This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123382, IEEE Access

Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2017.Doi Number

A Comprehensive Review of Intelligent Islanding Schemes and Feature Selection Techniques for Distributed Generation System

ARIF HUSSAIN[1], CHUL-HWAN KIM[1] (Senior Member, IEEE), AND ARIF MEHDI[1]

[1]Department of Electrical and Computer Engineering, Sungkyunkwan University, Suwon,16419, South Korea

Corresponding author: Chul Hwan Kim (e-mail: chkim@skku.edu).

"This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIP) (No. 2021R1A2B5B03086257)".

ABSTRACT Detection of unintentional islanding, defined as inadvertently separation of distributed generators (DGs) from the utility grid, is a major challenging issue for modern distribution networks. Islanding detection becomes problematic especially when the local generation matches or closely matches the local load. Therefore, there are strict requirements for accurate, fast, and reliable islanding detection of renewables and DG-based systems. Various islanding schemes have been proposed in the literature, which can be categorized as remote, local, and intelligent-classifier-based schemes. Recently, intelligent schemes have gained attention due to their superior properties and advantages relative to traditional approaches. This paper overviews the shift in research from traditional schemes to intelligent islanding schemes. It also highlights the major obstacles, challenges, advantages and disadvantages, and future research directions of intelligent schemes. In this study, the intelligent-classifier-based islanding detection schemes presented over the last decade are analyzed objectively and comprehensively from all aspects of islanding detection. This research further highlights feature selection schemes and the most common parameters used for islanding detection. Finally, based on a detailed and critical analysis, the findings and potential recommendations are presented.

INDEX TERMS Active islanding schemes, Distribution generation, Electrical power system, Intelligent-classifiers, Islanding detection, Microgrids, Passive islanding schemes, Remote islanding schemes.

NOMENCLATURE

DG	Distributed Generation
PQ	Power Quality
EPS	Electrical Power System
CB	Circuit Breaker
IDS	Islanding Detection Scheme
NDZ	Non-Detection Zone
PLCC	Power Line Carrier Communication
SCADA	Supervisory Control & Data Acquisition
SPD	Signals Produced Disconnect
PMU	Phasor Measurement Unit
IM	Impedance measurement
AFD	Active Frequency Drift
SFS	Sandia Frequency Shift
SVS	Sandia Voltage Shift
SMFS	Sliding Mode Voltage Shift
PCC	Point of Common Coupling
O/U V&F	Over/Under Voltage & Frequency
THD	Total Harmonic Distortion
ROCOF/P	Rate of Change of Frequency/Power
ROCOV	Rate of Change of Voltage
QF	Quality Factor
AF/VR	Acceptable Frequency/Voltage Range
DT	Decision Tree
ANN	Artificial Neural Networks
SVM	Support Vector Machine
FL	Fuzzy Logic
ANFIS	Adaptive Neuro-FL System
DNN	Deep Neural Networks
LSTM	Long Short-Term Memory

I. INTRODUCTION

Interconnection of distributed generators (DGs) has gained attention due to the electricity market deregulation, capital investments, requirement of reliable and better power quality (PQ), and environmental concerns. DG integration can reduce transmission and distribution losses, generate revenue from excess power, low or zero emissions (for renewables such as wind and solar), and capability of handling power operation during the absence of the main utility [1]. In the conventional electrical power system (EPS), the production of power is centrally operated, and power is delivered to customers through transmission and distribution networks. The primary disadvantages of conventional networks are their high cost and transmission losses, environmental issues, and the unidirectional flow in the network [2], [3]. However, DG interconnection also poses challenges such as elongated payback times, the intermittent nature of renewables, and glitches in the power system [4]. In addition, DG integration can also result in unbalanced voltage and frequency along with power quality problems [5].

With enhanced penetration of DGs, detection of unintentional islanding in the power system becomes a non-trivial task. Unintentional islanding occurs when the DG gets separated from the main utility without any planned intention, i.e. due to the tripping of the circuit breaker (CB) [6]. The tripping of circuit breaker could occur due to system failure, unbalanced power, line outage, generator tripping, human error, natural disasters, and other disturbances [7]. Failure to detect this issue can result in severe consequences for both the system (damage to DG and related equipment) and human life (maintenance workers and consumers). The islanding problem becomes more severe when the local generation matches or closely matches the local load. As per the IEEE 1547-2018 standard, islanding should be detected within a period of 0.16 to 2 s [8]. Therefore, islanding detection should justify these requirements of dependability, security, and fast response time. The islanding scenario in DG integrated EPS is shown in Fig. 1, once the CB1 is opened, the DG is isolated from the rest of the system and becomes the only available source for local loads.

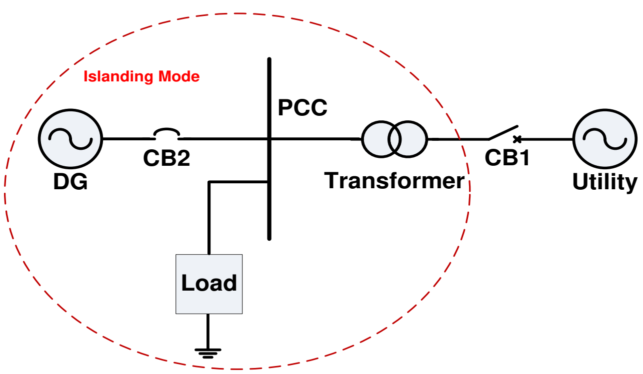

FIGURE 1. Islanding scenario in DG-EPS.

The islanding issue has been under study for several years, and different studies have been conducted to overcome this major issue of power systems with DGs. Various islanding detection schemes (IDSs) have been introduced in the literature. Each type has its pros and cons based on the non-detection zone (NDZ), detection time, and PQ. IDSs can be classified into three main categories, as shown in Fig. 2.

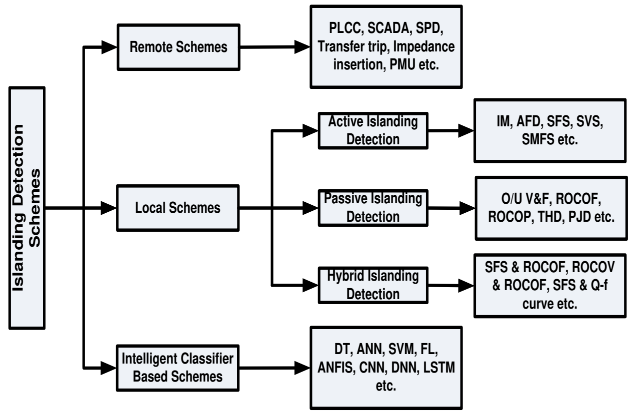

FIGURE 2. Types of various islanding detection schemes.

Remote IDS employs communication infrastructure for the detection of islanding. A communication link is deployed between the DG and main utility, this communication link requires additional instruments [9]–[11]. These instruments are generally high-cost sensors, telecommunication tools, and control systems. The remote IDS have comparatively higher system and running costs, compared to active and passive techniques. Therefore, for small-scale systems, remote IDSs are not suitable; however, these IDSs are commonly used for high-scale projects. The upside of remote IDS is that they have zero NDZ, no degradation of PQ, and can handle complex DG integrated EPS [12]. Some examples of remote IDSs are the power line carrier communication (PLCC) [13]–[15], supervisory control and data acquisition method (SCADA) [10], [16], [17], signals produced disconnect (SPD) [18]–[20], transfer trip schemes [21]–[23], impedance insertion method [21], and phasor measurement unit (PMU) [24]–[29].

Local schemes are based on monitoring various electrical parameters such as voltage, current, frequency, and power in addition to the injection of disturbances in DG-EPS for islanding detection. IDS are further categorized as active, passive, and hybrid islanding detection schemes. Active IDSs utilize external disturbances by injecting a troubling signal into DG output, this external signal injection introduces variation in system parameters [30], [31]. By calculating the variation in system parameters with thresholds, active methods detect islanding. The merits of active IDSs are low NDZ and lesser detection time, while they require additional setup for disturbance injection and may harm the PQ of DG-EPS. Various active IDSs are available in the literature, for example impedance measurement (IM) [32]–[34], active frequency drift (AFD) [35]–[38], Sandia frequency shift (SFS) [39]–[42], Sandia voltage shift (SVS) [43]–[46], and sliding mode frequency shift (SMFS) [31], [47]–[50].

Passive islanding is another commonly used IDS for DG-EPS, where system parameters are monitored at the point of common coupling (PCC), which shows variations when the utility is isolated from the DG-EPS [51]–[53]. Based on these variations, the protective relay operates to detect islanding by comparing it with the defined threshold values [54], [55]. Passive IDSs are economical and uncomplicated schemes that pose no harm for PQ, thus considered as realistic solutions for DG-EPS. The downside of these IDSs is their large NDZ and need for thresholds [56]–[58]. The passive IDSs used in literature are over/under voltage and frequency methods (O/U V&F) [59]–[62], the rate of change of frequency/power (ROCOF/P) [63]–[67], total harmonic distortion method (THD) [18], [68]–[71], and phase jump detection (PJD) methods [68], [72]–[75].

Hybrid IDSs are a combination of active and passive schemes. The PQ problem in active IDSs and large NDZ in passive IDSs can be resolved using the hybrid IDSs [76]–[78]. The downside of hybrid IDSs is complexity and higher detection time. Some hybrid schemes are presented in the literature which are based on positive feedback and voltage unbalance, SFS and ROCOF, voltage unbalance and frequency set point, voltage, and real power shift, RACOV and ROCOP, and hybrid SFS and Q-f Curve IDSs [70], [79]–[83].

Islanding detection based on remote and local schemes has its advantages and disadvantages [84]–[87]. Remote schemes require a communication interface and are reliable for large systems but impractical for small systems because of their complexity and higher cost [10], [88], [89]. In contrast, local schemes are simple, easily applicable, and are low-cost but they have some disadvantages, such as active methods have noise and PQ issues while passive islanding schemes have a large NDZ and low speed [36], [71], [90]–[92]. With bugs and pitfalls in local and remote schemes, intelligent classifier-based schemes are gaining more attention. The key reasons for shifting towards intelligent classifier-based IDS are the exemption from threshold settings, no noise and PQ problems, low NDZ, high speed, and no communication channel intervention, which make intelligent schemes more reliable and acceptable.

A. PREVIOUS STUDIES

Some researchers have conducted review studies on islanding detection strategies while concentrating primarily on traditional islanding systems such as remote, local (active and passive), and signal-processing-based schemes. A few researchers have reviewed intelligence-based islanding schemes. In [5], islanding schemes were categorized into four different groups: remote, local, signal-processing-based, and intelligent classifiers. A total of 85 research publications were reviewed and classified in this research. The comparison of different islanding schemes was also illustrated in [93]–[96]. Another review research for islanding detection of microgrids was conducted in [19], where the major focus was only on local and remote IDS. In this study, various performance indices like (NDZ, detection time, PQ) and other technical problems were also reviewed and analyzed. A study on the computational intelligence-based islanding detection of DGs was presented in [97]. This review summarises islanding strategies focused on conventional and computational intelligence-based schemes. It also presented a comparison of the performance of intelligence-based and traditional schemes [98]–[100].

The shifting trend in islanding detection from classical methods to machine learning-based methods was introduced in a comprehensive survey [101]. This study reviewed the basics of the islanding issue, types, test standards for islanding detection, and the reasons for the trend shifting from conventional to machine learning-based IDSs. The reasons highlighted in this research are the consequent threshold selection, fast detection, NDZ, PQ, and robustness in dealing with complex conditions, which make machine learning-based methods a rational choice for islanding detection [102].

A comprehensive analysis of modern islanding schemes for a DG network in terms of merits, efficiency, efficacy, and feasibility was presented in [103]. It also presented an investigation of different schemes by comparing their time of detection and the computational burden [20], [51], [104], [105]. A detailed review of various islanding schemes with their strengths and weaknesses was presented in [106]. In this research, the analysis was classified into three major groups: classical methods (local and remote), signal-processing methods, and intelligence-based methods. Various schemes were compared and assessed for future recommendations based on different performance metrics such as detection time, accuracy, and efficiency [107]–[109]. A review of the local and remote islanding detection techniques, with their advantages and disadvantages, was reviewed for the DG-based system in [110]. The technical issues of islanding detection proposed by different researchers were reviewed and compared in a detailed way in [1]. This study compared all the IDSs considering their advantages and disadvantages compared to each other and recommended future trends in the field of IDSs.

B. CONTRIBUTION

The main inspiration for this work is the availability of extensive literature and the shift in interest from traditional islanding schemes to intelligent classifier-based schemes over the last decade. The studies discussed in the previous paragraphs have stressed mainly traditional islanding schemes, their benefits, and drawbacks. The above review papers have not covered specific research focused only on intelligent islanding schemes. The research trend and recent advancements in state-of-the-art intelligent islanding schemes for the power system have shown a great deal of interest. It is also important to carry out a critical and thorough analysis of intelligent islanding schemes based on this void and the need for time. In intelligent islanding schemes, feature selection is a key factor affecting accurate and reliable classification, and this vital aspect of islanding schemes has not been studied previously. Furthermore, there exists no study on the electrical parameters that have the greatest influence on islanding detection, as reported in the literature. Therefore, the contribution of this study in comparison with existing review studies is outlined as follows.

- A detailed overview of islanding issues, various types of IDSs, test systems, and standards for islanding detection in DG-EPS is presented.
- A systematic and comprehensive analysis of islanding detection schemes based on various intelligent classifiers is performed along with their pros and cons.
- Different feature-selection schemes used for islanding detection and those that may be used in the future are outlined.
- The most important electrical parameters used for islanding detection are highlighted, based on different methods available in the literature.
- Comparison of various intelligent-classifier-based schemes is carried out based on performance indicators such as accuracy, NDZ, and detection time.
- Finally, potential guidance and recommendations have also been provided after the review of the IDSs.

The rest of this paper is organized as follows. Section II presents a brief introduction of the islanding types and their effects. In section III, the islanding test standards and test system topologies are presented. A complete survey and assessment of various state-of-the-art intelligent schemes studied from the last decade are presented in section IV. Section V presents the feature selection schemes for various IDSs. The most useful and dominating features for islanding detection are presented in section VI. In section VII performance indicators are discussed. Comparison, iscussion and future recommendations are presented in section VIII, and conclusions of this study are presented in section IX.

II. INTENTIONAL AND UNINTENTIONAL ISLANDING

The word islanding refers to the separation of an operating power system having both loads and generation from the central utility grid. In an EPS, the islanding phenomenon is categorized into two main types: 1) intentional islanding and 2) unintentional islanding. Intentional islanding is a planned operation used primarily for system maintenances and operational issues, whereas unintentional islanding events are caused by sudden faults, load switching, and CB tripping because of a main utility power outage.

A. INTENTIONAL ISLANDING

Intentional islanding is the anticipated and systematic separation of the main grid from the power network to avoid a major breakdown [111]. The main reason for this separation is to overcome the blackouts and cascading problems of a power system. Cascading failure can be described as a fault process that results in the tripping of another element of the grid successively [112]. This separation is also employed for system maintenance, voltage enhancement, power-loss scenarios, temporary faults, and improving the efficiency of the network. Intentional islanding is viable and worthwhile for the power system. Several researchers have worked on intentional islanding and control over several years to make it practically applicable and to shield the power system from the harsh outcomes of unintentional islanding [92]. It makes the power grid stable in a manageable island area to support the rest of the system. Effective and stable operation in islanding mode requires a balanced load and generation.

Numerous algorithms have been established for the detection and division of power systems to stable islands. Some of these include the wide-area measurement systems (WAMS) algorithm for a wide-area blackout [113], security-based method [114], effects of degraded communication, and load variability on-grid splitting [115], improved spectral clustering for a multi-objective controlled islanding system [116]. The algorithms used in different studies include ant search mechanism [117], fast greedy and bloom algorithms [118], comprehensive learning particle swarm optimization (CLPSO) algorithm [119], two-stage stochastic optimal islanding method [120], mixed-integer linear programming (MILP) [121], algebraic graph method [122], and ordered binary decision diagram (OBDD) method [123]. In addition to these methods, several countries have their own intentional islanding microgrid systems for realizing safe and reliable distribution networks [124].

B. UNINTENTIONAL ISLANDING

Unintentional islanding occurs without any planned intention or prior information from the main utility grid or independent power producers. There could be several reasons for this unknown tripping, but the dominating drivers are the occurrence of faults at the main utility grid, system failure on the utility side, human error due to negligence, and natural disasters [125]. The harsh outcome of this unintentional islanding is the separation of the DGs from the main power system. In power systems, several islanding standards have been prescribed to overcome this critical issue [126]. A detailed survey of international standards on islanding is presented in the next section. The undesirable consequences of unintentional islanding include the inability of DGs to handle the abrupt change, synchronization issues after re-connection, and the uncontrollable behavior of the DGs during islanding because of the load and generation mismatch [127]. Unintentional islanding poses a threat to the security of power systems, which can harm utilities, equipment, and maintenance personnel. The record of mega outages and power system failures due to unintentional islanding shows that a lack of power supply has contributed to major lapses in security and significant economic downturns [128], [129]. In this article, IDSs are critically analyzed to resolve these challenges and highlight the sensitivity of the security against anti-islanding.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123382, IEEE Access

TABLE I
VARIOUS INTERNATIONAL STANDARDS FOR ISLANDING DETECTION

Standard	QF	AFR	AVR	Detection Time
IEEE 1547-2018	1	59.3 ≤ f ≤ 60.5 Hz	88% ≤ V ≤ 110%	t = 0.16 to 2 s
IEEE 929-2000	2.5	59.3 ≤ f ≤ 60.5 Hz	88% ≤ V ≤ 110%	t < 2 s
UL 1741	2.5	59.3 ≤ f ≤ 60.5 Hz	88% ≤ V ≤ 110%	t < 2 s
IEC 62116	1	(f_o – 1.5Hz) ≤ f ≤ (f_o + 1.5Hz)	85% ≤ V ≤ 115%	t < 2 s
UK G83	0.5	47.5 ≤ f ≤ 51.5 Hz (stage 1)	87% ≤ V ≤ 110% (stage 1)	t < 0.5 s
		47 ≤ f ≤ 50 Hz (stage 2)	80% ≤ V ≤ 119% (stage 2)	
Canadian C22.2 No. 107-01	2.5	59.5 ≤ f ≤ 60.5 Hz	88% ≤ V ≤ 106%	t < 2 s
German VDE 0126-1-1	2	47.5 ≤ f ≤ 50.2 Hz	88% ≤ V ≤ 115%	t < 0.2 s
Austrian OVE E-8001-4-712		59.3 ≤ f ≤ 60 Hz	88% ≤ V ≤ 110%	t < 2 s
French std.	2	49.5 ≤ f ≤ 50.5 Hz	88% ≤ V ≤ 106%	Instantly
	0	Setting value	Setting value	t < 2 s
ERDF-NOI-RES 13E Japanese JIs		Setting value	Setting value	0.5 < t < 1 s
Korean std.	1	59.3 ≤ f ≤ 60.5 Hz	88% ≤ V ≤ 110%	t < 0.5 s

III. TEST STANDARDS AND SYSTEMS FOR ISLANDING DETECTION

A. TEST STANDARDS FOR ISLANDING DETECTION

Due to these islanding issues in the power system, several islanding detection standards have been set by different researchers and organizations. Several standards are being used globally for islanding detection considering specific quality factors (QF), detection time, acceptable frequency, and voltage ranges. These standards are used to direct the installation and construction of the power systems and distribution networks during islanding scenarios [130]–[135]. Table I. summarises the aforementioned international standards based on the thresholds of the QF, acceptable frequency range (AFR), acceptable voltage range (AVR), and detection time. Several countries have their standards for islanding detection, as presented in Table 2. The most widely used standards and benchmarks are IEEE 1547-2018, IEEE 929-2000, UL 1741, and IEC 62116. The variance in the thresholds of the QF, AFR, AVR, and detection time among the various global standards are because of differences in power network and distribution frequency criteria in different countries/regions.

B. TEST SYSTEM FOR ISLANDING DETECTION

Similar to islanding detection standards, there are several test systems for islanding tests. There is no global standardized and definite test system; different countries and organizations use their test systems for islanding detection. These systems include single DG, multiple DGs, same type DGs, different DG types, and hybrid-type test systems. Every country has its distinct test system for analyzing the consistency and practicality of its networks under islanding conditions.

One of the most commonly used and generic test systems is shown in Fig. 3, which is based on IEEE 1547-2018, IEEE 929-2000, UL 1741, and IEC 62116. This is the recommended test system for analyzing islanding conditions by opening the CB to isolate the DG from the main utility. A parallel resistor-inductor-capacitor (RLC) load is connected as the load for the test system because the RLC load is considered as the worst-case scenario for islanding detection.

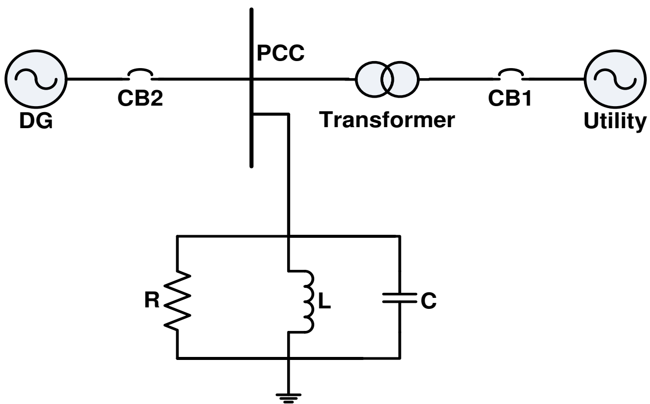

FIGURE 3. Generic test system for islanding detection.

IV. INTELLIGENT-CLASSIFIER-BASED ISLANDING SCHEMES

Local and remote IDSs have their benefits, but they also have some critical issues. In local methods, the large NDZ of the passive IDS and PQ issues in active IDS make them unsuitable for islanding detection. Furthermore, remote IDSs are costly and infeasible for small distribution networks. Because of the above concerns, researchers and engineers have shifted their focus towards intelligent-classifier-based IDSs. In this research, we summarize and critically analyze the shift in research from traditional IDSs to intelligent-classifier-based IDSs.

Advancements in artificial intelligence have improved life using machine-learning theories in every field of life such as medicine, material sciences, and engineering fields. Nowadays, the applications of state-of-the-art intelligent classifiers in electrical engineering, and primarily in EPSs, are growing rapidly. In EPSs, islanding detection is the most challenging issue that is required to be addressed around the world. The most commonly used intelligent-classifier-based schemes for islanding detection are decision trees (DTs),

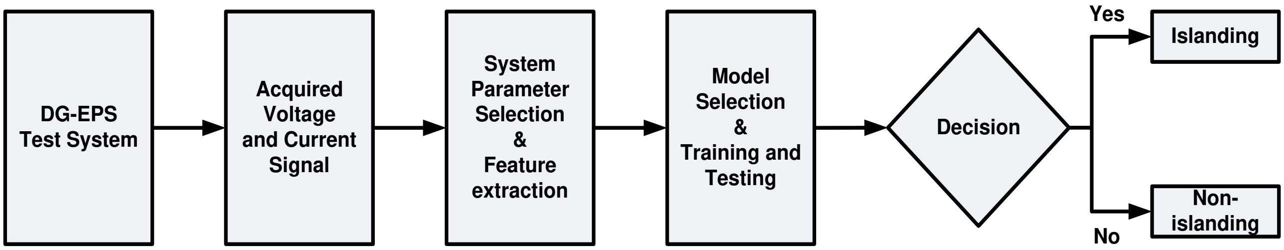

FIGURE 4. **Working principle of intelligent classifier-based IDS.**

artificial neural networks (ANNs), support vector machines (SVMs), fuzzy logic (FL), adaptive neuro-fuzzy inference systems (ANFISs), convolution neural networks (CNNs), and deep neural networks (DNNs). Intelligent classifier-based IDSs first derive features from the obtained signal, which are then used as an input to the intelligent classifier in the form of a feature vector, and the classifier makes decisions based on input features as shown in Fig. 4. The use of these methods for islanding detection has increased significantly. Fig.5 depicts the implementation of each technique for islanding detection discussed in this paper. As depicted by Fig. 5, several different forms of intelligent strategies have been used to detect islanding.

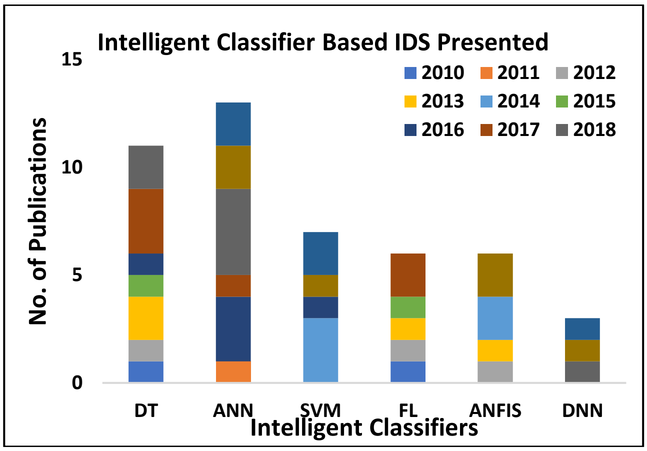

FIGURE 5. **Intelligent classifier-based IDS reviewed.**

A. DECISION-TREE-BASED IDS

DT is the most widely used tool as an intelligent classifier. The recursive partitioning process is applied to each attribute for its value authentication. The DT classifies the given data into pre-defined classes; it can be either binary or multiple classifications. To begin segmentation, a prediction is used to convert the root node into child nodes. The resolution can be done from a child node for additional divisions. The architecture of the DT is presented in Fig. 6, while Table II shows the summary of DT-based IDS presented.

The feature vectors are produced from the transient current and voltage data using discrete wavelet transformation (DWT) in [136] for islanding detection. Only the four most important characteristics were validated using classification and regression trees (CART) out of the twelve features. The expanded test system of [136] with voltage-source-converter (VSC)-based DC source was provided in [137], and the performance of the suggested approach was evaluated and compared to that of other passive islanding approaches in terms of noise impact, NDZ, and response time.

DWT and DT were utilized in [138], however, for multiple frequency bands with varied characteristics and features, only one transient signal (voltage) and low DWT levels, from D1–D9, were used. To determine the superiority the accuracy of the proposed scheme was compared to that of many passive IDSs and DT-based methods. In [85], the discrete Fourier transform (DFT) is used to extract the voltage and current signals, as well as their related characteristics, utilizing a data mining technique. The DFT was used to obtain a total of 27 characteristics that were influenced during islanding, and the DT was trained in real-time for islanding and non-islanding detection in the proposed method.

A novel hybrid IDS based on DT and inverter-based positive feedback was presented in [139]. An intelligent islanding relay based on multivariate analysis and data mining techniques is presented in [140]. Then, to manage the protection and thresholds of each DG, DT was utilized for the tripping logic. Before feeding them into the DT classifier, a total of eleven time-dependent characteristics were collected and pre-processed to eliminate noise and inconsistencies. The suggested approach was validated using the offline test results and a hardware-in-loop (HIL) experiment.

A hybrid IDS technique that combines the DT and Sandia frequency shift (SFS) methods for multiple inverters-based DGs was proposed in [141]. Two test systems were used to verify the resilience of the proposed IDS under varied operating circumstances and changing load configurations. A hybrid approach for both inverter-based and synchronous DGs was proposed in [142]. A real-time simulator was utilized to determine the NDZ border, and a DT was used to classify the islanding and non-islanding occurrences. The suggested IIR provides great reliability and security in addition to a large decrease in NDZ.

The selection of features is one of the most technical and critical measures in islanding detection. A novel feature selection technique was presented by [143] based on modified multi-objective differential evolution (MMODEA) and extreme learning machine (ELM). In the off-line mode, a total of 16 features were extracted using MMODEA-ELM, and subsequently, the optimum features were selected by objective

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123382, IEEE Access

function formulation. In the online mode, these optimal features were used to identify islanding and non-islanding scenarios using the DT classifier. A new scheme was presented in [144] to generate the DT logic for the categorization of islanding and non-islanding events based on the active and reactive power imbalance, which directly corresponds to the NDZ. A sequential feature selection method was applied to choose the 12 best features from a total of 30 electrical features. The proposed scheme reduces the NDZ by over 54% than the standard relay function and was verified on the HIL system.

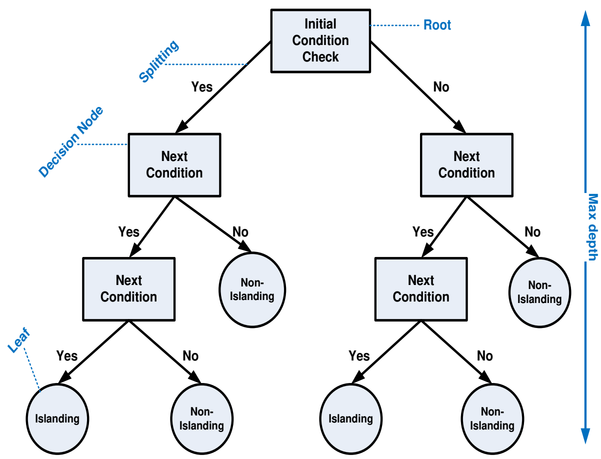

FIGURE 6. Architecture of the decision tree.

TABLE II
SUMMARY OF DT BASED IDS

Reference	Feature Extraction	No. of Features	Test System	Accuracy
[136]	DWT	12	CIGRE MV	98%
[137]	DWT	08	CIGRE VSC	99%
[138]	DWT	03	CIGRE	98%
[85]	DFT	27	IEC	100%
[139]	Passive	06	Hybrid	100%
[140]	Passive	11	UL 1741	100%
[141]	Passive	04	IEEE 13-bus	100%
[142]	Passive	12	Hybrid	99.2%
[143]	Passive	16	IEEE 13-bus	100%
[144]	Passive	12	Hybrid	99%

B. ARTIFICIAL-NEURAL-NETWORK-BASED IDS

ANNs are one of the main methods employed in machine learning. These are brain-inspired devices, as the "neural" part of its name implies, that are built to mimic how humans learn. Neural networks consist of input and output layers, as well as (in most cases) a hidden unit layer, which converts information into something that the output layer can use, as shown in Fig. 7 while Table III summarizes the ANN-based IDS that have been presented.

In [60], an IDS was introduced for inverter-based DGs using signal parameter estimation. The rotational invariance technique (ESPRIT) is used for the extraction of features at the point of common coupling (PCC) and the naïve Bayes classifier is used for the classification. The validity of the proposed scheme was confirmed via three-fold cross-validation. A framework was implemented based on an ANN for islanding detection of the distributed synchronous generators in [145]. The proposed method can detect the islanding situation by calculating the voltage waveform at the distributed generator terminals. In addition, a method for selecting the data was suggested to enhance the training of the ANN. To evaluate the system efficiency as well as non-detection areas, the concept of the time-performance region was implemented.

The optimization approach and minimum-feature-based IDS were presented in [146] with the use of an ANN. Evolutionary programming (EP) and particle swarm optimization (PSO) were introduced for improving the accuracy of ANNs. In this research, the behavior of 16 different features was analyzed, and only three features were selected for the training of the ANN. After a thorough assessment of the online and offline testing results, the ANN–PSO classifier exhibited the highest accuracy as compared with the stand-alone ANN and ANN–EP. In [147], an IDS for the reduction of the NDZ was presented, wherein the classification of the islanding and non-islanding events was conducted using DWT for feature extraction and ANN as a classifier. A modified ELM technique presented as weighted bidirectional ELM (WB-ELM) and Hilbert–Huang transform (HHT) was introduced as a novel IDS in [148]. The proposed IDS was implemented and assessed (dependability and security) on multiple DGs based on test systems and the IEEE 13-bus system. The HHT was used for the feature extraction from the non-stationary voltage signal at the DG end, and the extracted features were then fed to the WB-ELM classifier for islanding and non-islanding detection.

Two feature-extraction methods, the multiplier-based method (MBM) and Andrews's plot-based method (APBM) were introduced in [27] for feature extraction and dimension reduction. The phasor measurement units provide time-synchronized measurements to the phasor data concentrator (PDC). These raw data were then input into the APBM and MBM for pre-possessing before sending them to the ANN classifier. In islanding, optimal feature selection is the key moderator for appropriate and accurate detection, which is not emphasized in the literature. In [149], the author introduced the wrapper method for the selection of sensitive features and coupled the modified multi-objective differential evolution algorithm with a kernel-based ELM classifier. Only 3 out of 45 features were selected and used based on the proposed schemes by evaluating their performance indexes with and without noise. The proposed scheme performed well and accurately with acceptable detection time as compared to the existing intelligent-classifier-based and traditional schemes.

A unique and novel local-data-mining anti-islanding system for synchronous generator (LDMAIS-SG) was presented in [150], based on a powerful data-mining tool, which is known

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123382, IEEE Access

as a code repository (DAMICORE). A total of 10 different features were selected and pre-processed using low-pass Butterworth filters to eliminate the noise. The proposed scheme performed well in differentiating between islanding and other disturbances. In [151], an adaptive ensemble classifier called an ELM, and a phase-space feature extraction technique was introduced. The proposed IDS comprises two steps: in the first step, a unique feature extraction method (phase-space technique) is used to extract features from the three-phase voltage. Then, classification is carried out with ensemble ELM in the second step. Multiple events were tested on two test systems for the performance evaluation of the proposed IDS and compared with the random forest (RF) scheme. The proposed scheme performed well in all the evaluations.

A universal islanding detection scheme is introduced for both inverter- and synchronous DGs in [152], which performed well with high accuracy, zero NDZ for both DG types, and fast detection times. The proposed method comprised three parts: 1) feature extraction (twenty-one features were extracted, which can be influenced by islanding), 2) feature selection using forward feature selection and backward feature selection (four features are selected based on their accuracy in the shortest time), and 3) classification to differentiate islanding and non-islanding occurrences using RF algorithms. A modified DWT, known as slantlet transform (SLT) with a superior lead of two vanishing moments and a better time localization than DWT, has been implemented in [153] for the selection of features. The extracted features have been used to detect islanding and other disturbances while employing a ridgelet probabilistic neural network (RPNN). The combination of SLT and RPNN exhibited better performance with a 100% accuracy compared with the combination of DWT and RPNN and that of DWT and the probabilistic neural network.

An intelligent islanding detection system based on an intrinsic mode function feature-based grey wolf integrated artificial neural network is proposed in [6]. The nodal voltage is pre-processed to extract vital features by the Hilbert transform. Fourier transform (FT) and machine learning algorithm, K-nearest neighbor technique (KNN) is proposed for islanding detection of microgrids in [154]. In this study, nine features from the voltage and current signal were extracted using the discrete Fourier transform. An extreme machine learning and wavelet transform has been used as a classification to discriminate against islanding events from non-islanding events [155]. To exploit the various useful features of the DG bus, the negative sequence voltage and the current signal were used to obtain the 2 basic mathematical morphology operators, erosion dilation difference filter and opening-closing difference operator. Tunable Q-factor wavelet transforms (TQWT) and ANN-based schemes are proposed in [156], the feature extraction step is conducted using TQWT, and classification of islanding is done by ANN based on conjugate gradient algorithm.

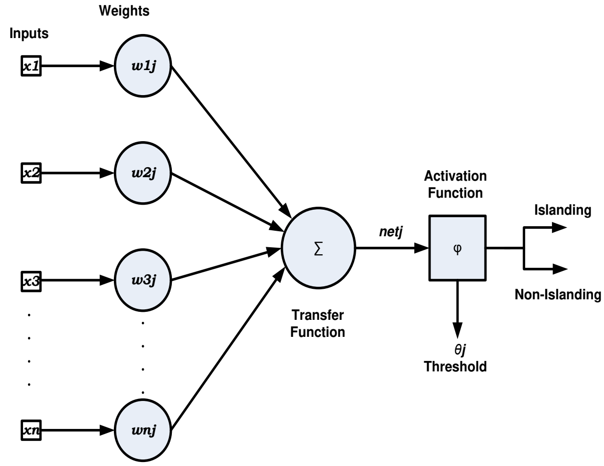

FIGURE 7. Architecture of the ANN.

TABLE III
SUMMARY OF ANN BASED IDS

Reference	Feature Extraction	No. of Features	Test System	Accuracy
[60]	ESPRIT	32	IEEE 34-bus	99.8%
[145]	Passive	16	UL 1741	99.88%
[146]	Passive	03	Hybrid	99.6%
[147]	DWT	06	UL 1741	100%
[148]	HHT	09	Hybrid	99.09%
[27]	MBM / APBM	12	IEEE 9-bus	96.98%
[149]	Passive	03	IEEE 13-bus	100%
[150]	Passive	09	UL 1741	100%
[151]	Phase space	-	IEEE 13-bus	99.72%
[152]	Passive	21	IEEE 34-bus	99%
[153]	SLT	06	UL 1741	100%
[154]	DFT	09	IEC	99%
[155]	WT	06	Hybrid	100%
[156]	TQWT	07	UL 1741	98%

C. SUPPORT-VECTOR-MACHINE-BASED IDS

An SVM is a discriminative classifier explicitly described by a hyperplane separator and first introduced by Vapnik in 1963 [157]. An SVM is based on the structural risk minimization theory which minimizes the upper limit on the expected risk. The tuning parameters of an SVM are the kernel, regularization, gamma, and margin. Fig. 8 presents the architecture of the SVM and the SVM-based IDS that have been presented are summarized in Table IV.

In [84], in order to overcome the confines of conventional islanding schemes, a scheme is proposed for islanding detection using multiple features and an SVM. Five features were used, which were obtained from five network parameters, namely, frequency, voltage, rotor angle, ROCOV, and ROCOF at PCC. A total of 2760 events were generated for offline SVM training, and the trained SVM is then employed for islanding detection in real-time. Based on the outcome of the above research, a multi-feature-based IDS was presented for the NDZ in the subcritical region of the vector surge relay [158]. From five network variables, the process of feature extraction was completed, and a total of 2022 incidents were produced for the SVM training and testing. Linear kernel, polynomial kernel, and Gaussian radial basis function kernel were used for the performance evaluation of the proposed scheme.

A new IDM for single-phase inverter-based DG was introduced in [90]. In the initial step, autoregressive (AR) signal modeling was used at the PCC for the extraction of the voltage and current signal features. In the next step, the SVM predicts the islanding state from the determined characteristics. The IEEE 13-bus system is used to conduct the study, and the trained SVM is tested under several islanding and non-islanding conditions. This scheme detects the islanding correctly within 50 ms after the event starts. The IDS for hybrid DGs comprising both photovoltaic and wind generation connected to the IEEE 30-bus system was presented in [159]. The negative sequence component of the voltage signal was pre-processed through three different advanced signal-processing schemes, namely, the hyperbolic S-transform, time–time transform (TTT), and mathematical morphology methods for feature extraction. The extracted features were then fed to the SVM for the classification of islanding and other PQ disturbances.

Wavelet transform (WT) is the widely applied signal processing technique for islanding feature extraction but has some shortcomings with non-linear loads and harmonics. To overcome this lag of the WT, in [160], Renyi entropy was employed with WT to identify and categorize seven PQ disturbances. The features extracted using Renyi and WT were then trained in SVM classifiers and tested in real-time scenarios. SVM is used as a dual-functional classifier for the detection of islanding and grid-connected modes and the classification of various faults during normal grid operation[161]. This scheme was implemented on a MATLAB model based on the parameters of a real-time PV power plant.

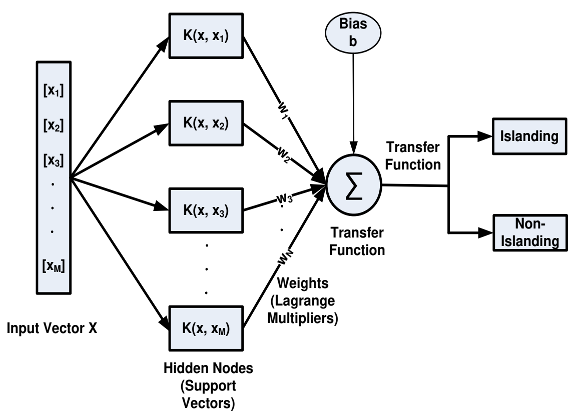

FIGURE 8. Architecture of the SVM.

TABLE IV
SUMMARY OF SVM BASED IDS

Reference	Feature Extraction	No. of Features	Test System	Accuracy
[84]	Passive	05	UL 1741	98%
[158]	Passive	05	Hybrid	100%
[90]	AR	62	IEEE 13-bus	98.49%
[159]	ST/TTT	08	IEEE 30-bus	>97%
[160]	WT	06	Hybrid	100%
[161]	Passive	07	UL 1741	100%

D. FUZZY-LOGIC-BASED IDS

Fuzzy logic is a problem-solving approach influenced by human decision-making, which benefits from the human ability to reason with ambiguous or provisional data and was presented by Dr. Lotfi Zadeh in the 1960s [162]. Fuzzy logic is a basic mathematical logic that uses partial truth as a continuous value between 0 and 1 instead of a discrete value, as shown in Fig. 9. The FL-based IDS that have been presented are summarized in Table V.

Islanding detection for DGs using the concept of a fuzzy membership function (MF) was demonstrated in [163] with an accuracy of 100% islanding detection. In the initial step of the proposed method, 11 features affected by islanding were extracted. The second step consists of two parts: the extracted features were fed to the DT for the initial classification boundaries, and the fuzzy MFs were then used for rule-based classification. In the case of large noise, the WT fails to detect islanding, and thus, a discrete fast S-transform (DFST) with a fuzzy expert system (FES) was proposed in [164] to resolve this problem. Negative voltage and current sequences were used and pre-processed by the DFST for extracting 24 different features, and only four significant features were then fed into the FES for the classification of islanding and non-islanding events. The validation of the proposed IDS was obtained by testing it on two different test systems with different islanding and non-islanding events. In addition, the performance is compared with previously implemented schemes and the proposed method has demonstrated superiority in terms of reliability, detection time, and sensitivity.

A novel hybrid scheme based on the SFS and FL was presented in [41] for the elimination of the NDZ. Initially, the fuzzy load parameter elimination is trained for the selection of the load parameters (R, L, and C) for the appropriate load quality factor and then the SFS for detection. A novel IDS was proposed in [165] using hybrid fuzzy positive feedback (PF) to reduce the interference injection. In the proposed scheme, the PF was continuously varied, while the PF gain was fixed in the traditional methods. The presented scheme shows a 77.3% decrease in detection time and low injection disturbances. The majority of the IDS measures exhibit a change in electrical parameters at a single point called the PCC, but in [76], a multi-connection point model has been implemented for smart grids focused on the probability of

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123382, IEEE Access

islanding (PoI). The PoI at various points was measured using active, passive, and communication-based islanding schemes and sent to the central microgrid control (CMGC). The parameters were obtained from the voltage and current signals using the DWT and then fuzzy neural networks are used for islanding detection.

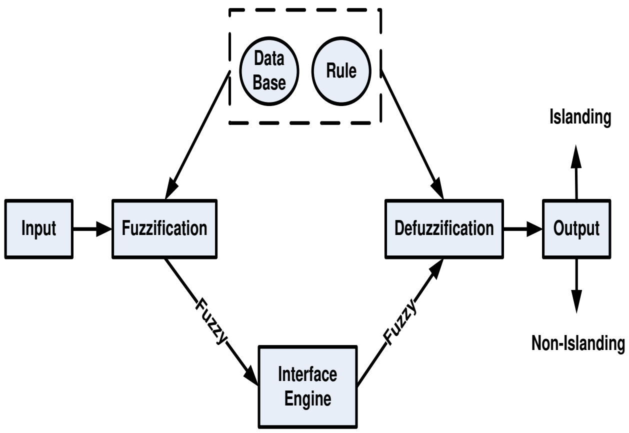

FIGURE 9. Architecture of the FL

TABLE V
SUMMARY OF FL BASED IDS

Reference	Feature Extraction	No. of Features	Test System	Accuracy
[163]	Passive	11	Hybrid	100%
[164]	DFST	04	Multi	97.22%
[41]	Active	-	UL 1741	>96%
[165]	Active	05	UL 1741	-
[76]	DWT	04	Multi	-

E. ADAPTIVE-NEURO–FUZZY-INFERENCE-SYSTEM-BASED IDS

ANFIS, a mixture of ANN and FL, is a robust computational system for a non-linear and complicated system with limited training data. It was first introduced in the early 1990s, with two parts called premise and consequence and five layers (fuzzification, rule, normalization, defuzzification, and summation layers) [166]. Fig. 10 presents the complete structure of the ANFIS while the ANFIS-based IDS demonstrated thus far are summarized in Table VI.

In [167], ANFIS-based IDS for inverter-based DGs was presented. During islanding, the proposed system checks the sensitivity of specified parameters at particular DG locations. It determines the pattern vector Xi by analyzing the behavior of the current and voltage data and then feeds it to the ANFIS for islanding detection. In [168], a two-step ANFIS-based IDS was presented. The distribution system was first simulated in PSCAD at the PCC for the extraction of five chosen indices. The retrieved data is then sent into the ANFIS toolbox in MATLAB for the categorization of islanding and non-islanding occurrences in the second phase. The energy analysis of wavelet coefficients and the ANFIS algorithm for the classification of islanding and non-islanding events were used to develop the new IDS presented in [169]. A total of eight distinct electrical signals that were impacted by any islanding or non-islanding disturbance were monitored; these parameters were then put into a wavelet energy calculator to extract features, which were then fed into ANFIS for islanding and non-islanding detection. The suggested IDS had an NDZ of almost zero, no threshold settings, and no PQ issues.

The ROCOF is the most widely used passive islanding detection approach; it was utilized as an input parameter for the ANFIS in [170] to identify islanding and non-islanding scenarios. Various non-islanding situations, including load switching, capacitor switching, and motor starting, were used to validate the suggested system, and the given IDS worked effectively with almost zero NDZ while overcoming threshold setting challenges. In [171] a unique ANFIS algorithm approach for low-voltage inverter-interfaced microgrid islanding detection. The relevant data for the ANFIS classifier was gathered from seven electrical characteristics utilizing relay metering sensors at the PCC. The suggested hybrid method may be customized to solve several problems. An ANN was utilized to provide flexible learning capabilities, while FL was used to discover nonlinear connections. The proposed IDS did not affect the system PQ and significantly reduced NDZ.

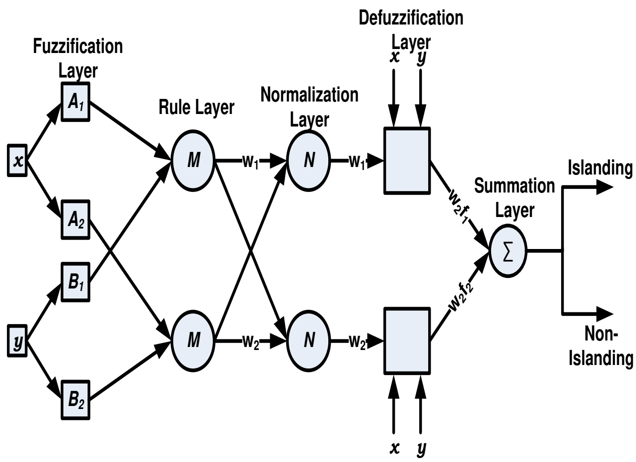

FIGURE 10. Architecture of the ANFIS.

TABLE VI
SUMMARY OF ANFIS BASED IDS

Reference	Feature Extraction	No. of Features	Test System	Accuracy
[167]	Passive	01	UL 1741	-
[168]	Passive	05	IEEE 13-bus	100%
[169]	DWT	08	UL 1741	-
[170]	Passive	01	UL 1741	-
[171]	Passive	07	UL 1741	78.71%

F. DEEP-NEURAL-NETWORK-BASED IDS

DNNs are a popular group of machine-learning algorithms that are implemented in the depths and widths of smaller architectures by stacking layers of neural networks [172]. DNN has a special structure as it has a relatively large and complex hidden layer in the middle of the input and output layers, as shown in Fig. 11. To be called a DNN, this hidden segment should contain at least two layers. Owing to their nature, DNNs can distinguish patterns better than shallow networks [173]. Machine-learning researchers extend the horizons of profound thinking by searching for potential applications of DNNs in other fields such as EPSs. Lately, the DNN has been used in EPSs for islanding detection and has shown excellent results in eliminating the islanding problem. Table VII summarizes the DNN-based IDS that have been presented.

The concept of deep neural learning was first implemented and demonstrated for the classification of islanding and other grid disturbances in [174]. A novel feature-extraction technique using wavelet decomposition and multi-resolution singular spectrum entropy was introduced. Initially, the PCC voltage signal during islanding and other grid disturbances were decomposed by the wavelet decomposition, and the multi-resolution singular spectrum entropy was then calculated. The extracted features were then used for the training and testing of the DNN. The training process of the deep architecture comprised two steps: 1) initialization of weights utilizing greedy layer-wise unsupervised learning, and 2) fine-tuning of the earlier initialized weights using supervised data. The proposed approach exhibits a better performance in terms of both accuracy (98.3%) and detection time (0.18 s) than other methods of classification.

CNN is also a type of DNN; however, similar to the DNN, this technique is not used much in EPSs for the detection and classification of islanding. CNN was first implemented in EPS applications in 2019, and IDS was proposed based on image classification with CNN [175]. The novelty of the proposed IDS is that it converts the time series data having distinct information about islanding and non-islanding events into images. These scalogram images obtained using continuous WT with Morse wavelet were then fed into the CNN classifier for the classification of islanding and non-islanding events. A total of 205 islanding and non-islanding events were generated for the validation of the proposed IDS, and 60% of the data was used for training purposes, while the remainder of the data was used for testing. The scheme demonstrates an accuracy of 98.78% and a preeminent performance for noisy data. Long short-term memory (LSTM) for the first time used for islanding detection in [176], the scheme proposed a two-step approach for islanding detection. In the first step, useful features were extracted from voltage and current signals using DFT, and then the extracted six features were fed to LSTM for event detection.

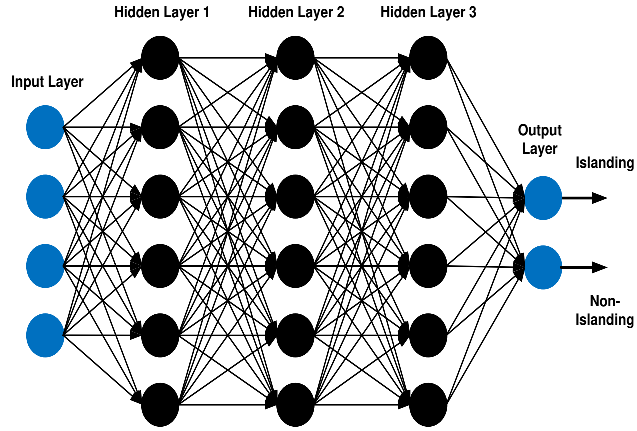

FIGURE 11. Architecture of the DNN.

TABLE VII
SUMMARY OF DNN BASED IDS

Reference	Feature Extraction	No. of Features	Test System	Accuracy
[174]	WT	Multi	UL 1741	98.3%
[175]	CWT	03	UL 1741	98.78%
[176]	DFT	06	Hybrid	99.61%

Intelligent-classifier-based IDSs are discussed critically in detail and a comparative investigation of intelligent schemes in islanding detection is summarized. Table VIII presents the pros and cons of intelligent classifiers discussed and used for islanding detection. While Table IX gives a comparison between intelligent IDSs and conventional IDSs based on various performance indices. Reliability refers to the accuracy of anything being evaluated by a process and DNN has the highest reliability. DT has the lowest reliability among intelligent classifiers while conventional IDSs (remote techniques) have the highest reliability. Complexity provides the means to conceptualize the research challenge as a complex adaptive process, focusing on the patterns of interactions between various system components at different points and times. ANN, FL, active, and passive IDS are the most desirable methods in terms of complexity. While DNN, CNN, ANN, and SVM score comparatively well in terms of accuracy. Finally, DNN, CNN, and ANFIS are influential in terms of detection speed. Intelligent classifiers have zero impact on the PQ of DG-EPS, while active IDSs have the highest impact on PQ. Implementation cost is an important aspect of the DG-EPS system modeling and construction. Intelligent-classifier-based IDSs are economical compared to remote and hybrid techniques.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123382, IEEE Access

TABLE VIII
PROS AND CONS OF INTELLIGENT CLASSIFIERS [177]-[179]

Technique	Pros	Cons
DT	• No need for scaling and normalization. • Easily handle missing values. • Easy for implementation and explanation. • Reduce complex problems to an elementary decision at the tree level.	• Susceptible to over-fitting. • Sensitive to the change in data. • For large data overlapping issue arises.
ANN	• Feasible for complex problems. • Can handle noisy data. • Ability to train multiple algorithms.	• High processing time. • Requires a large number of input features.
SVM	• Efficient to handle non-linear and higher-dimensional data. • Kernel trick is an incredible function of SVM. • Robust to outliers.	• Choosing a kernel is a very chaotic task. • Slow for large datasets. • Poor performance with overlapped classes.
FL	• Fuzzy membership boost accuracy significantly. • Rule-based functions have a positive impact on performance. • High flexibility for decision-making.	• Very sensitive to noisy data. • FL has limitations for being highly abstract due to several maximum and minimum class combinations
ANFIS	• It has both qualities of ANN and FL. • Robust to non-linear and complex problems. • Fast convergence time.	• High computational complexity.
CNN	• Automatically detects features without any supervision. • Best for classification problems. • Efficient in computation.	• It requires large training data. • Training time is high.
DNN	• It models the characterization of data hierarchically for data prediction. • High computational power. • High accuracy.	• Complex architecture.

TABLE IX
COMPARISON OF INTELLIGENT CLASSIFIERS BASED IDS AND CONVENTIONAL IDS [1],[97],[103]

Class	Technique	Reliability	Complexity	Accuracy	Detection Speed	Impact on PQ	Implementation Cost
Intelligent Classifier Based IDS	**DT**	Low	Intermediate	Intermediate	Intermediate	None	Low
	ANN	Intermediate	Low	High	Intermediate		
	SVM	Low	Intermediate	High	Slow		
	FL	Low	Low	Intermediate	Slow		
	ANFIS	Intermediate	Intermediate	Intermediate	Fast		
	CNN	Intermediate	High	High	Fast		
	DNN	High	Very High	High	Fast		
Conventional IDS	**Remote**	High	Intermediate	High	Fast	None	High
	Active	Intermediate	Low	High	Fast	High	Low
	Passive	Low	Low	Intermediate	Slow	None	Low
	Hybrid	High	High	Intermediate	Slow	Low	Intermediate

G. OTHER ISLANDING SCHEMES

Signal processing techniques are used in the modified passive IDSs to increase detection performance, minimize detection time, and reduce NDZ. The researchers improved existing islanding detection schemes and developed new methods by using techniques like the Fourier transform (FT), WT, S-Transform (ST), and TTT. These techniques facilitate the analysis and extraction of key features from a measured signal, allowing for more efficient power system operations. Identification of islanding and non-islanding occurrences is feasible with the knowledge of these retrieved features.

1) FT-BASED IDS

FT is a frequency-domain analysis technique for extracting signal characteristics at certain frequencies. Because the FT is incapable of incorporating time-domain analysis, a short-time Fourier transform (STFT) is used to evolve several frames of the signal in the moving window. Other popular approaches include DFT and fast FT, which convert a discrete-time series of finite duration into a discrete-frequency sequence. FT is used for feature extraction from voltage, current, and frequency signals in intelligence-based IDS, and many IDS have been suggested, which are addressed in section IV [85], [154], and [176].

2) WT-BASED IDS

WT is a useful technique for extracting important characteristics from distorted voltage, current, or frequency signals. The signals are converted into several temporary scales, such as the mother wavelet, which creates small waves called wavelets. The wavelet coefficients of the observed signal are compared to a pre-defined threshold value in WT-based IDSs. The islanding situation will be identified if these coefficients reach a value greater than the pre-defined threshold value. The drawbacks of such techniques are the effects of mother wavelet selection, threshold settings, and various sampling frequencies. Intelligent IDSs made extensive use of various forms of WT for islanding detection, as described in section IV [136], [138], [153], [155], and [160].

3) ST-BASED IDS

The ST idea is a development of the WT concept. It transforms a two-dimensional frequency-domain function into a time-domain function. The ST technique, like other time-domain approaches, is used to extract key characteristics from a recorded signal at PCC, allowing the islanding state to be detected. ST produces the S-matrix and the corresponding time-frequency contours from the recorded voltage or current signals at the DG terminals. The ST approach takes more computing memory to process a signal than other related techniques. Furthermore, such techniques have a long processing time. In [159], and [164] ST is used for feature extraction for intelligent IDSs discussed in section IV.

4) TTT-BASED IDS

By providing a time-time distribution on a specific window, the TTT method analyzes and transforms a one-dimensional time-domain signal into a two-dimensional time-domain signal. Low-frequency components are concentrated at various locations in the TTT technique, but high-frequency components are focused on the localization point with the highest energy concentration. TTT's time-local view usefulness through the scaled window is one of its characteristics, making it a good approach for change detection in signals and systems. In [159] employs TTT-based feature extraction of the negative sequence of the PCC voltage signal to detect islanding in 25 milliseconds. TTT is used in [180], where the TTT pattern of the three-phase disturbances clearly shows distinct signatures. Individual events are discovered to have a distinct pattern that can be utilized to detect islanding. The graphical result analysis in [181] illustrates the TTT capacity of detection and the localization of islanding disturbances in a hybrid DG system over WT, ST, and HST. The energy content and standard deviation of the converted signal are computed to assess performance.

V. FEATURE SELECTION SCHEMES

The most intelligent IDSs usually follow three basic steps, which consist of feature extraction, feature selection, and classification. Generally, more features mean more information, but it is practically difficult to implement because the extraction of multiple features requires more computational power. A significant problem, therefore, emerges in choosing the best and minimum features. Moreover, the collection of suitable features decreases the time needed for classification training and testing of a dataset. From the literature, we have found that not all features are valuable, and some of them are less sensitive to islanding detection and classification. To increase the efficiency and speed of rating classification, the use of various feature selection schemes omits redundant features. Intelligent-classifier-based learning schemes that use data for any output have been developed for different problems in the last decade. To train any intelligent-classifier-based scheme, a large amount of data is required in terms of several instances and features. This is called feature selection for managing high-dimensional data by identifying responsive and redundant features [182].

Machine-learning algorithms allow computers to create a method based on the input data. Thus, if relevant data is provided, the output of the learning algorithm will be improved. The quest for schemes that improve the quality of input data thus helps to improve the agent's output performance and thus improved data quality can be achieved. For example, by removing the noisy instances and by discriminating between relevant, irrelevant, and redundant data items, an optimal learning algorithm can be developed [183], [184].

The technical reasons for the requirement of feature selection schemes are as follows: a) curse of dimensionality (overfitting), b) Occam's razor (simplicity of model), and c) garbage in, garbage out (poor-quality input will produce poor-quality output). Various schemes for the selection of features have been presented and implemented by researchers, but the main approaches for the selection of features are of three types as summarized in Fig. 12 and the working principles are presented in Fig. 13.

The Wrapper method was presented in 1997 by two researchers in [185]. The Wrapper approaches work with a

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123382, IEEE Access

sub-set of features that test each subset based on the performance quality of an algorithm, using a search technique to observe the range of potential feature sub-set [186]. In any machine-learning algorithm, filter methods independently select features from a data set depending on the feature characteristics as the characteristics are extracted from the data before learning [187]. Embedded methods complete the selection process inside the machine's algorithm during the model training, which is why they are called embedded methods [188].

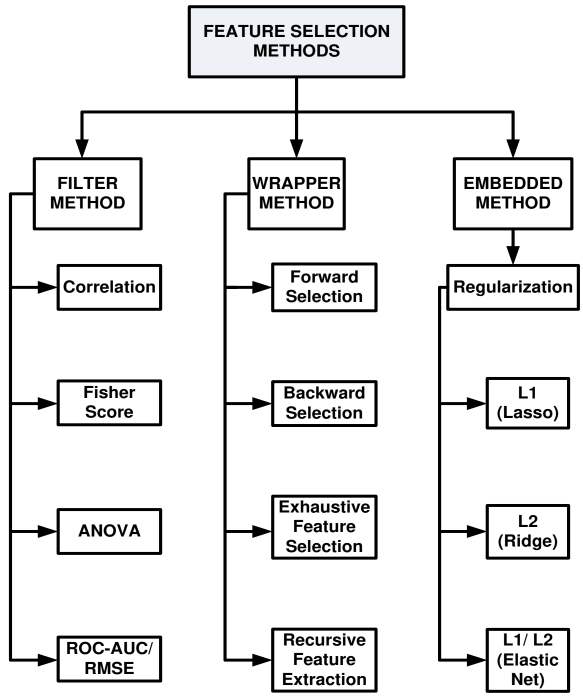

FIGURE 12. Methods for feature selection.

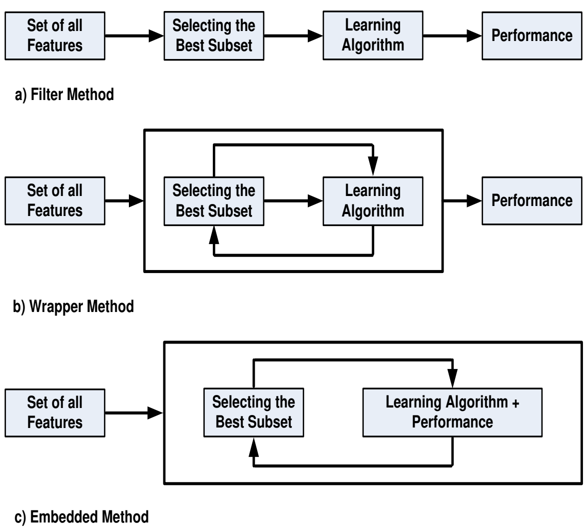

FIGURE 13. Architecture of feature selection methods.

The feature selection is the most significant and critical step, but several researchers have not emphasized this part in the islanding detection. The majority of the proposed IDSs select features explicitly based on the analysis of the literature without mentioning the selection criteria and selection reasons. For their proposed IDS, only a few researchers used feature selection schemes. The feature selection wrapper method has been used in [149] to select the three best features out of 45. In [136], CART was used to choose features. The sequential feature-selection process was employed to choose 12 of the best features out of a total of 30 electrical features in [144]. The forward sequential feature selection and the backward sequential feature selection were adopted for feature selection in [153]. As discussed above, considering the importance and need for optimal selection of features, IDSs should use any feature selection schemes based on their data and the requirements of the proposed scheme.

VI. MOST DOMINATING FEATURES FOR ISLANDING DETECTION

In islanding and non-islanding situations, the electrical features of EPS show various fluctuations as compared to those in normal operation. Some of these parameters are more sensitive to disturbances from islanding and non-islanding whereas, some are less sensitive, while some of them have no impact [189], [190]. Based on the sensitivity of these parameters under irregular circumstances, researchers have selected specific parameters for their proposed IDS. The number of parameters for each IDS depends on their method and the feature selection technique used. As mentioned in section 5, several researchers have not used any feature selection methodology and have selected parameters based on previous and evolving studies. In [136], 12 features were extracted, whereas in [85], 27 features were extracted for islanding detection. Similarly, a total of 16 features were extracted using MMODEA-ELM and by objective function formulation, the most optimum features were selected in[143]. In [149], initially, 45 features affected by islanding conditions were extracted, while in [71], 10 features were selected; a total of 21 features were selected in [152] during the feature-extraction step, and 11 features were extracted in [80]. A wide variety of features for islanding detection have been derived ranging from three to 45 features in the above IDSs. Some specific and significant features are impaired and very prone to islanding and non-islanding disturbances, which were utilized by the majority of researchers in their proposed schemes. Such features provide a lot of information concerning behavioral changes and are very useful for machine-learning classifiers to distinguish between these disturbances. ROCOF, ROCOV, total harmonic distortion (THD), power factor, ROCOP, and ROCOQ are widely used owing to their traits that are useful for classifying islanding and non-islanding situations. Table X provides a full overview of the most dominant features and their uses in the various IDSs.

TABLE X
DOMINATING FEATURES FOR ISLANDING DETECTION

Reference	ΔF	ROCOF	ΔV	ROCOV	THDv	THDc	PF	ROCOP	ROCOQ	dF/dP
[85]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
[139]	✓	✓	✓	✓	×	×	×	✓	✓	×
[140]	✓	✓	✓	✓	×	×	✓	✓	✓	✓
[141]	×	×	✓	✓	✓	×	×	×	×	×
[143]	×	✓	×	✓	×	×	×	✓	✓	✓
[144]	✓	✓	✓	✓	×	×	✓	✓	✓	✓
[27]	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
[149]	×	✓	×	✓	×	×	✓	×	×	×
[152]	✓	✓	✓	✓	✓	✓	✓	✓	×	×
[163]	✓	✓	✓	✓	✓	✓	✓	✓	×	✓
[169]	×	✓	×	✓	✓	✓	×	✓	✓	×

Where ✓: used and ×: not used.

TABLE XI
COMPARISON OF THE VARIOUS INTELLIGENT IDS

Reference	Technique name	Test system	Detection time (s)	Accuracy (%)	NDZ (%)
[141]	DT	Only IB DG	0.22	100	✓
[142]	DT	Both IB and SB DGs	0.425	97.1	1.91
[27]	ANN	IEEE-9 bus power system	0.5	97.1	3
[153]	ANN	Only IB DG	0.188	100	Almost zero
[191]	SVM	Only IB DG	0.040	100	9.52
[90]	SVM	Only IB DG	0.50	99.49	-
[192]	FL	Both IB and SB DGs	0.229	99.70	-
[150]	FL	Both IB and SB base DGs	fast	100	-
[171]	ANFIS	Two IB DG	0.040	78.71	Almost zero
[169]	ANFIS	Only IB DG	fast	-	Zero
[174]	DNN	Only IB DG	0.18	98.3	✓

VII. PERFORMANCE INDICATORS FOR IDSs

The timely and precise operation of the appropriate technique is critical to the IDSs' performance. The NDZ, parallel RLC load, and quality factor are the three primary performance indicators that describe an IDS's operating capabilities. A successful operation under these severe conditions confirms the use of IDSs. If a technique effectively identifies the islanding situation in such circumstances, the approach's superiority is highlighted, and international requirements are satisfied.

A. NDZ

NDZ is an area that is not easily identified by traditional protective relays in islanding detection. The NDZ is thought to be a summative assessment for IDSs. An NDZ is typically assessed based on a range of active and reactive power mismatches in which the voltage and frequency relays are unable to identify the islanding condition in a reasonable timeframe. The NDZ boundary limits may be established using (1) and (2), and the region of critical and non-critical operating conditions can be identified [103].

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

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

where V_{max}, V_{min}, f_{max}, and f_{min} are the maximum and minimum voltage/frequency threshold limits of the relay. ΔP and ΔQ represent the power mismatches prior to the main grid disconnection while Q_f is the load quality factor.

B. PARALLEL RLC LOADS

Most loads in power networks are inductive, but inverter-based DG units yield maximum kilowatt-hours by operating at unity power factor. When combined with a parallel RLC load, this is considered the worst-case situation for detecting islanding. Similarly, when the connected load and DG power are perfectly matched, islanding identification becomes more difficult [23]. The relationship between the PCC voltage and frequency in a parallel RLC circuit is as follows:

$$P_{load} = \frac{3V_{PCC}^2}{R} \tag{3}$$

$$Q_{load} = 3V_{PCC}^2 \left(\frac{1}{\omega L} - \omega C\right) \tag{4}$$

V_{PCC} is reliant on the active power of the islanded system, as shown in (3) and (4).

C. QUALITY FACTOR

The load quality factor is a critical element for determining the IDS's dependability and robustness [103]. Because the size of the NDZ and detection accuracy is affected by the load quality factor, the value of the load quality factor has a major impact on the performance analysis of the IDSs. The quality factor can be expressed mathematically as (5).

$$Q_f = R\sqrt{\frac{C}{L}} \tag{5}$$

where R, L, and C are the effective load resistance, inductance, and capacitance, respectively.

VIII. COMPARISON, DISCUSSIONS, AND FUTURE RECOMMENDATION

Table XI shows a comparison of several existing intelligent classifier-based IDSs based on many indices like the used test system, detection time (s), achieved accuracy, and the NDZ. Table IX compares intelligent classifiers with traditional IDS based on different criteria such as reliability, complexity accuracy, detection speed, impact on PQ, and implementation cost. In the recent research on islanding detection conducted by our team, various intelligent classifiers were compared based on accuracy, precision, recall, and F_1 score in [3]. Ada-boost performs very accurately with the highest accuracy, precision, recall, and F_1 score, while DT performance is worst among all models. Fig. 14 illustrates a comparison of the ensemble learning models (Ada-boost and RF) and canonical methods (MLP, DT, and SVM) with the same data and test system.

The change in research trends from traditional to intelligent-classifier-based IDS over the past decade has been outlined and objectively evaluated in this paper. This work was focused on intelligent-classifier-based IDSs such as DT, ANN, SVM, FL, ANFIS, CNN, and DNN. Different aspects of feature selection were also studied in this research, as this is the most critical step in islanding detection algorithms. The review also outlined the most widely used and influential features for islanding detection.

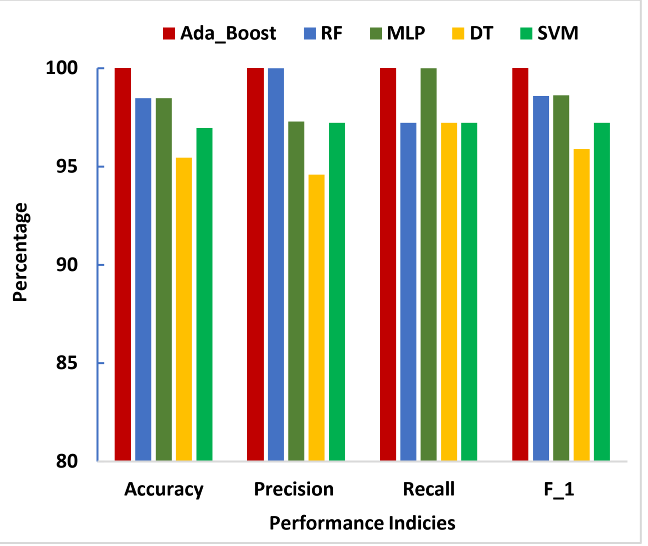

FIGURE 14. Comparison of intelligent classifiers in terms of various performance indices.

This study concludes that machine-learning-based schemes show a high degree of robustness in all performance indices that are important for any IDS, such as negligible NDZ, high PQ, multiple DGs, and fast detection time, and are capable of managing complex and large EPSs. Following are the recommendations for future studies, which are based on the evaluation and review of all the performance indices for islanding detection.

- Intelligent-classifier-based methods are strongly recommended based on performance indices that are significant for islanding system design.
- Based on this study, feature selection should be regarded as an essential step in any proposed islanding scheme.
- Several features offering a high accuracy is a fallacy in machine learning, as a larger number of features burdens the system and reduces the speed and accuracy of the algorithm. The selection of features should, therefore, be based on precision and prevalence and be as few as possible.
- DNN- and CNN-based approaches are desirable for large and complex systems, but conventional schemes offer the best efficiency and are still very convenient for implementation in small and basic systems.
- Signal processing techniques schemes such as DWT, DFT, TTT, and HHT can be used to reduce noise, maximize device performance, and minimize dimensionality during the extraction of features.
- In the future, advanced signal processing technologies combined with a machine-learning algorithm might be used to develop an accurate island detection method.
- In future research, hybrid strategies based on intelligent classifiers and conventional techniques are suggested.
- Several recent intelligent classifiers, such as LSTM, RNN, Encoder-Decoder, and so on, are not used in power system research, although they may be in future studies.

IX. CONCLUSION

A detailed and in-depth analysis of intelligent-classifier-based IDSs has been presented in this review. Systematic and detailed research is carried out based on intelligent/machine learning theories for islanding detection. This research outlines the feature-selection schemes used in the literature and those that could be used in the future for islanding detection. In this article, based on a literature review, the most important electrical parameters for islanding detection are also highlighted. The IDS were categorized into three main classes remote, local, and intelligent classifier-based scheme. Classic IDS approaches, such as active, passive, and remote approaches, have their own merits and demerits, and because of their shortcomings, researchers have recently shifted towards intelligent-classifiers-based schemes. The intelligent-classifier-based IDSs have major advantages in terms of performance indices, such as NDZ, detection time, precision, PQ, noise, and accuracy as compared to conventional schemes. It can be concluded that the implementation of intelligent classifier-based IDS can play a major role in the efficient and viable detection of DG islanding. Implementation of these techniques in islanding detection will also increase the stability of the power system and power supply efficiency. Therefore, artificial intelligence-based approaches are also favored and can be used in real-time applications to efficiently execute DG islanding operations.

ACKNOWLEDGMENT

This work was supported by the National Research Foundation of Korea (NRF) grant funded by the Korean government (MSIP) (No. 2021R1A2B5B03086257).

REFERENCES

[1] M. Mishra, S. Chandak, and P. K. Rout, "Taxonomy of Islanding detection techniques for distributed generation in microgrid," *Renew. Energy Focus,* vol. 31, no. December, pp. 9–30, 2019, doi: 10.1016/j.ref.2019.09.001.

[2] A. Llaria, O. Curea, J. Jiménez, and H. Camblong, "Survey on microgrids: Analysis of technical limitations to carry out new solutions," *2009 13th Eur. Conf. Power Electron. Appl. EPE* '09, 2009.

[3] A. Hussain, C. H. Kim, and S. Admasie, "An intelligent islanding detection of distribution networks with synchronous machine DG using ensemble learning and canonical methods," *IET Gener. Transm. Distrib*., no. June, pp. 1–14, 2021, doi: 10.1049/gtd2.12256.

[4] P. Dondi, D. Bayoumi, C. Haederli, D. Julian, and M. Suter, "Network integration of distributed power generation," *J. Power Sources*, vol. 106, no. 1–2, pp. 1–9, 2002, doi: 10.1016/S0378-7753(01)01031-X.

[5] A. Khamis, H. Shareef, E. Bizkevelci, and T. Khatib, "A review of islanding detection techniques for renewable distributed generation systems," *Renew. Sustain. Energy Rev.,* vol. 28, pp. 483–493, 2013, doi: 10.1016/j.rser.2013.08.025.

[6] S. Admasie, S. B. A. Bukhari, T. Gush, R. Haider, and C. H. Kim, "Intelligent Islanding Detection of Multi-distributed Generation Using Artificial Neural Network Based on Intrinsic Mode Function Feature," *J. Mod. Power Syst. Clean Energy*, vol. 8, no. 3, pp. 511–520, 2020, doi: 10.35833/MPCE.2019.000255.

[7] H. H. Alhelou, M. E. Hamedani-Golshan, T. C. Njenda, and P. Siano, "A survey on power system blackout and cascading events: Research motivations and challenges," *Energies*, vol. 12, no. 4, pp. 1–28, 2019, doi: 10.3390/en12040682.

[8] T. Basso, "IEEE 1547 and 2030 Standards for Distributed Energy Resources Interconnection and Interoperability with the Electricity Grid IEEE 1547 and 2030 Standards for Distributed Energy Resources Interconnection and Interoperability with the Electricity Grid," Nrel, no. December, p. 22, 2014.

[9] G. Bayrak, "A remote islanding detection and control strategy for photovoltaic-based distributed generation systems," *Energy Convers. Manag*., vol. 96, pp. 228–241, 2015, doi: 10.1016/j.enconman.2015.03.004.

[10] G. Bayrak and E. Kabalci, "Implementation of a new remote islanding detection method for wind-solar hybrid power plants," *Renew. Sustain. Energy Rev*., vol. 58, pp. 1–15, 2016, doi: 10.1016/j.rser.2015.12.227.

[11] K. L. Chen, Y. Guo, J. Wang, and X. Yang, "Contactless Islanding Detection Method Using Electric Field Sensors," *IEEE Trans. Instrum. Meas*., vol. 70, no. Im, 2021, doi: 10.1109/TIM.2020.3043096.

[12] H. Samet, F. Hashemi, and T. Ghanbari, "Minimum non detection zone for islanding detection using an optimal Artificial Neural Network algorithm based on PSO," *Renew. Sustain. Energy Rev.,* vol. 52, pp. 1–18, 2015, doi: 10.1016/j.rser.2015.07.080.

[13] W. Xu, G. Zhang, C. Li, W. Wang, G. Wang, and J. Kliber, "A power line signaling based technique for anti-islanding protection of distributed generators - Part I: Scheme and analysis," *IEEE Trans. Power Deliv*., vol. 22, no. 3, pp. 1758–1766, 2007, doi: 10.1109/TPWRD.2007.899618.

[14] M. Ropp et al., "Islanding Scheme Using a Commercial Automatic Meter Reading System," *IEEE 4th World Conf. Photovolt. Energy Convers*., pp. 2351–2354, 2006.

[15] J. Yang, J. Yuan, and S. Lin, "The study on island detection for distributed power combining power line zero-crossing communication technology," *Proc. 2017 IEEE 7th Int. Conf. Electron. Inf. Emerg. Commun. ICEIEC 2017*, pp. 304–307, 2017, doi: 10.1109/ICEIEC.2017.8076568.

[16] C. I. Chen and Y. C. Chen, "Intelligent Identification of Voltage Variation Events Based on IEEE Std 1159-2009 for SCADA of Distributed Energy System," *IEEE Trans. Ind. Electron*., vol. 62, no. 4, pp. 2604–2611, 2015, doi: 10.1109/TIE.2014.2348948.

[17] E. Lazar, R. Etz, D. Petreus, T. Patarau, and I. Ciocan, "SCADA development for an islanded microgrid," *2015 IEEE 21st Int. Symp. Des. Technol. Electron. Packag. SIITME* 2015, pp. 147–150, 2015, doi: 10.1109/SIITME.2015.7342314.

[18] D. Mlakic, H. R. Baghaee, and S. Nikolovski, "Gibbs Phenomenon-based Hybrid Islanding Detection Strategy for VSC-based Microgrids using Frequency Shift, THDU and RMSU," *IEEE Trans. Smart Grid*, vol. 10, no. 5, pp. 5479–5491, 2018, doi: 10.1109/TSG.2018.2883595.

[19] C. Li, C. Cao, Y. Cao, Y. Kuang, L. Zeng, and B. Fang, "A review of islanding detection methods for microgrid," *Renew. Sustain. Energy Rev.,* vol. 35, pp. 211–220, 2014, doi: 10.1016/j.rser.2014.04.026.

[20] A. G. Abokhalil, A. B. Awan, and A. R. Al-Qawasmi, "Comparative study of passive and active islanding detection methods for PV grid-connected systems," *Sustain.,* vol. 10, no. 6, pp. 1–15, 2018, doi: 10.3390/su10061798.

[21] A. Etxegarai, P. Eguía, and I. Zamora, "Analysis of remote islanding detection methods for distributed resources," *Renew. Energy Power Qual. J.*, vol. 1, no. 9, pp. 1142–1147, 2011, doi: 10.24084/repqj09.580.

[22] R. A. Walling, "Application of direct transfer trip for prevention of DG islanding," *IEEE Power Energy Soc. Gen. Meet*., pp. 5–7, 2011, doi: 10.1109/PES.2011.6039727.

[23] B. K. Panigrahi, A. Bhuyan, J. Shukla, P. K. Ray, and S. Pati, "A comprehensive review on intelligent islanding detection techniques for renewable energy integrated power system," *Int. J. Energy Res.*, no. October 2020, pp. 1–32, 2021, doi: 10.1002/er.6641.

[24] M. Hojabri, U. Dersch, A. Papaemmanouil, and P. Bosshart, "A comprehensive survey on phasor measurement unit applications

in distribution systems," *Energies*, vol. 12, no. 23, pp. 1–23, 2019, doi: 10.3390/en12234552.

[25] D. M. Laverty, R. J. Best, and D. J. Morrow, "Loss-of-mains protection system by application of phasor measurement unit technology with experimentally assessed threshold settings," *IET Gener. Transm. Distrib*., vol. 9, no. 2, pp. 146–153, 2015, doi: 10.1049/iet-gtd.2014.0106.

[26] M. M. Ostojić and M. B. Djurić, "The algorithm with synchronized voltage inputs for islanding detection of synchronous generators," *Int. J. Electr. Power Energy Syst.,* vol. 103, no. May, pp. 431–439, 2018, doi: 10.1016/j.ijepes.2018.06.023.

[27] D. Kumar and P. S. Bhowmik, "Artificial neural network and phasor data-based islanding detection in smart grid," *IET Gener. Transm. Distrib*., vol. 12, no. 21, pp. 5843–5850, 2018, doi: 10.1049/iet-gtd.2018.6299.

[28] X. Liu, D. M. Laverty, R. J. Best, K. Li, D. J. Morrow, and S. McLoone, "Principal Component Analysis of Wide-Area Phasor Measurements for Islanding Detection - A Geometric View," *IEEE Trans. Power Deliv.,* vol. 30, no. 2, pp. 976–985, 2015, doi: 10.1109/TPWRD.2014.2348557.

[29] S. Barczentewicz, T. Lerch, A. Bień, and K. Duda, "Laboratory Evaluation of a Phasor-Based Islanding Detection Method," *Energies,* vol. 14, no. 7, p. 1953, 2021, doi: 10.3390/en14071953.

[30] J. J. Justo, F. Mwasilu, J. Lee, and J. W. Jung, "AC-microgrids versus DC-microgrids with distributed energy resources: A review," *Renew. Sustain. Energy Rev*., vol. 24, pp. 387–405, 2013, doi: 10.1016/j.rser.2013.03.067.

[31] S. Murugesan and V. Murali, "Active Unintentional Islanding Detection Method for Multiple-PMSG-Based DGs," *IEEE Trans. Ind. Appl.,* vol. 56, no. 5, pp. 4700–4708, 2020, doi: 10.1109/TIA.2020.3001504.

[32] M. Hamzeh, S. Farhangi, and B. Farhangi, "A new control method in PV grid connected inverters for anti-islanding protection by impedance monitoring," *11th IEEE Work. Control Model. Power Electron. COMPEL* 2008, pp. 3–7, 2008, doi: 10.1109/COMPEL.2008.4634664.

[33] P. Yazdkhasti and C. P. Diduch, "An islanding detection method based on measuring impedance at the point of common coupling," *Can. Conf. Electr. Comput. Eng.*, vol. 2015-June, no. June, pp. 57–62, 2015, doi: 10.1109/CCECE.2015.7129160.

[34] T. S. Tran, D. T. Nguyen, and G. Fujita, "Islanding detection method based on injecting perturbation signal and rate of change of output power in DC grid-connected photovoltaic system," *Energies*, vol. 11, no. 5, pp. 1–18, 2018, doi: 10.3390/en11051313.

[35] T. Z. Bei, "Accurate active islanding detection method for grid-tied inverters in distributed generation," *IET Renew. Power Gener.*, vol. 11, no. 13, pp. 1633–1639, 2017, doi: 10.1049/iet-rpg.2017.0080.

[36] L. A. C. Lopes and H. Sun, "Performance assessment of active frequency drifting islanding detection methods," *IEEE Trans. Energy Convers.,* vol. 21, no. 1, pp. 171–180, 2006, doi: 10.1109/TEC.2005.859981.

[37] A. Yafaoui, B. Wu, and S. Kouro, "Improved active frequency drift anti-islanding detection method for grid connected photovoltaic systems," *IEEE Trans. Power Electron*., vol. 27, no. 5, pp. 2367–2375, 2012, doi: 10.1109/TPEL.2011.2171997.

[38] B. Wen, D. Boroyevich, R. Burgos, Z. Shen, and P. Mattavelli, "Impedance-based analysis of active frequency drift islanding detection for grid-tied inverter system," *IEEE Trans. Ind. Appl.*, vol. 52, no. 1, pp. 332–341, 2016, doi: 10.1109/TIA.2015.2480847.

[39] M. I. Chehardeh and E. M. Siavashi, "A novel hybrid islanding detection method for inverter-based dg," *arXiv*, vol. 32, no. 5, pp. 2162–2170, 2018.

[40] C. L. Trujillo, D. Velasco, E. Figueres, and G. Garcerá, "Analysis of active islanding detection methods for grid-connected microinverters for renewable energy processing," *Appl. Energy*, vol. 87, no. 11, pp. 3591–3605, 2010, doi: 10.1016/j.apenergy.2010.05.014.

[41] H. Vahedi and M. Karrari, "Adaptive fuzzy Sandia frequency-shift method for islanding protection of inverter-based distributed generation," *IEEE Trans. Power Deliv*., vol. 28, no. 1, pp. 84–92, 2013, doi: 10.1109/TPWRD.2012.2219628.

[42] M. V. G. Reis, T. A. S. Barros, A. B. Moreira, S. F. Paulo Nascimento, F. Ernesto Ruppert, and M. G. Villalva, "Analysis of the Sandia Frequency Shift (SFS) islanding detection method with a single-phase photovoltaic distributed generation system," *2015 IEEE PES Innov. Smart Grid Technol. Lat. Am. ISGT LATAM* 2015, pp. 125–129, 2016, doi: 10.1109/ISGT-LA.2015.7381140.

[43] M. El-Moubarak, M. Hassan, and A. Faza, "Performance of three islanding detection methods for grid-tied multi-inverters," *2015 IEEE 15th Int. Conf. Environ. Electr. Eng. EEEIC 2015 - Conf. Proc*., no. Idm, pp. 1999–2004, 2015, doi: 10.1109/EEEIC.2015.7165481.

[44] B. Bahrani, H. Karimi, and R. Iravani, "Nondetection zone assessment of an active islanding detection method and its experimental evaluation," *IEEE Trans. Power Deliv*., vol. 26, no. 2, pp. 517–525, 2011, doi: 10.1109/TPWRD.2009.2036016.

[45] P. Li, Y. Sheng, L. Zhang, X. Yang, and Y. Zhao, "A novel active islanding detection method based on current-disturbing," *Proc. - 12th Int. Conf. Electr. Mach. Syst. ICEMS 2009*, vol. 2, no. 1, pp. 5–9, 2009, doi: 10.1109/ICEMS.2009.5382711.

[46] H. Karimi, A. Yazdani, and R. Iravani, "Negative-sequence current injection for fast islanding detection of a distributed resource unit," *IEEE Trans. Power Electron*., vol. 23, no. 1, pp. 298–307, 2008, doi: 10.1109/TPEL.2007.911774.

[47] H. H. Zeineldin, E. F. El-Saadany, and M. M. A. Salama, "Impact of DG interface control on islanding detection and nondetection zones," *IEEE Trans. Power Deliv*., vol. 21, no. 3, pp. 1515–1523, 2006, doi: 10.1109/TPWRD.2005.858773.

[48] F. Liu, Y. Kang, Y. Zhang, S. Duan, and X. Lin, "Improved SMS islanding detection method for grid-connected converters," *IET Renew. Power Gener*., vol. 4, no. 1, pp. 36–42, 2010, doi: 10.1049/iet-rpg.2009.0019.

[49] S. Akhlaghi, A. Akhlaghi, and A. A. Ghadimi, "Performance analysis of the Slip mode frequency shift islanding detection method under different inverter interface control strategies," *2016 IEEE Power Energy Conf. Illinois, PECI* 2016, pp. 1–7, 2016, doi: 10.1109/PECI.2016.7459250.

[50] A. Emadi, H. Afrakhte, and J. Sadeh, "Fast active islanding detection method based on second harmonic drifting for inverter-based distributed generation," *IET Gener. Transm. Distrib.*, vol. 10, no. 14, pp. 3470–3480, 2016, doi: 10.1049/iet-gtd.2016.0089.

[51] R. Haider et al., "Passive islanding detection scheme based on autocorrelation function of modal current envelope for photovoltaic units," *IET Gener. Transm. Distrib*., vol. 12, no. 3, pp. 726–736, 2018, doi: 10.1049/iet-gtd.2017.0823.

[52] H. Abdi, A. Rostami, and N. Rezaei, "A Novel Passive Islanding Detection Scheme for Synchronous-type DG using Load Angle and Mechanical Power Parameters," *Electr. Power Syst. Res.,* vol. 192, no. November 2020, p. 106968, 2021, doi: 10.1016/j.epsr.2020.106968.

[53] X. Xie, C. Huang, and D. Li, "A new passive islanding detection approach considering the dynamic behavior of load in microgrid," *Int. J. Electr. Power Energy Syst*., vol. 117, no. November 2019, p. 105619, 2020, doi: 10.1016/j.ijepes.2019.105619.

[54] X. Xie, W. Xu, C. Huang, and X. Fan, "New islanding detection method with adaptively threshold for microgrid," *Electr. Power Syst. Res*., vol. 195, no. October 2020, p. 107167, 2021, doi: 10.1016/j.epsr.2021.107167.

[55] B. K. Choudhury, S. Member, P. Jena, and S. Member, "Superimposed Impedance Based Passive Islanding Detection Scheme for DC Microgrids," vol. 6777, no. c, pp. 1–15, 2021, doi: 10.1109/JESTPE.2021.3076459.

[56] A. G. Abd-Elkader, S. M. Saleh, and M. B. Magdi Eiteba, "A passive islanding detection strategy for multi-distributed generations," *Int. J. Electr. Power Energy Syst.,* vol. 99, no. February, pp. 146–155, 2018, doi: 10.1016/j.ijepes.2018.01.005.

[57] P. P. Mishra and C. N. Bhende, "Islanding Detection based on Variational Mode Decomposition for Inverter based Distributed Generation Systems," *IFAC-PapersOnLine*, vol. 52, no. 4, pp. 306–311, 2019, doi: 10.1016/j.ifacol.2019.08.216.

[58] A. Rostami, J. Olamaei, and H. Abdi, "Islanding Detection of Synchronous DG based on Inherent Feature Extracted from Mechanical Power," *Iran. J. Sci. Technol. - Trans. Electr. Eng*., vol. 43, no. 4, pp. 919–928, 2019, doi: 10.1007/s40998-019-00193-8.

[59] A. Shahmohammadi and M. T. Ameli, "Proper sizing and placement of distributed power generation aids the intentional islanding process," *Electr. Power Syst. Res*., vol. 106, pp. 73–85, 2014, doi: 10.1016/j.epsr.2013.08.005.

[60] W. K. A. Najy, H. H. Zeineldin, A. H. K. Alaboudy, and W. L. Woon, "A bayesian passive islanding detection method for inverter-based distributed generation using ESPRIT," *IEEE Trans. Power Deliv.*, vol. 26, no. 4, pp. 2687–2696, 2011, doi: 10.1109/TPWRD.2011.2159403.

[61] K. Naraghipour, K. Ahmed, and C. Booth, "A Comprehensive Review of Islanding Detection Methods for Distribution Systems," *9th Int. Conf. Renew. Energy Res. Appl. ICRERA 2020,* pp. 428–433, 2020, doi: 10.1109/ICRERA49962.2020.9242850.

[62] D. Motter and J. C. M. Vieira, "Improving the islanding detection performance of passive protection by using the undervoltage block function," *Electr. Power Syst. Res.*, vol. 184, no. November 2019, p. 106293, 2020, doi: 10.1016/j.epsr.2020.106293.

[63] P. Gupta, R. S. Bhatia, and D. K. Jain, "Active ROCOF Relay for Islanding Detection," *IEEE Trans. Power Deliv.*, vol. 32, no. 1, pp. 420–429, 2017, doi: 10.1109/TPWRD.2016.2540723.

[64] M. R. Alam, M. T. A. Begum, and K. M. Muttaqi, "Assessing the Performance of ROCOF Relay for Anti-Islanding Protection of Distributed Generation under Subcritical Region of Power Imbalance," *IEEE Trans. Ind. Appl*., vol. 55, no. 5, pp. 5395–5405, 2019, doi: 10.1109/TIA.2019.2927667.

[65] C. R. Reddy and K. H. Reddy, "Islanding Detection Method for Inverter Based Distributed Generation Based on Combined Changes of Rocoap and Rocorp," vol. 117, no. 19, pp. 433–440, 2017, [Online]. Available: http://www.ijpam.eu.

[66] D. Salles, W. Freitas, J. C. M. Vieira, and B. Venkatesh, "A Practical Method for Nondetection Zone Estimation of Passive Anti-Islanding Schemes Applied to Synchronous Distributed Generators," *IEEE Trans. Power Deliv*., vol. 30, no. 5, pp. 2066–2076, 2015, doi: 10.1109/TPWRD.2014.2360299.

[67] W. Freitas, W. Xu, C. M. Affonso, and Z. Huang, "Comparative analysis between ROCOF and vector surge relays for distributed generation applications," *IEEE Trans. Power Deliv.*, vol. 20, no. 2 II, pp. 1315–1324, 2005, doi: 10.1109/TPWRD.2004.834869.

[68] S. Khichar and M. Lalwani, "An Analytical Survey of the Islanding Detection Techniques of Distributed Generation Systems," *Technol. Econ. Smart Grids Sustain. Energy*, vol. 3, no. 1, pp. 1–10, 2018, doi: 10.1007/s40866-018-0041-1.

[69] G. Marchesan, M. R. Muraro, G. Cardoso, L. Mariotto, and A. P. De Morais, "Passive Method for Distributed-Generation Island Detection Based on Oscillation Frequency," *IEEE Trans. Power Deliv.*, vol. 31, no. 1, pp. 138–146, 2016, doi: 10.1109/TPWRD.2015.2438251.

[70] G. Wang, F. Gao, and J. Liu, "A Hybrid Islanding Detection Method Combining VU/THD and BRPV," *2018 IEEE Energy Convers. Congr. Expo. ECCE* 2018, pp. 3682–3687, 2018, doi: 10.1109/ECCE.2018.8557792.

[71] S. Il Jang and K. H. Kim, "An islanding detection method for distributed generations using voltage unbalance and total harmonic distortion of current," *IEEE Trans. Power Deliv*., vol. 19, no. 2, pp. 745–752, 2004, doi: 10.1109/TPWRD.2003.822964.

[72] A. Llaria, O. Curea, J. Jiménez, and H. Camblong, "Survey on microgrids: Unplanned islanding and related inverter control techniques," *Renew. Energy*, vol. 36, no. 8, pp. 2052–2061, 2011, doi: 10.1016/j.renene.2011.01.010.

[73] B. Singam and L. Y. Hui, "Assessing SMS and PJD schemes of anti-islanding with varying quality factor," *First Int. Power Energy Conf. (PECon 2006) Proc.*, pp. 196–201, 2006, doi: 10.1109/PECON.2006.346645.

[74] W. Bower, "Implementing Agreement on Photovoltaic Power Systems Grid Interconnection of Building Integrated evaluation of islanding detection methods for photovoltaic utility-interactive power systems," 2002.

[75] D. Velasco, C. L. Trujillo, G. Garcerá, and E. Figueres, "Review of anti-islanding techniques in distributed generators," *Renew. Sustain. Energy Rev*., vol. 14, no. 6, pp. 1608–1614, 2010, doi: 10.1016/j.rser.2010.02.011.

[76] S. D. Kermany, M. Joorabian, S. Deilami, and M. A. S. Masoum, "Hybrid Islanding Detection in Microgrid with Multiple Connection Points to Smart Grids Using Fuzzy-Neural Network," *IEEE Trans. Power Syst.,* vol. 32, no. 4, pp. 2640–2651, 2017, doi: 10.1109/TPWRS.2016.2617344.

[77] V. Nougain, S. Prakash, and S. Mishra, "Hybrid Islanding Detection Method based on ROCOF over Reactive Power and d-Axis Current Injection," *India Int. Conf. Power Electron. IICPE*, vol. 2018-Decem, pp. 7–10, 2018, doi: 10.1109/IICPE.2018.8709518.

[78] M. Seyedi, S. A. Taher, B. Ganji, and J. Guerrero, "A Hybrid Islanding Detection Method Based on the Rates of Changes in Voltage and Active Power for the Multi-Inverter Systems," *IEEE Trans. Smart Grid*, vol. 3053, no. c, 2021, doi: 10.1109/TSG.2021.3061567.

[79] K. Narayanan, S. A. Siddiqui, and M. Fozdar, "Hybrid islanding detection method and priority-based load shedding for distribution networks in the presence of DG units," *IET Gener. Transm. Distrib*., vol. 11, no. 3, pp. 586–595, 2017, doi: 10.1049/iet-gtd.2016.0437.

[80] V. Menon and M. H. Nehrir, "A hybrid islanding detection technique using voltage unbalance and frequency set point," *IEEE Trans. Power Syst*., vol. 22, no. 1, pp. 442–448, 2007, doi: 10.1109/TPWRS.2006.887892.

[81] S. Padmanaban, N. Priyadarshi, M. Sagar Bhaskar, J. B. Holm-Nielsen, V. K. Ramachandaramurthy, and E. Hossain, "A Hybrid ANFIS-ABC Based MPPT Controller for PV System With Anti-Islanding Grid Protection: Experimental Realization," *IEEE Access,* vol. 7, pp. 103377–103389, 2019, doi: 10.1109/access.2019.2931547.

[82] S. C. Paiva, R. L. de A. Ribeiro, D. K. Alves, F. B. Costa, and T. de O. A. Rocha, "A wavelet-based hybrid islanding detection system applied for distributed generators interconnected to AC microgrids," *Int. J. Electr. Power Energy Syst.*, vol. 121, no. November 2019, p. 106032, 2020, doi: 10.1016/j.ijepes.2020.106032.

[83] G. Wang, "Design Consideration and Performance Analysis of a Hybrid Islanding Detection Method Combining Voltage Unbalance/Total Harmonic Distortion and Bilateral Reactive Power Variation," *CPSS Trans. Power Electron*. Appl., vol. 5, no. 1, pp. 86–100, 2020, doi: 10.24295/cpsstpea.2020.00008.

[84] M. R. Alam, K. M. Muttaqi, and A. Bouzerdoum, "An approach for assessing the effectiveness of multiple-feature-based SVM method for islanding detection of distributed generation," *IEEE Trans. Ind. Appl*., vol. 50, no. 4, pp. 2844–2852, 2014, doi: 10.1109/TIA.2014.2300135.

[85] S. R. Samantaray and S. Kar, "Data-mining-based intelligent anti-islanding protection relay for distributed generations," *IET Gener. Transm. Distrib*., vol. 8, no. 4, pp. 629–639, 2014, doi: 10.1049/iet-gtd.2013.0494.

[86] A. Taheri Kolli and N. Ghaffarzadeh, "A novel phaselet-based approach for islanding detection in inverter-based distributed generation systems," *Electr. Power Syst. Res.*, vol. 182, no. January, 2020, doi: 10.1016/j.epsr.2020.106226.

[87] R. Bakhshi-Jafarabadi, J. Sadeh, J. de J. Chavez, and M. Popov, "Two-Level Islanding Detection Method for Grid-Connected Photovoltaic System-Based Microgrid with Small Non-Detection Zone," *IEEE Trans. Smart Grid*, vol. 12, no. 2, pp. 1063–1072, 2021, doi: 10.1109/TSG.2020.3035126.

[88] J. Merino, P. Mendoza-Araya, G. Venkataramanan, and M. Baysal, “Islanding Detection in Microgrids Using Harmonic Signatures,” *IEEE Trans. Power Deliv.*, vol. 30, no. 5, pp. 2102–2109, 2015, doi: 10.1109/TPWRD.2014.2383412.

[89] U. Markovic, D. Chrysostomou, P. Aristidou, and G. Hug, “Impact of inverter-based generation on islanding detection schemes in distribution networks,” *Electr. Power Syst. Res.*, vol. 190, no. October 2019, p. 106610, 2021, doi: 10.1016/j.epsr.2020.106610.

[90] B. Matic-Cuka and M. Kezunovic, “Islanding detection for inverter-based distributed generation using support vector machine method,” *IEEE Trans. Smart Grid*, vol. 5, no. 6, pp. 2676–2686, 2014, doi: 10.1109/TSG.2014.2338736.

[91] H. Samet, F. Hashemi, and T. Ghanbari, “Islanding detection method for inverter-based distributed generation with negligible non-detection zone using energy of rate of change of voltage phase angle,” *IET Gener. Transm. Distrib.*, vol. 9, no. 15, pp. 2337–2350, 2015, doi: 10.1049/iet-gtd.2015.0638.

[92] R. S. Kunte and W. Gao, “Comparison and review of islanding detection techniques for distributed energy resources,” *40th North Am. Power Symp. NAPS2008*, pp. 1–8, 2008, doi: 10.1109/NAPS.2008.5307381.

[93] G. Yin, “A distributed generation islanding detection method based on artificial immune system,” *Proc. IEEE Power Eng. Soc. Transm. Distrib. Conf.*, vol. 2005, pp. 1–4, 2005, doi: 10.1109/TDC.2005.1547072.

[94] M. V. De Oliveira and J. C. S. De Almeida, “Application of artificial intelligence techniques in modeling and control of a nuclear power plant pressurizer system,” *Prog. Nucl. Energy*, vol. 63, pp. 71–85, 2013, doi: 10.1016/j.pnucene.2012.11.005.

[95] N. W. A. Lidula, A. D. Rajapakse, J. P. Pham, and N. Denboer, “Prototype implementation of an islanding detection relay based on pattern classification of current and voltage transients,” *J. Natl. Sci. Found. Sri Lanka*, vol. 42, no. 1, pp. 03–15, 2014, doi: 10.4038/jnsfsr.v42i1.6675.

[96] D. F. Millie, G. R. Weckman, W. A. Young, J. E. Ivey, H. J. Carrick, and G. L. Fahnenstiel, “Modeling microalgal abundance with artificial neural networks: Demonstration of a heuristic ‘Grey-Box’ to deconvolve and quantify environmental influences,” *Environ. Model. Softw.*, vol. 38, pp. 27–39, 2012, doi: 10.1016/j.envsoft.2012.04.009.

[97] J. A. Laghari, H. Mokhlis, M. Karimi, A. H. A. Bakar, and H. Mohamad, “Computational Intelligence based techniques for islanding detection of distributed generation in distribution network: A review,” *Energy Convers. Manag.*, vol. 88, pp. 139–152, 2014, doi: 10.1016/j.enconman.2014.08.024.

[98] M. S. ElNozahy, E. F. El-Saadany, and M. M. A. Salama, “A robust wavelet-ANN based technique for islanding detection,” *IEEE Power Energy Soc. Gen. Meet.,* pp. 1–8, 2011, doi: 10.1109/PES.2011.6039158.

[99] K. H. Chao, C. L. Chiu, C. J. Li, and Y. C. Chang, “A novel neural network with simple learning algorithm for islanding phenomenon detection of photovoltaic systems,” *Expert Syst. Appl.,* vol. 38, no. 10, pp. 12107–12115, 2011, doi: 10.1016/j.eswa.2011.02.175.

[100] K. El-Arroudi, G. Joos, I. Kamwa, and D. T. McGillis, “Intelligent-based approach to islanding detection in distributed generation,” *IEEE Trans. Power Deliv.*, vol. 22, no. 2, pp. 828–835, 2007, doi: 10.1109/TPWRD.2007.893592.

[101] S. Dutta, P. K. Sadhu, M. Jaya Bharata Reddy, and D. K. Mohanta, “Shifting of research trends in islanding detection method - a comprehensive survey,” *Prot. Control Mod. Power Syst.,* vol. 3, no. 1, pp. 1–20, 2018, doi: 10.1186/s41601-017-0075-8.

[102] Özcanlı, Asiye Kaymaz, and Mustafa Baysal. "A novel Multi-LSTM based deep learning method for islanding detection in the microgrid." *Electric Power Systems Research* 202 (2022): 107574.

[103] M. S. Kim, R. Haider, G. J. Cho, C. H. Kim, C. Y. Won, and J. S. Chai, “Comprehensive review of islanding detection methods for distributed generation systems,” *Energies,* vol. 12, no. 5, pp. 1–21, 2019, doi: 10.3390/en12050837.

[104] H. Han, X. Hou, J. Yang, J. Wu, M. Su, and J. M. Guerrero, “Review of power sharing control strategies for islanding operation of AC microgrids,” *IEEE Trans. Smart Grid*, vol. 7, no. 1, pp. 200–215, 2016, doi: 10.1109/TSG.2015.2434849.

[105] R. Haider, C. H. Kim, T. Ghanbari, and S. B. A. Bukhari, “Harmonic-signature-based islanding detection in grid-connected distributed generation systems using Kalman filter,” *IET Renew. Power Gener.,* vol. 12, no. 15, pp. 1813–1822, 2018, doi: 10.1049/iet-rpg.2018.5381.

[106] S. K. G. Manikonda and D. N. Gaonkar, “Comprehensive review of IDMs in DG systems,” *IET Smart Grid,* vol. 2, no. 1, pp. 11–24, 2019, doi: 10.1049/iet-stg.2018.0096.

[107] G. Li, M. Zhou, Y. Luo, and Y. Ni, “Power quality disturbance detection based on mathematical morphology and fractal technique,” *Proc. IEEE Power Eng. Soc. Transm. Distrib. Conf.,* vol. 2005, pp. 1–6, 2005, doi: 10.1109/TDC.2005.1547030.

[108] A. Moeini, A. Darabi, S. M. R. Rafiei, and M. Karimi, “Intelligent islanding detection of a synchronous distributed generation using governor signal clustering,” *Electr. Power Syst. Res.,* vol. 81, no. 2, pp. 608–616, 2011, doi: 10.1016/j.epsr.2010.10.023.

[109] I. Kumarswamy, T. K. Sandipamu, and V. Prasanth, “Analysis of islanding detection in distributed generation using fuzzy logic technique,” *Proc. - Asia Model. Symp. 2013 7th Asia Int. Conf. Math. Model. Comput. Simulation, AMS* 2013, pp. 3–7, 2013, doi: 10.1109/AMS.2013.57.

[110] C. Rami Reddy and K. Harinadha Reddy, “Islanding detection techniques for grid integrated distributed generation -A review,” *Int. J. Renew. Energy Res.*, vol. 9, no. 2, 2019.

[111] R. L. Vasquez-Arnez, D. S. Ramos, and T. E. Del Carpio-Huayllas, “Microgrid dynamic response during the pre-planned and forced islanding processes involving DFIG and synchronous generators,” *Int. J. Electr. Power Energy Syst.*, vol. 62, pp. 175–182, 2014, doi: 10.1016/j.ijepes.2014.04.044.

[112] Wang, Jinan. "Power grid cascading failure blackouts analysis." In *AIP Conference Proceedings*, vol. 2066, no. 1, p. 020046. AIP Publishing LLC, 2019.

[113] H. Shao et al., “A three-stage procedure for controlled islanding to prevent wide-area blackouts,” *Energies,* vol. 11, no. 11, pp. 1–15, 2018, doi: 10.3390/en11113066.

[114] M. Mureddu, G. Caldarelli, A. Damiano, A. Scala, and H. Meyer-Ortmanns, “Islanding the power grid on the transmission level: Less connections for more security,” *Sci. Rep.,* vol. 6, pp. 1–11, 2016, doi: 10.1038/srep34797.

[115] D. A. Tian and G. Sansavini, “Impact of degraded communication on interdependent power systems: The application of grid splitting,” *Electron.*, vol. 5, no. 3, 2016, doi: 10.3390/electronics5030049.

[116] M. Goubko and V. Ginz, “Improved spectral clustering for multi-objective controlled islanding of power grid”, vol. 10, no. 1. *Springer Berlin Heidelberg*, 2019.

[117] M. R. Aghamohammadi and A. Shahmohammadi, “Intentional islanding using a new algorithm based on ant search mechanism,” *Int. J. Electr. Power Energy Syst.*, vol. 35, no. 1, pp. 138–147, 2012, doi: 10.1016/j.ijepes.2011.10.006.

[118] S. Pahwa, M. Youssef, P. Schumm, C. Scoglio, and N. Schulz, “Optimal intentional islanding to enhance the robustness of power grid networks,” *Phys. A Stat. Mech. its Appl.*, vol. 392, no. 17, pp. 3741–3754, 2013, doi: 10.1016/j.physa.2013.03.029.

[119] A. El-Zonkoly, M. Saad, and R. Khalil, “New algorithm based on CLPSO for controlled islanding of distribution systems,” *Int. J. Electr. Power Energy Syst.*, vol. 45, no. 1, pp. 391–403, 2013, doi: 10.1016/j.ijepes.2012.08.076.

[120] M. Golari, N. Fan, and J. Wang, “Two-stage stochastic optimal islanding operations under severe multiple contingencies in power grids,” *Electr. Power Syst. Res.,* vol. 114, pp. 68–77, 2014, doi: 10.1016/j.epsr.2014.04.007.

[121] P. A. Trodden, W. A. Bukhsh, A. Grothey, and K. I. M. McKinnon, “MILP formulation for controlled islanding of power networks,” *Int. J. Electr. Power Energy Syst.*, vol. 45, no. 1, pp. 501–508, 2013, doi: 10.1016/j.ijepes.2012.09.018.

[122] E. A. R. Theodoro, R. A. S. Benedito, J. B. A. London, and L. F. C. Alberto, "Algebraic-graph method for identification of islanding in power system grids," *Int. J. Electr. Power Energy Syst.,* vol. 35, no. 1, pp. 171–179, 2012, doi: 10.1016/j.ijepes.2011.10.010.

[123] Q. Zhao, K. Sun, D. Z. Zheng, J. Ma, and Q. Lu, "A Study of System Splitting Strategies for Island Operation of Power System: A Two-Phase Method Based on OBDDs," *IEEE Trans. Power Syst.,* vol. 18, no. 4, pp. 1556–1565, 2003, doi: 10.1109/TPWRS.2003.818747.

[124] N. W. A. Lidula and A. D. Rajapakse, "Microgrids research: A review of experimental microgrids and test systems," *Renew. Sustain. Energy Rev.*, vol. 15, no. 1, pp. 186–202, 2011, doi: 10.1016/j.rser.2010.09.041.

[125] F. De Mango, M. Liserre, A. Dell'Aquila, and A. Pigazo, "Overview of anti-islanding algorithms for PV systems. Part I: Passive methods," *EPE-PEMC 2006 12th Int. Power Electron. Motion Control Conf. Proc*., pp. 1878–1883, 2007, doi: 10.1109/EPEPEMC.2006.283133.

[126] T. S. Basso and R. DeBlasio, "IEEE 1547 series of standards: Interconnection issues," *IEEE Trans. Power Electron*., vol. 19, no. 5, pp. 1159–1162, 2004, doi: 10.1109/TPEL.2004.834000.

[127] H. Vahedi, R. Noroozian, A. Jalilvand, and G. B. Gharehpetian, "A new method for islanding detection of inverter-based distributed generation using DC-Link voltage control," *IEEE Trans. Power Deliv.*, vol. 26, no. 2, pp. 1176–1186, 2011, doi: 10.1109/TPWRD.2010.2093543.

[128] H. Jiayi, J. Chuanwen, and X. Rong, "A review on distributed energy resources and MicroGrid," *Renew. Sustain. Energy Rev.*, vol. 12, no. 9, pp. 2472–2483, 2008, doi: 10.1016/j.rser.2007.06.004.

[129] S. B. A. Bukhari, M. Saeed Uz Zaman, R. Haider, Y. S. Oh, and C. H. Kim, "A protection scheme for microgrid with multiple distributed generations using superimposed reactive energy," *Int. J. Electr. Power Energy Syst*., vol. 92, pp. 156–166, 2017, doi: 10.1016/j.ijepes.2017.05.003.

[130] IEEE Standard Association, IEEE Std. 1547-2018. Standard for Interconnection and Interoperability of Distributed Energy Resources with Associated Electric Power Systems Interfaces. 2018.

[131] R. M. Hudson, T. Thome, F. Mekanil, M. R. Behnke, and S. Gonzalez, "Implementation and testing of anti-islanding algorithms for IEEE 929-2000 compliance of single phase photovoltaic inverters," pp. 1414–1419, 2000.

[132] B. Eggertson, "Distributed resources," *Refocus*, vol. 5, no. 5, pp. 56–57, 2004, doi: 10.1016/S1471-0846(04)00227-6.

[133] H. H. Figueira, H. L. Hey, L. Schuch, C. Rech, and L. Michels, "Brazilian grid-connected photovoltaic inverters standards: A comparison with IEC and IEEE," *IEEE Int. Symp. Ind. Electron.*, vol. 2015-Septe, pp. 1104–1109, 2015, doi: 10.1109/ISIE.2015.7281626.

[134] Y. K. Wu, J. H. Lin, and H. J. Lin, "Standards and Guidelines for Grid-Connected Photovoltaic Generation Systems: A Review and Comparison," *IEEE Trans. Ind. Appl*., vol. 53, no. 4, pp. 3205–3216, 2017, doi: 10.1109/TIA.2017.2680409.

[135] S. Vyas, R. Kumar, and R. Kavasseri, "Data analytics and computational methods for anti-islanding of renewable energy based Distributed Generators in power grids," *Renew. Sustain. Energy Rev.*, vol. 69, no. July 2016, pp. 493–502, 2017, doi: 10.1016/j.rser.2016.11.116.

[136] N. W. A. Lidula and A. D. Rajapakse, "A pattern recognition approach for detecting power islands using transient signals - Part I: Design and implementation," *IEEE Trans. Power Deliv*., vol. 25, no. 4, pp. 3070–3077, 2010, doi: 10.1109/TPWRD.2010.2053724.

[137] N. W. A. Lidula and A. D. Rajapakse, "A pattern-recognition approach for detecting power islands using transient signals-part II: Performance evaluation," *IEEE Trans. Power Deliv.,* vol. 27, no. 3, pp. 1071–1080, 2012, doi: 10.1109/TPWRD.2012.2187344.

[138] M. Heidari, G. Seifossadat, and M. Razaz, "Application of decision tree and discrete wavelet transform for an optimized intelligent-based islanding detection method in distributed systems with distributed generations," *Renew. Sustain. Energy Rev.*, vol. 27, pp. 525–532, 2013, doi: 10.1016/j.rser.2013.06.047.

[139] B. Zhou et al., "Hybrid islanding detection method based on decision tree and positive feedback for distributed generations," *IET Gener. Transm. Distrib*., vol. 9, no. 14, pp. 1819–1825, 2015, doi: 10.1049/iet-gtd.2015.0069.

[140] S. Li, A. J. Rodolakis, K. El-Arroudi, and G. Joós, "Islanding protection of multiple distributed resources under adverse islanding conditions," *IET Gener. Transm. Distrib*., vol. 10, no. 8, pp. 1901–1912, 2016, doi: 10.1049/iet-gtd.2015.1105.

[141] R. Azim, F. Li, Y. Xue, M. Starke, and H. Wang, "An islanding detection methodology combining decision trees and Sandia frequency shift for inverter-based distributed generations," *IET Gener. Transm. Distrib.,* vol. 11, no. 16, pp. 4104–4113, 2017, doi: 10.1049/iet-gtd.2016.1617.

[142] Q. Cui, K. El-Arroudi, and G. Joós, "Real-time hardware-in-the-loop simulation for islanding detection schemes in hybrid distributed generation systems," *IET Gener. Transm. Distrib*., vol. 11, no. 12, pp. 3050–3056, 2017, doi: 10.1049/iet-gtd.2016.1562.

[143] S. Chandak, M. Mishra, and P. K. Rout, "Hybrid islanding detection with optimum feature selection and minimum NDZ," *Int. Trans. Electr. Energy Syst.*, vol. 28, no. 10, pp. 1–22, 2018, doi: 10.1002/etep.2602.

[144] Q. Cui, K. El-Arroudi, and G. Joos, "Islanding detection of hybrid distributed generation under reduced non-detection zone," *IEEE Trans. Smart Grid*, vol. 9, no. 5, pp. 5027–5037, 2018, doi: 10.1109/TSG.2017.2679101.

[145] V. L. Merlin, R. C. Santos, A. P. Grilo, J. C. M. Vieira, D. V. Coury, and M. Oleskovicz, "A new artificial neural network based method for islanding detection of distributed generators," *Int. J. Electr. Power Energy Syst.*, vol. 75, pp. 139–151, 2016, doi: 10.1016/j.ijepes.2015.08.016.

[146] S. Raza, H. Mokhlis, H. Arof, K. Naidu, J. A. Laghari, and A. S. M. Khairuddin, "Minimum-features-based ANN-PSO approach for islanding detection in distribution system," *IET Renew. Power Gener*., vol. 10, no. 9, pp. 1255–1263, 2016, doi: 10.1049/iet-rpg.2016.0080.

[147] M. Hashemi, F., & Mohammadi, "Islanding detection approach with negligible non-detection zone based on feature extraction discrete wavelet transform and artificial neural network," *Int. Trans. Electr. energy Syst.,* vol. 20, no. February, pp. 1–21, 2016, doi: 10.1002/etep.

[148] M. Mishra, M. Sahani, and P. K. Rout, "An islanding detection algorithm for distributed generation based on Hilbert–Huang transform and extreme learning machine," *Sustain. Energy, Grids Networks,* vol. 9, pp. 13–26, 2017, doi: 10.1016/j.segan.2016.11.002.

[149] S. Chandak, M. Mishra, S. Nayak, and P. K. Rout, "Optimal feature selection for islanding detection in distributed generation," *IET Smart Grid,* vol. 1, no. 3, pp. 85–95, 2018, doi: 10.1049/iet-stg.2018.0021.

[150] E. A. P. Gomes, J. C. M. Vieira, D. V. Coury, and A. C. B. Delbem, "Islanding detection of synchronous distributed generators using data mining complex correlations," *IET Gener. Transm. Distrib.*, vol. 12, no. 17, pp. 3935–3942, 2018, doi: 10.1049/iet-gtd.2017.1722.

[151] A. Khamis, Y. Xu, Z. Y. Dong, and R. Zhang, "Faster Detection of Microgrid Islanding Events Using an Adaptive Ensemble Classifier," *IEEE Trans. Smart Grid*, vol. 9, no. 3, pp. 1889–1899, 2018, doi: 10.1109/TSG.2016.2601656.

[152] O. N. Faqhruldin, E. F. El-Saadany, and H. H. Zeineldin, "A universal islanding detection technique for distributed generation using pattern recognition," *IEEE Trans. Smart Grid,* vol. 5, no. 4, pp. 1985–1992, 2014, doi: 10.1109/TSG.2014.2302439.

[153] M. Ahmadipour, H. Hizam, M. L. Othman, and M. A. Radzi, "Islanding detection method using ridgelet probabilistic neural network in distributed generation," *Neurocomputing*, vol. 329, pp. 188–209, 2019, doi: 10.1016/j.neucom.2018.10.053.

This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: DOI 10.1109/ACCESS.2021.3123382, IEEE Access

[154] A. Ezzat, B. E. Elnaghi, and A. A. Abdelsalam, "Microgrids islanding detection using Fourier transform and machine learning algorithm," *Electr. Power Syst. Res.,* vol. 196, no. April, 2021, doi: 10.1016/j.epsr.2021.107224.

[155] M. Mishra and P. K. Rout, "Loss of main detection in distribution generation system based on hybrid signal processing and machine learning technique," *Int. Trans. Electr. Energy Syst.*, vol. 29, no. 1, pp. 1–26, 2019, doi: 10.1002/etep.2676.

[156] S. Ananda Kumar et al., "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*, vol. 13, no. 6, 2020, doi: 10.3390/en13164238.

[157] VAPNIK and V. N., "The Nature of Statistical Learning," *Theory.* 1995, [Online]. Available: https://ci.nii.ac.jp/naid/10020951890.

[158] M. R. Alam, K. M. Muttaqi, and A. Bouzerdoum, "A multifeature-based approach for islanding detection of DG in the subcritical region of vector surge relays," *IEEE Trans. Power Deliv*., vol. 29, no. 5, pp. 2349–2358, 2014, doi: 10.1109/TPWRD.2014.2315839.

[159] S. R. Mohanty, N. Kishor, P. K. Ray, and J. P. S. Catalao, "Comparative study of advanced signal processing techniques for islanding detection in a hybrid distributed generation system," *IEEE Trans. Sustain. Energy*, vol. 6, no. 1, pp. 122–131, 2015, doi: 10.1109/TSTE.2014.2362797.

[160] Y. Wang, J. Ravishankar, and T. Phung, "Wavelet transform-based feature extraction for detection and classification of disturbances in an islanded micro-grid," *IET Gener. Transm. Distrib.,* vol. 13, no. 11, pp. 1989–1993, 2019, doi: 10.1049/iet-gtd.2018.5131.

[161] H. R. Baghaee, D. Mlakic, S. Nikolovski, and T. Dragicevic, "Support Vector Machine-Based Islanding and Grid Fault Detection in Active Distribution Networks," *IEEE J. Emerg. Sel. Top. Power Electron*., vol. 8, no. 3, pp. 2385–2403, 2020, doi: 10.1109/JESTPE.2019.2916621.

[162] L. A. Zadeh, "The Evolution of Systems Analysis and Control: A Personal Perspective," *IEEE Control Syst.,* vol. 16, no. 3, pp. 95–98, 1996, doi: 10.1109/37.506401.

[163] S. R. Samantaray, K. El-Arroudi, G. Joós, and I. Kamwa, "A fuzzy rule-based approach for islanding detection in distributed generation," *IEEE Trans. Power Deliv*., vol. 25, no. 3, pp. 1427–1433, 2010, doi: 10.1109/TPWRD.2010.2042625.

[164] P. K. Dash, M. Padhee, and T. K. Panigrahi, "A hybrid time-frequency approach based fuzzy logic system for power island detection in grid connected distributed generation," *Int. J. Electr. Power Energy Syst*., vol. 42, no. 1, pp. 453–464, 2012, doi: 10.1016/j.ijepes.2012.04.003.

[165] C. R. Aguiar, G. Fuzato, R. F. Bastos, A. F. Q. Gonçalves, and R. Q. Machado, "Hybrid fuzzy anti-islanding for grid-connected and islanding operation in distributed generation systems," *IET Power Electron.,* vol. 9, no. 3, pp. 512–518, 2016, doi: 10.1049/iet-pel.2014.0717.

[166] D. Karaboga and E. Kaya, "Adaptive network based fuzzy inference system (ANFIS) training approaches: a comprehensive survey," *Artif. Intell. Rev.,* vol. 52, no. 4, pp. 2263–2293, 2019, doi: 10.1007/s10462-017-9610-2.

[167] F. Hashemi, N. Ghadimi, and B. Sobhani, "Islanding detection for inverter-based DG coupled with using an adaptive neuro-fuzzy inference system," *Int. J. Electr. Power Energy Syst*., vol. 45, no. 1, pp. 443–455, 2013, doi: 10.1016/j.ijepes.2012.09.008.

[168] H. Bitaraf, M. Sheikholeslamzadeh, A. M. Ranjbar, and B. Mozafari, "Neuro-fuzzy islanding detection in distributed generation," *2012 IEEE Innov. Smart Grid Technol. - Asia, ISGT Asia*, pp. 1–5, 2012, doi: 10.1109/ISGT-Asia.2012.6303292.

[169] H. Shayeghi and B. Sobhani, "Zero NDZ assessment for anti-islanding protection using wavelet analysis and neuro-fuzzy system in inverter based distributed generation," *Energy Convers. Manag*., vol. 79, pp. 616–625, 2014, doi: 10.1016/j.enconman.2013.12.062.

[170] N. Ghadimi, "An adaptive neuro-fuzzy inference system for islanding detection in wind turbine as distributed generation," *Complexity*, vol. 21, no. 1, pp. 1–11, 2014, doi: 10.1002/cplx.

[171] D. Mlakic, H. R. Baghaee, and S. Nikolovski, "A Novel ANFIS-Based Islanding Detection for Inverter-Interfaced Microgrids," *IEEE Trans. Smart Grid,* vol. 10, no. 4, pp. 4411–4424, 2019, doi: 10.1109/TSG.2018.2859360.

[172] A. Mahmood et al., "Deep Learning for Coral Classification," *Handb. Neural Comput*., no. July, pp. 383–401, 2017, doi: 10.1016/B978-0-12-811318-9.00021-1.

[173] H. P. Chan, R. K. Samala, L. M. Hadjiiski, and C. Zhou, "Deep Learning in Medical Image Analysis," *Adv. Exp. Med. Biol*., vol. 1213, pp. 3–21, 2020, doi: 10.1007/978-3-030-33128-3_1.

[174] X. Kong, X. Xu, Z. Yan, S. Chen, H. Yang, and D. Han, "Deep learning hybrid method for islanding detection in distributed generation," *Appl. Energy,* vol. 210, no. August 2017, pp. 776–785, 2018, doi: 10.1016/j.apenergy.2017.08.014.

[175] S. K. G. Manikonda and D. N. Gaonkar, "IDM based on image classification with CNN," *J. Eng*., vol. 2019, no. 10, pp. 7256–7262, 2019, doi: 10.1049/joe.2019.0025.

[176] A. A. Abdelsalam, A. A. Salem, E. S. Oda, and A. A. Eldesouky, "Islanding Detection of Microgrid Incorporating Inverter Based DGs Using Long Short-Term Memory Network," *IEEE Access*, vol. 8, pp. 106471–106486, 2020, doi: 10.1109/ACCESS.2020.3000872.

[177] M. Z. Alom et al., "A state-of-the-art survey on deep learning theory and architectures," *Electron.,* vol. 8, no. 3, 2019, doi: 10.3390/electronics8030292.

[178] S. R. Safavian and D. Landgrebe, "A Survey of Decision Tree Classifier Methodology," *IEEE Trans. Syst. Man Cybern*., vol. 21, no. 3, pp. 660–674, 1991, doi: 10.1109/21.97458.

[179] L. E. Juarez-Orozco, O. Martinez-Manzanera, S. V. Nesterov, S. Kajander, and J. Knuuti, "The machine learning horizon in cardiac hybrid imaging," *Eur. J. Hybrid Imaging*, vol. 2, no. 1, 2018, doi: 10.1186/s41824-018-0033-3.

[180] Khamis, Aziah, H. Shareef, and M. Z. C. Wanik. "Pattern recognition of islanding detection using tt-transform." Journal of Asian Scientific Research 2, no. 11 (2012): 607.

[181] Mohanty, Soumya R., Nand Kishor, Prakash K. Ray, and João PS Catalão. "Islanding detection in a distributed generation based hybrid system using intelligent pattern recognition techniques." In 2012 3rd IEEE PES Innovative Smart Grid Technologies Europe (ISGT Europe), pp. 1-5. IEEE, 2012.

[182] H. Dash, M., & Liu, Feature selection for clustering in pacific-asia conference on knowledge discovery and data mining Springer, Berlin, Heidelberg, vol. 1317. 2000.

[183] E. R. Ziegel, The Elements of Statistical Learning, vol. 45, no. 3. 2003.

[184] R. E. Bellman, Adaptive control processes: a guided tour. 1961.

[185] R. Kohavi and G. H. John, "Wrappers for feature subset selection," *Artif. Intell*., vol. 97, no. 1–2, pp. 273–324, 1997, doi: 10.1016/s0004-3702(97)00043-x.

[186] R. M. Sánchez-Maroño, N., Alonso-Betanzos, A., & Calvo-Estévez, "A Wrapper Method for Feature Selection in Multiple Classes Datasets," *in International Work-Conference on Artificial Neural Networks*, 2009, vol. 5517 LNCS, no. PART 1, pp. 204–211, doi: 10.1007/978-3-642-02478-8_26.

[187] M. Sánchez-Maroño, N., Alonso-Betanzos, A., & Tombilla-Sanromán, "Filter methods for feature selection–a comparative study," *in International Conference on Intelligent Data Engineering and Automated Learning*, 2007, vol. 5005 LNCS.

[188] A. Lal, T. N., Chapelle, O., Weston, J., & Elisseeff, "Embedded methods, In Feature extraction," 2006, vol. 4, no. 1, pp. 137–165.

[189] S. Raza, H. Mokhlis, H. Arof, J. A. Laghari, and H. Mohamad, "A Sensitivity Analysis of Different Power System Parameters on Islanding Detection," *IEEE Trans. Sustain. Energy*, vol. 7, no. 2, pp. 461–470, 2016, doi: 10.1109/TSTE.2015.2499781.

[190] T. Rabuzin, F. Hohn, and L. Nordström, "Computation of sensitivity-based islanding detection parameters for synchronous generators," *Electr. Power Syst. Res*., vol. 190, no. July 2020, p. 106611, 2021, doi: 10.1016/j.epsr.2020.106611.

[191] H. R. Baghaee, D. Mlakic, S. Nikolovski, and T. Dragicevic, "Anti-Islanding Protection of PV-Based Microgrids Consisting of PHEVs Using SVMs," *IEEE Trans. Smart Grid*, vol. 11, no. 1, pp. 483–500, 2020, doi: 10.1109/TSG.2019.2924290.

[192] T. Chakravorti, R. K. Patnaik, and P. K. Dash, "Detection and classification of islanding and power quality disturbances in microgrid using hybrid signal processing and data mining techniques," *IET Signal Process.,* vol. 12, no. 1, pp. 82–94, 2018, doi: 10.1049/iet-spr.2016.0352.

ARIF HUSSAIN completed his BS in electrical engineering in 2014 and MS degree from the National University of Science and Technology (NUST) Pakistan in the field of electrical (power) engineering in 2019. Recently, he is enrolled in the electrical and electronics department of SKKU, Korea for his Ph.D. studies, and the area of research is on Islanding detection in hybrid AC/DC systems and power system protection of microgrids.

CHUL-HWAN KIM received the B.S., M.S., and Ph.D. degrees in electrical engineering from Sungkyunkwan University, Suwon, Korea, in 1982, 1984, and 1990, respectively. In 1990, he joined Jeju National University, Jeju, Korea, as a Full- Time Lecturer. He was a Visiting Academic with the University of Bath, Bath, U.K., in 1996, 1998, and 1999. He has been a Professor at the College of Information and Communication Engineering, Sungkyunkwan University, since 1992, where he is currently the Director of the Center for Power Information Technology. His current research interests include power system protection, artificial intelligence applications for protection and control, modeling, and protection of microgrid and DC systems.

ARIF MEHDI received a B.S degree in Electrical Engineering from Comsats University Islamabad, Abbottabad Campus, Pakistan, in 2016. At present, he is enrolled in the combined master and doctorate programs at Sungkyunkwan University. His research interests include power system protection, islanding detection, hosting capacity, auto-reclosing schemes in AC, DC, and Hybrid transmission lines, and artificial intelligence applications for the power system.