A Universal Islanding Detection Technique for Distributed Generation Using Pattern Recognition

by

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A thesis
presented to the University of Waterloo
in fulfilment of the
thesis requirement for the degree of
Master of Applied Science
in
Electrical and Computer Engineering

Waterloo, Ontario, Canada, 2013

AUTHOR'S DECLARATION

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

I understand that my thesis may be made electronically available to the public.

Omar Faqhruldin

Abstract

In the past, distribution systems were characterized by a unidirectional power flow where power flows from the main power generation units to consumers. However, with changes in power system regulation and increasing incentives for integrating renewable energy sources, Distributed Generation (DG) has become an important component of modern distribution systems. Reducing system losses and increasing system reliability can be achieved by integrating DG units into a system. However, when a portion of the system is energized by one or more DG and is disconnected from the grid, this portion becomes islanded and might cause several operational and safety issues. Therefore, an accurate and fast islanding detection technique is needed to avoid these issues as per IEEE Standard 1547-2003 [1]. Islanding detection techniques are dependent on the type of the DG connected to the system and can achieve accurate results when only one type of DG is used in the system. Thus, a major challenge is to design a universal islanding technique to detect islanding accurately and in a timely manner for different DG types and multiple DG units in the system.

This thesis introduces an efficient universal islanding detection method that can be applied to both Inverter-based DG and Synchronous-based DG. The proposed method relies on extracting a group of features from measurements of the voltage and frequency at the Point of Common Coupling (PCC) of the targeted island. Then, a feature selection algorithm is used to select the best features for islanding detection in order to reduce the detection time while maintaining high accuracy. After that, the Random Forest (RF) classification technique is used to distinguish between islanding and non-islanding situations with the goals of achieving a zero Non-Detection Zone (NDZ), which is a region where islanding detection techniques fail to detect islanding, as well as avoiding nuisance DG tripping during non-islanding conditions. Islanding and non-islanding cases have been generated, under different system topologies taking into consideration island size, type of DGs connected to the system, and number of DGs connected to the system, using the IEEE 34 bus system in order to train and test the proposed technique. The accuracy of the proposed technique is evaluated using a cross-validation technique. The methodology of the proposed islanding detection technique is shown to have a zero NDZ, 98% accuracy, and fast response when applied to both types of DGs. Finally, four other classifiers are compared with the Random Forest classifier, and the RF technique proved to be the most efficient approach for islanding detection.

Acknowledgments

Completed with the grace of Allah on 25 July 2013. All praise and thanks are due to Allah alone, the Exalted, the Lord of the universe, for all His blessings that He bestowed upon us. May Allah accept our humble efforts and be pleased with us.

I would like first to express my sincere appreciation and gratefulness to my advisor, Professor Ehab El-Saadany, for his leadership, patience, encouragement, and unrelenting support all the way through my academic program. I also must extend my gratitude and thankfulness to my co-advisor, Professor Hatem Zeineldin, for his constructive comments and enormous support from the beginning of this research to writing this thesis. Thank you professors for making this work a success; I unquestionably learned a great deal of skills from this journey.

I would also like to thank Professor Magdy Salama and Professor Tarek Abdelgalil for the time they have put in reviewing this thesis. Their effort and constructive comments are highly appreciated.

I am also thankful to all the members of my research group: Abdelwahed, Abdulsalam, Aboelsood, Ali, Amr, Ayman, Elham, Fatima, Hany, Hassan, Hatem, Maher, Mohamed, Morad, Mostafa, Wael, and Yousef for their friendship, daily academic and non-academic discussions and adding different flavors to my life. This thanks is extended to all my friends in Waterloo who enriched my life and made the past couple years an unforgettable experience.

Last but most importantly, to my amazing parents, whose love, pains, sacrifices, and hard work in making me and my brother who we are today, these few lines and words can never do justice to what you have done to us. I say thank you from the bottom of my heart. I hope you live a long and happy life, and may Allah reward you with happiness and peace of mind. I hope I made you proud. My thanks to my brother and family members for their love and support during my study.

Dedication

To my beloved parents, for all the support you have provided me. Whatever I do can never pay you back. Without you in my life, this thesis would have never seen the light. May Allah help me make you proud and bring joy to your eyes in this life and in the hereafter.

Omar

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Chapter 1

Introduction

1.1 Overview

In traditional power systems, the generation of power is characterized as being centralized power generation, meaning that the power flows from bulk power-generation plants, such as nuclear power plants and hydro dams, to consumers by transmission links. As the human population increases, the demand for electricity increases. For example, in Canada, electrical consumption has been growing in the last twenty years at a rate of 1.1% every year [2]. However, political, physical, environmental, and economical constraints restrict building new large electrical power plants. Therefore, to overcome these limitations and react to the increased power demand, the concept of installing Distributed Generation (DG) has been introduced. DG units (DGs) can supply both active and reactive power in order to assist the grid in meeting the increased power demand.

Installing DGs within a distribution system has several advantages, such as improving power quality, system reliability, system performance, and reducing system losses. Such units can provide backup in case of power failure by having them as a backup units. DGs can also be used to provide ancillary services such as spinning reserve. Finally, due to environmental concerns, DGs that run on renewable resources such as wind and solar can be very appealing.

Although DGs have been0020receiving attention due to their many advantages, several issues are associated with the increased penetration of decentralized power generation units into distribution systems [3]. For example, one major issue is their high capital cost per kW compared to that of large power generation plants. Another issue associated with the high penetration of DGs into the system is their unpredictable power output. It is difficult to forecast the power profile of DGs such as wind and solar. Protection issues can also be a challenge with the integration of DGs into current power systems. Since the existing distribution systems are usually as radial, the electric power flows in one directional from the grid to the consumers. However, when DGs are introduced into the system, power will also flow the other way, causing a bi-directional power flow. This change from unidirectional to bi-directional power flow requires new protection schemes. Finally, DGs can be operated in both grid-connected mode or planned islanded mode. In this latter mode, part of the grid, including one or more DGs, is disconnected from the main grid by opening the circuit breaker at the Point of Common Coupling (PCC) by the utility. However, as shown in Figure 1, unintentional islanding can occur and causes several operational and safety issues [4], for instance, poor power quality due to the mismatch in active and reactive power between the load and generation. This mismatch causes a deviation in the voltage and frequency, which can lead to damaging customers' and network equipment. Another issue is out-of-phase re-closing of circuit breakers, which might damage the DG unit when the island is reconnected to the main grid. This damage occurs because the DG will most likely be out of synchronism with the gird at the time of reconnection, perhaps resulting in large transient currents that will damage the DG. Finally, unintentional islanding can be a threat to the safety of line workers since the island remains energized by the DG while they assume it to be disconnected. Therefore, the issues of islanding call for immediate detection as per IEEE Standard 1547-2003.

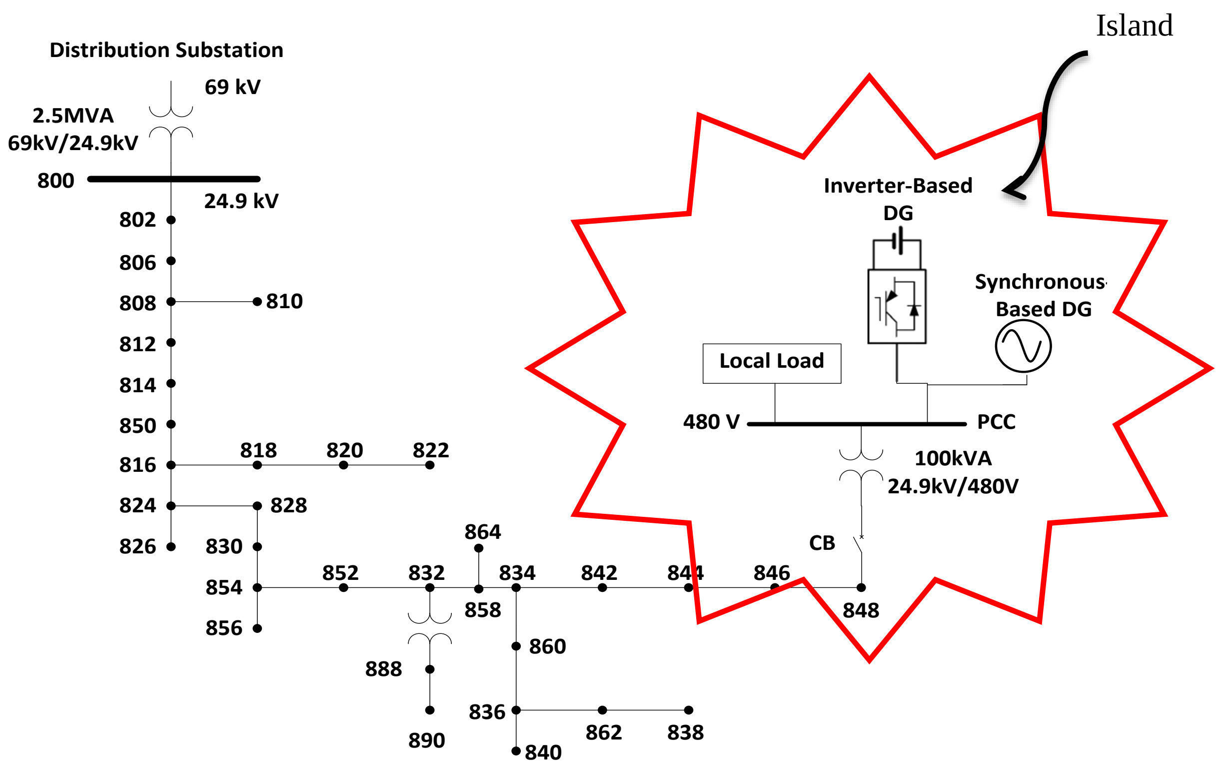


Figure 1: An Overview of Islanding

As mentioned, islanding detection techniques are DG dependent, and the detection accuracy will greatly depend on the DG type connected to the system. DGs can be divided into two main categories: Synchronous-based (rotary based) DGs and Inverter-based DGs. Table 1 summarizes the different types of DGs and in which technology they can be used. Because of the two possible categories, islanding detection techniques developed for Inverter-based DGs will fail to detect islanding accurately for Synchronous-based DGs and vice versa.

Table 1: Types Of DG

Technology	DG type

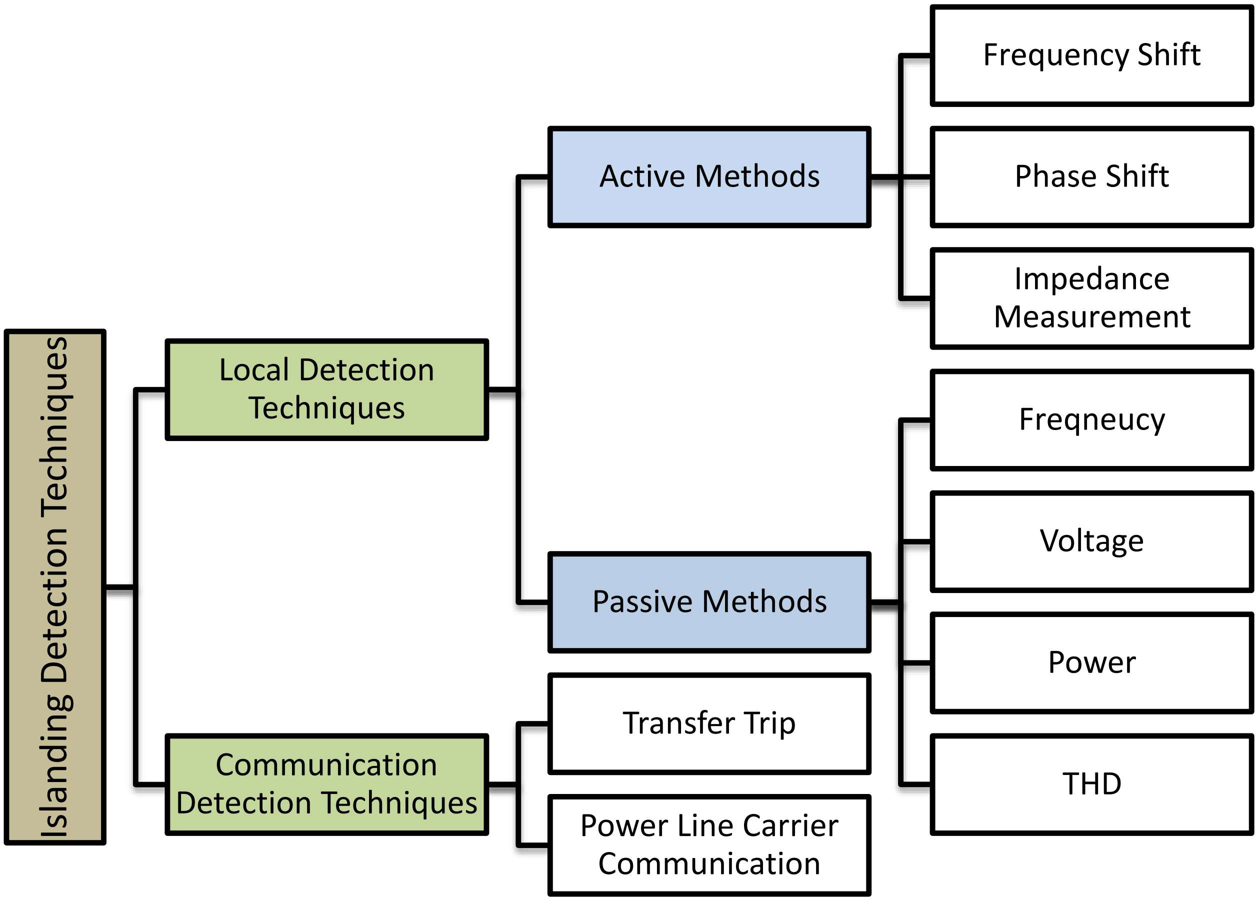
Photovoltaic	Inverter-Based DG
Fuel Cells	Inverter-Based DG
Wind Turbines	Doubly-Fed Induction Generator, Synchronous Generator behind a full inverter
Small Hydro	Induction, Synchronous-Based DG
Gas Turbines	Inverter-Based DG
Geothermal	Synchronous-Based DG

1.2 Islanding Detection Techniques

Islanding detection techniques can be divided into three main categories: passive, active, and communication based techniques. Figure 2 shows an overall view of islanding detection techniques that are commonly available and used by utilities. Communication based techniques are the most reliable and accurate; however, they are very difficult to implement in complex systems and are the most expensive detection techniques. Active methods depend on introducing a disturbance into the system or injecting a noise into it near the targeted DG; the resulting response is then compared to pre-defined scenarios. Passive methods depend on a set of measurements such as voltage, frequency, power, and Total Harmonic Distortion (THD) in order to detect islanding. Each detection technique has its own advantages and disadvantages and Table 2 summarizes these for each method.

Table 2: A Comparison of the Main Islanding Detection Techniques

Feature / Technique	Communication Techniques	Local Techniques		
		Active	Passive	Hybrid
Principle of operations	Uses communication equipment to communicate between the utility and DG unit	Inject noise signal into the system and compare the response to a pre-set threshold	Based on local measurements such as voltage, frequency, power, and THD at PCC	Mixture of passive and active techniques
Additional equipment	Communication devices	requires some equipment	Minimum equipment	Equipment of active and passive
Cost	Very expensive	Medium	Lowest	High
Multiple DG units operation	Possible	Not possible	Possible	Possible
Effect on power quality	No effect	Reduce power quality, voltage stability and introduce transient response	No effect	Reduce power quality, voltage stability and introduce transient response
Time required	Very fast	Short	Slightly longer than passive	Longer than active
Effectiveness	Most effective	Depends on the mismatch between the load and DG unit	Effective even in small mismatch	Very effective
NDZ	Non	Large	Small	small
DG Dependent	No	Yes	Yes	Yes



1.3 Research Motivation

Figure 2: Islanding Detection Techniques

From Table 2, it is clear that no perfect islanding detection technique exists that can be used without having disadvantages. Some of these disadvantages are: high implementation cost, as in communication based techniques; reduction in power quality and system stability, as in active techniques as a result of injecting disturbance into the system; presence of NDZ, as in passive techniques which might results in false islanding detection for small mismatched scenarios; and false operation when multiple DG units are connected in the system. To overcome these disadvantages, many islanding detection techniques have been proposed in the literature. The proposed techniques were able to detect islanding very effectively, achieving very accurate results and eliminating most of the discussed disadvantages. However, all the proposed techniques were DG dependent and were directed to a single type of DG. These techniques would either fail to operate properly, when applied to other types of DG, or cannot be integrated in the same way. For example, techniques that detect islanding for systems with Inverter-based DG might not work properly or would fail to detect islanding for systems with Synchronous-based DG and vice versa. Therefore, a universal islanding detection technique is clearly needed, one that can detect islanding when both types of DGs are connected together in the same system, which is the case in modern distribution systems.

This thesis proposes a novel universal islanding detection technique that incorporates data mining and Artificial Intelligence (AI) techniques. The proposed algorithm depends on measuring multiple features at the PCC of the targeted island. The extracted features are sampled and passed through a feature-selection process in which top features are selected based on certain criteria. After that, the features are fed to the classifier in order to distinguish between islanding and non-islanding conditions.

The proposed algorithm is able to detect islanding under different system conditions. First, it can detect islanding under large and small power mismatches between local loads and DG units in the island. More importantly, it can detect islanding under perfectly match scenarios where the power consumed by the local loads is equal to the power generated by DG units inside the island. Thus, the proposed technique has a zero NDZ. Furthermore, the proposed technique can work for different DG types such as Inverter-based and Synchronous-based DGs, and also works if one DG is present or multiple DGs are used, independently of the DG type.

1.4 Thesis Organization

This thesis is divided into five main chapters. Chapter 1 introduces the work, and Chapter 2 provides background on some major islanding detection techniques proposed in the literature. Chapter 3 explains the proposed islanding detection technique, and Chapter 4 presents the simulation results followed by discussion. Finally, Chapter 5 concludes the work.

Chapter 2

Literature Review

Islanding is a condition in which part of a distribution network is disconnected from the remainder of the grid, and yet is powered by one or more Distributed Generation (DG) units connected to it. It is difficult to compare islanding detection techniques since each type and technique operates better and more efficiently than other technique in a specific situation and system. For example, techniques that depend on the change of terminal voltage will work effectively for Synchronous-based DG, whereas techniques that depend on frequency shift will be ideal for Inverter-based DG.

In recent years, various islanding detection methods have been proposed with an overall aim of minimizing the non-detection zone (NDZ). NDZ is the range in active and reactive power mismatch ($\Delta \mathrm{P}$ and $\Delta \mathrm{Q}$, respectivly) between the load demand and the power supplied by the DG unit in the island where the islanding will not be detected as shown in Figure 3. The limits of this NDZ are based on active power and reactive power mismatch equations (1-4) as shown below ([22]:

For an active power mismatch (ΔP) , the equation is:

$$\left(\frac{V}{V_{max}}\right)^2 - 1 \leq \frac{\Delta P}{P} \leq \left(\frac{V}{V_{min}}\right)^2 - 1 \qquad (1)$$

Based on IEEE standards the limits for the voltage are $V_{min} = 0.88\ pu$ and $V_{max} = 1.1\ pu$, so the limits of the NDZ due to the active power mismatch are

$$-17.36\% \leq \frac{\Delta P}{P} \leq 29.13\%1 \qquad (2)$$

For a reactive power mismatch(ΔQ), the equation is:

$$1-\left(\frac{f}{f_{min}}\right)^2 \leq \frac{\Delta Q}{P} \leq 1-\left(\frac{f}{f_{max}}\right)^2 1 \qquad (3)$$

Based on IEEE standards, the limits for the frequency are $f_{min} = 59.3\ Hz$ and $f_{max} = 60.5\ Hz$, so the limits of the NDZ due to reactive power mismatch are

$$-2.37\% \leq \frac{\Delta Q}{P} \leq 1.646\%1 \qquad (4)$$

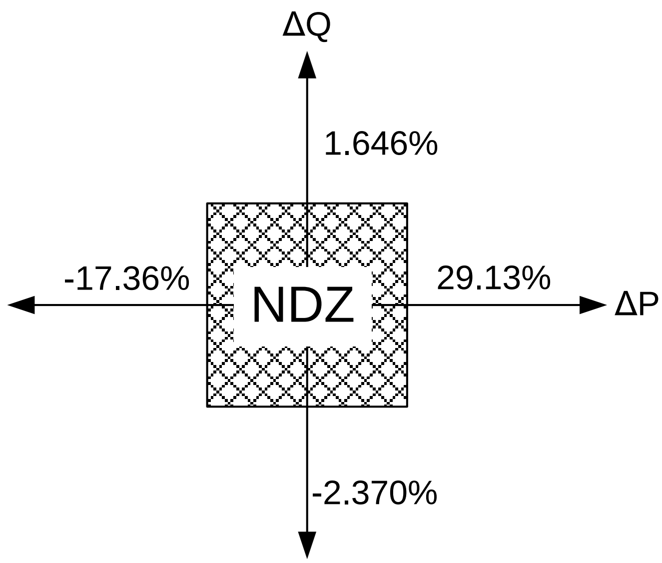


Figure 3: NDZ Limits

Islanding detection methods can be divided into three main categories: communication based [5, 6], active based [7-15], and passive based [16-22]. Communication based methods are very accurate but are the most expensive among islanding detection techniques. Active methods rely on introducing a small noise signal into the system. Under normal conditions, this signal will not cause much deviation in system parameters, due to the presence of the substation. However, during islanding, this signal becomes amplified, facilitating islanding detection. Passive islanding detection methods are simple and rely on measurable quantities such as voltage, frequency, etc., at the PCC to detect islanding. Under each of the aforementioned categories, there exist different designs and models for islanding detection.

2.1 Communication based Islanding Detection Techniques

Having communication between DGs and the utility is the most effective and reliable islanding detection technique. However, this communication is very expensive and uneconomical to implement unless it is required by the utility. Under this category, there are two main islanding detection techniques: Transfer Trip (TT) and Power Line Carrier Communication (PLCC).

2.1.1 Transfer Trip

Transfer Trip is the most common islanding detection technique and is used by many utilities, including Hydro One in Ontario, because of its very simple concept. All circuit breakers that island the DG must be monitored by a Supervisory Control and Data Acquisition (SCADA) system and linked directly to the DG control unit [5]. Thus, when there is a disconnection in the system, TT scheme will determine the islanded area and disconnect the DG from the system.

If this method is installed correctly in a simple radial network, there will be zero NDZ. The main disadvantages of this technique are the implementation cost and increased complexity as the system gets larger and larger. The larger the system is, the more complex the control unit will become and the higher the implementation cost. With a large system and many DG units installed, implementing this method becomes infeasible.

2.1.2 Power Line Carrier Communication

In the Power Line Carrier Communication (PLCC) islanding detection technique, a signal is generated from a signal generator at the substation and transmitted through power lines to the DG units connected in the system as demonstrated in figure 4 [6]. Each DG unit is then equipped with a signal detector. If the signal detector receives the transmitted signal, this means that the DG unit is connected to the system and operating under normal conditions. However, under islanding conditions, the transmitted signal will not be received by the signal detector since the circuit breaker at the substation is open. Consequently, the DG is disconnected from the system due to islanding.

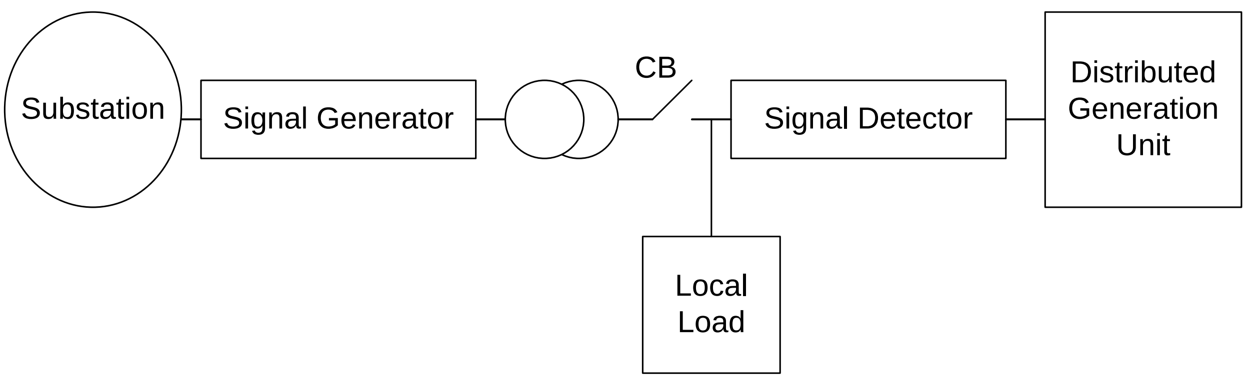


Figure 4: Power Line Carrier Communication

Similar to the TT method, PLCC has the advantages of simplicity and reliability. In simple radial systems, only one signal generator unit is needed to generate signals to any DG unit connected in the system. If the circuit breaker is open or there is a fault in the line, then the signal will not be received at the DG site and the DG will be disconnected.

However, similar to the TT, this method has the practical implementation problems: the larger and more complex the system gets, the more complex line communication will be.

Therefore, in systems with many connected DGs, PLCC becomes very complex, and implementing it becomes infeasible.

2.2 Active Islanding Detection Techniques

Active islanding detection techniques depend on introducing a disturbance into the system. Under normal conditions, this disturbance does not alter system parameters. However, in islanded mode, the injected noise causes system parameters to change significantly. In the next subsections, various islanding detection methods are introduced.

2.2.1 Slip Mode Frequency Shift

Slip Mode Frequency Shift (SMS) islanding detection technique is based on the idea of changing the phase shift at the PCC to be miss-aligned with the grid [7, 8]. Under grid-connected mode, the utility keeps the Inverter-DG in phase, and therefore this phase shift will have very little effect on the frequency of the system. However, during islanding, the frequency is changed linearly with the phase shift, so when the grid is missing, the Phase-Locked Loop (PLL) will continue to drift the phase and send the frequency into a positive feedback loop that will intersect with the load curve at a higher frequency where islanding can be detected easily.

One of the main advantages of SMS is that it has been tested and proven to have a very small NDZ if used correctly. SMS is also very simple to implement, as doing so only requires some modification to existing components in the Inverter-based DG control unit, and works with multiple DGs in the system. However, the main challenge in SMS is to come up with a generalized load curve to fit all load curves. SMS also works very well when applied to Inverter-based DG systems but fails to operate correctly when used with Synchronous-based DG systems.

2.2.2 Active Frequency Drift

With Active Frequency Drift (AFD) islanding detection technique, the output current waveform is altered by adding a dead-time portion "drift" at the end of every half cycle, as shown in Figure 5 [9, 10, 11, and 12]. The ratio $\frac{t_z}{t_v}$ is called the chopping factor. In grid-connected mode, this chopping factor is constant due to the presence of the utility. However, during islanding, the chopping factor increases continuously because the frequency is seeking to match the load resonance frequency. As soon as the chopping factor passes a certain pre-defined threshold, islanding is signaled and the DG is disconnected.

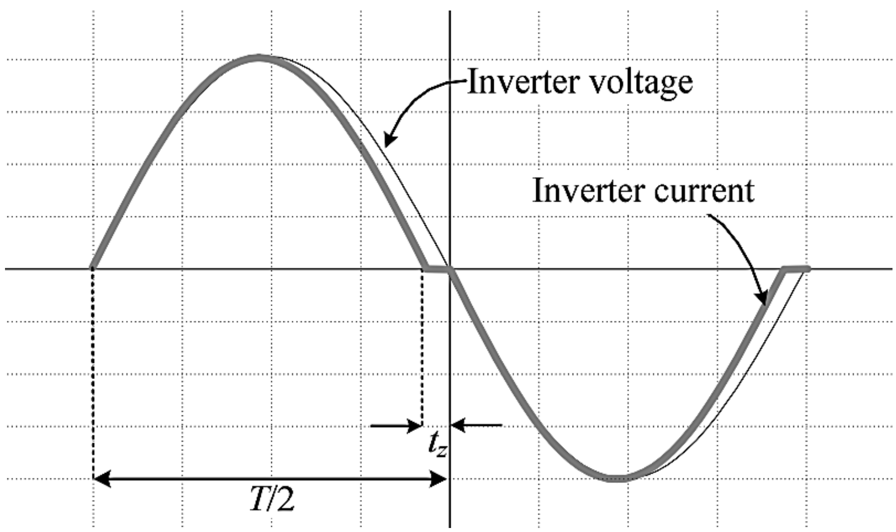


Figure 5: AFD Islanding Detection Method

This method has been tested and found to result in larger NDZ than that of SMS. It also introduces a distortion to the output of the DG in order to detect islanding, a distortion that might cause transient problems and power quality issues.

2.2.3 Sandia Frequency Shift

Sandia Frequency Shift (SFS) is an improved version of AFD in which a positive feedback is used in determining the chopping factor (t_v), as shown in the equation (5), where $\mathrm{CF_o}$ is the chopping factor in grid-connected mode where there is no frequency deviation, K is the positive feedback gain, f is the measured frequency, and $\mathrm{f_o}$ is the nominal frequency (60 Hz) [13,14,15].

$$CF = CF_o + K(f - f_o)1 \tag{5}$$

During grid-connected mode, the change in frequency is very small, and $\mathrm{f - f_o}$ is almost zero so the chopping factor is a small value and negligible. However, during islanding, the DG unit comes into control, and frequency will deviate to match the load resonance frequency. Therefore, the chopping factor will increase according to the above equation until the inverter trips.

This method hugely improves on the normal AFD, and has the advantage of having a small NDZ. However, it also results in reduced power quality due to the positive feedback. This method is designed to be implemented for Inverter-based DG system.

2.2.4 Sandia Voltage Shift

Sandia Voltage Shift (SVS) is a usually implemented in conjunction with SFS in which the positive feedback is applied to the amplitude of the voltage. In SVS, the inverter reduces its power output in order to reduce its voltage. In grid-connected mode, this reduction in power has negligible effect on the output voltage. However, during islanding, the voltage drops because of the reduction in the power. The positive feedback will keep reducing the voltage until the under voltage relay trips and disconnects the DG unit from the system [5].

SVS method can be easily implemented and can detect islanding effectively when used with SFS. The main drawbacks are the reduction of DG efficiency and reduction in power quality due to the positive feedback. Active islanding detection techniques have the advantages of providing very accurate results and a small NDZ. These advantages come at a cost of reduced power quality, reduced DG unit efficiency, and slow detection time.

2.3 Passive Islanding Detection Techniques

Passive islanding detection techniques depend on measuring specific system parameters (e.g. voltage, frequency, total harmonic distortion, etc.) in order to detect islanding. These methods do not interfere with the operation of the DG and do not introduce noise into the system. Some examples of passive islanding detection methods are presented in the next subsections.

2.3.1 Over/Under Frequency, and Rate of Change of Frequency

Over/Under Frequency islanding detection technique relies on the frequency at the PCC of the island to detect islanding [16, 17, 18]. As discussed earlier, frequency deviation depends on the mismatch in reactive power. In grid-connected mode, since there is no mismatch between generated and consumed reactive power, there is no deviation in the frequency. However, in islanding mode, there is a mismatch between the reactive power generated by the DG unit and the reactive power consumed by the local load in the island. Depending on the percentage of this mismatch, the frequency will deviate to a certain level. If there is a large mismatch, then the frequency will deviate beyond a pre-defined threshold value ($59.3 > f > 60.5$) and the relay will trip and disconnect the DG.

Another islanding detection technique that uses frequency is the Rate of Change of Frequency (ROCOF). ROCOF uses $\frac{\Delta f}{\Delta t}$ in order to detect islanding. The DG will trip if $\frac{\Delta f}{\Delta t}$ passes a pre-defined value, usually between 0.1 Hz/s and 1.2 Hz/s in a 60 Hz system, depending on the size of the DG unit.

2.3.2 Over/Under Voltage, and Rate of Change of Voltage

Over/Under islanding detection technique is often used in conjunction with Over/Under Frequency. Over/Under voltage technique depends on mismatches in active power in order to detect islanding [18, 19]. During grid-connected mode, there is no mismatch between the generated and consumed power at the PCC. As soon as islanding happens, a mismatch occurs in the active power between the DG and the local load connected inside the island. Depending on the mismatch percentage, the voltage will deviate to a certain value, and if this deviation in voltage passes the pre-defined threshold, then the relay opens the breaker and disconnects the DG unit.

Another method that depends on voltage is Rate of Change of Voltage (ROCOV), where $\frac{\Delta v}{\Delta t}$ is used to detect islanding. During the presence of the utility, the variation in voltage is small and negligible. However, during islanding, the ROCOV is large, and the DG will be disconnected if this ROCOV passes the preset threshold value.

The four techniques discussed above have the advantages of being fast and not introducing any disturbance to the system. They can also be considered as universal techniques that can be used for both types of DG. However, these techniques suffer from a large NDZ, and the choice of the pre-defined thresholds is very complicated. On one hand, if the threshold is set to a large value, then the NDZ becomes large and the techniques are not able to detect small islanding cases where the mismatch is small. On the other hand, if the threshold is set to a small value, then the NDZ becomes small and the detection techniques become very sensitive and prone to nuisance trips.

2.3.3 Voltage and Current Total Harmonic Distortion

Total Harmonic Distortion (THD) is generally used with Inverter-based DGs where harmonics are present. In this technique, the sensor measures the THD and compares it with a threshold value [20]. In grid-connected mode, the THD is negligible due to the presence of the utility. In islanded mode, the THD is much larger. This method is the most difficult to use since it is very hard to measure and predict the harmonics. It is also very difficult to choose the threshold value since load switching during grid-connected mode can also causes a spike in THD that results in false islanding detection.

2.4 Artificial Intelligence Islanding Detection Techniques

Recently, Artificial Intelligence (AI) techniques have gained popularity, and several papers have proposed their use for islanding detection. This increased interest in AI techniques is due to the capability of determining the most suitable combination of features/parameters as well as thresholds for significantly reducing the non-detection zone of islanding detection methods.

An islanding detection technique based on a data mining approach using a decision tree (DT) was proposed in [23]. The proposed DT had limitations such as the dependency of the threshold values on the splitting criteria, which resulted in low accuracy of detection. In [24], the IEEE 7-bus system was used to test and compare three AI techniques for islanding detection. The current signals were sampled at 20 kHz, and Daubechie's four wavelets with six levels of decomposition were used. The comparison was between support vector machines (SVM), a probabilistic neural network (PPN), and decision tree (DT) classifiers. The study showed that the worst classifier for detecting islanding was SVM, with an overall accuracy of less than 74%, followed by PNN, with 85% accuracy, and DT with the highest accuracy was around 86%. A similar study was done in [25] using the same classifiers but with different features. In this work, seven features were extracted from voltage and frequency waveforms. Again, SVM showed the minimum overall accuracy, with an overall accuracy of 85%. DT improved its overall accuracy to 90%, and PNN remarkably, achieved 97%. This work proved that AI techniques require more variety in their training data in order to achieve higher accuracies. Again, a Probabilistic Neural Network islanding detection technique was proposed [26]. Multiple parameters were derived and used as input to the probabilistic neural network in order to detect islanding. This technique showed very high accuracy in detecting islanding, with a mismatch of less than 6% for the worst-case scenario.

In [27], an intelligent islanding detection technique that uses a DT classifier in order to detect islanding was proposed. This technique analyzed current and voltage signals at the targeted DG in order to extract eleven features to detect islanding. The extracted features were stored with their corresponding class in a pattern-classification data module. The developed module was then used to train and test the decision tree classifier. However, the method was not capable of capturing all possible islanding events, and had a mismatch rate of 16.67%. In order to improve the detection accuracy, a Fuzzy Rule-based approach was developed and proposed in [28]. The proposed technique used the top three features recommended by the DT from the previous work [27] (ROCOF $\frac{\Delta f}{\Delta t}$, ROCOP $\frac{\Delta p}{\Delta t}$, and Change in frequency Δf) in order to generate fuzzy Membership Functions. With the approach moving from Decision Tree to Fuzzy Logic, the threshold values moved from “crisp” values to “soft” values. This technique yielded very accurate results in terms of islanding detection. Nevertheless, the main disadvantage of the proposed method is that it was implemented on a Synchronous-based DG system only.

Another islanding detection technique was proposed in [29] in which a Bayesian classifier was used to detect islanding based on 64 parameters calculated by ESPRIT. The proposed technique used voltage and frequency waveforms in order to generate features, and these were fed to a Naïve Bayesian classifier to distinguish between islanding and non-islanding scenarios. The proposed technique provided 100% accuracy but was only implemented on an Inverter-based DG system. Additionally, in [30, 31] a pattern recognition approach was implemented for islanding detection. Voltage and current transient signals were discretized by discrete wavelet transformation in order to extract twelve features. A Decision Tree was then modeled in order to discriminate between islanding and non-islanding events based on the energy content in the wavelet coefficients. The proposed technique provided 97% overall accuracy. However, it was implemented only on a Synchronous-based DG. Another DT based islanding detection technique was proposed in [32, 33], in which eleven features were extracted and used to detect islanding. The proposed islanding intelligent relay performed very well and had a very insignificant NDZ. However, it was implemented on a Synchronous-based DG system.

Of all the above techniques [23,33], the AI techniques showed the most accurate results in detecting islanding, if proper features were extracted and a proper classifier was used. Nevertheless, all the techniques were implemented and tested based on one DG type (Synchronous or Inverter). This thesis takes advantage of the AI technique capabilities by proposing a robust universal islanding detection method that can be applied to both types of DG (Synchronous and Inverter based).

Chapter 3

Technical Details of the Proposed Method

The proposed universal islanding detection method has three main phases, which include feature extraction, feature selection, and classification. First, the voltage and current waveforms are measured to extract the 21 possible features presented in section 3.4. Second, a feature selection algorithm is used to determine the most effective combination of features that can be used to detect islanding accurately and that can be applied to both the Inverter-based DG and the Synchronous-based DG. The sequential feature selection methods, such as the Forward Feature Selection (FFS) and the Backward Feature Selection (BFS), are used to select the best features [29, 30] to be used for islanding detection. At the end, the Random Forest algorithm is used to distinguish islanding from non-islanding events. Since the Decision Tree classifier can disintegrate a very complicated classification process into a manageable and basic logic decision process; RF is used because it has the ability to combine output from multiple DTs, and thus, provide higher and more robust results than a single DT. Furthermore, three other classifiers are used to compare the used algorithm and robustness of the chosen features. This section explains all the basic theories of the algorithms used in this universal islanding detection technique. The system under study, the methodology and the basics of the classifiers are explained in the following subsections.

3.1 System under Study

In this thesis, the IEEE 34-bus distribution system, which is modeled in MATLAB/SIMULINK, is used in the simulation. A sample system is shown in Figure 6, which demonstrates the system with a DG connected at the Point of Common Coupling (PCC). There is a local load of 100 kW connected at the PCC. The DG and the load are connected to the remaining distribution system by a 100 kVA 24.9kV/480V transformer. There are two different DG types that will be connected to the system: Synchronous-based DG and Inverter-based DG. The Synchronous-based DG includes a synchronous generator, an exciter and a governor modeled as in [29]. The other DG is an Inverter-based DG with a current controlled interface as displayed in Figure 7 [5].

The control unit works as follows: To determine the frequency (ω) and the phase angle (θ), the control unit measures the voltage at the PCC point, and, in turn, supplies it to the phase-locked loop (PLL). In addition, the current at the PCC is measured and fed into the Park transformation (*abc/dq*) to acquire the *dq* component of the current. The *iq* and id are compared to the iq_{ref} and id_{ref} after extracting the *dq* components of the current, and the difference between them is used as an input for the proportional-integral controller Finally, to control the Inverter-based DG switches, the frequency ω with the output of the proportional-integral controller are used as input for the Pulse Width Modulation (PWM).

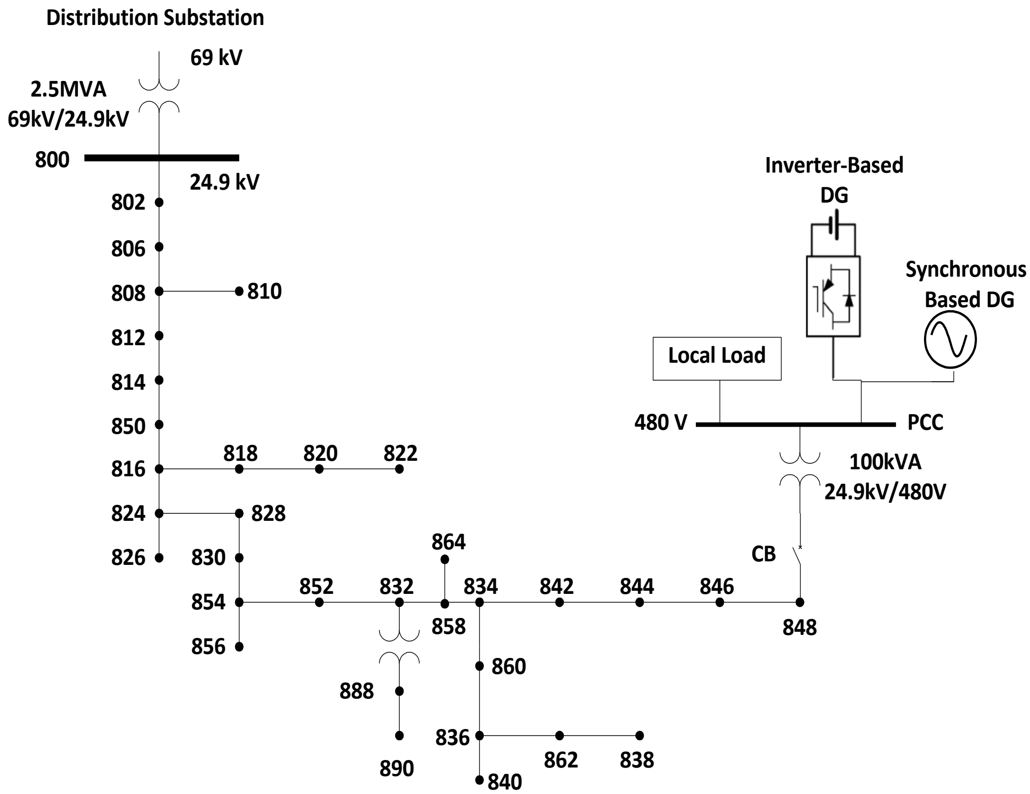


Figure 6: IEEE 34-Bus Test System

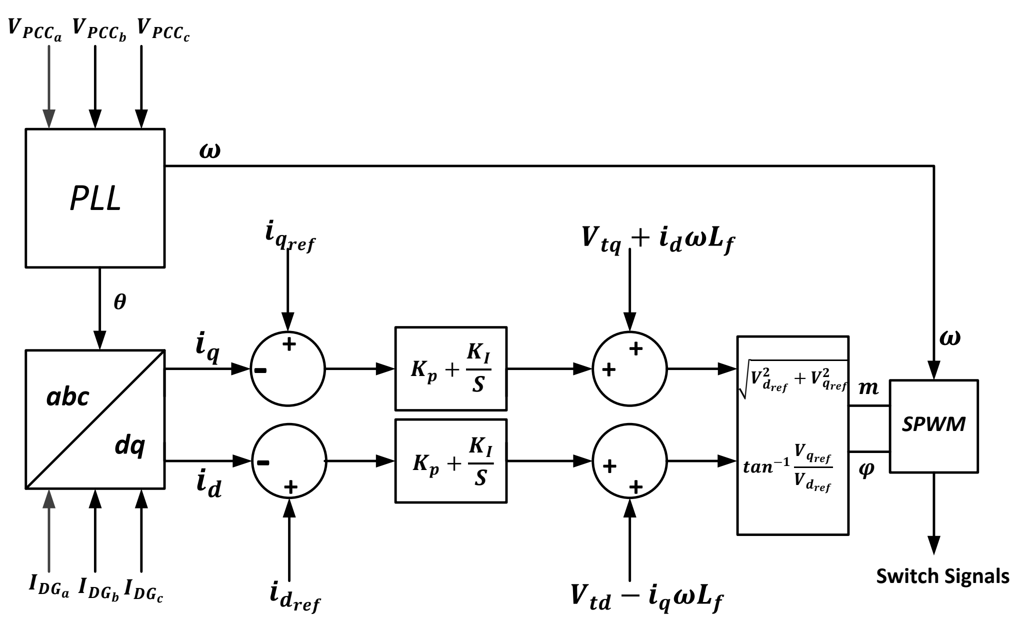


Figure 7: Constant Current Controller Schematic to Control the DG

3.2 Data Generation

A wide range of simulated cases is performed to provide the classifier with a distinctive information to differentiate between islanding and non-islanding conditions. To simulate islanding conditions, different mismatches in generated power by the local DG and consumed power by the local load inside the island are simulated as described in Table 3. The range of active power mismatch is from 0% up to ±30% and reactive power mismatch is between 0% up to ±5%. However, in this research, the focus is on the small mismatch as it is harder to detect islanding during small mismatched or even perfect-matched scenarios [32]. In contrast, the capacitor bank switching, load switching, and motor switching are performed to produce the non-islanding scenarios as indicated in Table 3. Table 3 summarizes the simulated cases used in this research. Multiple cases for generating the island exist:

- Disconnecting from the PCC to generate a small island that includes load and a DG only
- Disconnecting from the middle of the system to generate a larger island that includes local loads and multiple DG
- Disconnecting from the main substation to create a large island that includes all the loads in the system with multiple DGs

In any of these scenarios, the generation and demand active and reactive powers are matched in order to perform the desired mismatch. In each of the proposed islands, the following scenarios are followed:

1) Scenario 1: All Inverter-based DG system
2) Scenario 2: All Synchronous-based DG system
3) Scenario 3: Multiple DG types connected in the system

Table 3: Simulated Cases

Scenario	Case Description	Case
1	P mismatch Up to ±30%	Islanding
	Q mismatch Up to ±5%	Islanding
	Up to ±30% of P-mismatch and ±5% of Q-mismatch	Islanding
	Load switching at different buses	Non-Islanding
	Capacitor switching at different buses	Non-Islanding
	Motor switching at different buses	Non-Islanding
2	P mismatch Up to ±30%	Islanding
	Q mismatch Up to ±5%	Islanding
	Up to ±30% of P-mismatch and ±5% of Q-mismatch	Islanding
	Load switching at different buses	Non-Islanding
	Capacitor switching at different buses	Non-Islanding
	Motor switching at different buses	Non-Islanding
3	P mismatch Up to ±30%	Islanding
	Q mismatch Up to ±5%	Islanding
	Up to ±30% of P-mismatch and ±5% of Q-mismatch	Islanding
	Load switching at different buses	Non-Islanding
	Capacitor switching at different buses	Non-Islanding
	Motor switching at different buses	Non-Islanding

3.3 Measured Features

As previously mentioned, various islanding detection methods have been proposed that rely on a selection of a finite set of system features. In this thesis, a combination of various features or system parameters have been chosen from previous islanding detection methods focusing on Inverter-based and Synchronous-based DGs [22-26]. Twenty one features are measured locally in order to include as many parameters as possible that could be affected by islanding in the system. The extracted features include the following:

X_1: Voltage in *pu*

X_2: Voltage deviation (ΔV)

X_3: Frequency in Hz

X_4: Frequency deviation (Δf)

X_5: Rate of change of voltage ($\frac{\Delta V}{\Delta t}$)

X_6: Rate of change of frequency ($\frac{\Delta f}{\Delta t}$)

X_7: Rate of change of power ($\frac{\Delta \mathrm{p}}{\Delta \mathrm{t}}$)

X_8: Voltage total harmonic distortion (THD_v)

X_9: Current total harmonic distortion (THD_i)

X_{10}: Magnitude of Positive sequence

X_{11}: phase of Positive sequence

X_{12}: Rate of change of Positive sequence magnitude

X_{13}: Magnitude of Negative sequence

X_{14}: Phase of Negative sequence

X_{15}: Rate of change of Negative sequence magnitude

X_{16}: Magnitude of Zero sequence

X_{17}: Phase of Zero sequence

X_{18}: Rate of change of Zero sequence magnitude

X_{19}: Voltage Unbalance

X_{20}: Rate of change of Voltage Unbalance

X_{21}: Power Factor

3.4 Feature Selection

The Forward Sequential Feature Selection (FSFS) and the Backward Sequential Feature Selection (BSFS) are implemented for the feature selection process. In sequential feature selections, a number of features are selected to reduce the overall number of features used to classify a problem. This selection is done by using forward or backward approaches. In the forward approach, the process starts with an empty set of features and adds one feature at a time. The addition of a feature is based on the information gain, and therefore, the feature that maximizes the information gain is selected, and the process is repeated until the number of features required is reached. In the backward feature selection algorithm, the opposite occurs. The process starts with full set of features and one feature is eliminated at a time. The elimination process eliminates the feature with the lowest information gain. Then, the process is repeated until the required number of features is achieved. In this research, four features are select as optimum number of features. The reason of choosing four features is due to the required detection accuracy and time. Choosing more features will increase the detection time but without much improvement in the accuracy. On the other hand, choosing three features will reduce the accuracy significantly.

After performing the feature selection process, the number of features is reduced from twenty one features to only four features. The selected number of features is based on accuracy vs. required detection time. On one hand, reducing the number to three features results in a reduced accuracy in the classification process; on the other hand, increasing the number above four increases the detection time while maintaining a similar accuracy. The chosen features are: Voltage, Frequency, Magnitude of Negative sequence, Phase of Negative sequence.

3.5 Data Preparation

In this thesis, the k-fold cross-validation method is used to prepare the data for the classifier. In the k-fold cross-validation technique, the data is divided into subsets (k subsets). To train the classifier, k-1 subsets are used, and then the testing is conducted using the remaining subset. This process is then repeated k times, and the average accuracy is calculated as the overall frequency of the classifier [22].

3.6 Classification Techniques

This section provides a brief introduction on the various possible classification techniques that can be used for islanding detection.

3.6.1 Naïve Bayes Classifier

The Naïve Bayesian classifier is one of the most effective and popular classifiers due to its simplicity, computational efficiency, and its excellent performance for real-world problems. The Naïve Bayesian determines from the training set of data the conditional probability of each feature Xi using the class label C (with c being the name of the class) as expressed in equation (6).

$$\rho(\mathrm{C} = \mathrm{c}|\mathrm{X} = \mathrm{x}) = \frac{\rho(\mathrm{X} = \mathrm{x}|\mathrm{C} = \mathrm{c})\rho(\mathrm{C} = \mathrm{c})}{\rho(\mathrm{X} = \mathrm{x})} \quad (6)$$

This formula is used to estimate the probability of a given test point belonging to class c given its set of features {xi}. The probability of C is calculated using the samples of X_1, X_2… Xn, where n is number of features. Using the calculated probabilities of each C, the classifier predicts the class with the highest posterior probability. The “Naïve” attribute derived from the fact that this classifier assumes that all features are statistically independent, which is particularly helpful because it is difficult to calculate the joint probability $\rho(\mathrm{X} = \mathrm{x}|\mathrm{C} = \mathrm{c})$ since the data is significant with many features. By assuming the features are independent, the probabilities are estimated as follows:

$$\rho(X = \{x_i\}|C = c) = \prod_i \rho(X = x_i|C = c) \quad (7)$$

3.6.2 Support Vector Machine

Support Vector Machine is a popular approach used in classification applications. The main idea behind this approach is to create *N*-dimensional hyper-plane and map the input features to it using a set of mathematical functions, known as kernels. The theory behind a support vector machine is as follows:

Given a set of training data in the form

$$\mathcal{D} = \{(\mathrm{x_i}, \mathrm{y_i})|\mathrm{x_i} \in \mathbb{R}^{\mathcal{P}}, \mathrm{y_i} \in \{-1,1\}\}_{\mathrm{i}=1}^{\mathrm{n}} \quad (8)$$

where y_i indicates the class at which point x_i belongs, the main objective in the SVM classifier is to find the maximum hyper-plane ($W^T \cdot X_i + b = 0$) that divides the samples into two main groups $y_i = 1$ and $y_i = -1$.

$$W^T \cdot X_i + b \geq 1 \qquad \text{for first class} \tag{9}$$

$$W^T \cdot X_i + b \leq 1 \qquad \text{for second class} \tag{10}$$

The optimization problem becomes

$$\text{Minimize } \frac{1}{2} \parallel W \parallel^2 \tag{11}$$

Subject to

$$y_i(W \cdot X_i - b) - 1 \geq 0 \tag{12}$$

The final problem expression is

$$\min_{W,b} \max_{\alpha \geq 0} \{\frac{1}{2} \parallel W \parallel^2 - \sum_{i=1}^{n} \alpha_i [\, y_i (W \cdot X_i - b) - 1]\} \tag{13}$$

where b is

$$b = \frac{1}{Nsv} \sum_{i=1}^{Nsv} W \cdot X_i - y_i \tag{14}$$

The solution is expressed linearly using Karush-Tucker condition:

$$W = \sum_{i=1}^{n} \alpha_i y_i \, X_i \tag{15}$$

To have a more accurate results, the soft margin SVM is used, which have the following problem expression:

$$\min_{W,\xi,b} \max_{\alpha\geq 0} \{\frac{1}{2} \parallel W \parallel^2 + C\sum_{i=1}^{n}\xi_i - \sum_{i=1}^{n}\alpha_i[y_i(W \cdot X_i - b) - 1 + \xi_i]\} \qquad (16)$$

where C is the cost parameter, and controls the trade-off between minimizing the training error and maximizing the margin (Figure 8). This process increases the separation margin between the input data and categorizes them into two categories (in this case, islanding and non-islanding) (Figure 9). One difficulty when dealing with SVM is choosing the kernel function that is used in the mapping process. SVM classifier uses different types of kernel functions for mapping, such as linear, polynomial, sigmoid, and RBF. In this thesis, the RBF was used as a kernel for the tested SVM since it provided the highest accuracy between the four kernels.

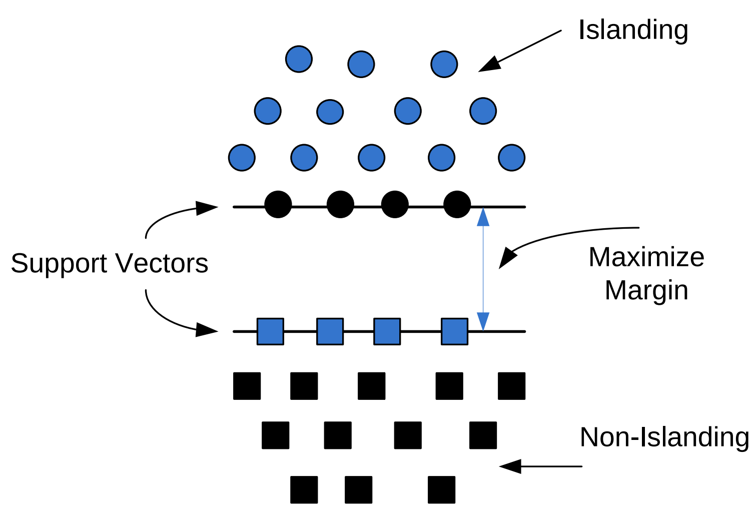


Figure 8: Support Vector Machine

Non-Islanding

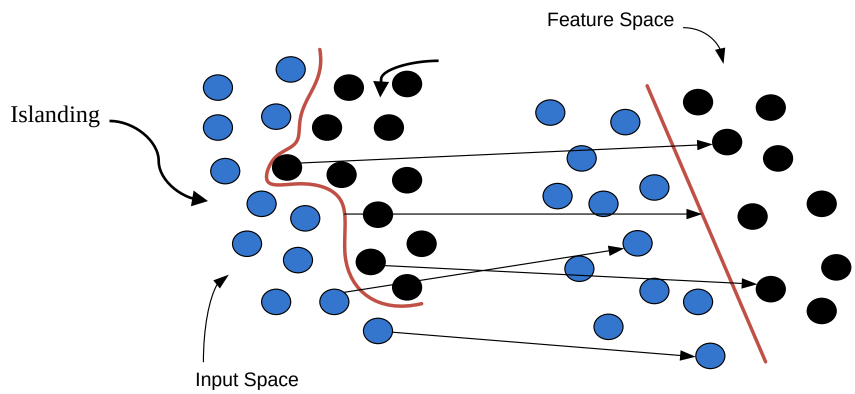


Figure 9: Support Vector Machine Mechanism

3.6.3 Neural Network

Neural network is very popular in power system classification applications. It has several advantages over traditional classification techniques such as faster training, which makes it perfect for islanding detection application. In addition, it is based on a probabilistic model (Bayesian) which provides very accurate results.

Figure 10 shows the basic idea behind the probabilistic neural network. The network consists of four main nodes: input, hidden, class, and decision node. The input nodes are the features/class data module. The hidden layer (also called the pattern layer) forms a product of input layer output and the weight vector. The class node works as a summation node that adds the output of the hidden nodes together. Finally, at the decision node, a particular class is decided.

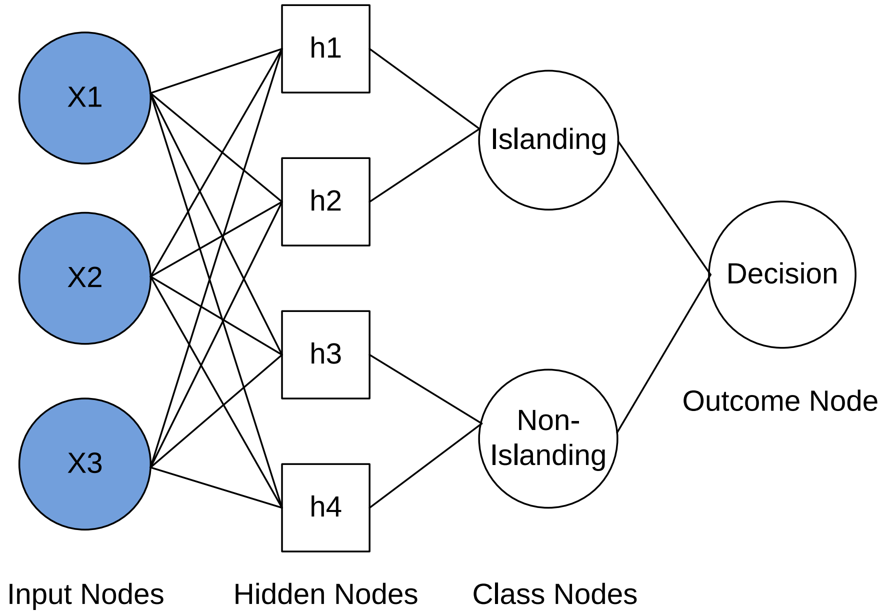


Figure 10: Neural Network Topology

3.6.4 Random Forest Classifier

In this research, C4.5 decision tree is used in order to distinguish between islanding and non-islanding cases. This tree uses entropy and Information Gain in order to split the nodes and construct the tree:

$$Entropy(S) = -\sum_{i} f_i \log_2(f_i) \qquad (17)$$

where f_i is the frequency of the value *i* in the dataset. Now let us consider the entropy when Subset *T* has been partitioned in accordance with *n* outcomes of one attribute test *X*, then

$$Entropy_x(T) = -\sum_{i=1}^{n} \frac{T_i}{T} \times Entropy(T_i) \qquad (18)$$

$$Information\ Gain(X) = Entropy(S) - Entropy_x(T) \qquad (19)$$

Equation (19) measures the information gained by partitioning T in accordance with the test X. When using the entropy, the main goal is to select a feature that maximizes the information gain index. Random Forest is a combination of various C4.5 decision trees. RF algorithm combines these trees based on a voting criterion. Each tree provides a decision and the majority vote of these trees gives the final decision on whether an islanding or a non-islanding condition has occurred. Unlike DT, there is no pruning in RF; instead all the trees are grown to the maximum depth they can achieve, which helps to keep the bias toward one class low. The forest error rate relies on strength and correlation. On one hand, the higher the accuracy (strength) of the individual tree, the less forest error rate. On the other hand, the more correlation between trees, the more forest error rate is observed. Decreasing the number of potential predictors (*m*) decreases both accuracy and correlation. To have a balance between them, finding the optimum value for *m* is significant, and it can be done by using out-of-bag (*obb*) error rate. During bootstrapped sampling, two thirds of the original data is used, and the remaining third is the *obb* data.

Given $(\mathrm{X_i}, \mathrm{Y_i})$ pairs$(\mathrm{i} = 1, \dots, \mathrm{n})$, where $\mathrm{X_i} \in \mathbb{R}^{\mathrm{d}}$denotes the d-dimensional predictor variable and the response $\mathrm{Y_i} \in \mathbb{R}$ (regression) or $\mathrm{Y_i} \in \{0,1, \dots, \mathrm{J} - 1\}$ (classification with J classes). The function estimator for the given pairs is

$$\hat{g}(.) = h_n\big((X_1, Y_1), \dots, (X_n, Y_n)\big)(.)\colon \mathbb{R}^d \to \mathbb{R} \qquad (20)$$

where the function $h_n(.)$ defines the estimator as a function of the data. A bootstrapped sample $(X_1^*, Y_1^*), \dots, (X_n^*, Y_n^*)$ is constructed by randomly drawing n times with replacement from the original data $(X_1, Y_1), \dots, (X_n, Y_n)$ and its estimator $\hat{g}^*(.) = h_n((X_1^*, Y_1^*), \dots, (X_n^*, Y_n^*))(.)$ is computed by plugging those samples into the estimator function. This process is repeated M times (chosen by user, theoretically is equal to infinity). Then, the average of the bootstrapped probabilities is calculated. Namely, at the end of the run, search the class that had majority of votes every time case *n* was *obb*. The ratio of number of cases that J is not equal to n to over all cases is the *obb* error estimate. Such error estimating eliminates the necessity to obtain an estimate of the training error for any accuracy estimation procedures including cross-validation, bootstrap, and a separate testing data.

3.7 Proposed Methodology

In this thesis, the proposed methodology includes three main stages:

- Feature extraction
- Feature selection
- Training the classifiers and detecting islanding.

Figure 11 summarizes the methodology followed in this thesis and described below:

1) Simulate the events (described in table 3) using MATLAB/SIMULINK
2) Using voltage and current waveforms at the PCC of the target DG, twenty one features are extracted
3) The top four features are selected by FFS or BFS
4) The process is repeated for all the events described in table 3 until data module is built
5) Apply *k*-Fold Cross validation technique to divide the data into training and testing subsets
6) Using the training subset, RF classifier is trained to distinguish between islanding a non-islanding
7) Using the testing subset, the accuracy of the RF classifier is obtained
8) Detection time is measured for the RF classifier
9) The accuracy and detection time of the RF classifier is compared to that of Decision Tree, Naïve Bayes, Support Vector Machine, and Neural Network.

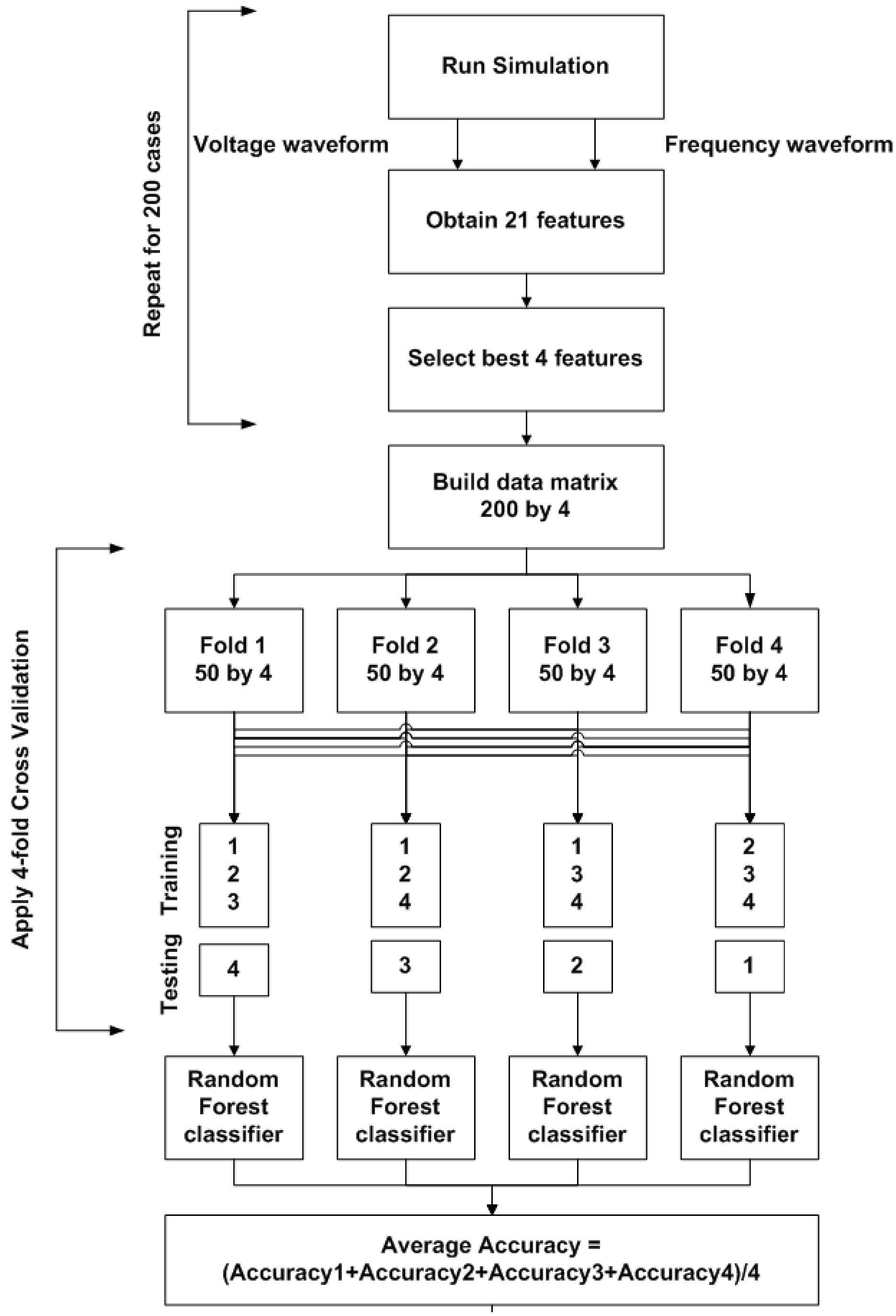


Figure 11: Proposed Approach for Islanding Detection

Chapter 4

Simulation Results and Discussion

4.1 Simulation Results

The cases, presented in Table 3, are applied to the IEEE 34 bus system, which is modeled using MATLAB/SIMULINK. All 21 features have been extracted considering all the three scenarios mentioned earlier with respect to number of DGs installed such as single Inverter-based DG, single Synchronous-based DG, and a hybrid mix of Inverter and Synchronous based DGs system. The number of features is then reduced to four features by using the feature selection techniques discussed earlier in this thesis. The voltage, frequency, negative sequence magnitude, and negative sequence phase waveforms under various conditions are presented to highlight the main differences during islanding and non-islanding conditions.

Figure 12 to Figure 14 shows the responses of the PCC voltage and frequency considering an islanding condition with a single Inverter-based DG connected at the PCC (scenario 1), single Synchronous-based DG connected at the PCC (scenario 2), and Inverter-based and Synchronous-based DG both connected at the PCC (scenario 3), respectively. The islanding condition is initiated at t = 1 sec with a 10% deficit and 1% deficit in active and reactive power mismatch, respectively. For inverter-based DG, the voltage and frequency remain within the IEEE Std. 1547 limits. With a small mismatch in the active power such (10%), the voltage deviates to 0.96 pu, which is within the IEEE 1547 standard limits. Alternatively, the frequency deviation is mainly due to the reactive power mismatch. The used test system and its control unit are designed to operate at unity power factor. Therefore, the frequency under 1% mismatch in reactive power mismatch deviates to

60.3Hz in order to match the load's resonance frequency. In Figure 13, the Inverter-based DG was substituted with a Synchronous-based DG and 10% active power mismatch and 1% reactive power mismatch are applied. The voltage deviates to 0.93 pu while the frequency deviates slowly to 61Hz in the 2 second window but continue to deviates. This means that voltage stays within the IEEE limits but the frequency deviates outside the boundary. Similarly to Inverter-based DG, the deviation in frequency for Synchronous-based DG is primarily due to the active power mismatch. It is easier to detect islanding for Synchronous-based DG system due to the continuous deviation in the frequency. In Figure 14, Inverter-based and Synchronous-based DGs are connected together at the PCC. With the same percentage of the mismatch, the voltage remains inside the IEEE limits while the frequency deviates continuously due to the presence of the Synchronous-based DG. From Figures 12-14, there is a small deviation in the waveforms of the voltage and the frequency and it most of the time stays inside the limits of the IEEE 1547 standard. Therefore, the conventional islanding detection techniques such as passive and active techniques are not being able to detect islanding because of the presence of the NDZ. In contrast, some of the non-islanding scenarios are shown in Figures 15-17. These Figures show the voltage and frequency during non-islanding scenario (capacitor bank switching at t=1s at bus 838) with Inverter-based DG, Synchronous-based DG, and a hybrid system, correspondingly. Figures 15-17 show that the disturbance in the frequency lasts less than 100ms and then stabilizes to its nominal values at 60Hz. However, the voltage deviates from 1 pu but the deviation is minimal and within the IEEE limits.

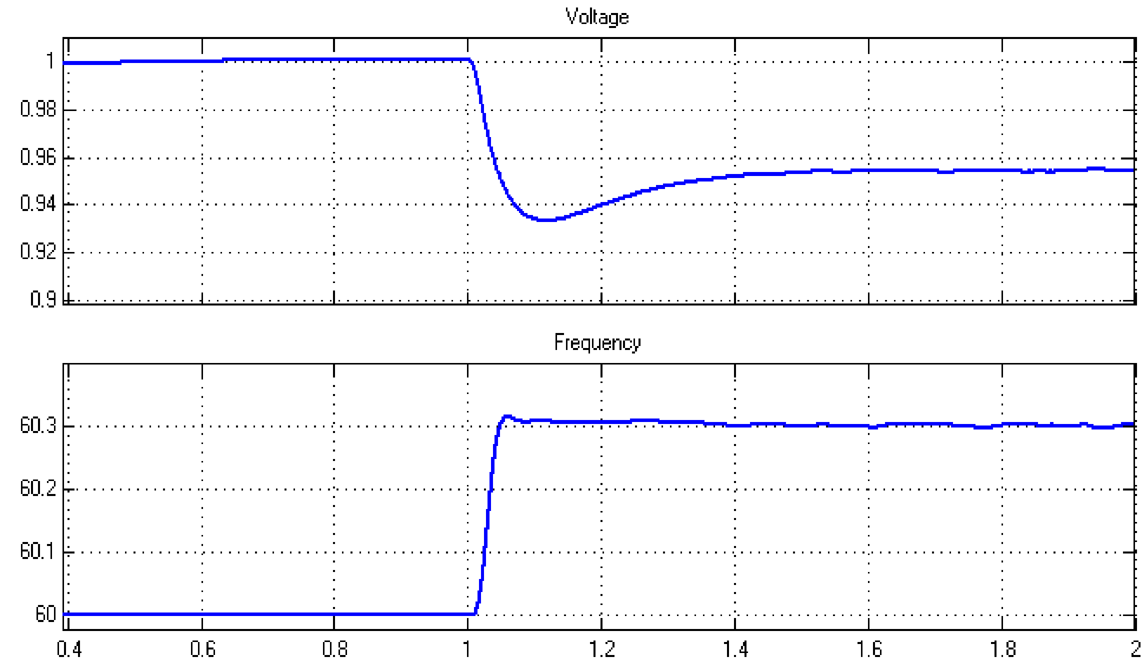


Figure 12: Voltage and frequency during islanding for Inverter-based DG with 10% active and 1% reactive power mismatch

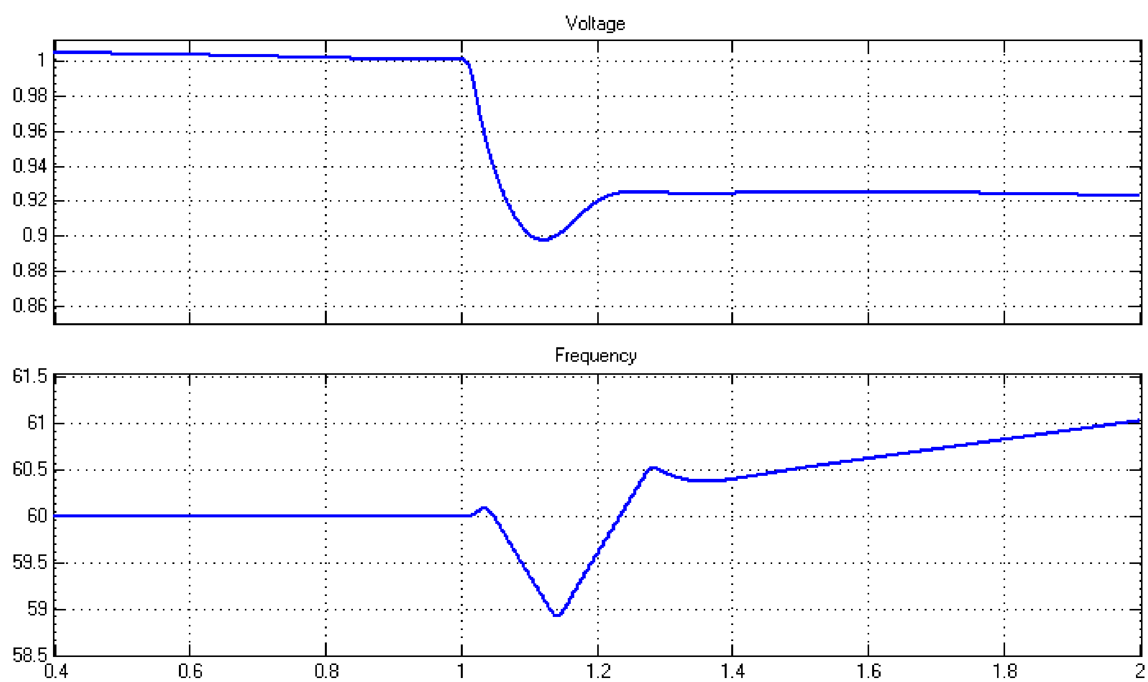


Figure 13: Voltage and frequency during islanding for Synchronous-based DG with 10% active and 1% reactive power mismatch

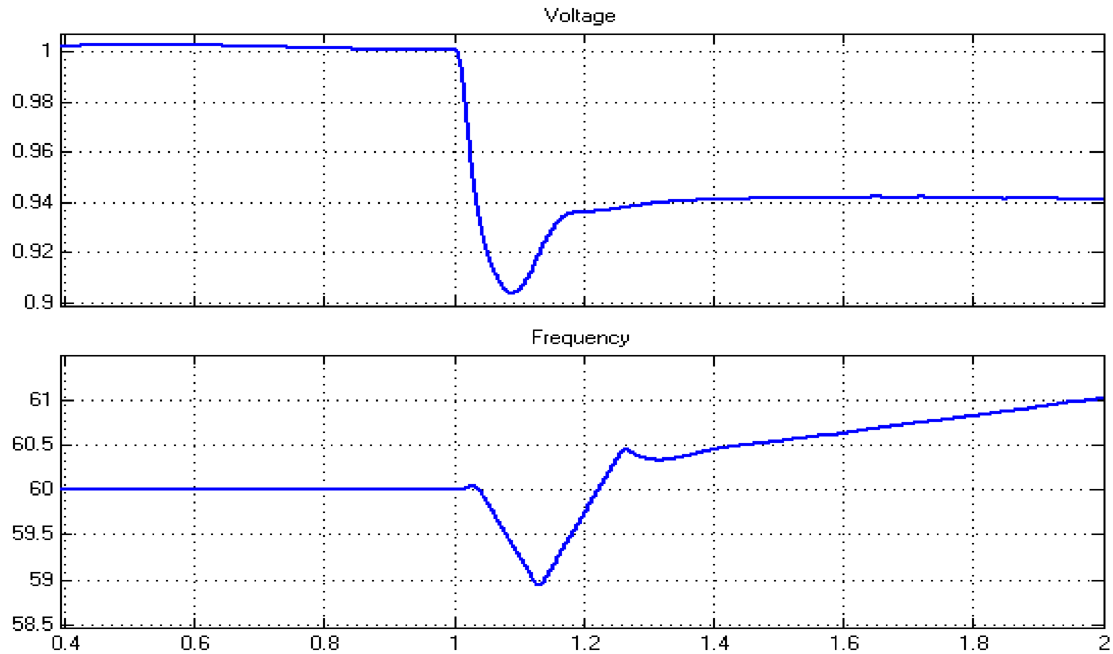


Figure 14: Voltage and frequency during islanding for hybrid system with 10% active and 1% reactive power mismatch

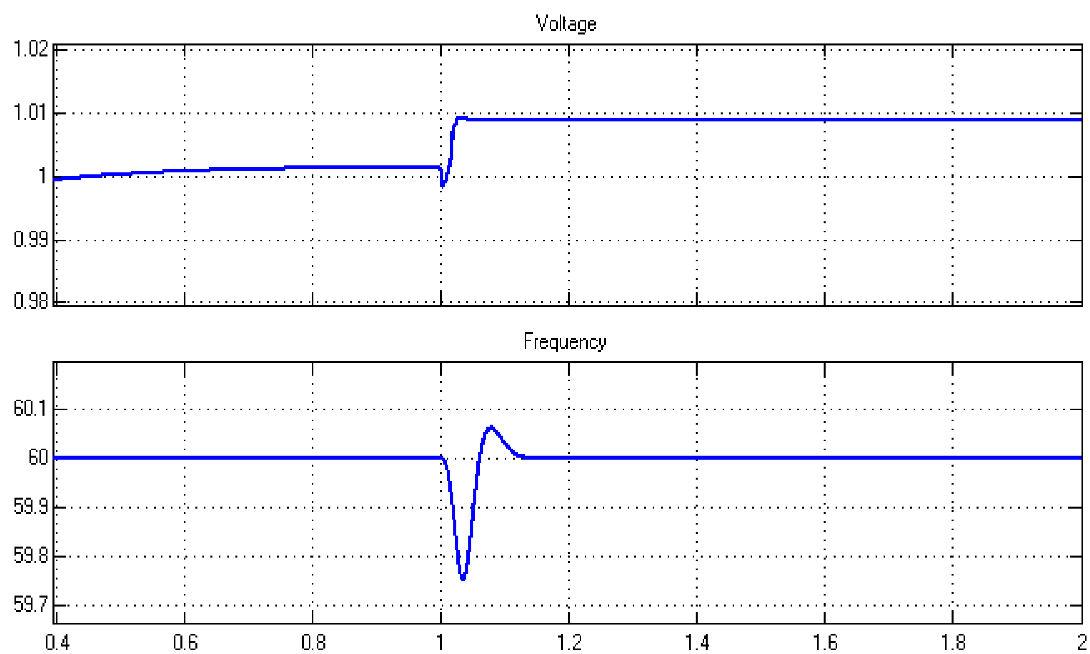


Figure 15: Voltage and frequency during non-islanding for Inverter-based DG (Capacitor bank switching)

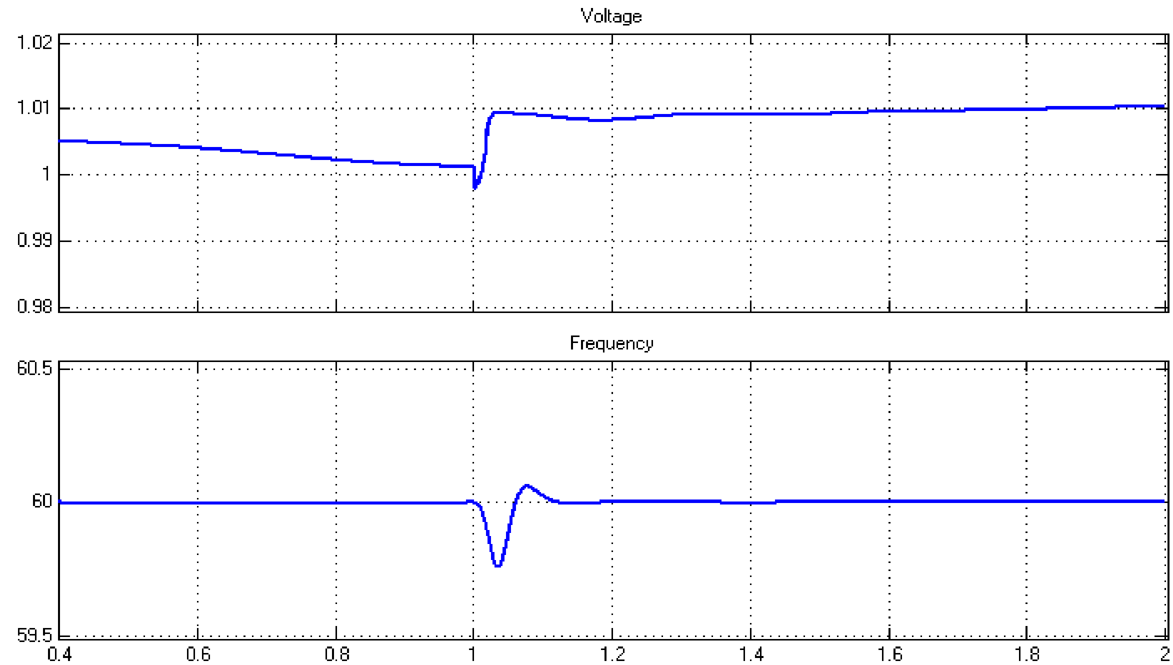


Figure 16: Voltage and frequency during non-islanding of Synchronous-based DG (Capacitor bank switching)

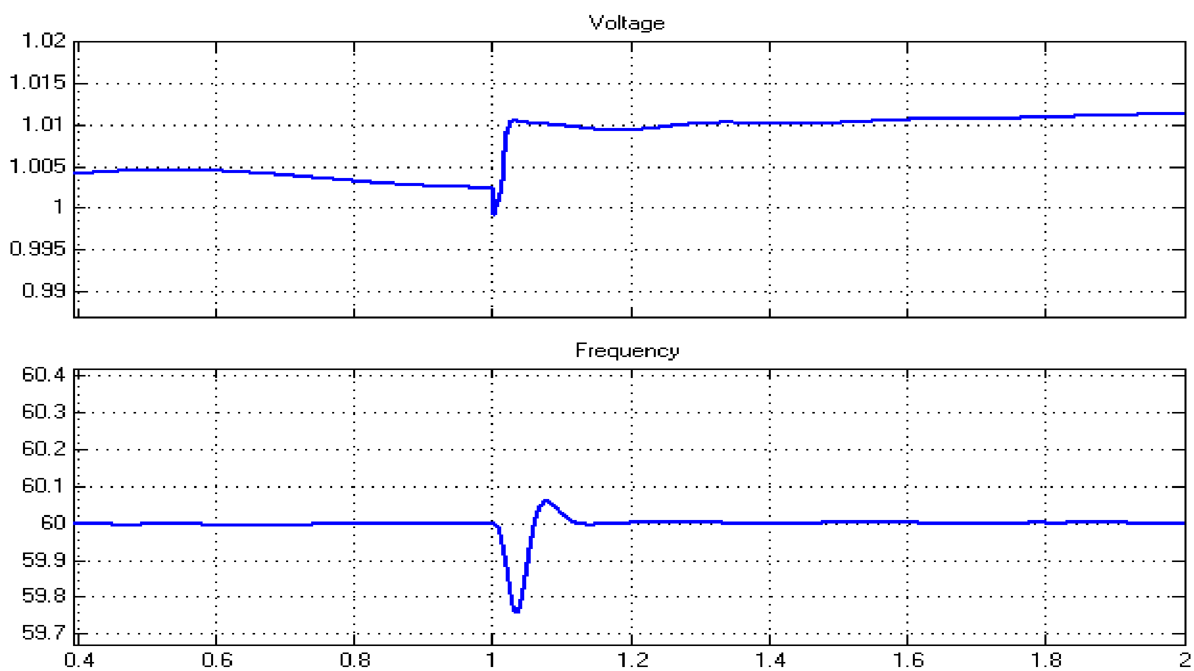


Figure 17: Voltage and frequency during non-islanding for hybrid system (Capacitor bank switching)

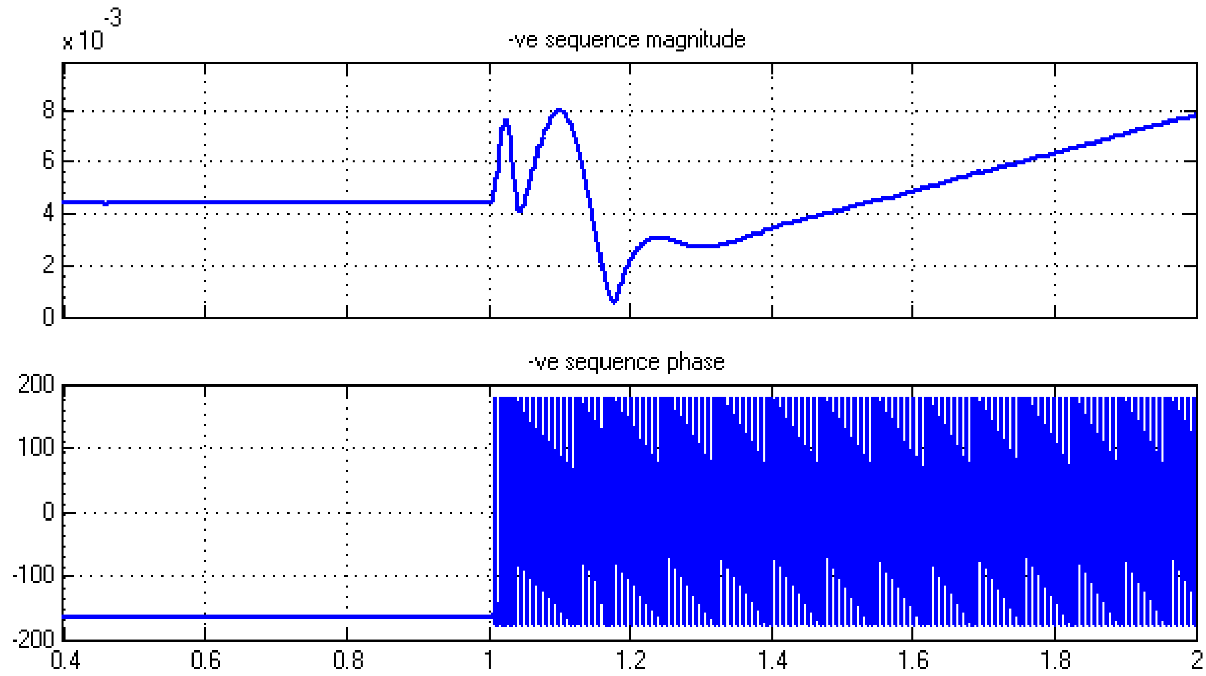


Figure 18: -ve Sequence Magnitude and Phase response during islanding of Inverter-based DG for 10% active and 1% reactive power mismatch

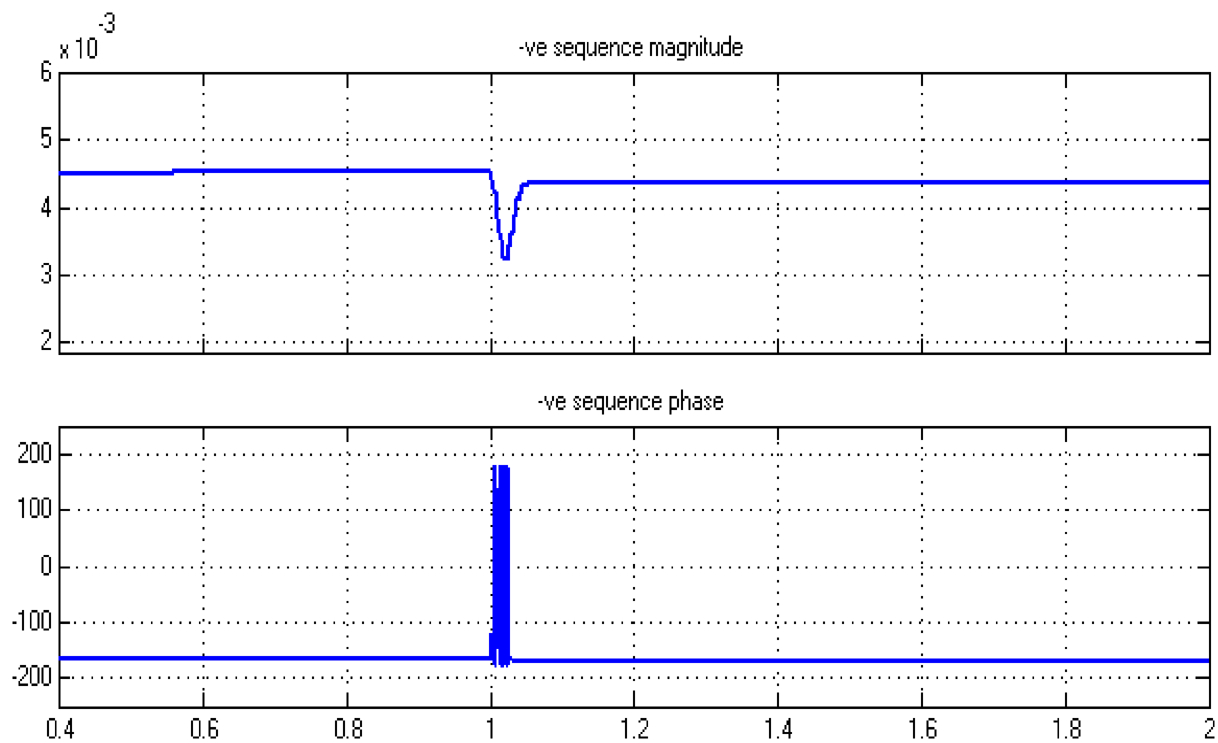


Figure 19: –ve Sequence Magnitude and Phase response due to Non-Islanding event due to capacitor bank

As seen from the previous simulation results, the performance of a specific feature in detecting islanding can vary depending on the DG technology used. Voltage and frequency can provide a basic detection scheme and can detect islanding when large mismatch is present. However, they fail when small mismatch scenarios occur. Accordingly, different features are required to detect islanding accurately with zero NDZ for a system that includes both DG types at the same time. Those features are the negative sequence magnitude and phase. These two features help in detecting islanding when voltage and frequency are unsuccessful to do so, e.g. in small and perfect matched cases

Looking at the negative sequence magnitude and phase in Figure 18, it is clear that the phase response changed dramatically as soon as islanding happens. Initially, it is -180^{o} and as soon as islanding occurred it starts to fluctuate between -180^{o} and +180^{o}. On the other hand, Figure 19 demonstrates the negative sequence magnitude and phase response during non-islanding case. The phase sequence only fluctuates for less than 100ms and goes back to normal state. These two diverse responses are very important to distinguish between islanding and non-islanding due to the difference in their waveforms pattern. Similar results are obtained for the negative sequence magnitude and phase when replacing the Inverter-Based DG with Synchronous-DG and hybrid system.

4.2 Comparison between RF Classifier and Various Data Mining Techniques

The results of RF classifier and other tested classifiers are shown in Table 4-6. Table 4, displays the accuracies of the proposed classifier in comparison to other classifiers when all 21 extracted features are used to detect islanding while Table 5 shows the accuracies when only four features (voltage, frequency, negative sequence magnitude, and negative sequence phase) are used for the detection. Finally, Table 6 shows the computation time that is needed to detect islanding for the proposed technique and the second highest accuracy classifier.

Since RF uses multiple DTs, it results in much more robust and very accurate results. In Table 4, when using all features, RF gives a perfect 100% classification accuracy for all possible scenarios. Moreover, when the number of features is limited to 4, it still outperforms all other classifiers with overall accuracy of 99%. In order to prove that the proposed detection technique works very well using RF, the same datasets are used to test other well-known classifier to compare the results with the ones obtained with RF. Below are the other tested classifiers with a brief description on their results.

Table 4: All 21 Features are used in Classification

	Inverter DG	Synchronous DG	Multiple DGs	Average
NB	82%	97%	100%	93.00%
SVM	97%	100%	100%	99.00%
DT	98%	97%	97%	97.33%
RF	100%	100%	100%	100.00%
NN	97%	100%	100%	99.00%

Table 5: Only four Features are used in Classification

	Inverter DG	Synchronous DG	Multiple DG’s	Average
NB	56%	100%	100%	85.33%
SVM	94%	100%	99%	97.67%
DT	95%	97%	96%	96.00%
RF	98%	100%	100%	99.33%
NN	97%	100%	100%	99.00%

Table 6: Detection Time

	RF		NN	
Inverter DG	All	0.37 s	All	0.88 s
	4	0.18 s	4	0.30 s
Synchronous DG	All	0.29 s	all	0.81 s
	4	0.18 s	4	0.20 s
Multiple DGs	All	0.115 s	All	0.76 s
	4	0.18 s	4	0.26 s

4.2.1 Naïve Bayesian Classifier

A 4-fold cross-validation study is carried on in order to test the Naïve Bayesian Classification. NB classifier is a very straightforward classifier but very powerful. Tables 4 and 5 show different results from the NB classifier. Table 4 shows different accuracies when all 21 features are used in the classification process while Table 5 shows the accuracies when only four features are used to classify the data. Naïve Bayes Classifier performed very well when a Synchronous-based DG system is used and with multiple DG system with accuracy of almost 100%. However, the NB struggles with Inverter-based DG system and only could reach an accuracy of 82% when all features are used and very low accuracy of 52% when only 4 features are used. This is because NB classifier requires large amount of data in order to learn all possible scenarios to distinguish between islanding and non-islanding. When only four features are used, the amount of information the classifier can use to classify the unseen data is very limited.

4.2.2 Support Vector Machine Classifier

Similar study is performed using WEKA Data Mining Software [35] in order to perform SVM classification. Again, Table 4 shows different accuracies when all 21 features are used in the classification process while Table 5 shows the accuracies when only four features are used to classify the data. SVM showed very good results in terms of accuracies with an average of 99% when all features are used and 97% when only four features are used. Remarkably, the lowest accuracy is 94% when, again, a single Inverter-based DG unit is used.

4.2.3 Decision Tree

Using Decision Tree as a classifier for islanding has been very popular and many proposed techniques uses it due to its straightforward logic. When using all features the average accuracy of islanding detection is 97% and when the number of features is limited to four, the accuracy dropped by 1% only. This results shows the main proposed islanding detection techniques used this classifier as the core of the technique. In addition, this consistency in the accuracy, even with the reduction in number of features, is the main motivation to use the more sophisticated RF classifier in this research.

4.2.4 Neural Network

Neural Network classifier is very close to Random Forest in terms of accuracy especially when only four features are used. First, when all features are used the average accuracy was 99% and when the number of features is reduced to four it provided the same accuracy. However, even with these high accurate results, NN is not implemented for islanding detection due to its complexity and presence of hidden layer.

4.2.5 Random Forest

Random Forest is the most robust classifier out of all the tested classifiers. It provided 100% accuracy when all features are used and it also provided 99.3% when only four features are used. The reason why RF is much preferred in classification problems, such as islanding detection, is the simplicity of it over NN, as it is a combination of simple DTs. It also performs much faster than NN as it is shown in the next section.

4.3 Detection Time

In terms of detection time, both Random Forest classifier and Neural Network classifier performed in a fast manner and stayed with the acceptable IEEE time limit. Nevertheless, RF classifier performed much faster than NN as shown in Table 6. When all features are used, RF is almost 3-5 times faster than NN. In addition, when the number of features was set to four, RF is still twice as fast as NN.

Chapter 5

Conclusion

A new universal islanding detection technique that performs accurately for both Inverter-based and Synchronous-based DGs is proposed. The proposed technique depends on twenty one features that are used in order to detect and identify an islanding condition while achieving zero Non-Detectable Zones and avoiding nuisance tripping due to other non-islanding events. These features were extracted from voltage and frequency waveforms at the PCC of the targeted island. Next, a feature selection process is used to reduce the number of features to four features only. Using these features, a Random Forest classifier was trained and tested using k-fold cross validation technique to measure its performance and accuracy to detect islanding. Furthermore, systems with single and multiple DG units were tested in order to test the classifier performance under different topologies. In the end, for both DG types, Random Forest classifier was found to be the best classifier for detecting an islanding condition for two main reasons. First, it outperformed all other classifiers with an average accuracy of 99% and achieved zero NDZ for both types of DG. Second, it is extremely fast in detecting islanding, which is a very important factor in choosing an islanding detection technique. Finally, the selected features provided sufficient information to distinguish between islanding and non-islanding regardless of the type of the classifier used in the classification process.

List of Publications

1. Faqhruldin, O.N.; El-Saadany, E. F.; Zeineldin, H. H., "A Universal Islanding Detection Technique for Distributed Generation using Pattern Recognition, " *Smart Grid, IEEE Transactions on*, Submitted 1 Jul. 2013

2. Faqhruldin, O.N.; El-Saadany, E. F.; Zeineldin, H. H., " Islanding Detection for Multi DG System using Inverter Based DGs ," *Power and Energy Society General Meeting, 2013 IEEE* , Apr. 2013

3. Faqhruldin, O.N.; El-Saadany, E.F.; Zeineldin, H.H., "Naive Bayesian Islanding Detection Technique for Distributed Generation in Modern Distribution System," *Electrical Power and Energy Conference (EPEC), 2012 IEEE* , vol., no., pp.69,74, 10-12 Oct. 2012

4. Faqhruldin, O.N.; El-Saadany, E. F.; Zeineldin, H. H., "Evaluation of Islanding Detection Techniques for Inverter-Based Distributed Generation," *Power and Energy Society General Meeting, 2012 IEEE* , vol., no., pp.1,7, 22-26 Jul. 2012

References

1. *IEEE Application Guide for IEEE Standard 1547, IEEE Standard for Inter-connecting Distributed Resources With Power Systems*, IEEE Std. 1547.2-2008, 2009.

2. Kevin J. Dasso., “The Reliability of Bulk Electric Systems in North America,’ *Technical report, North American Electric Reliability Council*, Sept. 2006.

3. Coster, E.J.; Myrzik, J. M A; Kruimer, B.; Kling, W.L., "Integration Issues of Distributed Generation in Distribution Grids," *Proceedings of the IEEE* , vol.99, no.1, pp.28,39, Jan. 2011

4. Jouybari-Moghaddam, H.; Hosseinian, S.H.; Vahidi, B., "An Introduction to Active Distribution Networks Islanding Issues," *Electrical Power Distribution Networks (EPDC), 2012 Proceedings of 17th Conference on* , vol., no., pp.1,6, 2-3 May 2012

5. Ward Bower and Michael Ropp. “Evaluation of Islanding Detection Methods for Photovoltaic Utility-Interactive Power Systems.” *Sandia National Laboratories Photovoltaic Systems Research and Development*, Mar 2002.

6. Ropp, M.E.; Aaker, K.; Haigh, J.; Sabbah, N., "Using Power Line Carrier Communications to Prevent Islanding [of PV Power Systems]," *Photovoltaic Specialists Conference, 2000. Conference Record of the Twenty-Eighth IEEE* , vol., no., pp.1675,1678, 2000

7. G.-K. Hung, C.-C. Chang, and C.-L. Chen, “Automatic Phase-Shift Method for Islanding Detection of Grid-Connected Photovoltaic Inverters,” *Energy Conversions, IEEE Transactions on*, vol. 18, no. 1, pp. 169–173, Mar. 2003.

8. M. Ropp, M. Begovic, A. Rohatgi, G. Kern, S. Bonn, R. H. , and S.Gonzalez, “Determining The Relative Effectiveness of Islanding Detection Methods using Phase Criteria and Nondetection Zones,” *Energy Conversions, IEEE Transactions on*, vol. 15, no. 3, pp. 290–296, Sep. 2000.

9. L. Lopes and H. Sun, “Performance Assessment of Active Frequency Drifting Islanding Detection Methods,” *Energy Conversions, IEEE Transactions on*, vol. 21, no. 1, pp. 171–180, Mar. 2006.

10. L. Lopes and H. Sun, “Performance Assessment of Active Frequency Drifting Islanding Detection Methods,” *Energy Conversions, IEEE Transactions on*, vol. 21, no. 1,pp. 171–180, Mar. 2006.

11. P. Du, Z. Ye, E. Aponte, J. Nelson, and L. Fan, “Positive-Feedback-Based Active Anti-Islanding Schemes for Inverter-Based Distributed Generators: Basic Principle, Design

Guideline, and Performance Analysis," *Power Electronics, IEEE Transactions on*, vol. 25, no. 12, pp. 2941–2948, Dec. 2010.

12. Yafaoui, A.; Wu, B.; Kouro, S.; , "Improved Active Frequency Drift Anti-islanding Detection Method for Grid Connected Photovoltaic Systems," *Power Electronics, IEEE Transactions on*, vol. PP, no.99, pp.1, Oct. 2011

13. Zeineldin, H.H.; Kennedy, S.; "Sandia Frequency-Shift Parameter Selection to Eliminate Nondetection Zones," *Power Delivery, IEEE Transactions on* , vol.24, no.1, pp.486-487, Jan. 2009

14. Zeineldin, H.H.; Conti, S.; "Sandia Frequency Shift Parameter Selection for Multi-Inverter Systems to Eliminate Non-Detection Zone," *Renewable Power Generation, IET*, vol.5, no.2, pp.175-183, March 2011

15. H. H. Zeineldin and M. M. A. Salama, "Impact of Load Frequency Dependence on the NDZ and Performance of the SFS Islanding Detection Method*," Industrial Electronic, IEEE Transactions on*, vol. 58, no. 1, pp. 139–146, Jan. 2011.

16. T. Funabashi, K. Koyanagi, and R. Yokoyama, "A Review of Islanding Detection Methods for Distributed Resources," *in Proc. IEEE Bologna Power Tech Conf*., 2003, vol. 2, pp. 6–11.

17. Freitas, W., Xu, W., Affonso, C. M., and Huang, Z., "Comparative Analysis between ROCOF and Vector Surge Relays for Distributed Generation Applications," *Power Delivery, IEEE Transactions on,* Vol. 20, pp. 1315–1324, 2005.

18. Zeineldin, H.H.; Kirtley, J.L.; , "Performance of the OVP/UVP and OFP/UFP Method With Voltage and Frequency Dependent Loads," *Power Delivery, IEEE Transactions on*, vol.24, no.2, pp.772-778, Apr. 2009

19. M. Redfern, O. Usta, and G. Fielding, "Protection Against Loss of Utility Grid Supply for a Dispersed Storage and Generation Unit," *Power Delivery, IEEE Transactions on*, vol. 8, no. 3, pp. 948–954, Jul. 1993.

20. S.-I. Jang and K.-H. Kim, "An Islanding Detection Method for Distributed Generations Using Voltage Unbalance and Total Harmonic Distortion of Current," *Power Deleviry, IEEE Transactions on*, vol. 19, no. 2, pp. 745–752, Apr. 2004.

21. W. Freitas, Z. Huang, and W. Xu, "A Practical Method for Assessing the Effectiveness of Vector Surge Relays for Distributed Generation Applications," *Power Delivery, IEEE Transactions on*, vol. 20, no. 1, pp. 57–63, Jan. 2005.

22. W. Xu, K. Mauch, and S. Martel, "An Assessment Oof DG Islanding Detection Methods and Issues for Canada," *CANMET Energy Technology Centre—Varennes*, Natural Resources Canada Rep., 2004.

23. M.S. Thomas, P.P. Terang, "Islanding Detection using Decision Tree Approach*," in Power Electronics, Drives and Energy Systems (PEDES)*., 14 Feb. 2011, pp. 1-6.

24. N. Lidula, N. Perera, and A. Rajapakse, "Investigation of a Fast Islanding Detection Methodology using Transient Signals," *IEEE Power and Energy Society General Meeting, IEEE*, pp. 1–6. 2012

25. Faqhruldin, O.N.; El-Saadany, E. F.; Zeineldin, H. H., "Evaluation of Islanding Detection Techniques for Inverter-Based Distributed Generation," *Power and Energy Society General Meeting, 2012 IEEE* , vol., no., pp.1,7, 22-26 July 2012

26. S. R. Samantaray, B. Chitti Babu & P. K. Dash, "Probabilistic Neural Network Based Islanding Detection in Distributed Generation," *Electric Power Components and Systems*, 39:3, 191-203.

27. K. El-Arroudi, G. Joos, I. Kamwa, and D. McGillis, "Intelligent-Based Approach to Islanding Detection in Distributed Generation," *Power Delivery, IEEE Transactions on*, vol. 22, no. 2, pp. 828–835, Apr. 2007.

28. Samantaray, S.R.; El-Arroudi, K.; Joós, G.; Kamwa, "A Fuzzy Rule-Based Approach for Islanding Detection in Distributed Generation," *Power Delivery, IEEE Transactions on* , vol.25, no.3, pp.1427-1433, July 2010

29. Najy, W.K.A.; Zeineldin, H.H.; Alaboudy, A.H.K.; Wei Lee Woon, "A Bayesian Passive Islanding Detection Method for Inverter-Based Distributed Generation Using ESPRIT," *Power Delivery, IEEE Transactions on* , vol.26, no.4, pp.2687-2696, Oct. 2011

30. Lidula, N.W.A.; Rajapakse, A.D.; , "A Pattern Recognition Approach for Detecting Power Islands Using Transient Signals—Part I: Design and Implementation," *Power Delivery, IEEE Transactions on* , vol.25, no.4, pp.3070-3077, Oct. 2010

31. Lidula, N.W.A.; Rajapakse, A.D.; , "A Pattern-Recognition Approach for Detecting Power Islands Using Transient Signals—Part II: Performance Evaluation," *Power Delivery, IEEE Transactions on* , vol.27, no.3, pp.1071-1080, July 2012

32. Jadric, I., Borojevic, D., and Jadric, M., "Modeling And Control Of Synchronous Generator With Active DC Load," *Power Electronic, IEEE Transactions on,* pp. 303-311, 2000

33. Far, H.G.; Rodolakis, A.J.; Joos, G., "Synchronous Distributed Generation Islanding Protection Using Intelligent Relays," *Smart Grid, IEEE Transactions on* , vol.3, no.4, pp.1695,1703, Dec. 2012

34. P. Domingos and M. Pazzani, "On the Optimality of the Simple Bayesian Classifier Under Zero-One Loss," Mach. Learn., vol. 29, pp.103–130, Nov. 1997.

35. WEKA, Data Mining with Open Source Machine Learning Software, available at: http://www.cs.waikato.ac.nz/ml/weka/

36. Pattern Recognition Tools, available at: http://prtools.org