applied sciences

Review

Application of Artificial Neural Networks to Islanding Detection in Distribution Grids: A Literature Review

Slaven Kaluđer [1], Krešimir Fekete [2,*], Kristijan Čvek [2] and Zvonimir Klaić [2]

[1] HEP Distribution System Operator, Elektroslavonija, 31000 Osijek, Croatia; slaven.kaluder@gmail.com
[2] Faculty of Electrical Engineering, Computer Science and Information Technology, Department of Power Engineering, Josip Juraj Strossmayser University of Osijek, 31000 Osijek, Croatia; kcvek@etfos.hr (K.Č.); zvonimir.klaic@ferit.hr (Z.K.)
* Correspondence: kresimir.fekete@ferit.hr

Abstract: Active distribution grids that contain energy sources (so-called distributed generation or DG) are nowadays a reality. Besides the many benefits DGs bring to the distribution grid, some challenges are associated with their integration. Since there are DGs now in the distribution grid, the occurrence of islanding operation is possible. Since an islanding operation can be dangerous, it is necessary to have an effective method to detect it. In the last decade, scientists have made a great effort to develop and test various islanding detection methods (IDMs). Many approaches have been tested, and the methods based on computational intelligence (CI) have shown great potential. Among them, artificial neural networks (ANNs) gained most of the research attention. This paper focuses on ANN application for islanding detection. It gives an exhaustive review of the ANN types used for islanding detection, the types of input data, and their transformation to fit the ANNs. Furthermore, various applications based on specific input data, preprocessing types, different learning algorithms, real-time implementation, and various distribution models used for ANN are reviewed. This paper investigates the potential of ANNs to enhance islanding detection accuracy, reduce non-detection zone (NDZ), and contribute to an overall efficient detection method.

Keywords: artificial neural network; distribution grid; islanding detection; local methods; distributed generation

Citation: Kaluđer, S.; Fekete, K.; Čvek, K.; Klaić, Z. Application of Artificial Neural Networks to Islanding Detection in Distribution Grids: A Literature Review. *Appl. Sci.* **2023**, *13*, 13047. https://doi.org/10.3390/app132413047

Academic Editor: Manuela Sechilariu

Received: 8 November 2023
Revised: 30 November 2023
Accepted: 1 December 2023
Published: 7 December 2023

1. Introduction

Significant changes are taking place in the electrical distribution network due to the growing integration of DGs. While these innovations promise a more sustainable energy infrastructure, they also introduce new challenges like the islanding operation (ID). One of the challenges is the upgrading of traditional protection schemes in order to enable the effective detection of the occurrence of the islanding operation. In many scientific articles, numerous islanding detection methods (IDMs) are described and tested. The ever-growing body of scientific articles has been systematized and analyzed in many review papers. The work in [1] presents an early overview of islanding detection methods in systems with photovoltaic power plants. It deals in detail with passive and active IDMs in networks with photovoltaic inverters. A valuable review of central and remote (at the distributed generator site) IDMs is presented in [2].

Most of the early developed methods detect the islanding operation by observing changes in available measured quantities (voltage, frequency, active and reactive power, rotor angle of the synchronous generator, etc.) during the duration of the islanding operation. If the change in the mentioned quantities is high, the detection is easy and straightforward. Otherwise, some methods fail to detect islanding operations correctly, and there is a large zone of active and reactive power changes in which islanding operations cannot be detected (so-called non-detection zone or NDZ). To reduce or eliminate the previously mentioned shortcomings of IDMs, scientists are starting to use methods for signal processing and methods based on computer intelligence (CI). One of the first review papers that deals with new signal processing procedures and methods based on computational intelligence is [3]. In [4], authors made a more detailed presentation of modern trends in the development of IDM. Most authors [1–4] agree that artificial neural networks (ANNs) are a promising tool for islanding detection applications and certainly one of the most investigated with a large body of scientific literature published in the last decade. In particular, in [5], which deals with review of different computational intelligence methods for ID, authors noted that neural networks and decision trees are the most used methods. The accuracy of the ANN-based method is high (according to [5], the accuracy can be as high as 98.19%). Also, they are capable of islanding detection with high accuracy in multi-inverter systems [6], they can deal with nonlinear systems, and they can also overcome the requirement of threshold settings [7].

Since the authors of the previously published review papers [1–8] make a general comparison of different islanding detection methods and do not present a detailed analysis of the neural network application to islanding detection, the authors of this paper decided to conduct a comprehensive review of ANN applications for the islanding detection problem. This paper aims to make a literature review to answer the following questions regarding the use of ANN for islanding detection:

1. How are ANNs integrated into islanding detection?
2. What types of input data are used for ANN?
3. How are the "raw" input data transformed and processed to make it suitable for ANN?
4. What types of ANN architectures are used in islanding detection applications?
5. Which ANN learning algorithms are used for ID applications?

The structure of the paper is as follows. In Section 2, the islanding detection principles are explained, and a general IDM description and classification are presented. Section 3 describes the general architecture of artificial neural networks and associated learning algorithms. Analysis of the used input data and their transformation is described in Section 4, while in Section 5, ANN architectures and learning algorithms are reviewed. In the last section, types of the analyzed electrical grids and types of DGs involved in the islanding operation are reviewed.

2. Islanding Detection Principles and Methods

2.1. Islanding Operation in Distribution Grids

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

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

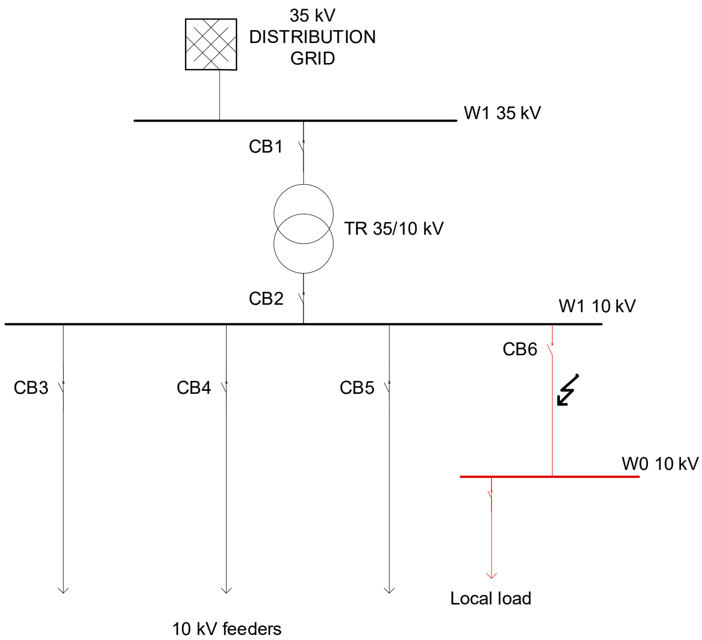

Figure 1. Passive distribution grid.

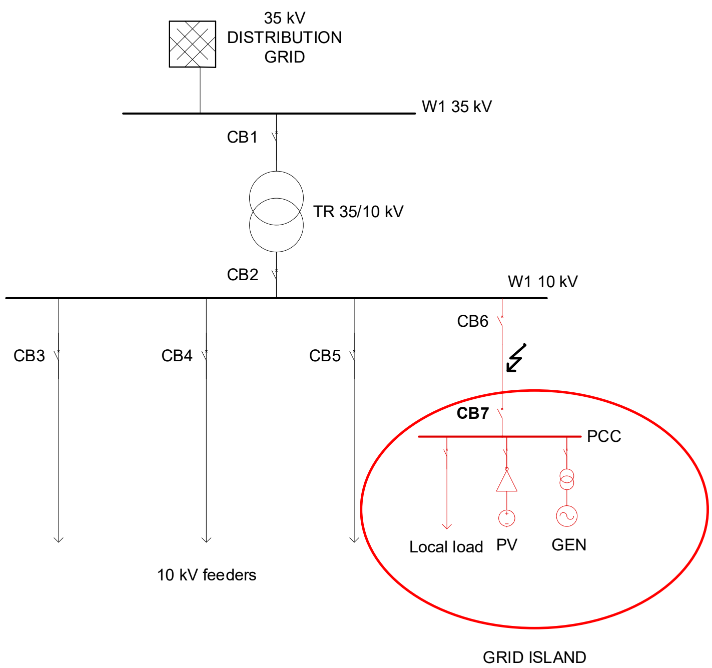

Figure 2. Active distribution grid.

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

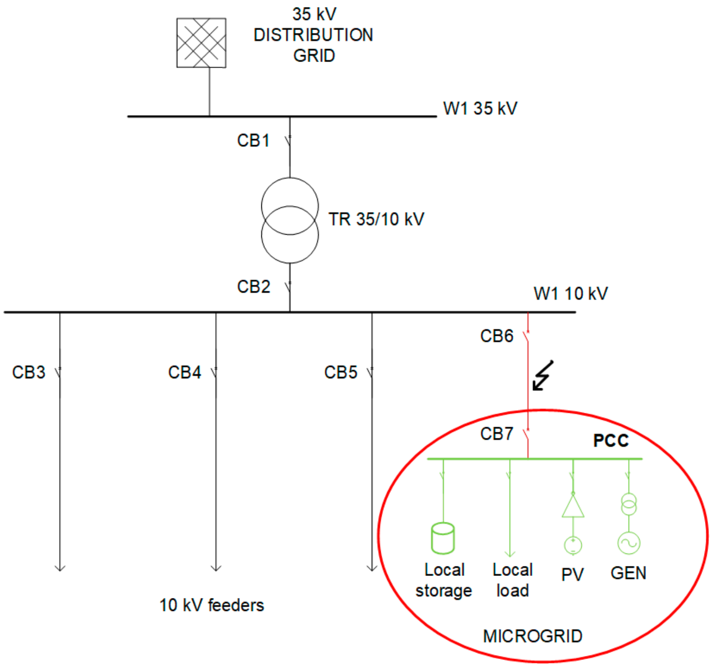

Figure 3. An example of a microgrid.

Many authors [6,7,10,11] agree that quality IDM needs to satisfy several criteria concerning detection time, accuracy, implementation cost, influence on power quality, etc.

There are many technical standards worldwide in which restrictions such as the voltage range, frequency range, detection time, and quality factor are indicators for IDM [8]. Detection time differs from 0.2 s (defined in VDE 0126-1-1 [12]) to 2 s (defined in IEEE 1547 [13]). The main goal of all researchers is to create an IDM that can detect islanding as soon as possible.

Regarding accuracy, IDM must reduce the non-detection zone (NDZ). The NDZ represents the zone where the IDM cannot detect islanding (illustrated in Figure 4). The accuracy of IDM is high when the NDZ is low and vice versa. Active (ΔP) or reactive power (ΔQ) mismatches between the generation and the consumption in the islanded part of the network can be used to evaluate NDZ. The oscillations in frequency or voltage following the islanding event will not change enough to detect the islanding operation if the power mismatches P and Q at PCC are too low.

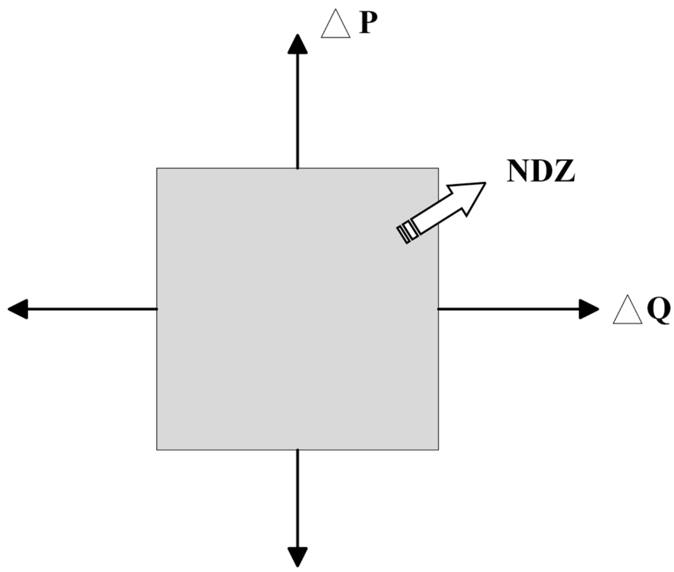

Figure 4. Illustration of the NDZ.

2.2. IDM Method Classification

IDM methods are generally classified into two distinct groups: remote and local methods. Remote methods are based on islanding detection from a distant site (grid operator/dispatcher-based), while local methods detect islanding based on the measurement at the DG site or at the PCC site [3]. The general systematization of the IDMs is shown in Figure 5.

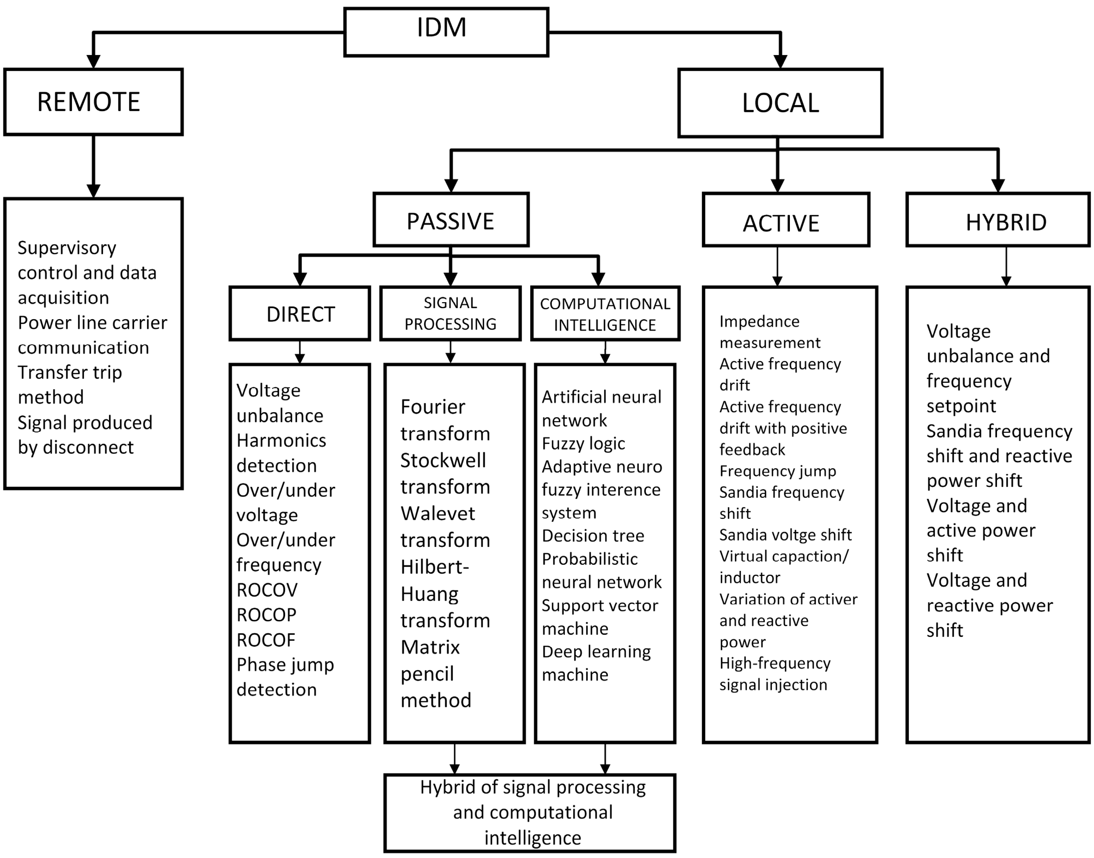

Figure 5. Islanding detection method classification.

Remote IDM usually requires communications between the distribution network management center and local DGs. The main advantage is that the accuracy of islanding detection is high, but additional communication equipment can be costly. Some of the usually investigated remote methods are based on the supervisory control and data acquisition systems (SCADA) [14], power line carrier communication [15], transfer trip method [16], the signal produced by disconnect [17], etc.

On the other hand, local methods detect islanding operations based on locally available devices and their measurements. In most cases, they do not require additional equipment cost, but their disadvantage is lower accuracy than remote methods. Local IDMs are further divided into three main groups: passive, active, and hybrid methods (Figure 5).

Passive local methods are based on local measurements of variables such as voltage, frequency, active power change, reactive power change, etc. In the case of an islanding operation, the above-mentioned variables will be changed (some to a lesser extent and some to a greater extent), and in the case that observed variables change beyond or below the predefined threshold value, the passive method will detect islanding. Since they rely on simple variable changes for detecting islanding conditions, they are easy to implement, and they are not expensive. Commonly observed variables are voltage (voltage unbalance [18], voltage harmonics [19], over/under voltage [20], rate of change of voltage—ROCOV [20], phase jump detection [19]), frequency (over/under frequency and rate of change of frequency—ROCOF [21]), and active or reactive power (rate of change of power—ROCOP [20]). On the other hand, defining appropriate variable thresholds and large NDZ are disadvantages of passive methods. A large NDZ occurs when local generation and consumption (in the islanded part of the network) are similar. Then, the change in the observed variables in the case of islanding is too low, and the passive method can fail in detecting the islanding operation.

To overcome the limitations of passive methods, researchers began to use active methods. Active methods operate on the external disturbance signal injection principle, and islanding detection is based on the system response. Although these methods are slower than passive methods, they are more accurate and have lower NDZ. As disadvantages, active methods interfere with power quality, as the signal injection can distort the voltage waveform, which affects harmonic distortion. Some of the commonly used active methods are impedance measurements [21], active frequency drift [22], active frequency drift with positive feedback [23], frequency jump [24], Sandia frequency shift [24], Sandia voltage shift [24], virtual capacitor/inductor [25], variation in active and reactive power [26], and high-frequency signal injection [27].

To combine the benefits of both passive (fast detection and simple implementation) and active (small NDZ) methods and to alleviate their disadvantages, researchers created hybrid methods that engage both passive and active detection principles. The foundation of hybrid approaches is the presence of both active and passive components. Island detection is initially performed by the passive component. If successful, the procedure stops, and the islanding operation is detected quickly. If the passive component is unable to detect islanding, the active component is activated and injects signals to perform islanding detection. Thus, the additional signal is injected only when the passive component is inefficient. Good examples of hybridization between passive and active methods (see Figure 5) are voltage unbalance and frequency setpoint [28], Sandia frequency shift and reactive power shift [29], voltage and active power shift [30], voltage and reactive power shift [31], etc.

Based on the previously published review papers [3,6,7,10] in which detailed analysis and comparison of different IDMs are performed, the conclusion is that passive methods gain great attention, and there is a plethora of research papers that deal with improvements of passive methods. Passive methods can be further classified (see Figure 5) into direct passive methods, signal processing (SP), and computational intelligence (CI) passive methods. Direct passive methods simply check the change in variable signal without changing and processing the signal itself. They show a rather high NDZ, and to improve the accuracy, researchers start processing the input signal and extract the appropriate features that make up the essence of the SP passive methods. It is the passive method form with the capability for hidden feature extraction of any signal, which is an added advantage. Commonly used SP methods are Fourier transform [32], Stockwell transform [33], wavelet transform [34], Hilbert–Huang transform [35], matrix pencil method [36], etc. Although the accuracy of islanding operation detection is improved by the SP approaches, the detection based on the extraction signal feature can be hard in more complicated network structures. Therefore, the next step is to add computational intelligence (CI) methods already proven in data classification. Instead of checking whether some values are below or above the prespecified threshold, the signal is sent to the intelligent classifier, trained to detect islanding operation. Before an intelligent classifier is applied, the signal can be processed and appropriate features extracted. In that case, it can be said that signal processing methods and computational intelligence-based methods are hybridized (see Figure 5). Some of the computational intelligence methods used in islanding detection are artificial neural network (ANN) [37], fuzzy logic [38], adaptive neuro-fuzzy inference system (ANFIS) [39], decision tree [40], probabilistic neural network (PNN) [41], support vector machine (SVM) [42], and deep learning [43].

3. Artificial Neural Networks

3.1. Artificial Neural Network Performance for Islanding Detection

As noted in the previous section, the IDM should be as fast and precise as possible and the non-detection zone should be as small as possible. Also, the method should be simple to implement in existing equipment (protection systems) with as little additional investment as possible. Regarding the criteria of cost, implementation complexity, and minimal impact on power quality, passive islanding detection methods have an advantage over active ones. Direct passive methods are easy to use and usually do not require additional investments in equipment; however, they have lower accuracy and a large non-detection zone. Setting the appropriate detection threshold for direct passive methods represents a special challenge on which the accuracy of the method depends. In some situations (especially when, in the grid island, the energy that is produced is almost or completely equal to the energy that is consumed), the changes in electrical quantities during islanding operation are minimal and will not exceed the set threshold, and therefore, IDM will not detect the islanding operation properly. In order to improve the performance of the direct passive methods (especially the threshold-setting problem), researchers have started to modify input signals using signal processing methods. The goal is to find some hidden features of the signal that can improve islanding detection. Further improvement is carried out by adding an intelligent classifier that will based on the extracted features to classify the occurrence of the islanding operation. Further improvement is accomplished by adding an intelligent classifier that will based on the extracted features to classify the occurrence of the islanding operation. According to [5], commonly used intelligent classifiers are ANNs, Fuzzy Logic Control (FLC), Adaptive Neuro-fuzzy Inference System (ANFIS), Support Vector Machine (SVM), and Decision Tree (DT). As for accuracy, according to [5], ANN-based methods show high accuracy (up to 98.19%), although ANFIS and DT-based methods show 100% accuracy in some applications [5]. Another advantage of ANN-based methods is their wide application possibilities to different kinds of real-life situations. They are capable of handling situations with DGs based on synchronous generators as well as multi-inverter DGs (photovoltaics) [6]. Since the ANN makes a decision based on the data that were used for training, setting the activation threshold is no longer necessary, but choosing the appropriate dataset for training is crucial. A review of the literature reveals that the ANN as a classifier for islanding detection, despite many advantages, also has its drawbacks. According to the literature [6,7], authors discuss the quality of the input data and the potential shortcomings of the extensive training with huge and irrelevant data. This all can lead to bad performance of the ANN.

3.2. Application of Artificial Neural Network to Islanding Detection

The step-by-step islanding detection procedure adopted in ANN is depicted in Figure 6. In general, the methodology of applying neural networks in the detection of islanding operations can be broken down into three phases, as shown in Figure 6. In the first phase, which represents the training of the selected neural network, the input data first go through transformation and reduction with the various mathematical transformations, which are described in more detail in Section 4.2. Transformed data are then divided into testing and training datasets. The most common ratio of training and testing is 66/33 [44]. The training dataset then goes to the neural network which is learned to detect islanding operation. The second phase serves as a testing of a trained neural network. The testing dataset is sent to the neural network and the decision (islanding operation or not) is checked in order to evaluate the neural network accuracy. In the third phase, after the neural network is tested, implementation of the developed method to a real-world system follows. Most of the reviewed papers failed to realize this phase and only performed the first two. Some examples of successfully implemented islanding detection methods in practice are reviewed in Section 6.3.

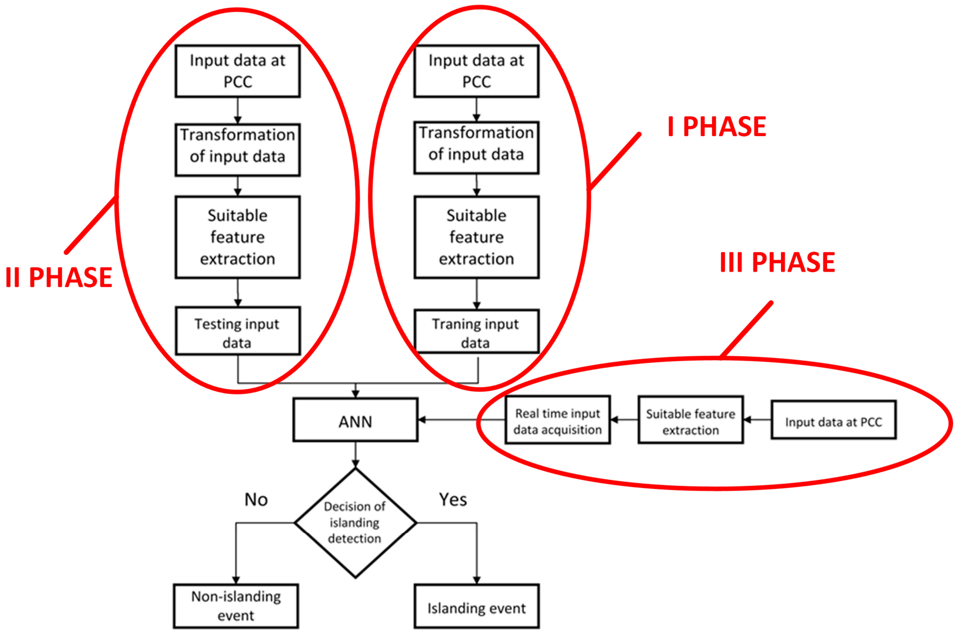

Figure 6. Flow chart of artificial neural network method in islanding detection.

4. Classification and Analysis of the Input Data

4.1. Types and Sources of Input Data

Input data commonly refer to physical values such as voltage amplitude, frequency, active power, current, etc. Input data related to physical values are most often taken locally, near DG or on the PCC. Figure 7 shows the input data used for islanding detection using ANN. It also shows that the number and type of input data are determined based on one's knowledge and experience. Some methods and authors use only one type of input data, mostly voltage amplitude. The other authors use several types of input data, most of which are voltage amplitude and current. The introduction of rotor stability into the detection of islanding operation by monitoring the rotor angle [44,45] should be specially highlighted, with the help of which it is much easier to conclude whether the generator is in synchronism with the grid or has gone into islanding.

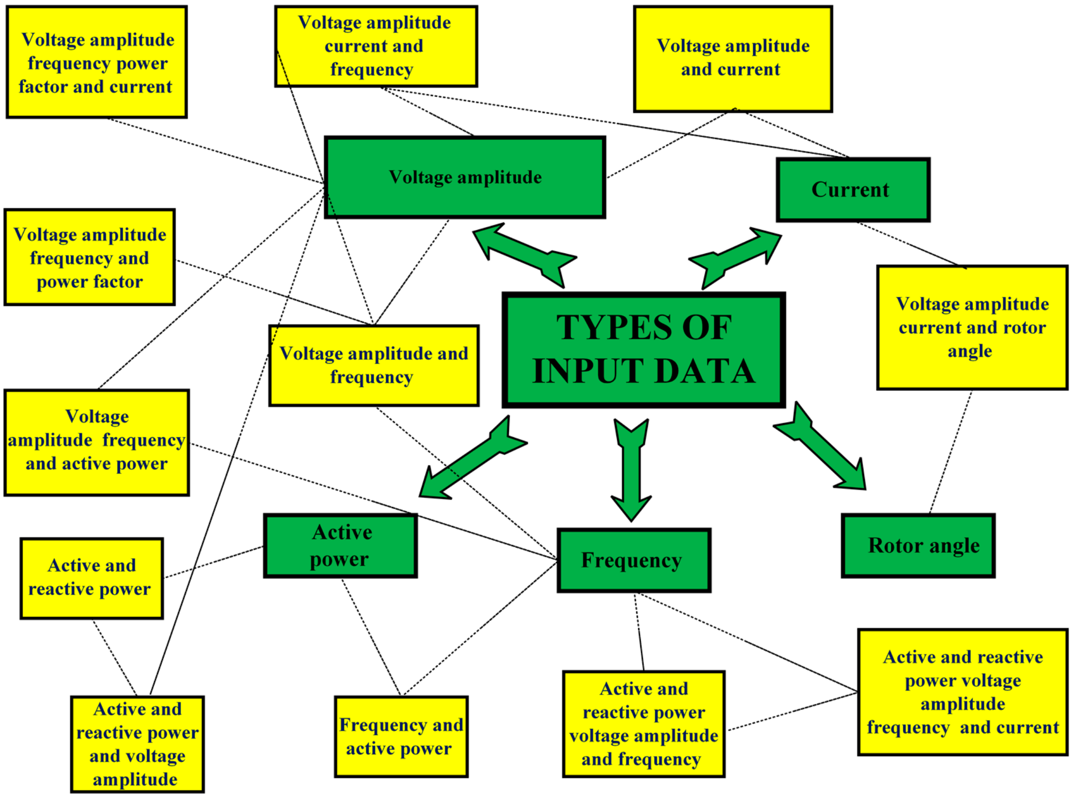

Figure 7. Different types of input data for artificial neural network.

Different types of input data with associate research papers are shown in Table 1.

Table 1. Review of input data types and associated literature.

Input data	Reference
voltage amplitude	[46–56]
current	[57]
rotor angle	[44,45]
frequency	[58]
active power	[59]
voltage and current amplitude	[45,60–65]
voltage, current and frequency	[66]
voltage, current, frequency and power factor	[67]
voltage, frequency and active power	[68]
voltage, current and rotor angle	[45]
voltage amplitude and frequency	[69]
voltage, frequency, current, active and reactive power	[70–73]
voltage, frequency, active and reactive power	[74]
frequency and active power	[75]
voltage, active and reactive power	[76]
active and reactive power	[77,78]

The sources of input data used for training and testing the IDMs are extracted into data obtained by measurement and downloaded from relays that can record data or fault recorders, or they are extracted in dynamic analysis real-time simulation using programs such as PSCAD-EMTDC, DIgSILENT, ATP, PSIM, and MATLAB. Table 2 shows the sources of input data, and most papers use measurements as a source of the input data.

Table 2. Sources of input data.

Measurements	**Simulation**	
Papers	Software	Papers
[49–70]	PSCAD-EMTDC	[64,74,76,79,80]
	DIgSILENT	[49–51,81]
	ATP	[52]
	PSIM	[53]
	MATLAB	[54,59,78,82–91]
	No name	[44,65,69,72,73,92]

4.2. Transformation and Reduction in Input Data

Data processing essentially includes data preparation in an extensive sense, i.e., data cleaning, supplementing, extracting attributes, transformation and reduction, and many other less important actions. The speed of the next ANN layer is faster because the input data are smaller than when there is no processing. The flaw of processing is the slower operation of the input data layer due to the action. Table 3 shows different transformation methods in input data processing that use complex mathematics, the most common of which is the discrete wavelet transformation (DWT). The authors of the most recent papers use input data processing. The transformation and reduction in input data aim to present the input data as more compact as an algorithm that is sophisticated and computationally demanding and calculates the problem faster and easier. A certain share of information is lost during data reduction and transformation. The focus is on data reduction and transformation using a transformation, although the reduction process can be carried out in several different ways. What the transformation does is that it turns one column of data into several columns of shorter length and less complexity, i.e., it makes more than one dimension, which is the case with DWT. The essence of the transformation is dual, i.e., to reduce the complexity and increase the transferability of data.

Table 3. Transformation of input data.

Transform	**Papers**
Discrete wavelet transform (DWT)	[45,47,49,54,55,59,65,66,72,75,80,83,88–97]
Wavelet transform (WT)	[48,59,62,73,78,87,89,98,99]
S-transform (ST)	[41,47,52,54,100]
Wavelet packet transform (WPT)	[77]
Fast Fourier transform (FFT)	[58]
Discrete Fourier transform (DFT)	[44,65,85,101]
Slantlet transform (SLT)	[41,54,84]
Hilbert transform (HT)	[82,84]
Continuous wavelet transform (CWT)	[56]
Tunable Q wavelet transform (TQWT)	[69]
Phase space technique (PST)	[49]

Fourier transformation provides a representation of a signal in the frequency domain. This is useful for analyzing the frequency components of a signal, which is essential for understanding the characteristics of the input data. Fourier transformation is widely used to analyze the non-stationary signal, but computational time can be slow due to the complexity. The authors of [61] used DFT to transform the data in order to speed up standard FT. The symmetrical components of the second harmonic of voltage and current signals were used as input to MPNN. The second harmonics of voltage and current signals are almost zero under normal conditions, whereas in islanding, the symmetrical components of the second harmonic of voltage and current signals have remarkable values. The wavelet transform provides a representation of a signal in the time and frequency domain. Wavelet transformation has a high computational speed due to less complexity than Fourier transformation. Batch processing, high-frequency integration, and being heavily affected by noise are the drawbacks. The authors of [54] used DWT of the currents and voltages to capture unique signatures that can be used to reveal the cause of the corresponding transient signals. The transients generated during the islanding event contain special specific information that can be used to distinguish the islanding operation from normal operation. The DWT is based on non-stationary phenomena studies and has proven to be of value in the characterization of transient signals.

5. Artificial Neural Network Architectures and Learning Algorithms

5.1. Types of Artificial Neural Networks

During the literature review, a division of different types of ANNs applied as IDM in distribution networks was carried out. Table 4 shows the types of neural networks used in islanding detection. Depending on the method of solving the identification problem, types of neural networks intended to solve these types of problems were used. Depending on the complexity of the islanding problem, the input data, the type of DG, and the author's subjective option, one of the ANN types shown in Table 4 is selected for IDM.

Table 4. Types of artificial neural networks.

Type of Artificial Neural Network	Papers
Multilayer perceptron neural network (MPNN)	[46–49,52,58,60,61,63,65,66,68–70,74–76,78,79,82,83,86,87,90–92,95,97–99,102–104]
Probabilistic neural network (PNN)	[41,50,55,64,65,77,84,96,100]
Adaptive neuro-fuzzy information system (ANFIS)	[47,59,62,72,73,75,78,97]
Self-organizing map (SOM) neural network	[44,103]
CMAC neural network (CMACNN)	[67]
Extreme learning machine (ELM)	[50,90,95,98]
Extension neural network type-2 (ENN-2)	[78]
Recurrent neural network (RNN)	[81,85]

Figure 8 shows the chart of different types of ANN over a selected time. Authors continuously use MPNN over an analyzed time period because they are simple, with very low NDZ and high accuracy. SOM for IDM was used for a very short time and in fewer articles, where it was realized that this type was unsuitable for IDM. PNN has appeared in papers over the years but in much smaller numbers than MPNN because they are a more complex type. ANFIS, just like PNN, has appeared over the years, but in fewer numbers than MPNN and higher than PNN because it is a more complex type, because its architecture includes a fuzzy layer. The literature review leads to the conclusion that the most common type of ANN that is used as an IDM is MPNN.

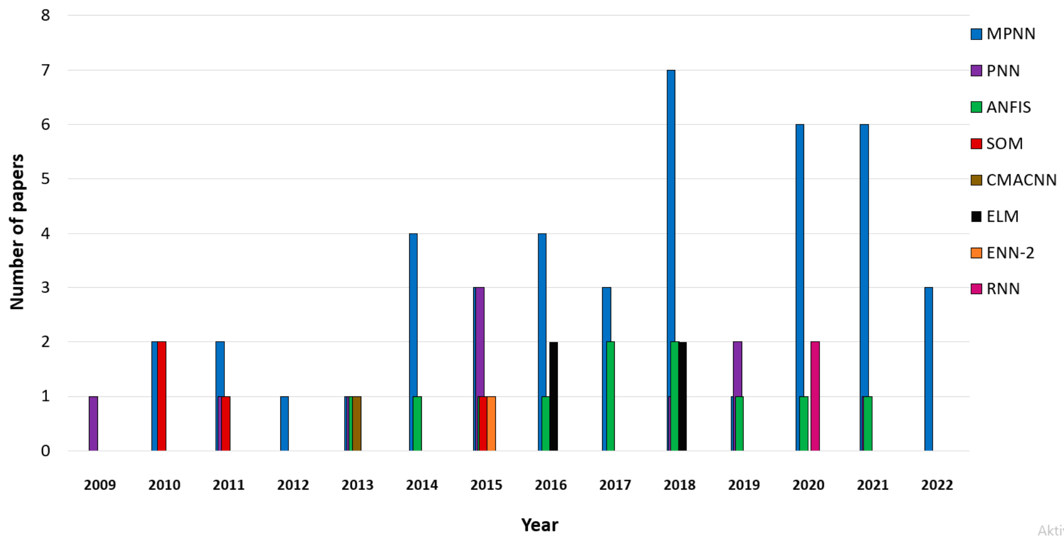

Figure 8. Different types of ANNs used in the observed time period.

5.2. Types of Learning Algorithms

Table 5 shows the types of learning algorithms used in ANNs for islanding detection. Depending on which type of ANN is used for islanding detection, it has a corresponding learning algorithm.

Table 5. Types of learning algorithm.

Type of Learning Algorithm	Papers
Back-propagation	[46–49,52,58,60,61,63,65,66,68–70,74–76,78,79,82,83,86,87,90–92,95,97–99,102–104]
Boltzmann learning algorithm	[81,85]
Bayesian function	[41,55,64,77,96]
Differential evolution	[41,51,78,84]
Fuzzy logic	[59,62,72,73,75,78,92,97]
Vector quantization	[44,45]
Machine learning	[50,63,67,88,98]
Optimized learning algorithm	[65,76,82,83,95]

5.3. Discussion of Input Data, Types of Artificial Neural Networks, and Types of Learning Algorithms

The most common type of ANN in islanding detection is MPNN—Table 5 and Figure 8. In the literature review, MPNN is used continuously by the authors. The reason for this is the speed of detection and adequate accuracy of the method. Authors of [84,99] claim that MLP's main advantages are flexibility and capability of capturing system nonlinearity. The other most common types of ANN are PNN and ANFIS. PNNs generate accurately predicted target probability output and can be more accurate than MPNNs. ANFIS's advantage over MPNN is adaptation capability and rapid learning capacity. ANFIS takes more time to process detection due to the fuzzy layer than MPNN and PNN [53,62]. The advantage of ANFIS is high accuracy and very small NDZ. Also, in [55], RNN is used, which is a novelty in island detection. It has proven effective, and the authors compare it with SOM and MPNN.

The back-propagation learning algorithm is the most widely used learning algorithm for MPNN. The back-propagation learning algorithm is a widely used and well-established algorithm for training MPNN, effective in handling complex and non-linear relationships in data, but may suffer from slow convergence [87]. The Boltzmann learning algorithm is suitable for training Boltzmann machines (a type of recurrent neural network) and it can capture dependencies between variables over time but it has low computational efficiency [85].

PNNs can learn different algorithms, the most common of which are based on Bayesian function, differential evolution, etc. ANFIS is a combination of two learning algorithms: fuzzy-logic and back-propagation, from which they derive the best advantages of both algorithms. The learning algorithm can be optimized where the amount of input data is reduced, and the learning process is improved. The best example of learning optimization is grey wolf and PSO. The above algorithms are supervised learning algorithms, while vector quantization is an example of an unsupervised learning algorithm. Vector quantization is based on competitive learning, so it is related to the SOM.

As shown in Figure 7, the input data in ANN are diverse. By reviewing the literature, most authors often use voltage amplitude, with or without more quantities like current, power, etc. Input data are taken from the relays or by dynamic analysis on a real-time simulator. The amount of input data is often huge, so it is transformed by reduction, most commonly by DWT. Figure 9 shows a chart of ANN types with the associated type of transformation of input data.

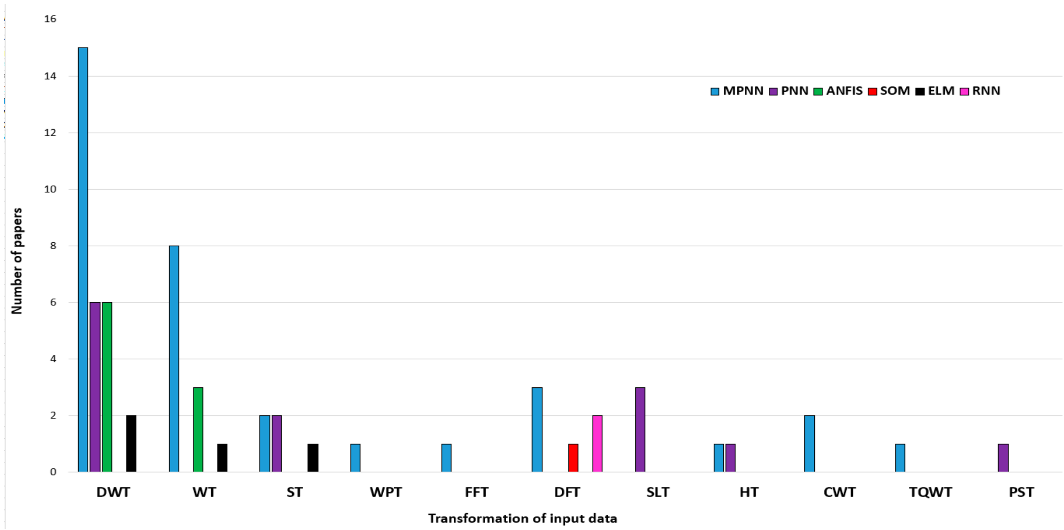

Figure 9. Different transformations of input data for different types of ANNs.

6. Types of DGs and Network Application

6.1. Types of DGs

DGs such as synchronous generators, PVs, and wind power plants with asynchronous generators are the most common types that appear in the islanding. Figure 10 shows a chart of three types of DG that appear in the islanding detection. The largest representation among the literature review are PVs, for which islanding is detected, followed by the classic synchronous generator, whose turbine is driven by steam, and the asynchronous generator driven by wind. The reason for the large presence of PVs in solving the problem of islanding detection is that it is possible to implement it at a low voltage level (distribution), with low power and low costs of equipment, installation, and maintenance, whereas in the case of plants with synchronous and asynchronous generators, it requires considerable investment, and at the same time, they are connected to a medium- or high-voltage network, so it is expected that there will be fewer of them in research.

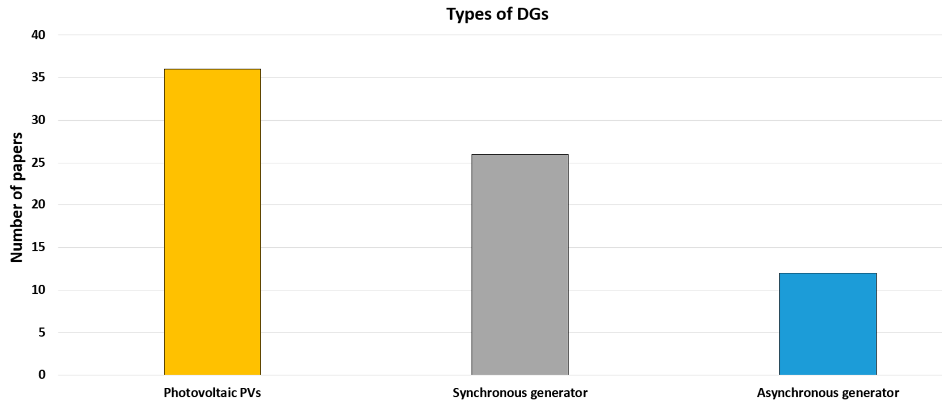

Figure 10. Types of DGs.

6.2. Types of Network Application

As explained in detail in Section 2, islanding is possible in active networks and microgrids. Figure 11 shows the applications of developed ANN-based IDMs to active distribution networks or microgrids. By reviewing the literature, Figure 11 shows that most authors deal with the problems of islanding detection using ANN in an active distribution grid, while a small number of articles are classified in the microgrid. The reason for this might be that, in an electric distribution grid, active distribution networks are more common than microgrids. Figure 8 also shows that the first papers on the islanding detection topic of DGs using ANN appeared in 2009 and are still relevant in 2022. The first papers on the islanding detection topic in microgrids using ANN appeared in 2015 and are still relevant.

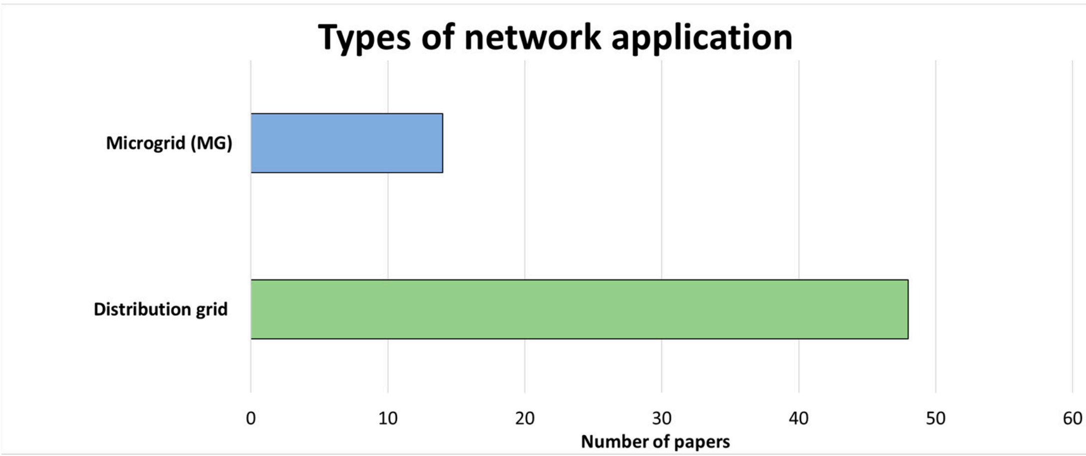

Figure 11. Types of network applications.

In the case of an active distribution network, islanding operation is generally avoided and in the event of its occurrence, protection devices should disconnect down-distributed production within the stipulated time (depending on the applied standard, from a few hundred milliseconds to 2 s). In the case of a microgrid, there are two possible scenarios. One is when islanding can be sustained and the microgrid continues to operate in islanding mode and another one is when islanding is unwanted and the microgrid needs to be disconnected. In both scenarios, quick and effective IDM is needed to provide accurate information to the microgrid control unit. Structurally, there is no significant difference between the methods that are developed for active distribution grids or microgrids. The same ANN architecture and the same input data can be used in both cases. In some cases, methods that are applied to microgrids need to be quicker than those applied to active distribution grids.

6.3. Practical Implementation of ANN-Based IDMs

Research in the field of islanding detection in the distribution system using neural networks goes in two directions. The first direction is the conceptual development and testing of the off-line model in order to obtain the best synergy between the selection of input data, data preparation, validation of these data with a neural network, and the obtained results, and this constitutes the majority of papers currently in this scientific field. The second direction is the online implementation of methods in the real power system, where there are fewer published papers [62,96]. The aforementioned papers present online applications for the islanding detection of photovoltaic systems.

The authors in [62] presented an active online method for islanding detection using a fuzzy neural network. The method is integrated into an inverter control unit that has the ability to function with fuzzy information to detect the islanding operation of the photovoltaic system. Data transformation was carried out using wavelet transform (WT) to reduce the data and gain the speed of the algorithm. A passive online method for islanding detection using a neural network is presented in [47]. The method is integrated into the protection device to avoid setting the threshold of the protection device and to perform intelligent islanding detection of the photovoltaic system. Data preparation was carried out using wavelet packet transform (WPT) in order to reduce data and increase the response of the protection device.

There are a certain number of obstacles that should be taken into account when implementing the method in a real power system with distributed generation (online). The first obstacle is that the installed protective (control) equipment has certain inputs as physical variables that are followed by certain outputs that act on precisely specified circuit breakers, and with that, we are limited in the choice of input variables that feed the method.

7. Conclusions

This paper performs a literature review on the application of ANN for distribution grids for islanding detection. Through this review paper, various types of different ANNs have been addressed. Researchers mostly used multilayer perceptron neural networks (MPNNs) and ANFIS because they show good performance in relation to their complexity. Also, in order to boost accuracy and decrease the non-detection zone, almost all the new papers use data processing in which transformation and reduction in the raw data occur. Although many different types of transformation are tested, the dominance of the wavelet-based method is evident as well as the trend of including transformations related to the power quality (Fourier-based).

Due to the growing connection of DGs to the distribution grid worldwide, research interest in developing efficient IDMs is still high. Generally, most of the methods are developed for application in active distribution grids, while fewer are developed for microgrid applications, which opens future research potential in light of microgrid development. Although the subject review shows that the application of neural networks to the detection of islanding operation is a well-researched area with an abundance of published scientific papers, the potential for further research and improvement certainly exists in the area of microgrids.

Author Contributions: Conceptualization, S.K. and K.F.; methodology, S.K. and K.Č.; formal analysis, K.F.; investigation, K.Č.; resources, Z.K.; data curation, S.K.; writing—original draft preparation, K.Č. and K.F.; writing—review and editing, K.F. and Z.K.; visualization, S.K.; supervision, K.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Conflicts of Interest: Author Slaven Kaluđer was employed by the company HEP Distribution System Operator. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Abbreviations

DG	Distributed Generation
ANN	Artificial Neural Network
IDM	Islanding Detection Method
CI	Computational Intelligence
NDZ	Non-Detection Zone
ID	Islanding detection
CB	Circuit Breaker
PV	Photovoltaic
PCC	Point of Common Coupling
ROCOV	Rate of Change of Voltage
ROCOF	Rate of Change of Frequency
ROCOP	Rate of Change of Power
SP	Signal Processing
ANFIS	Adaptive Neuro-Fuzzy Inference System
PNN	Probabilistic Neural Network
SVM	Support Vector Machine
NN	Neural Network
FFNN	Feed-Forward Neural Network
RNN	Recurrent Neural Network
MPNN	Multilayer Perceptron Neural Network
SOM	Self-Organizing Map Neural Network
ELM	Extreme Learning Machine
ENN-2	Extension Neural Network Type-2
CMACNN	CMAC Neural Network
DWT	Discrete Wavelet Transform
WT	Wavelet Transform
ST	S-Transform
WPT	Wavelet Packet Transform
FFT	Fast Fourier Transform
DFT	Discrete Fourier Transform
SLT	Slantlet Transform
HT	Hilbert Transform
CWT	Continuous Wavelet Transform
TQWT	Tunable Q Wavelet Transform
PST	Phase Space Technique

References

1. De Mango, F.; Liserre, M.; Dell'Aquila, A.; Pigazo, A. Overview of Anti-Islanding Algorithms for PV Systems. Part I: Passive Methods. In Proceedings of the 2006 12th International Power Electronics and Motion Control Conference, Portoroz, Slovenia, 30 August–1 September 2006; pp. 1878–1883. [CrossRef]
2. Velasco, D.; Trujillo, C.L.; Garcerá, G.; Figueres, E. Review of anti-islanding techniques in distributed generators. *Renew. Sustain. Energy Rev.* **2010**, *14*, 1608–1614. [CrossRef]
3. Khamis, A.; Shareef, H.; Bizkevelci, E.; Khatib, T. A review of islanding detection techniques for renewable distributed generation systems. *Renew. Sustain. Energy Rev.* **2013**, *28*, 483–493. [CrossRef]
4. Dutta, S.; Sadhu, P.K.; Reddy, M.J.B.; Mohanta, D.K. Shifting of research trends in islanding detection method—A comprehensive survey. *Prot. Control. Mod. Power Syst.* **2018**, *3*, 1. [CrossRef]
5. Laghari, J.A.; Mokhlis, H.; Karimi, M.; Bakar, A.H.A.; Mohamad, H. Computational Intelligence based techniques for islanding detection of distributed generation in distribution network: A review. *Energy Convers. Manag.* **2014**, *88*, 139–152. [CrossRef]
6. Kim, M.-S.; Haider, R.; Cho, G.-J.; Kim, C.-H.; Won, C.-Y.; Chai, J.-S. Comprehensive Review of Islanding Detection Methods for Distributed Generation Systems. *Energies* **2019**, *12*, 837. [CrossRef]
7. Chaitanya, B.K.; Yadav, A.; Pazoki, M.; Abdelaziz, A.Y. A comprehensive review of islanding detection methods. In *Uncertainties in Modern Power Systems*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 211–256. [CrossRef]
8. Usama, M.; Mokhlis, H.; Moghavvemi, M.; Mansor, N.N.; Alotaibi, M.A.; Muhammad, M.A.; Bajwa, A.A. A Comprehensive Review on Protection Strategies to Mitigate the Impact of Renewable Energy Sources on Interconnected Distribution Networks. *IEEE Access* **2021**, *9*, 35740–35765. [CrossRef]

9. Huang, W.; Nengling, T.; Zheng, X.; Fan, C.; Yang, X.; Kirby, B.J. An impedance protection scheme for feeders of active distribution networks. *IEEE Trans. Power Deliv.* **2014**, *29*, 1591–1602. [CrossRef]
10. Li, C.; Cao, C.; Cao, Y.; Kuang, Y.; Zeng, L.; Fang, B. A review of islanding detection methods for microgrid. *Renew. Sustain. Energy Rev.* **2014**, *35*, 211–220. [CrossRef]
11. Jalil, M.W.; Ishtiaque, W.; Arif, A. A Review of Islanding Detection Techniques for Inverter-Based Distributed Generation. *Eng. Proc.* **2023**, *46*, 40. [CrossRef]
12. *DIN VDE V 0126-1-1 VDE V 0126-1-1:2013-08*; Automatic Disconnection Device between a Generator and the Public Low-Voltage Grid. VDE Publishing House: Berlin, Germany, 2013. Available online: https://www.vde-verlag.de/standards/0100178/din-vde-v-0126-1-1-vde-v-0126-1-1-2013-08.html (accessed on 11 March 2021).
13. *IEEE 1547-2018*; IEEE Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces. IEEE: Piscataway, NJ, USA, 2018. Available online: https://standards.ieee.org/standard/1547-2018.html (accessed on 11 March 2021).
14. Silva-Saravia, H.; Singh, I.; Chynoweth, J.; Mateo, N.; Mejia, M.; Amadis, S.; Alvarez, R. Islanding detection and resynchronization based upon wide-area monitoring and situational awareness in the Dominican Republic. In Proceedings of the 2020 IEEE PES Transmission and Distribution Conference and Exhibition—Latin America (T&D LA), Montevideo, Uruguay, 28 September–2 October 2020. [CrossRef]
15. Xu, W.; Zhang, G.; Li, C.; Wang, W.; Wang, G.; Kliber, J. A Power Line Signaling Based Technique for Anti-islanding Protection of Distributed Generators: Part I: Scheme and Analysis. In Proceedings of the 2007 IEEE Power Engineering Society General Meeting, Tampa, FL, USA, 24–28 June 2007; p. 1. [CrossRef]
16. Walling, R.A. Application of direct transfer trip for prevention of DG islanding. In Proceedings of the IEEE Power and Energy Society General Meeting, Detroit, MI, USA, 24–28 July 2011. [CrossRef]
17. Almonacid, F.; Fernandez, E.F.; Mellit, A.; Kalogirou, S. Review of techniques based on artificial neural networks for the electrical characterization of concentrator photovoltaic technology. *Renew. Sustain. Energy Rev.* **2017**, *75*, 938–953. [CrossRef]
18. Ruchika; Gupta, P.; Jain, D.K.; Bhatia, R.S. Islanding detection technique for a distributed generation with perfectly matched load condition. In Proceedings of the IEEE International Conference on Computing, Communication and Automation, ICCCA 2017, Greater Noida, India, 5–6 May 2017; pp. 1503–1506. [CrossRef]
19. Singam, B.; Hui, L.Y. Assessing SMS and PJD schemes of anti-islanding with varying quality factor. In Proceedings of the First International Power and Energy Conference, (PECon 2006), Putra Jaya, Malaysia, 28–29 November 2006; pp. 196–201. [CrossRef]
20. Bakhshi-Jafarabadi, R.; Sadeh, J.; de Jesus Chavez, J.; Popov, M. Two-Level Islanding Detection Method for Grid-Connected Photovoltaic System-Based Microgrid with Small Non-Detection Zone. *IEEE Trans. Smart Grid* **2021**, *12*, 1063–1072. [CrossRef]
21. Chen, H.; Huang, Q.; Li, W.; Xiang, X.; Luo, H.; He, X. An Impedance-Based Islanding Detection Method for DC Microgrids with multiple DGs. In Proceedings of the 2020 4th International Conference on HVDC, HVDC 2020, Xi'an, China, 6–9 November 2020; pp. 1025–1030. [CrossRef]
22. Wang, S.; Zhang, S.; Liu, L.; Jia, Y.; Qie, C. An improved active frequency drift anti-islanding detection method. In Proceedings of the 2016 IEEE 11th Conference on Industrial Electronics and Applications, ICIEA 2016, Hefei, China, 5–7 June 2016; pp. 2170–2173. [CrossRef]
23. Li, Z.; Liu, X.; Liu, X.; Wang, X.; Wang, H. Active Frequency Drift Islanding Detection Method with the Positive Feedback by Absolute Value of Voltage Frequency. In Proceedings of the 2018 Chinese Automation Congress, CAC 2018, Xi'an, China, 30 November–2 December 2018; pp. 578–582. [CrossRef]
24. Larik, N.A.; Tahir, M.F.; Elbarbary, Z.M.S.; Yousaf, M.Z.; Khan, M.A. A comprehensive literature review of conventional and modern islanding detection methods. *Energy Strategy Rev.* **2022**, *44*, 101007. [CrossRef]
25. Jou, H.L.; Chiang, W.J.; Wu, J.C. A simplified control method for the grid-connected inverter with the function of islanding detection. *IEEE Trans. Power Electron.* **2008**, *23*, 2775–2783. [CrossRef]
26. De Mango, F.; Liserre, M.; Dell'Aquila, A.; Pigazo, A. Overview of Anti-Islanding Algorithms for PV Systems. Part II: ActiveMethods. In Proceedings of the 2006 12th International Power Electronics and Motion Control Conference, Portoroz, Slovenia, 10 February 2009; pp. 1884–1889. [CrossRef]
27. Reigosa, D.; Briz, F.; Charro, C.B.; Garcia, P.; Guerrero, J.M. Active islanding detection using high-frequency signal injection. *IEEE Trans. Ind. Appl.* **2012**, *48*, 1588–1597. [CrossRef]
28. Menon, V.; Nehrir, M.H. A hybrid islanding detection technique using voltage unbalance and frequency set point. *IEEE Trans. Power Syst.* **2007**, *22*, 442–448. [CrossRef]
29. Vahedi, H.; Noroozian, R.; Jalilvand, A.; Gharehpetian, G.B. Hybrid SFS and Q-f islanding detection method for inverter-based DG. In Proceedings of the PECon2010—2010 IEEE International Conference on Power and Energy, Kuala Lumpur, Malaysia, 29 November–1 December 2010; pp. 672–676. [CrossRef]
30. Mahat, P.; Chen, Z.; Bak-Jensen, B. A hybrid islanding detection technique using average rate of voltage change and real power shift. *IEEE Trans. Power Deliv.* **2009**, *24*, 764–771. [CrossRef]
31. Chang, W.Y. A hybrid islanding detection method for distributed synchronous generators. In Proceedings of the 2010 International Power Electronics Conference—ECCE Asia—IPEC 2010, Sapporo, Japan, 21–24 June 2010; pp. 1326–1330. [CrossRef]
32. Dash, P.K.; Panigrahi, B.K.; Sahoo, D.K.; Panda, G. Power quality disturbance data compression, detection, and classification using integrated spline wavelet and S-transform. *IEEE Trans. Power Deliv.* **2003**, *18*, 595–600. [CrossRef]

33. Menezes, T.S.; Coury, D.V.; Fetnandes, R.A.S. Islanding detection based on artificial neural network and S-transform for distributed generators. In Proceedings of the 2019 IEEE Milan PowerTech, Milan, Italy, 23–27 June 2019. [CrossRef]
34. Koduri, O.; Duvvuri, S.S.S.R.S.; Varma, S.D.K. A Novel Passive Islanding Detection Methods Using Wavelet Transform for Grid Connected PV System. In Proceedings of the 2018 13th International Conference on Industrial and Information Systems, ICIIS 2018, Rupnagar, India, 1–2 December 2018; pp. 422–426. [CrossRef]
35. Chaitanya, B.K.; Yadav, A. Hilbert-huang transform based islanding detection scheme for Distributed generation. In Proceedings of the 8th IEEE Power India International Conference, PIICON 2018, Kurukshetra, India, 10–12 December 2018. [CrossRef]
36. Nale, R.; Venkatanagaraju, K.; Biswal, S.; Biswal, M.; Kishor, N. Islanding detection in distributed generation system using intrinsic time decomposition. *IET Gener. Transm. Distrib.* **2019**, *13*, 626–633. [CrossRef]
37. Jain, A.K.; Mao, J.; Mohiuddin, K.M. Artificial neural networks: A tutorial. *Computer* **1996**, *29*, 31–44. [CrossRef]
38. Samantaray, S.R.; El-Arroudi, K.; Joós, G.; Kamwa, I. A fuzzy rule-based approach for islanding detection in distributed generation. *IEEE Trans. Power Deliv.* **2010**, *25*, 1427–1433. [CrossRef]
39. Jang, J.S.R. ANFIS: Adaptive-Network-Based Fuzzy Inference System. *IEEE Trans. Syst. Man Cybern.* **1993**, *23*, 665–685. [CrossRef]
40. Kantardzic, M. *Data Mining: Concepts, Models, Methods, and Algorithms*; John Wiley & Sons: Hoboken, NJ, USA, 2011. Available online: https://books.google.hr/books?hl=en&lr=&id=ZZ7l6v0CvRMC&oi=fnd&pg=PA1&dq=M.+Kantardzic,+Data+Mining:+Concepts,+Models,+Methods,+and+Algorithms,+second+ed.,+John+Wiley+%26+Sons,+Hoboken&ots=pPAjrnrDHf&sig=j2eO1KUYqQhpqjxqxuCHusRSFOI&redir_esc=y#v=onepage&q&f=false (accessed on 24 January 2023).
41. Ahmadipour, M.; Hizam, H.; Othman, M.L.; Radzi, M.A. Islanding detection method using ridgelet probabilistic neural network in distributed generation. *Neurocomputing* **2019**, *329*, 188–209. [CrossRef]
42. Matic-Cuka, B.; Kezunovic, M. Islanding detection for inverter-based distributed generation using support vector machine method. *IEEE Trans. Smart Grid* **2014**, *5*, 2676–2686. [CrossRef]
43. Manikonda, S.K.G.; Gaonkar, D.N. IDM based on image classification with CNN. *J. Eng.* **2019**, *2019*, 7256–7262. [CrossRef]
44. Do, H.T.; Zhang, X.; Nguyen, N.V.; Li, S.S.; Chu, T.T.T. Passive-Islanding Detection Method Using the Wavelet Packet Transform in Grid-Connected Photovoltaic Systems. *IEEE Trans. Power Electron.* **2016**, *31*, 6955–6967. [CrossRef]
45. Moeini, A.; Darabi, A.; Rafiei, S.M.R.; Karimi, M. Intelligent islanding detection of a synchronous distributed generation using governor signal clustering. *Electr. Power Syst. Res.* **2011**, *81*, 608–616. [CrossRef]
46. Mishra, M.; Rout, P.K.; Sahu, R.; Ray, D.; Swarup, S. Study the performance of S-transform based extreme learning Machine for islanding detection in distributed generation. In Proceedings of the 2016 National Power Systems Conference (NPSC), Bhubaneswar, India, 19–21 December 2016; pp. 1–6. [CrossRef]
47. Kumar, D.; Bhowmik, P.S. Artificial neural network and phasor data-based islanding detection in smart grid. *IET Gener. Transm. Distrib.* **2018**, *12*, 5843–5850. [CrossRef]
48. Merlin, V.L.; Santos, R.C.; Grilo, A.P.; Vieira, J.C.M.; Coury, D.V.; Oleskovicz, M. A new artificial neural network based method for islanding detection of distributed generators. *Int. J. Electr. Power Energy Syst.* **2016**, *75*, 139–151. [CrossRef]
49. Khamis, A.; Shareef, H.; Mohamed, A. Islanding detection and load shedding scheme for radial distribution systems integrated with dispersed generations. *IET Gener. Transm. Distrib.* **2015**, *9*, 2261–2275. [CrossRef]
50. Khamis, A.; Xu, Y.; Dong, Z.Y.; Zhang, R. Faster Detection of Microgrid Islanding Events Using an Adaptive Ensemble Classifier. *IEEE Trans. Smart Grid* **2018**, *9*, 1889–1899. [CrossRef]
51. Khamis, A.; Shareef, H.; Mohamed, A.; Bizkevelci, E. Islanding detection in a distributed generation integrated power system using phase space technique and probabilistic neural network. *Neurocomputing* **2015**, *148*, 587–599. [CrossRef]
52. Menezes, T.S.; Gomes, E.A.P.; Coury, D.V.; Oleskovicz, M. A Hybrid Method for Islanding Stability Detection of Distributed Generators using Wavelet Transform and Artificial Neural Networks. In Proceedings of the 2018 Simposio Brasileiro de Sistemas Eletricos (SBSE), Niteroi, Brazil, 12–16 May 2018.
53. Wang, M.H.; Huang, M.L.; Liou, K.J. Islanding detection method for grid connected photovoltaic systems. *IET Renew. Power Gener.* **2015**, *9*, 700–709. [CrossRef]
54. Ahmadipour, M.; Hizam, H.; Othman, M.L.; Radzi, M.A.M.; Murthy, A.S. Islanding detection technique using Slantlet Transform and Ridgelet Probabilistic Neural Network in grid-connected photovoltaic system. *Appl. Energy* **2018**, *231*, 645–659. [CrossRef]
55. Samantaray, S.R.; Babu, B.C.; Dash, P.K. Probabilistic Neural Network Based Islanding Detection in Distributed Generation. *Electr. Power Compon. Syst.* **2011**, *39*, 191–203. [CrossRef]
56. Pedrino, E.C.; Yamada, T.; Lunardi, T.R.; Vieira, J.C.d.M. Islanding detection of distributed generation by using multi-gene genetic programming based classifier. *Appl. Soft Comput. J.* **2019**, *74*, 206–215. [CrossRef]
57. Hashemi, F.; Mohammadi, M.; Kargarian, A. Islanding detection method for microgrid based on extracted features from differential transient rate of change of frequency. *IET Gener. Transm. Distrib.* **2017**, *11*, 891–904. [CrossRef]
58. Lopez-Garcia, T.B.; Coronado-Mendoza, A.; Domínguez-Navarro, J.A. Artificial neural networks in microgrids: A review. *Eng. Appl. Artif. Intell.* **2020**, *95*, 103894. [CrossRef]
59. Hashemi, F.; Ghadimi, N.; Sobhani, B. Islanding detection for inverter-based DG coupled with using an adaptive neuro-fuzzy inference system. *Int. J. Electr. Power Energy Syst.* **2013**, *45*, 443–455. [CrossRef]
60. Alam, M.R.; Muttaqi, K.M.; Bouzerdoum, A. A short length window-based method for islanding detection in distributed generation. In Proceedings of the The 2012 International Joint Conference on Neural Networks (IJCNN), Brisbane, QLD, Australia, 10–15 June 2012; pp. 1–6. [CrossRef]

61. Azim, R.; Sun, K.; Li, F.; Zhu, Y.; Saleem, H.A.; Shi, D.; Sharma, R. A Comparative Analysis of Intelligent Classifiers for Passive Islanding Detection in Microgrids. In Proceedings of the 2015 IEEE Eindhoven PowerTech, Eindhoven, The Netherlands, 29 June–2 July 2015. [CrossRef]
62. Lin, F.-J.; Tan, K.-H.; Chiu, J.-H. Active islanding detection method using wavelet fuzzy neural network. In Proceedings of the 2012 IEEE International Conference on Fuzzy Systems, Brisbane, QLD, Australia, 10–15 June 2012; pp. 1–8. [CrossRef]
63. Behera, S.; Nayak, P.; Mallick, R.K.; Sinha, N. Islanding detection of microgrid using Neural Network. In Proceedings of the 2020 International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE), Keonjhar, India, 29–31 July 2020; pp. 1–6. [CrossRef]
64. Lidula, N.W.A.; Perera, N.; Rajapakse, A.D. Investigation of a fast islanding detection methodology using transient signals. In Proceedings of the 2009 IEEE Power & Energy Society General Meeting, Calgary, AB, Canada, 26–30 July 2009; pp. 1–6. [CrossRef]
65. Samet, H.; Hashemi, F.; Ghanbari, T. Minimum non detection zone for islanding detection using an optimal Artificial Neural Network algorithm based on PSO. *Renew. Sustain. Energy Rev.* **2015**, *52*, 1–18. [CrossRef]
66. Faqhruldin, O.N.; El-Saadany, E.F.; Zeineldin, H.H. A universal islanding detection technique for distributed generation using pattern recognition. *IEEE Trans. Smart Grid* **2014**, *5*, 1985–1992. [CrossRef]
67. Chao, K.H.; Yang, M.S.; Hung, C.P. Islanding detection method of a photovoltaic power generation system based on a CMAC neural network. *Energies* **2013**, *6*, 4152–4169. [CrossRef]
68. Abd-Elkader, A.G.; Allam, D.F.; Tageldin, E. Islanding detection method for DFIG wind turbines using artificial neural networks. *Int. J. Electr. Power Energy Syst.* **2014**, *62*, 335–343. [CrossRef]
69. Kumar, S.A.; Subathra, M.S.P.; Kumar, N.M.; Malvoni, M.; Sairamya, N.J.; George, S.T.; Suviseshamuthu, E.S.; Chopra, S.S. A novel islanding detection technique for a resilient photovoltaic-based distributed power generation system using a tunable-Q wavelet transform and an artificial neural network. *Energies* **2020**, *13*, 4238. [CrossRef]
70. Habibi, M.R.; Baghaee, H.R.; Dragicevic, T.; Blaabjerg, F. False Data Injection Cyber-Attacks Mitigation in Parallel DC/DC Converters Based on Artificial Neural Networks. *IEEE Trans. Circuits Syst. II Express Briefs* **2021**, *68*, 717–721. [CrossRef]
71. Baghaee, H.R.; Mlakic, D.; Nikolovski, S.; Dragicevic, T. Support Vector Machine-Based Islanding and Grid Fault Detection in Active Distribution Networks. *IEEE J. Emerg. Sel. Top. Power Electron.* **2020**, *8*, 2385–2403. [CrossRef]
72. Shayeghi, H.; Sobhani, B. Zero NDZ assessment for anti-islanding protection using wavelet analysis and neuro-fuzzy system in inverter based distributed generation. *Energy Convers. Manag.* **2014**, *79*, 616–625. [CrossRef]
73. Shayeghi, H.; Sobhani, B.; Shahryari, E.; Akbarimajd, A. Optimal neuro-fuzzy based islanding detection method for Distributed Generation. *Neurocomputing* **2016**, *177*, 478–488. [CrossRef]
74. Laghari, J.A.; Mokhlis, H.; Karimi, M.; Bakar, A.H.A.; Shahriari, A. Artificial Neural Network based Islanding Detection Technique for Mini hydro type distributed generation. In Proceedings of the 3rd IET International Conference on Clean Energy and Technology (CEAT) 2014, Kuching, Malaysia, 24–26 November 2014.
75. Kermany, S.D.; Joorabian, M.; Deilami, S.; Masoum, M.A.S. Hybrid Islanding Detection in Microgrid with Multiple Connection Points to Smart Grids Using Fuzzy-Neural Network. *IEEE Trans. Power Syst.* **2017**, *32*, 2640–2651. [CrossRef]
76. Raza, S.; Mokhlis, H.; Arof, H.; Naidu, K.; Laghari, J.A.; Khairuddin, A.S.M. Minimum-features-based ANN-PSO approach for islanding detection in distribution system. *IET Renew. Power Gener.* **2016**, *10*, 1255–1263. [CrossRef]
77. Tan, K.H.; Lan, C.W. DG system using PFNN controllers for improving islanding detection and power control. *Energies* **2019**, *12*, 506. [CrossRef]
78. Wang, G.; Wang, J.; Zhou, Z.; Wang, Q.; Wu, Q.; Jiang, X.; Santana, E. State variable technique islanding detection using time-frequency energy analysis for DFIG wind turbine in microgrid system. *ISA Trans.* **2018**, *80*, 360–370. [CrossRef] [PubMed]
79. Mohanty, A.; Rout, B. Island Detection based on voltage ratio and artificial neural network for inverter-based distributed generation. In Proceedings of the 2022 International Conference on Intelligent Controller and Computing for Smart Power (ICICCSP), Hyderabad, India, 21–23 July 2022; pp. 1–6. [CrossRef]
80. *Proceedings of the IEEE Electrical Power and Energy Conference (EPEC) 2010: Sustainable Energy for an Intelligent Grid, Halifax, NS, Canada, 25–27 August 2010*; IEEE: Piscataway, NJ, USA, 2010.
81. Mohapatra, S.S.; Maharana, M.K.; Pradhan, A.; Panigrahi, P.K.; Prusty, R.C. Detection and diagnosis of islanding using artificial intelligence in distributed generation systems. *Sustain. Energy Grids Netw.* **2022**, *29*, 100576. [CrossRef]
82. Admasie, S.; Bukhari, S.B.A.; Gush, T.; Haider, R.; Kim, C.H. Intelligent Islanding Detection of Multi-distributed Generation Using Artificial Neural Network Based on Intrinsic Mode Function Feature. *J. Mod. Power Syst. Clean Energy* **2020**, *8*, 511–520. [CrossRef]
83. Zeng, Y.R.; Zeng, Y.; Choi, B.; Wang, L. Multifactor-influenced energy consumption forecasting using enhanced back-propagation neural network. *Energy* **2017**, *127*, 381–396. [CrossRef]
84. Swarnkar, N.K.; Mahela, O.P.; Khan, B.; Lalwani, M. Identification of Islanding Events in Utility Grid with Renewable Energy Penetration Using Current Based Passive Method. *IEEE Access* **2021**, *9*, 93781–93794. [CrossRef]
85. Abdelsalam, A.A.; Salem, A.A.; Oda, E.S.; Eldesouky, A.A. Islanding Detection of Microgrid Incorporating Inverter Based DGs Using Long Short-Term Memory Network. *IEEE Access* **2020**, *8*, 106471–106486. [CrossRef]
86. Ali, W.; Ulasyar, A.; Mehmood, M.U.; Khattak, A.; Imran, K.; Zad, H.S.; Nisar, S. Hierarchical Control of Microgrid Using IoT and Machine Learning Based Islanding Detection. *IEEE Access* **2021**, *9*, 103019–103031. [CrossRef]

87. De Biaz, B.M.; Fortes, M.Z.; Ferreira, V.H. Islanding Detection in Distributed Generation using Supervised Learning Techniques. In Proceedings of the 2018 Simposio Brasileiro de Sistemas Eletricos (SBSE), Niteroi, Brazil, 12–16 May 2018.
88. *Proceedings of the IEEE 2014 Eighteenth National Power Systems Conference (NPSC), Guwahati, India, 18–20 December 2014*; IEEE: Piscataway, NJ, USA, 2014.
89. Soumya, A.V.; Edward, J.B. An Intelligent Method of Anti Islanding Detection using ANN. In Proceedings of the 2021 Innovations in Power and Advanced Computing Technologies (i-PACT), Kuala Lumpur, Malaysia, 27–29 November 2021; pp. 1–6. [CrossRef]
90. Phafula, I.; De Mello Koch, E.; Nixon, K. Preliminary study of fault detection on an islanded microgrid using artificial neural networks. In Proceedings of the 2020 International SAUPEC/RobMech/PRASA Conference, SAUPEC/RobMech/PRASA 2020, Cape Town, South Africa, 29–31 January 2020; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2020. [CrossRef]
91. Najar, A.; Karegar, H.K.; Esmaeilbeigi, S. Intelligent Islanding Detection Scheme for Microgrid Based on Deep Learning and Wavelet Transform. In Proceedings of the 2020 10th Smart Grid Conference, SGC 2020, Kashan, Iran, 16–17 December 2020; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2020. [CrossRef]
92. Ahmed, R.; Sreeram, V.; Mishra, Y.; Arif, M.D. A review and evaluation of the state-of-the-art in PV solar power forecasting: Techniques and optimization. *Renew. Sustain. Energy Rev.* **2020**, *124*, 109792. [CrossRef]
93. Korbicz, J. Artificial Neural Networks in Fault Diagnosis of Dynamical Systems. In Proceedings of the 2010 IEEE Region 8 International Conference on Computational Technologies in Electrical and Electronics Engineering (SIBIRCON), Irkutsk, Russia, 11–15 July 2010.
94. Fayyad, Y.; Osman, A. Neuro-wavelet based islanding detection technique. In Proceedings of the 2010 IEEE Electrical Power & Energy Conference, Halifax, NS, Canada, 25–27 August 2010; pp. 1–6. [CrossRef]
95. Das, G.; Pattnaik, P.K.; Padhy, S.K. Artificial Neural Network trained by Particle Swarm Optimization for non-linear channel equalization. *Expert Syst. Appl.* **2014**, *41*, 3491–3496. [CrossRef]
96. Tan, K.H.; Lan, C.W.; Chang, Y.R.; Der Lee, Y.; Liu, L.Y. Intelligent controlled distributed generator system for P-Q control and islanding detection. In Proceedings of the 2018 International Symposium on Computer, Consumer and Control, IS3C 2018, Taichung, Taiwan, 6–8 December 2018; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2019; pp. 364–367. [CrossRef]
97. Mohanty, S.R.; Ray, P.K.; Kishor, N.; Panigrahi, B.K. Classification of disturbances in hybrid DG system using modular PNN and SVM. *Int. J. Electr. Power Energy Syst.* **2013**, *44*, 764–777. [CrossRef]
98. Xie, D.; Zang, D.; Gao, P.; Xiang, M.; Yang, L. Research on islanding detection technology for multi grid-connected inverters. In Proceedings of the 2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC), Chongqing, China, 25–26 March 2017; pp. 2505–2508. [CrossRef]
99. Shahryari, E.; Nooshyar, M.; Sobhani, B. Combination of neural network and wavelet transform for islanding detection of distributed generation in a small-scale network. *Int. J. Ambient Energy* **2019**, *40*, 263–273. [CrossRef]
100. Esmaeilbeigi, S.; Karegar, H.K. Intelligent Fault Detection and Location Scheme for Low Voltage Microgrids based on Recurrent and Radial Basis Function Neural Networks. In Proceedings of the 2020 28th Iranian Conference on Electrical Engineering (ICEE), Tabriz, Iran, 4–6 August 2020; pp. 1–6. [CrossRef]
101. Maresch, K.; Marchesan, G.; Freitas-Gutierres, L.F. Passive Islanding Detection Based on Angular Velocity Harmonic Patterns with Perceptron Neural Network. *IEEE Lat. Am. Trans.* **2021**, *19*, 1665–1673. [CrossRef]
102. Reddy, C.R.; Reddy, K.H.; Goud, B.S.; Pakkiraiah, B. A Deep learning approach for Islanding Detection of Integrated DG with CWT and CNN. In Proceedings of the 2021 International Conference on Sustainable Energy and Future Electric Transportation, SeFet 2021, Hyderabad, India, 21–23 January 2021; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2021. [CrossRef]
103. ElNozahy, M.S.; El-Saadany, E.F.; Salama, M.M.A. A robust wavelet-ANN based technique for islanding detection. In Proceedings of the 2011 IEEE Power and Energy Society General Meeting, Detroit, MI, USA, 24–28 July 2011; pp. 1–8. [CrossRef]
104. Macedo, M.N.Q.; Galo, J.J.M.; de Almeida, L.A.L.; Lima, A.C.d.C. Demand side management using artificial neural networks in a smart grid environment. *Renew. Sustain. Energy Rev.* **2015**, *41*, 128–133. [CrossRef]