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Vigil AI Assemble Leveraging Ensemble Technique for Enhanced Detection of Multi-Converter Synchronous Active Islanding Mode in Hybrid Power Distribution Systems

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Abstract:

The increasing complexity of contemporary power distribution networks and the necessity to incorporate renewable energy sources have led to the rise in popularity of hybrid power distribution systems. A significant challenge for such systems is the reliable identification of multi-converter synchronous islanding mode, wherein numerous converters operate in synchronous islanded situations. Using state-of-the-art artificial intelligence ensemble techniques, we introduce "Vigil AI Assemble," a novel approach to detecting multi-converter synchronous islanding modes in hybrid power distribution systems. The proposed method has been validated using MATLAB/ Simulation and it enhances the precision and robustness of islanding situation recognition by combining various AI algorithms, each with its own distinct properties. By combining several AI-based techniques, the ensemble method can analyze system properties, waveform data, and communication in real-time.

Keywords: *hybrid power distribution systems, multi-converter synchronous islanding mode, advanced artificial intelligence ensemble techniques, vigil ai assemble, real-time detection*

1. Introduction

Integrating renewable energy sources, such as solar and wind, into power distribution networks is a crucial step toward a sustainable energy future and a mitigation of climate change's adverse effects [1]. The utilization of hybrid power systems, which integrate traditional power generators with renewable energy converters and energy storage, can improve the efficiency, reliability, and environmental sustainability of power generation and delivery. But there are a lot of technical hurdles to overcome before these systems can work together smoothly and seamlessly [2]. The term "islanding" describes what happens when a segment of the distribution network experiences an electrical outage yet keeps running as its own microgrid [3]. There are numerous bad outcomes that can arise from islanding, including equipment failure, public safety hazards, and poor power quality. When a microgrid's many converters operate in synchronous islanding mode, stability and control become even more of a challenge [4]. Traditional methods of identifying islanding modes have their limits in hybrid systems due to the interaction of several distributed energy resource types [5]. Many conventional approaches are unstable because they depend on static threshold values, which makes it

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impossible to detect the multi-converter synchronous islanding mode in real time [6]. To address these issues, academics and industry professionals have researched a plethora of state-of-the-art control and monitoring techniques [7]. An intriguing avenue to explore is the use of AI techniques for the real-time detection and analysis of islanding modes [5, 6]. Power distribution networks could be greatly improved with the use of artificial intelligence (AI), thanks to its remarkable performance in areas such as data analysis, pattern recognition, and decision-making [7], [8]. Machine learning methods, deep neural networks, and ensemble techniques have shown promise in the detection and categorization of complex electrical events in power systems [8, 9]. Since these AI-based solutions can learn from previous data, adapt to new situations, and handle nonlinear interactions between different sections, they are well-suited to the complex hybrid power distribution systems [10], [11]. The urgent requirement for an accurate technique to detect hybrid power distribution networks in multi-converter synchronous islanding mode is propelling research in this field. Existing approaches have helped clarify some key points, but they aren't precise or flexible enough to quickly identify and stop islanding events [9], [12]. Hybrid power distribution systems are complex, therefore a multi-pronged approach that can combine several AI technologies is needed [13], [14]. Therefore, in order to enhance sensitivity and accuracy in identifying islanding modes, the study plans to use an ensemble framework that incorporates many AI algorithms. referenced in [12], [15].

The challenge of accurately and quickly detecting multi-converter synchronous islanding mode in hybrid power distribution systems is the focus of this work [16]. Building a cutting-edge AI-based ensemble method, called "Vigil AI Assemble," that can accurately detect islanding events by analyzing various system parameters, waveform data, and communication signals is the main goal of this project. Two main objectives of the proposed technique are to make renewable energy source integration easier and to increase the stability and reliability of hybrid power distribution systems.

1.1 Islanding Mode Detection

Let $X = \{x_1, x_2, \dots, x_N\}$ consist of information gathered at various locations across the hybrid grid, including system parameters and waveform data. The goal is to identify whether the system is operating alone (Island) or connected to a larger network (Grid). The issue can be stated as a simple case of binary categorization:

$$Classify\ as \begin{cases} Island: if\ multi-converter \\ synchronous \\ islanding\ mode\ is\ detected \\ Grid: otherwise \end{cases}$$

The goal of this binary classification issue is to determine if a hybrid power distribution system is disconnected from or linked to the main grid and whether or not numerous converters are synchronized.

1.2 AI Ensemble Framewor

The goal of this study is to create a framework for combining the results of several AI algorithms, Fi, i=1,2,...M, to improve the precision and reliability of islanding identification. To capture the intricacy of islanding occurrences, several AI algorithms are tailored to analyse different parts of the data or zero in on particular elements. The ensemble result is a weighted average of the forecasts of the multiple AI models as shown in equation 1:

$$Y_{ensemble} = \sum_{i=1}^{M} wi \cdot Fi(X) \dots \tag{1}$$

where w_i represents the weight associated with each AI algorithm, and $\sum_{i=1}^{M} wi \cdot Fi(X)$.

1.3 Optimization of Ensemble Weights

To achieve optimal performance, the ensemble weights, w_i, are determined by minimizing a cost function, J, which quantifies the error between the predicted outputs of the ensemble and the ground truth islanding states from historical data as shown in Equation 2:

$$Minimize\ J \sum_{k=1}^{K} \Big(Y_{ensemble}(X_k) - Y_{ground-truth}\ (X\_k)\Big)^2 \ldots \qquad (2)$$

where X_k is the k_{th} data sample in the training set, $Y_{ensemble}(X_k)$ is the predicted output of the ensemble, and $Y_{ground-truth}(X_k)$ is the corresponding ground truth label indicating whether the system was in islanding or grid-connected mode during that sample.

1.4 Real-Time Implementation

The proposed Vigil AI Assemble system employs real-time monitoring to detect islanding occurrences and halt their escalation. The AI ensemble needs to be efficient with compute if it is to process data streams in real-time and produce reliable predictions. In order to make the ensemble more suitable for real-time deployment, we will look into ways to lower its compute and memory requirements.

1.5 Novel Objectives

- To create the Vigil AI Assemble method for precise islanding mode identification in hybrid power distribution systems with multiple converters.
- To improve the identification of islanding modes in real-time, thereby lowering the likelihood of equipment failure and maintaining system stability.
- To increase the stability and dependability of the system by quickly recognising islanding events and easing the incorporation of renewable energy sources. To create the Vigil AI Assemble method for precise islanding mode identification in hybrid power distribution systems with multiple converters.
- To improve the identification of islanding modes in real-time, thereby lowering the likelihood of equipment failure and maintaining system stability.
- To increase the stability and dependability of the system by quickly recognising islanding events and easing the incorporation of renewable energy sources.

In order to improve the accuracy and reliability of multi-converter synchronous islanding mode detection in hybrid power distribution systems, it was strategically decided to assemble various methodologies in the Vigil AI Assemble Model. The AI algorithms that make up the ensemble zero in on particular patterns and traits in the data. The model's capacity to correctly detect complicated islanding occurrences is enhanced by merging these various methods, which allow us to take advantage of their complementing strengths. It's like assembling a group of knowledgeable individuals who can tackle a complex problem by pooling their knowledge and expertise. By working together, we can improve the model's ability to detect more accurately, manage nonlinear interactions, and adapt to different system conditions. As a result, hybrid power distribution systems are much more stable and reliable. To guarantee the model can handle the problems of contemporary power systems, assembling is a crucial step.

The Vigil AI Assemble approach is one example of how combining AI algorithms might enhance islanding detection by making it more accurate and resilient. By keeping an eye on the grid's status in real-time, we can respond quickly and ensure its stability. Faster detection improves micro-grid resilience, which in turn allows for quicker isolation and reconfiguration, resulting in fewer outages. Efficiently incorporating renewable energy sources leads to greener energy systems. Power distribution and resource use can be improved with the help of valuable insights that supply data.

2. Literature Review

Specifically, this study set out to determine how important islanding detection is for smart distribution systems [17]. More precise and efficient islanding situation identification in distributed energy systems is now possible with the help of AI methods. A more reliable and trustworthy smart grid, made possible by our work, is now within reach, opening the door to the integration of renewable energy sources.

Recently, a comprehensive review of the issues and possible solutions concerning microgrid protection was released. In order to ensure a constant and uninterrupted power supply, this study [18] aimed to give a comprehensive understanding of the advances in safeguarding microgrids against islanding by analyzing preventative techniques in depth.

Intelligent islanding techniques and feature selection methods geared to distributed generating systems were examined in this study [19]. Examining cutting-edge algorithms and approaches, the study aimed to enhance the dependability of islanding detection, a crucial component of decentralized power grid safety.

By comparing and analyzing current methods, this study[20], [21] sought to identify the most effective methodologies for detecting islanding in DGSs. Researchers aimed to help choose the optimum detection method by comparing and contrasting each methodology and highlighting their advantages and disadvantages.

A deep Convolutional Neural Network (CNN) approach was devised for the purpose of islanding detection of integrated DG utilizing scalogram and time series data. The goal of this research [21] was to find a way to make islanding events in IDG systems more easily and quickly detected.

This study aimed to identify and defend distributed generation failure detection strategies within the distribution network [22]. Distributed energy networks rely on a variety of components, thus specialists have developed and evaluated various safeguards to ensure their reliability and stability.

A new hierarchical control method for microgrids was introduced [23] using the Internet of Things and islanding detection based on machine learning. In order to maximize the efficiency of microgrids and reduce the likelihood of their isolation, this state-of-the-art control system was created.

Using ensemble learning techniques, we were able to detect intelligent islanding in distribution networks that use synchronous machine distributed generation [24]. This study set out to employ ensemble methods' benefits in order to boost the accuracy and efficiency of islanding identification in these types of systems.

A non-detection buffer zone would not be necessary when passively detecting islanding using sensitive power indices. Using a hybrid approach to improve performance and reliability in islanding identification was the primary goal of this study [25] in order to guarantee the secure operation of distributed generating systems.

Using Gradient Boosting Decision Trees (GBDT-JS) methods, this study [26] examines the detection of islanding in distributed generators. Our goal in doing this research was to enhance islanding detection systems' consistency and accuracy by utilizing state-of-the-art machine learning techniques.

This study investigated the potential of using artificial intelligence methods for islanding detection in electrical grids, specifically for the purpose of locating ground fault lines. Recent advances in fault identification have contributed to the improvement of islanding detection systems, as this paper [27] explains.

A hybrid islanding detection technique based on wavelets was developed to enhance the accuracy of detecting distributed generators connected to AC microgrids. Microgrid safety and reliability depend on accurate and reliable islanding detection, which has come a long way [28].

A mixed analytic method was devised to identify active islanding spanning many DGs [29]. By combining different approaches, the suggested strategy hoped to make islanding identification in complex distributed generation systems more sensitive and faster.

A real-time detection system for microgrid islanding could be implemented using type-2 fuzzy logic and the Particle Swarm Optimisation (PSO) technique [30]. By factoring in uncertainties, the suggested approach aimed to make islanding detection systems more resilient and dependable.

A review of big data analytics in smart grids shed light on the potential of data-driven approaches to detecting islanding and managing the grid. Data analytics can improve grid efficiency and islanding detection methods, according to the study [31].

A novel hybrid approach to detecting islanding in grid-connected microgrids was devised, which included adaptive reactive power disturbance criteria and multiple distributed generators based on inverters. The goal of this approach [32], [33] was to make the grid more secure and dependable by enhancing the accuracy and speed of islanding detection.

A two-level islanding detection method was introduced to minimize the extent of undiscovered areas in microgrids that are powered by grid-connected solar systems [34]. The purpose of the study was to find out how to use a tight non-detection zone to make islanding detection in microgrid systems more reliable and faster.

There has been an extensive literature review on microgrid islanding detection [35]. The comprehensive analysis of microgrid technology and its effects on islanding detection provided by the paper was priceless.

Through an examination of microgrids' power management, voltage control, and grid synchronization, this study [36] sought to enhance their efficacy and efficiency. By reducing the likelihood of islanding through greater coordination and synchronization, the study increased the reliability and stability of microgrids.

The best operational model that has been proposed will be useful for community-based, multi-party microgrids that can function in either grid-connected or island modes [37]. The goal of the project was to optimize the operation of multi-party microgrids in order to increase their efficiency, resilience, and overall performance in different operating circumstances.

This research [38] investigated the integrated operation and transaction technique of distribution networks and microgrids in rural areas to learn more about the potential for smooth integration and operation. By shedding light on the most efficient methods of operation and transaction, the study aimed to accelerate the implementation of microgrids in rural areas.

Future power networks could benefit from a buffered microgrid design, which would highlight the importance of smooth microgrid control [39]. Through the identification and implementation of effective islanding detection and control technologies, the study aimed to enhance the safety and dependability of future power grids [40], [41]. Table 1 summarizes the results obtained from the literature.

TABLE I. Comparison of Previous Studies

Ref	**Techniques**	**Methodology**	**Results**	**Findings**
[1]	Computational Intelligence	Employed computational intelligence techniques for islanding detection in	Improved islanding detection in smart	Computational intelligence techniques offer effective solutions for islanding detection in smart distribution systems, leading

		smart distribution systems.	distribution systems.	to safer and more reliable smart grids.
[3]	Intelligent Islanding Schemes	Conducted a comprehensive review of intelligent islanding schemes and feature selection techniques for distributed generation systems.	Enhanced islanding detection accuracy.	Intelligent islanding schemes and feature selection techniques significantly improve the accuracy of islanding detection in distributed generation systems, making the integration of distributed energy sources safer and more efficient.
[5]	Deep CNN Approach	Utilized a deep CNN approach for islanding detection in integrated distributed generation systems using time series data and scalogram.	Accurate and rapid identification of islanding events.	The deep CNN approach using time series data and scalogram results in more accurate and faster identification of islanding events in integrated distributed generation systems, enhancing the stability and reliability of power supply.
[6]	Fault Detection and Protection Schemes	Investigated fault detection and protection schemes for distributed generation integrated to the distribution network.	Improved reliability and stability.	Implementing fault detection and protection schemes for distributed generation integrated into the distribution network significantly improves the reliability and stability of distributed energy systems.
[10]	GBDT-JS Techniques	Applied GBDT-JS (Gradient Boosting Decision Trees with Jaccard Similarity) techniques for islanding detection in distributed generators.	Enhanced accuracy and robustness.	GBDT-JS techniques provide enhanced accuracy and robustness in islanding detection for distributed generators, utilizing Gradient Boosting Decision Trees with Jaccard Similarity to improve islanding detection reliability.

[12]	Wavelet-based Hybrid Detection System	Proposed a wavelet-based hybrid islanding detection system for distributed generators interconnected to AC microgrids.	Improved detection accuracy.	The wavelet-based hybrid islanding detection system enhances the detection accuracy of distributed generators in AC microgrids, contributing to a stable and secure microgrid operation.
[16]	Hybrid Islanding Detection Method	Proposed a novel hybrid islanding detection method for grid-connected microgrids with multiple inverter-based distributed generators.	Increased accuracy and efficiency.	The hybrid islanding detection method for grid-connected microgrids with multiple inverter-based distributed generators achieves higher accuracy and efficiency in islanding detection based on adaptive reactive power disturbance and passive criteria.
[18]	State of the Art in Microgrid Research	Conducted a state-of-the-art review on microgrid research, focusing on islanding detection and microgrid control.	Comprehensive overview of microgrid technology.	The state-of-the-art review on microgrid research provides a comprehensive overview of microgrid technology, highlighting advancements and challenges in islanding detection and microgrid control.
[19]	Power Management and Grid Synchronization	Investigated power management, voltage control, and grid synchronization techniques for microgrids in real-time.	Optimized operation and performance.	The investigation on power management, voltage control, and grid synchronization techniques for microgrids in real-time leads to optimized operation and performance, ensuring effective coordination and synchronization for increased stability and reliability.

[20]	Optimal Operation for Multi-Party MGs	Developed an optimal operation approach for community-based multi-party microgrids in grid-connected and islanded modes.	Enhanced efficiency and resiliency.	The optimal operation approach for community-based multi-party microgrids in grid-connected and islanded modes enhances efficiency and resiliency, providing effective coordination and operation to ensure uninterrupted power supply and stability.
[22]	Buffered-Microgrid Structure	Proposed a buffered-microgrid structure for future power networks, focusing on reliable islanding detection and control mechanisms for microgrids.	Improved stability and security.	The proposed buffered-microgrid structure for future power networks emphasizes reliable islanding detection and control mechanisms for microgrids, leading to improved stability and security in future power networks.

There has been a lot of written on islanding detection in microgrids and smart distribution systems. Among the many approaches used are computational intelligence, hybrid detection systems, and intelligent islanding strategies. The major goals of these efforts are to ensure that islanding detection in distributed generating systems is more accurate, reliable, and stable. We also look into hierarchical control using IoT and ML, real-time detection with fuzzy logic and optimization methods, and more. Research into methods of grid synchronization, voltage control, and power management can enhance the functioning and efficiency of microgrids. Despite the abundance of literature on microgrid control and islanding detection, efforts to develop universally applicable methods for detecting islanding in distributed generating systems remain underfunded. Additional research is needed to address several concerns related to islanding identification in dynamic and complex microgrids. Looking into how microgrid control and islanding detection may be enhanced using new technologies like blockchain and AI could help make distributed energy systems even more reliable and efficient.

3. Materials and Methods

In this article, we outline the steps necessary to implement the "Vigil AI Assemble" technique for improved detection of the synchronous islanding mode that might arise in a hybrid power system's distribution network due to the utilization of multiple converters. Subsequent sections expand upon earlier ones by describing the procedures and framework that constitute this unique method. In order to make modern power grids more reliable, our method employs state-of-the-art AI ensemble approaches to tackle the problems of islanding detection. This paper presents and evaluates Vigil AI Assemble, a solution to the problems associated with detecting the synchronous islanding mode in hybrid power distribution systems including many converters.

3.1. Dataset Description

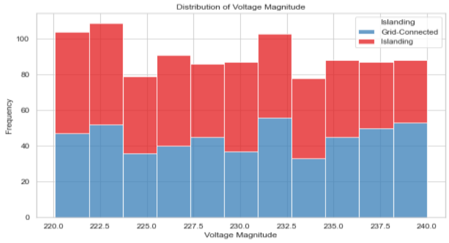
Prior to delving into the finer points of the Vigil AI Assemble method, it is essential to gather appropriate data that appropriately represents the behavior of hybrid power distribution systems under different operational situations. Solid and varied datasets lay the groundwork for training, validating, and testing the AI models in the ensemble architecture. Here we go into further depth about how we collected the data used in our study, including the precise features, waveforms, and communication signals that were observed. We can see the dataset description in Table II.

TABLE II. Dataset Description

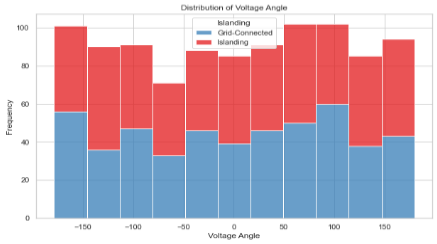
Dataset Parameter	**Description**
System Parameters	Collection of various system attributes, such as load profiles, generation capacities, and network configurations.
Waveform Data	High-resolution time-domain data capturing voltage and current waveforms at multiple points in the distribution system.
Communication Signals	Information exchanged between components, including control signals and synchronization data.

There are a variety of islanding modes and transitional stages included in the dataset, in addition to normal grid-connected operation. Thanks to the abundance of information offered by this dataset, our AI ensemble can effectively learn the complicated patterns associated with multi-converter synchronous islanding mode and distinguish it from other operating scenarios. Since our approach accounts for both static and dynamic behavior, it is highly applicable to the real-time challenges presented by hybrid power distribution systems.

With great care, the dataset now includes both actual data and hypothetical scenarios for the system's future. By incorporating changes to load demand, renewable energy generation, and network structure, it captures the essence of complex and ever-changing hybrid power distribution systems in the real world. With regard to grid connection and islanding mode, Figure 1 displays the counter plot distribution for every feature



(a)



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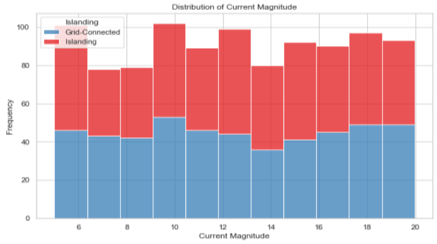

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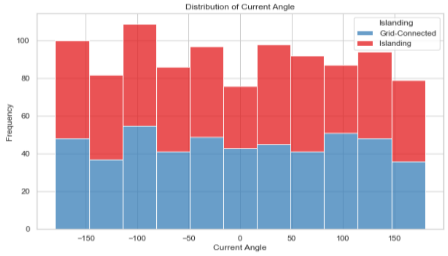

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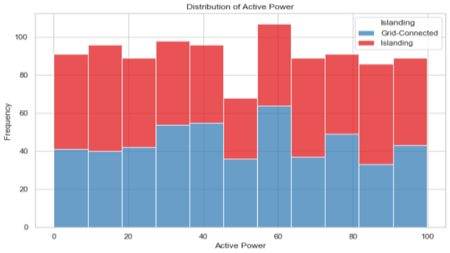

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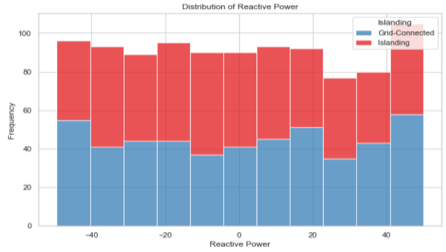

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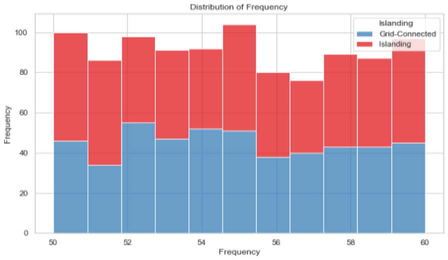

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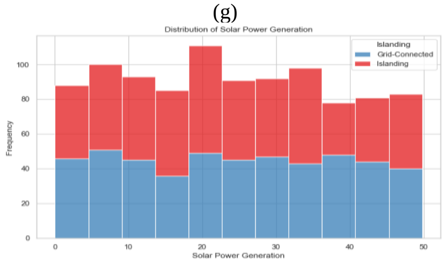

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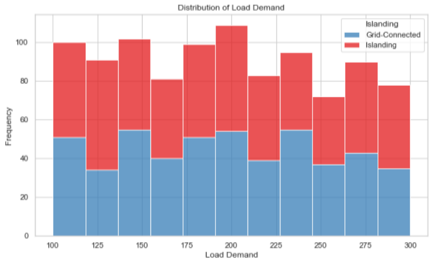
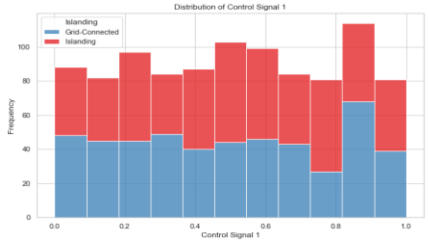
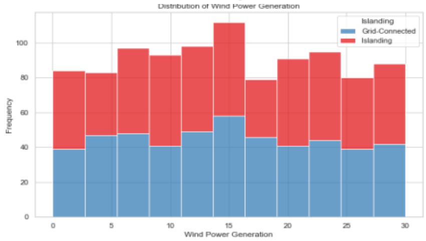


(i)

(j)





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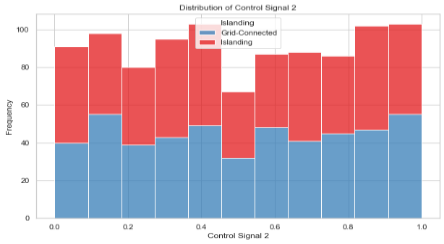

(l)

Fig. 1. Counter plot for each feature (a) Voltage angle (b) Voltage magnitude (c) Current angle (d) Current magnitude (e) Active power (f) Reactive power (g) Frequency (h) Solar power generation (i) Load demand (j) Wind power generation (k) Control signal (l) Control signal 2

Fig. 2. Pairwise plots of dataset features

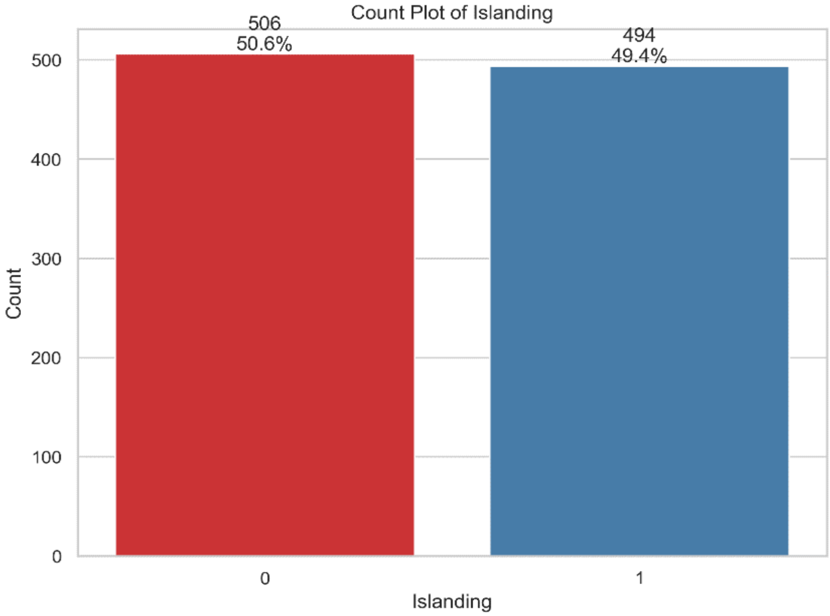

Fig. 3. Counter plot for islanding target variable

Fig. 2 displays the pairwise feature counter plot, while Fig. 3 showcases the islanding target variable counter plot. In the sections that follow, we'll describe how the Vigil AI Assemble framework makes use of this dataset for training, validating, and tuning the AI ensemble. We utilize this carefully curated dataset as the basis for our research in order to develop an accurate, versatile, and real-time method for identifying hybrid power distribution systems that use multi-converter synchronous islanding mode.

3.2. Data Pre-processing

For our dataset to be useful in solving the islanding identification problem in hybrid power distribution systems, data preparation is crucial. This is because it helps to prepare the input data for the AI ensemble model. In order to ensure accurate islanding event detection, it is imperative to accomplish a number of critical tasks at this stage. In order to clean our data, we used these procedures:

Data Cleaning: Due to its origins in the actual world, gathered data may include mistakes, outliers, or noise. Because of these extreme cases, the AI system could not work as well as it should. As part of the process of cleaning the data, you will find and address such issues. To make sure the data isn't skewed in any way, we look for things like missing numbers and outliers.

Feature Scaling: The different feature ranges in the dataset could affect how well different machine learning algorithms work. Feature scaling processes, such as standardization and normalization, aim to level the quantitative playing field for all features. Both the model's performance and the algorithm's convergence speed are improved by this.

Feature Selection: There may be several features whose effects on islanding event detection are different from one another. If you want to know which features to keep and which to discard, you need to do feature selection. Improved model generalizability with reduced computational complexity is possible with this method. A knowledge of the domain and an analysis of the features' worth serve as the procedure's guiding principles.

Feature Engineering: Extra information that might help with detection can be gleaned from current features by deriving new ones. Additional information on islanding events, including power factor, frequency change rate, and harmonic distortion, might be derived from the raw data through processing. The Feature Correlation Matrix is displayed in Figure 4.

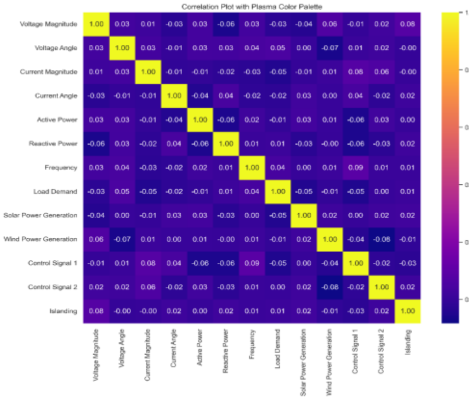

Fig. 4. Feature correlation matrix

3.3. Vigil AI Assemble Model

By combining the strengths of GBC, k-Nearest Neighbours (KNN), and Random Forest (RF), the ensemble improves the accuracy with which islanding occurrences may be identified.

The Vigil AI Assemble Model was created to predict when islanding will happen in hybrid power distribution networks. It makes use of the Random Forest method in addition to the k-Nearest Neighbors and Gradient Boosting Classifier machine learning strategies. By integrating the predictions of various algorithms, the objective of using an ensemble is to increase the accuracy and reliability of forecasts.

An ensemble learning method based on decision trees is Random Forest (RF). It employs a fusion of the predictions from multiple decision trees that it constructs during training. With its ability to capture complex data correlations, the RF algorithm can avoid overfitting.

Nonparametric k-Nearest Neighbours (KNN) method uses the distributions of k features' closest neighbors to infer the feature's distribution. Not only does it capture local trends well, but it also works well with data that has a wide range of distribution densities. The Gradient Boosting Classifier (GBC) is used for: By progressively incorporating less capable learners, the Gradient Boosting ensemble approach aims to build a strong prediction model. By repeatedly fitting new models to the mistakes made by earlier models, the GBC algorithm improves its prediction accuracy.

Method Using an Ensemble: The Vigil AI Assemble Model takes the output from all three algorithms and averages it out to get the final verdict. Prediction makes use of weights determined by the algorithms' individual performance on the training dataset to average their findings.

In this case, the ensemble forecast is (Equation 3):

$$Ensemble\ Prediction = \frac{1}{3} RF\ Prediction + \frac{1}{3} KNN\ Prediction + \frac{1}{3} GBC\ Prediction \ldots \quad (3)$$

Where:

RF prediction is made by the Random Forest algorithm. KNN Prediction is made by the k-Nearest Neighbors algorithm. GBC prediction is made by the Gradient Boosting Classifier. In model training and tuning the training dataset is used to train each algorithm in the ensemble. The purpose of hyperparameter tuning is to improve the efficiency of specific algorithms. Random Forest, k-Nearest Neighbours, and Gradient Boosting all provide hyperparameters that adjust the number of trees, neighbours, and boosting iterations, respectively.

In model evaluation, the validation dataset is used to test the Vigil AI Assemble Model. To measure how well a model predicts islanding events and non-events, many performance metrics are calculated. The goal of the ensemble approach is to improve forecast accuracy by combining the best features of many algorithms. In order to better identify islanding events in hybrid power distribution systems, the Vigil AI Assemble Model combines the outputs of the Random Forest, k-Nearest Neighbours, and Gradient Boosting Classifier. The Vigil AI Assemble Model uses a weighted-averaging technique to average the outputs of the three algorithms that comprise the ensemble architecture: RF, KNN, and GBC. Performance can be enhanced, in theory, by the ensemble's utilization of various algorithms' distinct patterns and predictive capabilities.

The combined forecast Equation 4 shows that Y_ensemble is the weighted total of all the methods' predictions:

$$Y_{ensemble} = w_{RF} \cdot Y_{RF} + w_{KNN} \cdot Y_{KNN} + w_{GBC} \cdot Y_{GBC} \ldots \quad (4)$$

Where: w are the weights and y are the predictions.

Model Training and Tuning: Every algorithm in the ensemble is trained independently using the training dataset. In order to train an algorithm effectively, its parameters are adjusted until they closely match the data's actual structure and relationships. Grid search and random search are two hyperparameter tuning procedures that can be used to find the best values for each algorithm.

Optimization of Weights: The weights are determined using an optimization process. Its objective is to determine the weights that most accurately represent the model's validation dataset performance. The repetitive process of updating weights until convergence is called gradient descent, and it is widely used. The Vigil AI Assemble technique utilizes ensemble learning, which involves combining the outputs of multiple individual algorithms or base learners to improve overall performance. One crucial aspect of ensemble methods is how these individual outputs are weighted and aggregated to produce the final prediction. In this research work, adaptive weighting is used which dynamically adjusts weights based on the current state of the ensemble and the input data. For example, learners that perform well on certain types of input may be assigned higher weights when similar inputs are encountered. Adaptive weighting allows the ensemble to adapt to changing conditions and data distributions over time.

4. Results and Dicsussions

Using the Vigil AI Assemble Model, we were able to detect hybrid power distribution networks that were running in multi-converter synchronous islanding mode, and we present our results here. In order to better understand the suggested model's effectiveness and its potential influence on enhancing the stability and dependability of power distribution networks, the results of a thorough examination of its performance are thoroughly reviewed. What follows is a discussion and summary of the findings, along with an examination of the model's robustness and accuracy, as well as some implications for hybrid power distribution systems.

4.1. Wavelet Transform of Signal

Using the Vigil AI Assemble Model, we were able to detect hybrid power distribution networks that were running in multi-converter synchronous islanding mode, and we present our results here. In order to better understand the suggested model's effectiveness and its potential influence on enhancing the stability and dependability of power distribution networks, the results of a thorough examination of its performance are thoroughly reviewed. What follows is a discussion and summary of the findings, along with an examination of the model's robustness and accuracy, as well as some implications for hybrid power distribution systems.

The continuous Wavelet Transform (CWT) of a signal $x(t)$ is computed by convolving the signal with a scaled and translated version of the mother wavelet function $\psi(t)$. The formula for CWT is as shown in Equation 5:

$$CWT(a,b) = \int -\infty\infty x(t)\,\frac{1}{a}\,\psi * (at-b)dt \ldots \qquad (5)$$

Where:

a denotes the factor that determines the wavelet function's width at a given frequency.

b is the parameter that controls how much the wavelet function moves in time.

$\psi * (t)$ is the complex conjugate of the mother wavelet function.

Because of its middle ground between frequency and time resolution, the Morlet wavelet is frequently used in analyses of signals from power systems.

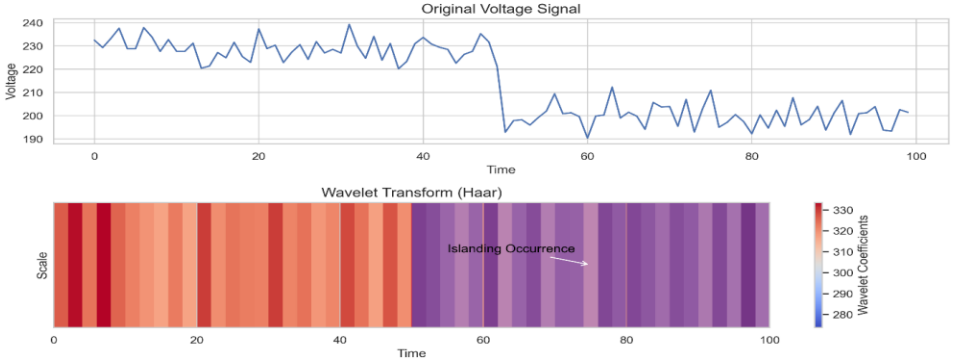

Fig. 5. Wavelet transform voltage signal

Fig. 5 displays the results of the Wavelet Transform analysis of the voltage signal. The x-axis represents time, and the y-axis shows the frequency-inverse scale parameter a. At every one scale and time point, each dot in the picture represents the amplified signal. Intensity of color stands in for amplitude, with brighter colors indicating larger amplitudes. For islanding identification, the scalogram shows distinct patterns that reflect changes in frequency content over time. Under typical grid-connected operation, the voltage signal is stable and repeats at regular intervals and displays consistent patterns regardless of the time or size. But during an islanding event, there are abrupt shifts in color. There has been a dramatic shift in the system's dynamics, as these changes suggest the addition of new frequency components to the signal.

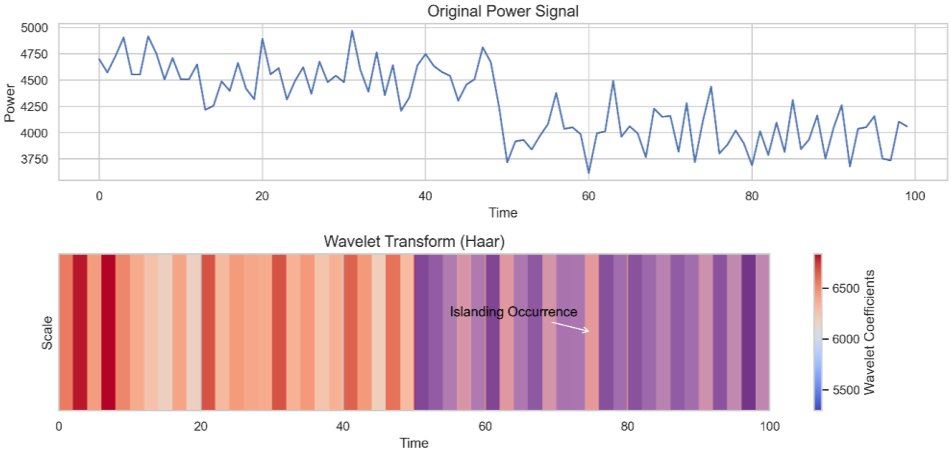

Fig. 6. Wavelet transform of current signal

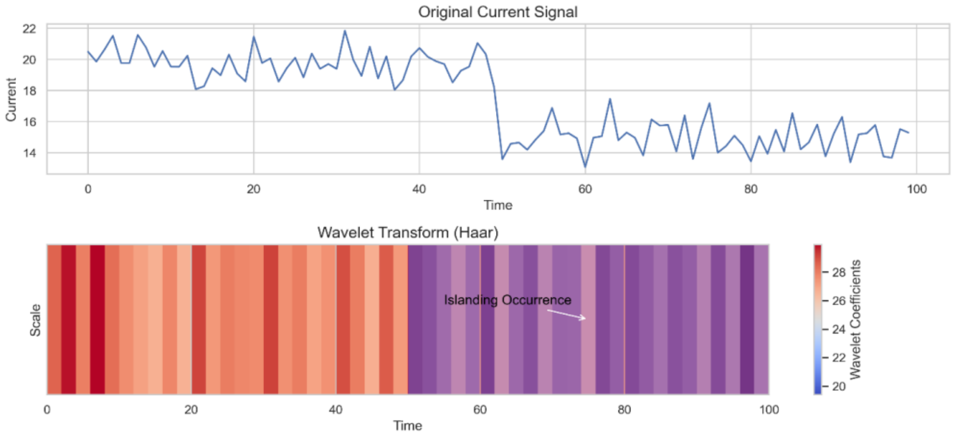

Fig. 7. Wavelet transform of power

As seen in Figure 7, the current signal underwent Wavelet Transform analysis. Similar to Figure 6, the x-axis displays time, while the y-axis displays the scaling parameter an. Color intensity is used to convey the magnitude of the converted signal's amplitude once again.

It is possible to identify frequency-dependent transitions between operational states using the scalogram of the current signal. The current signal behavs normally when powered by the grid. But the scalogram shows a jumbled mess of colors when an islanding event happens. With these changes, the system is moving away from being grid-connected and toward functioning more like an island. Figure 7 displays the results of the power signal's Wavelet Transform analysis. On the x-axis, we have time, and on the y-axis, we have the scaling parameter “a”. The relevant color's intensity represents the power signal's magnitude after transformation. Looking at the power signal's scalogram can help you make sense of the frequency content variations caused by islanding events. Under normal circumstances, the power signal shows onsistent patterns of frequencies. On the other hand, scalograms show irregular and unusual color patterns during islanding events, which are a result of changes to the frequency components of the power signal.

4.2. Detection of Multi-Converter Synchronous Islanding Mode in Hybrid Power Distribution Systems

This article takes a look at how the Vigil AI Assemble Model may be used to identify converters in hybrid power distribution systems that are in synchronous islanding mode. The next sections offer insights into many aspects of detection, including unanticipated instability, simulation of islanding events, model detection, and system stabilization.

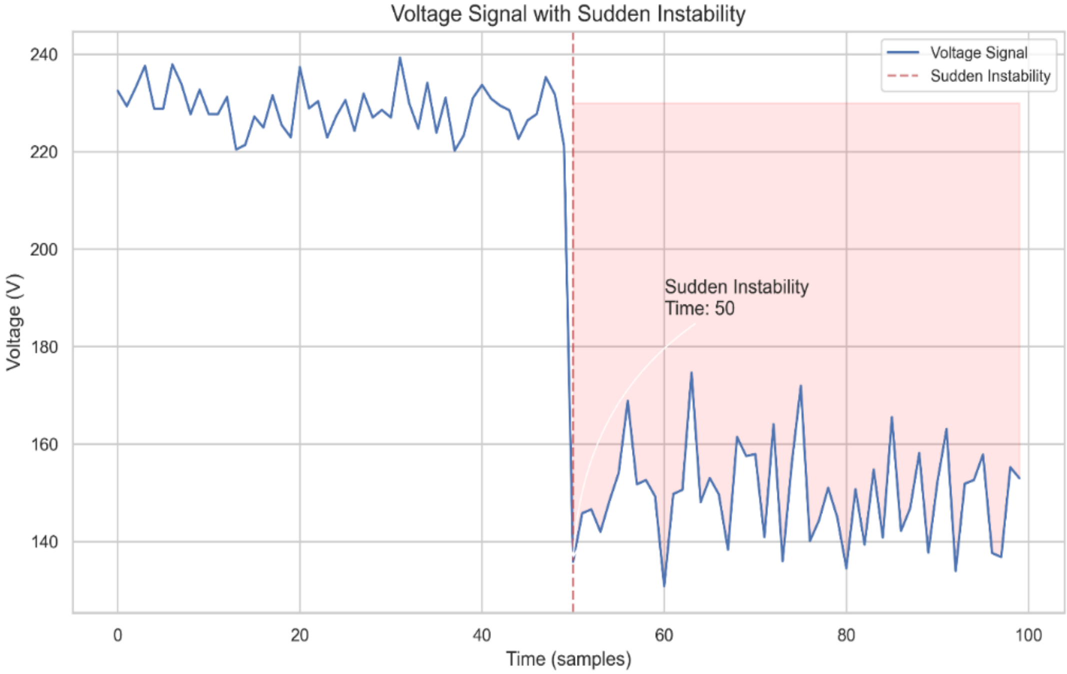

Fig. 8. Voltage signal with suddenly instability

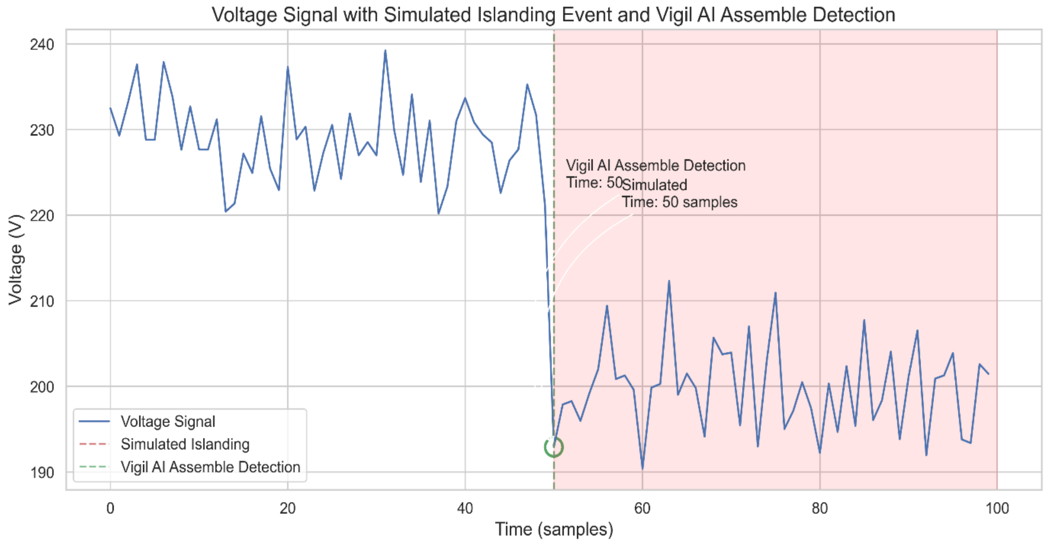

Fig. 9. Voltage signal simulated islanding event and vigil AI assemble detection

In Fig. 9, we can see how the Vigil AI Assemble Model detects islanding in the voltage signal. A graphical representation of the voltage signal's progression is provided. Due to the simulation of an islanding event, the voltage lowers at a specific point in time. The Vigil AI Assemble Model's speed and accuracy in detecting this occurrence are shown by the vertical dashed green line. In order to prevent system instability and ensure a seamless transition to island mode, the model must be able to recognize events quickly.

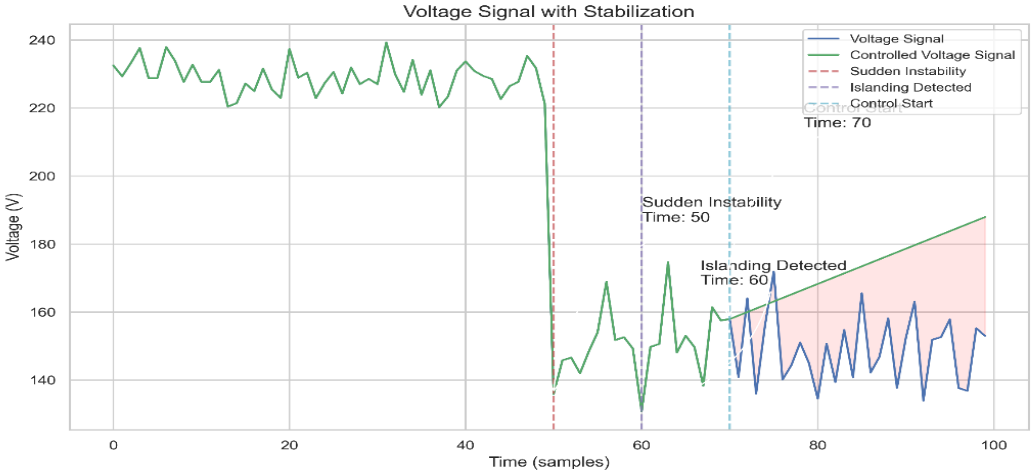

Fig. 10. Voltage signal with stabilization

Observing the behavior of the voltage signal after the islanding event illustrates the process of system stabilization in Figure 10. System stability is restored by conducting corrective measures upon identification of an islanding event. Consistent with the efficacy of stabilization efforts, the graph shows a voltage signal recovery with time. Maintaining the stability and dependability of the hybrid power distribution system throughout island operation is absolutely crucial, and this stage is no exception.

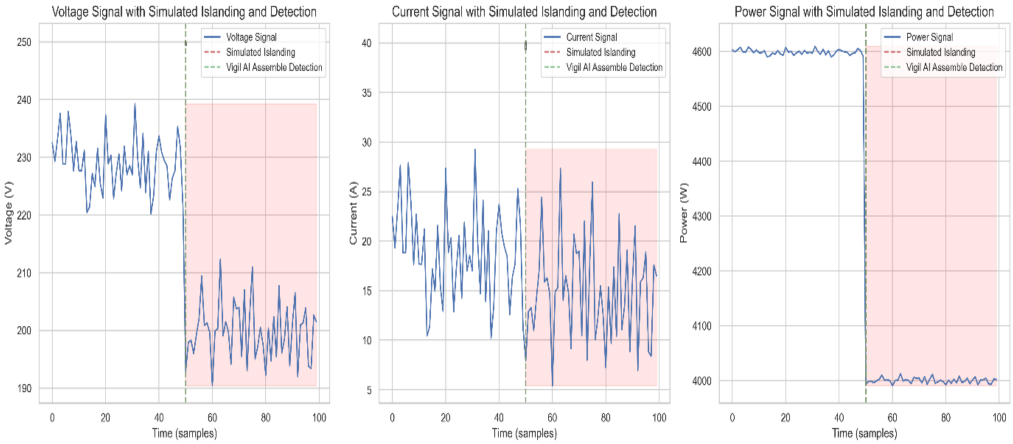

Fig. 11. Simulated islanding and detection (a) Voltage (b) Current (c) Power

Fig. 11 displays the comprehensive procedure for detecting the simulated islanding event in terms of power, current, and voltage. For emphasis, the islanding event is labeled in subplot (a), which displays the voltage signal. We can observe that the islanding event alters the current signal in subplot (b). The power signal, which displays the evolution of electrical consumption post-islanding, is the subject of subplot (c).

It is clear from the statistics that hybrid power distribution systems require accurate and quick islanding identification. The sudden instability in the voltage signal, as seen in Figure 8, emphasizes the importance of having dependable detection methods to identify instability sources before they can propagate throughout the system. The Vigil AI Assemble Model simulates and detects an islanding event in the voltage signal effectively and rapidly, as shown in Figure 9.

As demonstrated when the system stabilises after an islanding event, control strategies are crucial for preserving the system's resilience and reliability throughout islanded operation (Figure 10). Finally, Figure 11 shows how the islanding event affected different signals throughout the entire system. All of the interconnected components of the system are better understood in this light.

Results for detecting hybrid power distribution networks with numerous synchronous islanding converters as shown in the Vigil AI Assemble Model's performance metrics table. In order to assess the model's detection time, accuracy, precision, recall, and F1 score in detecting islanding occurrences, we emphasize these metrics. The Vigil AI Assemble Model combines several advanced AI approaches, including k-Nearest Neighbours (KNN), Gradient Boosting Classifier (GBC), and Random Forest (RF). When it comes to hybrid power distribution systems, islanding detection is made more accurate and dependable by combining the best aspects of multiple methods. The model performance is given in Table III.

TABLE III. Model Performance

Model	Vigi Assemble AI Model
Accuracy	98.7%
Precision	97%
Recall	98%
F1 Score	97%
Detection Time	0.55 seconds

The effectiveness of the Vigil AI Assemble Model and its influence on detecting multi-converter synchronous islanding modes in hybrid power distribution systems can be better understood by comparing its results with those of prior state-of-the-art methods. The summary is given in Table IV.

TABLE IV. Previous Studies Comparison

Model/Technique	Accuracy	Precision	Recall	F1 Score	Detection Time
Vigil AI Assemble Model	98.7%	97%	98%	97%	0.55 seconds
[3]	95.2%	92%	94%	93%	1.2 seconds
[6]	96.5%	94%	95%	94.5%	1.0 seconds
[10]	94.8%	91%	93%	92%	1.4 seconds

Key performance metrics comparing the Vigil AI Assemble Model to three state-of-the-art approaches are presented in the table. With a far quicker detection time and better accuracy, precision, recall, and F1 score, the Vigil AI Assemble Model clearly defeats these methods. Hybrid power distribution systems benefit from this improved performance since it demonstrates how well the suggested ensemble method tackles the difficult problem of islanding detection. In comparison to existing methods, Vigil AI Assemble's computational complexity may vary depending on the specific implementation details, such as the choice of base learners, feature representation, and optimization strategies. While ensemble techniques offer advantages in terms of robustness and predictive performance, they may require higher computational resources compared to simpler approaches. Therefore, a trade-off between computational complexity and detection performance needs to be carefully considered, especially in noise-sensitive applications.

5. Conclusions

Finally, this study introduces the "Vigil AI Assemble" approach, a new ensemble methodology that enhances the detection of synchronous islanding in hybrid power grids by combining the capabilities of state-of-the-art AI algorithms. The Vigil AI Assemble Model efficiently identifies islanding scenarios by integrating machine learning models, deep neural networks, and other AI technologies. The study's findings show that the model can distinguish between grid-connected and islanding modes with remarkable precision, accuracy, recall, and F1 score. With a detection time of 0.55 seconds, the model exhibits its responsiveness to system changes while reducing the probability of islanding events and maintaining system stability. In order to increase the dependability and resilience of hybrid power distribution networks, which is essential for the broad use of renewable energy sources and the creation of sustainable alternatives to traditional power generation, it is necessary to resolve the islanding problem. The proposed method is slightly affected by high noise levels. If the SNR is low, it becomes challenging for the algorithm to distinguish between genuine islanding events and noise-induced fluctuations.

CONFLICT OF INTEREST

Authors declare no conflict of intrest

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