}_t = tanh(W_c.[h_{t-1}, x_t] + b_c) \quad (2.3)$$

Accordingly, the cell state C_t is calculated by summing the product of the f_t and C_{t-1} with the product of i_t and $\tilde{C}_t$, as shown in Equation 2.4. Then, the output values are calculated using the output gate, which applies the sigmoid function to the inputs of the current time instance as shown in Equation 2.5, and the product of the output by the cell state, after applying the tanh function to it, as shown in Equation 2.6.

$$C_t = f_t \times C_{t-1} + i_t \times \tilde{C}_t \quad (2.4)$$

$$o_t = \sigma(W_o.[h_{t-1}, x_t] + b_o) \quad (2.5)$$

$$h_t = o_t \times tanh(C_t) \quad (2.6)$$

where *W* represents the weights of the corresponding layer, *b* represents the bias, *t* is the current time instance and *t-1* is the previous time instance for all the above equations.

2.5. PERFORMANCE EVALUATION

Two main measures can be used to evaluate the performance of an islanding detection system, which are the Dependability Index (DI) and Security Index (SI). An islanding detection system is considered dependable when the energy in the grid is maintained during non-islanding events. Hence, the DI can be calculated as the ratio between the number of correctly predicted non-islanding events to the total number of non-islanding events that occur in the DG grid. The security of the system reflects its ability in detecting islanding events, so that, the safety of the equipment and workers in the DG grid is maintained. Thus, the SI is calculated as the ratio between the correctly predicted islanding events to the total number of islanding events that occur in the DG grid [61].

3. METHODOLOGY

The use of active islanding detection methods degrades the quality of the power as it injects some noise to the grid and measure its effect on it in order to detect the islanding events, while the communication-based methods require expensive infrastructure and are very dependent on the communication system, so that islanding events are not detected in case of communication system failure. Passive techniques, on the other hand, have no effect on the power quality and require no communication, as they are based on measuring some variable at a specific point in the DG grid.

3.1. THE PROPOSED METHOD

Machine learning techniques can be divided into two main categories, supervised and unsupervised methods. The unsupervised machine learning techniques find relations among the features and tuples in the dataset. Thus, no data labeling is required in order to use an unsupervised technique. Clustering is an example of an unsupervised machine learning, where tuples in the dataset are grouped in a way that a tuple in a certain group is more similar to tuples in that group than any tuple in other groups. Supervised machine learning, on the other hand, requires labeled data in order to find relations between the values of each attribute and the label given to that tuple. Classification is one of the supervised machine learning techniques, where classifies data must be provided to the classifier in order to find relations between the values of the features that cause the tuple to be in a specific class.

This study uses artificial neural networks as classifiers, thus, the data provided to these classifiers must be labeled. Two classes are used to label the collected data, which are islanding and non-islanding state. The classifiers use these data to find relations between the provided features that lead to more accurate prediction. Then, this knowledge is used to predict new tuples, whether to be in an islanding or non-islanding state. Moreover, it is important to evaluate the performance of the classifiers, by measuring how accurate their predictions are. As these predictions are expected to happen in the future, it is not possible to evaluate the performance using new data. It is also not acceptable to use the training data for performance evaluation, as these classifiers are already trained to handle such values.

The standard procedure used to evaluate the performance of classifiers is by splitting the labeled dataset into two parts, one part is used for training and the other is used for performance evaluation. The procedure that is used to evaluate the performance of each classifier is shown in Figure 3.1.

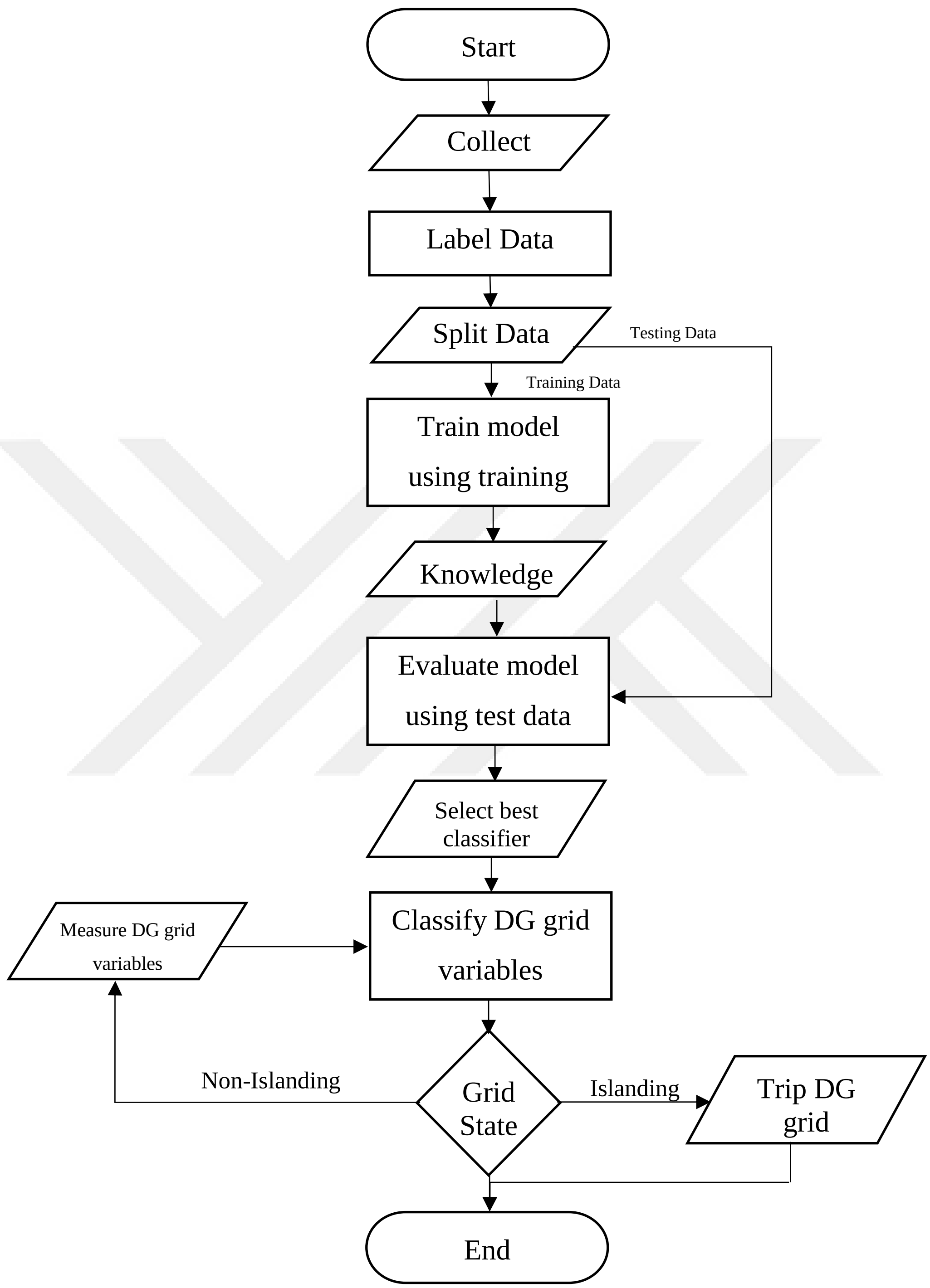

Figure 3.1: The use of machine learning to detect islanding events.

3.2. DATA REPRESENTATION

Although it is difficult to use the instantaneous values when an alternating current is used, the use of a set of sequential values may indicate a specific type of change. For example, Figure 3.2 shows two different voltage waveforms that have different frequencies. From the illustration, it is obvious which waveform has the higher frequency and which waveform has the lower one. Thus, it is possible to graphically compare waveforms and conclude the waveform that has specific characteristics from the other, without the need to calculate any further values. It is also possible to tell that these voltages have equal RMS values, as they share the same peak values and both are sinusoidal waveforms.

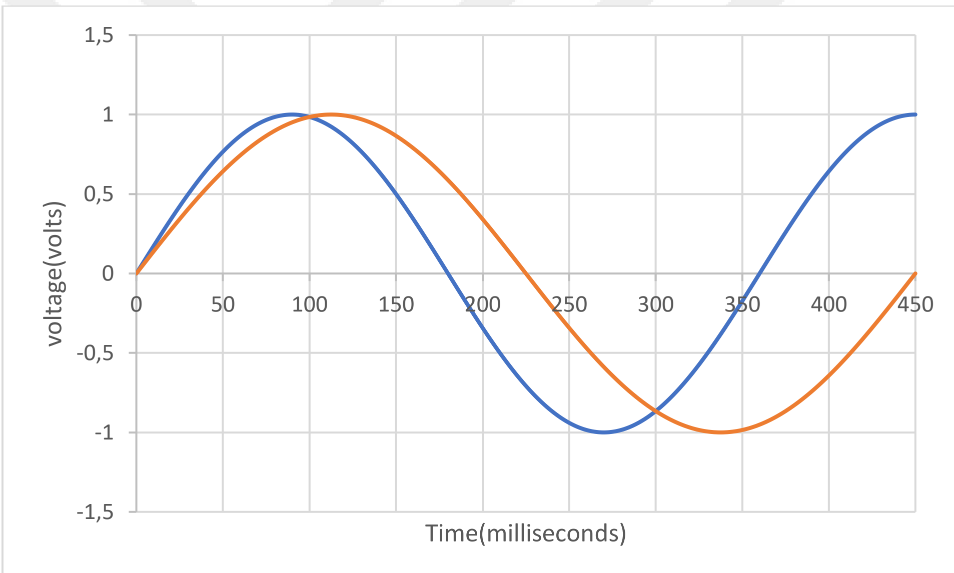

Figure 3.2: Two voltage waveforms with different frequencies.

Moreover, it is also possible to accurately conclude some of the states and values of the waveform by looking at a specific portion of the wave. For example, it is still possible to distinguish the waveform with the higher frequency by just looking at the portion of the waveforms shown in Figure 3.3. The overall values of the required variable could also be calculated using only the provided portions, if the size and location of the snapshot are provided. Thus, the use of multiple sequential instantaneous values provides a good overview of the system, and some changes may be detected instantly, without the need to wait for the measurement devices to detect and update the change in the summarizing values.

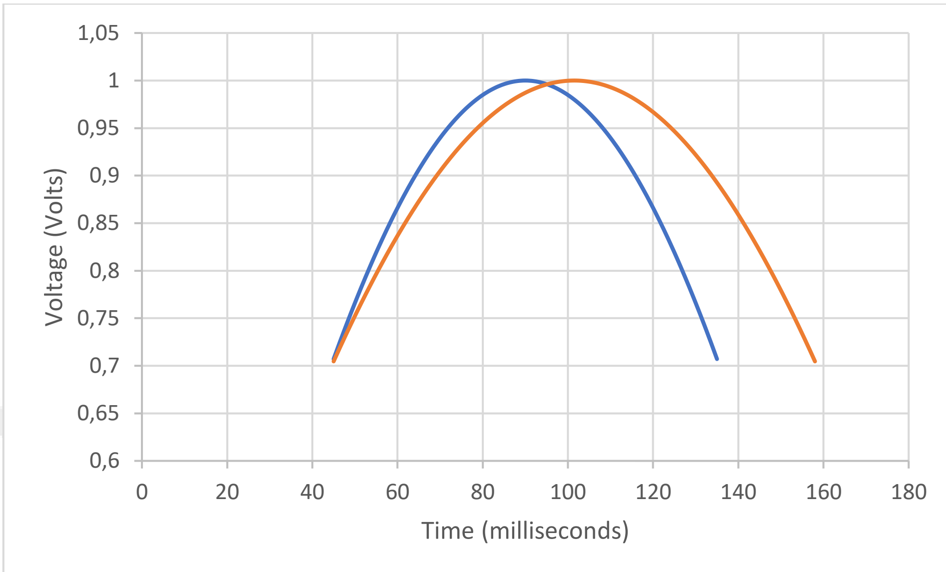

Figure 3.3: Snapshot of a certain portion of the waveforms.

Many features are also detectable directly from the presentation of the waveforms, so that no further processing is required for any values. For example, the waveforms shown in Figure 3.4 have started with the same phase and frequency, but at the moment they reach the peak value, the frequency of both waves change. Hence, the rate of change in form1 is less than the rate of change of frequency in form2. Although some details may not be quite obvious for the human eye, even the smallest changes in values are detectable by computers, so that accurate values may be computed using only a small slice of sequential instantaneous values. These variable and so on driven values are not only detectable at certain portions of the waveform, such as the peaks used in the examples, they can be computed using different portions as long as the size and location of the snapshot are known to the computer.

Thus, in the proposed method, the voltages instantaneous values are fed to the artificial neural networks sequentially, in order to create an image-like data for the classifier. Then, the neural network detects any deformation in the waveform, which may be used to classify the event that caused this deformation as an islanding or a non-islanding event. The use of the instantaneous values assists shortening the time required to process these values, whether by the measurement device or when the data is pre-processed in order to be used by the classifier.

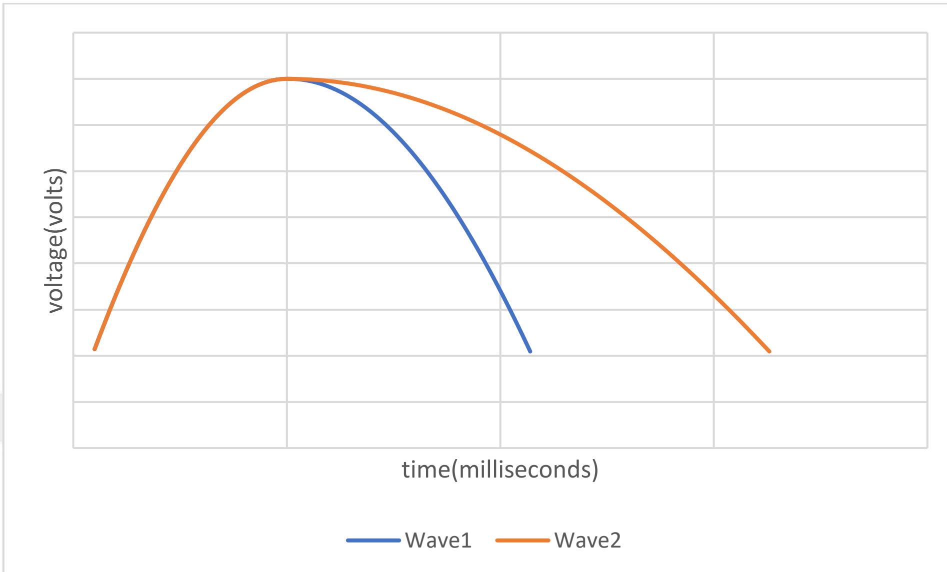

Figure 3.4: Portion of deformed waveforms.

4. EXPERIMENTAL RESULTS

The performances of the ANN-based classifiers are evaluated for islanding detection. In order to use instantaneous values, it is important to provide historical data to the classifier, so that, the classifier can predict the nature of the current instantaneous values. Thus, the convolutional, recurrent and Long- Short-Term Memory (LSTM) neural networks are used, according to their abilities of accepting two-dimensional arrays as input. The IEEE 13 node distribution feeder, shown in Figure 4.1, is implemented in Matlab's Simulink to simulate the events described in Table 4.1. Each event is simulated under 24 load distributions and solar irradiation levels of the Photovoltaics (PV) array [62], shown in Table 4.2. The classifiers are implemented using Python programming language [63] using Tensorflow [64] and Keras [65] libraries to implement and train the neural networks. All evaluations are conducted using 10-fold cross-validation to measure the accuracy, Dependability Index (DI) and Security Index (SI).

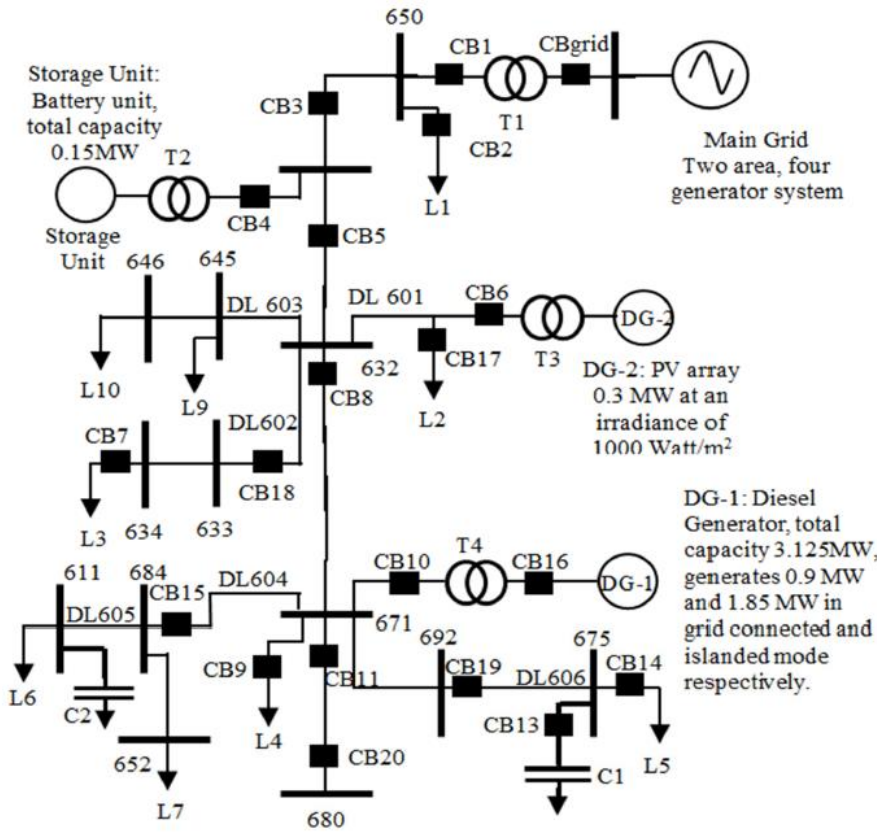

Figure 4.1: The implemented IEEE 13 node distribution feeder [34].

Table 4.1: Simulated events and their islanding status.

Index	Event description	Status
E-1	Tripping of utility circuit breaker (CBgrid)	Islanding
E-2	Tripping of PCC breaker (CB1)	Islanding
E-3	Tripping of CB1 and CB2 simultaneously	Islanding
E-4	Tripping of CB5 leading to loss of dist. Line	Islanding
E-5	Tripping of CB8 leading to loss of dist. Line	Islanding
E-6	Tripping of CB6 causing loss of PV unit	Non-islanding
E-7	Tripping of CB4 causing loss of storage unit	Non-islanding
E-8	Tripping of CB3,CB4,CB5; loss of dist. Line	Islanding
E-9	Tripping of CB18 leading to loss of dist. Line	Non-islanding
E-10	Tripping of CB19 leading to loss of dist. Line	Non-islanding
E-11a	Sudden load change (increase) at PCC	Non-islanding
E-11b	Sudden load change (decrease) at PCC	Non-islanding
E-12a	Abrupt load increase at target DG location	Non-islanding
E-12b	Abrupt load decrease at target DG location	Non-islanding
E-13a	Sudden increase in microgrid loading	Non-islanding
E-13b	Sudden decrease in microgrid loading	Non-islanding
E-14	Capacitor bank switching	Non-islanding
E-15	Normal system operation	Non-islanding

Table 4.2: Load (pu) and irradiation values per every hour of the day [62].

Hour	Load (pu)	Irradiation
1	0.544181	0
2	0.503066	0
3	0.473728	0
4	0.457491	0
5	0.454773	0
6	0.46662	0
7	0.489477	18
8	0.508223	90
9	0.535958	270
10	0.570523	486
11	0.590941	684
12	0.598676	846
13	0.605505	873
14	0.595052	900
15	0.595679	873
16	0.599791	738
17	0.628153	630
18	0.741045	405
19	0.770035	126

20	0.747247	63
21	0.718397	27
22	0.678537	0
23	0.618537	0
24	0.546202	0

4.1. PERFORMANCE OF THE CNN

As the data is provided to the neural network in a single batch, i.e. no relative positioning can be concluded by the CNN, the data is arranged according to the timing each value is collected. Per each input, 100 values are collected, including the current measurements, where the value is normalized to a scale of 100 and used to set a value positioned at the current time instance to one. The vertical position of the value is selected based on the normalized voltage value, so that, an instantaneous value of 0 is positioned at the vertical position 50 and the maximum positive value, i.e. peak value, is positioned at the 25th row, as shown in Figure 4.2. This approach allows mapping abnormal values up to twice the peak value, so that, the CNN can detect anomaly in these values.

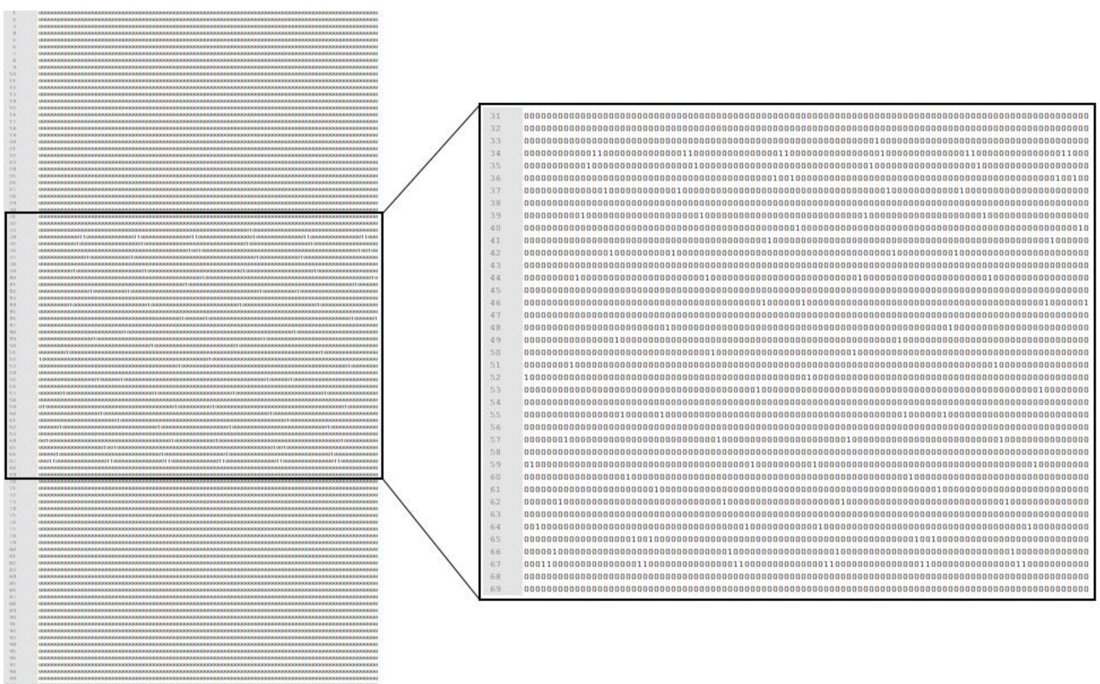

Figure 4.2: Sample of the array generated for one of the phase voltages.

Such an array is generated per each phase voltage, producing an input array of 100×100×3 dimensions per each time instance. Table 4.3 summarizes the structure of the implemented CNN in this experiment.

Table 4.3: Structure of the implemented CNN for islanding detection.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 98, 98, 32)        896
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 49, 49, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 47, 47, 16)        4624
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 23, 23, 16)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 8464)              0
_________________________________________________________________
dense_1 (Dense)              (None, 16)                135440
_________________________________________________________________
dense_2 (Dense)              (None, 8)                 136
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 9
=================================================================
```

The predictions of the CNN described in the confusion matrix shown in Table 4.4, illustrate the performance of the proposed method using this neural network, which shows that the accuracy of the predictions is 98.84%, with 98.96% DI and 98.61% SI. Accordingly, the proposed islanding detection system has been able to achieve slightly better dependability, compared to its security, when the CNN is used to predict the state of the DG grid. These measures indicate that this system is less likely to shut the power sources on the grid when non-islanding events occur but the possibility of keeping the grid energized during an islanding event is slightly higher.

Table 4.4: Confusion matric of the CNN's predictions.

		Predicted	
		Non-Islanding	**Islanding**
Actual	**Non-Islanding**	285	3
	Islanding	2	142

4.2. PERFORMANCE OF THE RNN

In this experiment, the proposed system is implemented based on the predictions of the RNN. According to the ability of this type ANNs to accept only two-dimensional arrays as inputs, the most recent 100 instantaneous values of the three phases are fed to the network in the shape of 100×3. The structure of the implemented neural network is shown in Table 4.5.

Table 4.5: Structure of the implemented RNN for islanding detection.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
simple_rnn_1 (SimpleRNN)     (None, 100, 32)           1152
_________________________________________________________________
simple_rnn_2 (SimpleRNN)     (None, 16)                784
_________________________________________________________________
dense_1 (Dense)              (None, 16)                272
_________________________________________________________________
dense_2 (Dense)              (None, 8)                 136
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 9
=================================================================
```

According to the summary of the predictions from this classifier, shown in Table 4.6, the accuracy of the predictions is 51.39%, with 51.04% DI and 52.08% SI. These results show that the use of the RNN is not applicable in the proposed method, as the performance measures are significantly lower than those scored by the CNN.

Table 4.6: Confusion matric of the RNN's predictions.

		Predicted	
		Non-Islanding	**Islanding**
Actual	**Non-Islanding**	147	141
	Islanding	69	75

4.3. PERFORMANCE OF THE LSTM

In this experiment, the proposed system is implemented based on the predictions of the LSTM neural network. As this type of neural network also has the ability to accept only two-dimensional arrays as inputs, the most recent 100 instantaneous values of the three phases are fed to the network in the shape of 100×3. The structure of the implemented neural network is shown in Table 4.7.

Table 4.7: Structure of the implemented LSTM neural network for islanding detection.

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
cu_dnnlstm_1 (CuDNNLSTM)     (None, 100, 32)           4736
_________________________________________________________________
cu_dnnlstm_2 (CuDNNLSTM)     (None, 16)                3200
_________________________________________________________________
dense_1 (Dense)              (None, 16)                272
_________________________________________________________________
dense_2 (Dense)              (None, 8)                 136
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 9
=================================================================
```

The predictions from this classifier, summarized in Table 4.8, shows that the use of the LSTM neural network has achieved the highest performance for the proposed system, with 99.77% accuracy, 100% DI and 99.31% SI. The perfect dependability index of the proposed system using the LSTM neural network indicates that the grid maintains its energy flowing to the consumers at all non-islanding events. However, one of the islanding events has not been detected by the LSTM neural network, which has produced the 99.31% SI.

Table 4.8: Confusion matric of the LSTM neural network's predictions.

		Predicted	
		Non-Islanding	**Islanding**
Actual	**Non-Islanding**	288	0
	Islanding	1	143

5. DISCUSSION

As the proposed islanding detection system relies on the predictions provided by the neural network about the current state of the DG grid, the quality of these predictions, summarized in Table 5.1, is the key to measure the performance of the system. According to these results, which are illustrated in Figure 5.1, the LSTM neural network has been able to produce the most accurate prediction. Hence, the best performance of the proposed system can be achieved by employing this neural network. The lowest performance is achieved when the simple RNN is used, with significantly lower performance measures, compared to the other methods. Moreover, the performance of the proposed system, when the LSTM neural network is used, has been able to outperform the employment of the CNN in all the three performance measures.

Table 5.1: Performance summary for the evaluated neural networks.

Classifier	Accuracy (%)	DI (%)	SI (%)
CNN	98.84	98.96	98.61
RNN	51.39	51.04	52.08
LSTM	99.77	100	99.31

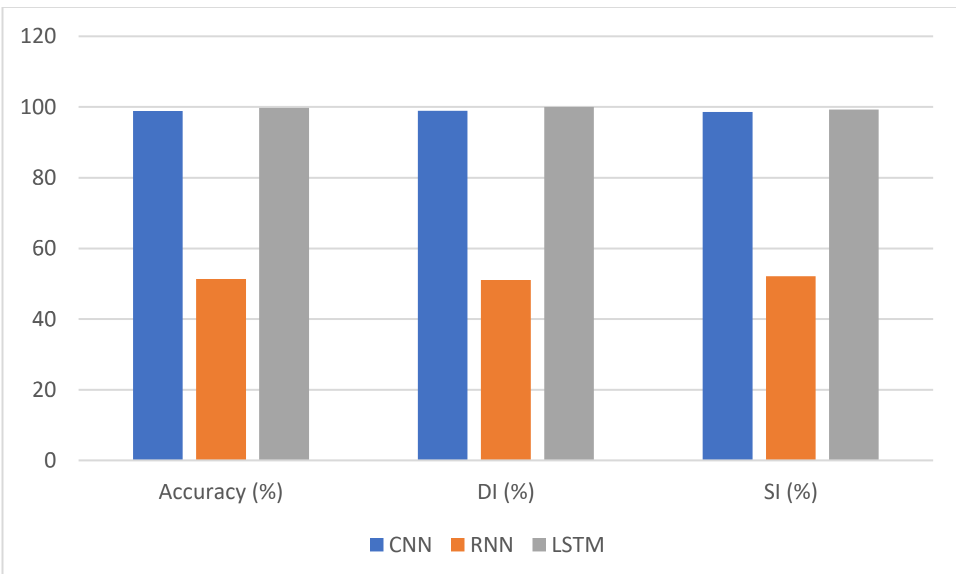

Figure 5.1: Illustration of the performance measure for the proposed system.

The use of the LSTM neural network in the proposed system produces a perfect dependability index, i.e. the power sources in the DG are maintained in operation when a non-islanding event occurs in the grid. Moreover, this type of neural networks has been able to produce a relatively high security index, as 99.31% of the islanding events are detected, so that, the power sources are disconnected from the DG grid, to protect the equipment and reduce the risk toward any maintenance operations on the grid. Moreover, the performance of the neural network is limited by the unbalance in the data collected from the simulated grid, according to the high ratio of non-islanding events, as shown in Table 4.2. Such unbalanced data can produce biased learning toward the dominant class, which is the case in the performance of the LSTM neural network.

The performance of the proposed system using all types of neural networks is compared to the existing state-of-the-art methods, which are also evaluated using the same model and events, as shown in Table 5.2. The comparison shows that the proposed system, based on the instantaneous values of the voltages, shows that despite the relatively lower performance of the simple RNN neural network, the CNN has been able to achieve very similar performance measures, compared to the other methods. Moreover, the employment of the LSTM neural network has produced an islanding detection system that outperforms the existing methods, despite the slightly lower SI of the proposed method compared to the use DT classifier in [34], as shown in Figure 5.2. Moreover, the use of the instantaneous values, instead of summarized value similar to the frequency's rate of change, allows the system to provide faster decisions.

Table 5.2: Comparison of the performance measures with earlier studies.

Study	Classifier (Feature)	Accuracy (%)	DI (%)	SI (%)
This Study	CNN	98.84	98.96	98.61
	RNN	51.39	51.04	52.08
	LSTM	**99.77**	**100**	99.31
Azim et al. [34]	DT (Δf/Δt)	99.38	99.38	**99.38**
	DT (VU)	99.18	99.38	99.07
	DT (ΔV/ΔQ)	99.18	99.38	99.07
	DT (ΔV/Δt)	99.18	99.38	99.07
Azim et al. [15]	DT	96.71	96.3	97.53
	Naïve Bayes	93.62	96.91	87.04
	SVM	88.27	90.12	84.57
	MLP	97.32	97.53	96.91
	RBF	94.85	94.75	95.05

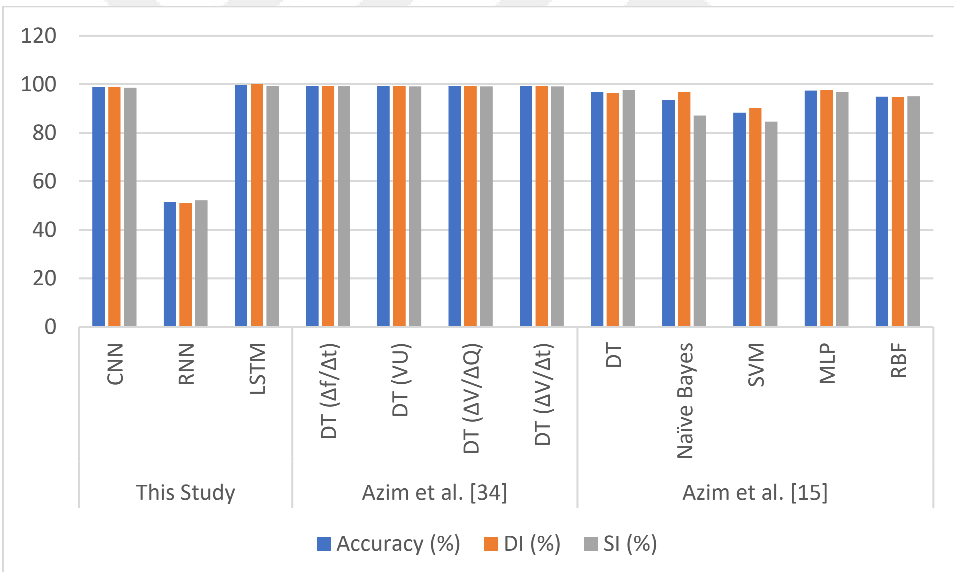

Figure 5.2: Illustration of the performance measures for different islanding detection methods.

6. CONCLUSION

The recent interest in the environment has led to a huge emphasis on using renewable energy such as solar panels and wind turbines. This led to more power sources, located locally, unlike the traditional ways, where huge power plants are used to feed the power grid, which has created the distributed generation (DG) power grids. The implementation and integration of any new technology have always been an issue of introducing them. DGs are not an exception, one of the most important challenges that are faced by the new DG power grids is the islanding detection. Islanding is the state where a section of the power grid remains energized from the local power sources, despite the fact that this section is disconnected from the main grid. The IEEE standard time recommended to detect and shut off power sources in an islanded DG region is 2 seconds. Thus, it is important to detect the islanding states as soon as possible in order to take the appropriate action. This quick detection must not be achieved away from the accuracy of that detection. A quick accurate decision is required.

In this study, a passive islanding detection system is proposed, which relies on artificial neural networks to predict the state of the DG grid when an event occurs on that grid. According to the ability of some types of neural networks in processing multi-dimensional inputs, these networks are used to predict the type of event based on a set of instantaneous values collected from the phases' voltages. Three types of neural networks are evaluated in this study, the CNN, simple RNN and LSTM. The proposed system shows the best performance when the LSTM neural network is used to predict the type of the event occurring in the grid, with 99.77% accuracy of the predictions. Using this type of neural networks, the proposed system has achieved a 100% dependability index, where all non-islanding events are predicted correctly, and 99.31% security index, according to misclassifying one of the islanding events. The performance of the proposed system using the LSTM neural network has outperformed the state-of-the-art methods in the literature, while the CNN has achieved a very similar performance. The lowest performance is scored by the simple RNN, which has only 51.39% accurate predictions.

In future work, a hybrid neural network is going to be implemented for the proposed system, which is going to employ both the LSTM and convolutional layers. The convolutional layers collect the inputs from the grid and detect local features in the waveforms of the phases. Then, these features are passed through a set of LSTM layers, so that, more relevant features can be detected. Such a neural network is expected to improve the security index of the proposed system by combining the benefits of both types of layers.

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