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Original Article

SVM Classifier Based Islanding Detection and Seamless Mode Transition in Microgrids

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Abstract - *The use of Distributed Generation (DG) and Microgrid(MG) systems, which integrate with the utility grid via power electronic inverters, is rapidly growing in the energy sector. Anti-islanding protection is implemented to prevent the unintended flow of electricity back into the utility grid during power outages. The automated switchover of the microgrid to stand-alone mode is addressed as a solution to this problem, which allows the local load to be powered by the microgrid during grid failures. Intelligent islanding techniques have drawn more interest since they are faster and more accurate than conventional methods. This paper describes an improved SVM classifier-based islanding detection in a microgrid system that is connected to an IEEE 6-bus test system. The high accuracy and prediction speed enable the microgrid system to switch to stand-alone mode when an islanding event is found to occur. The proposed method demonstrates a smooth mode transfer between grid-tied and stand-alone modes. Simulation results show that the SVM model-based approach for the islanding detection technique is highly reliable with high accuracy and detection speed. The non-detection zone is negligible and ensures uninterrupted power supply to the local loads even in case of grid failure, by islanding operation.*

Keywords - *Distributed generation systems, Islanding Detection, Microgrid, Seamless Transfer, Stand-alone operation.*

1. Introduction

Advancements in power conversion technologies facilitate the efficient integration of Renewable Energy Systems (RES) into the complex power grid. These technologies enable more efficient energy conversion, dynamic control, and interaction between RES and the grid. So, higher levels of RES penetration into the grid become possible with enhanced grid flexibility. Increased energy security and economic advantage with less pollution are the major reasons for promoting RES units. Microgrids (MGs) can inject high-quality electricity to the grid, with the help of advanced inverter control techniques. In case of a grid outage, all the Distributed Generators (DGs) connected to the microgrid are to be disconnected from the grid to maintain the safety of the grid maintenance staff and to prevent operational issues in the sensitive loads within the microgrid. As a result, these DGs cannot deliver power even to the critical loads within the MG until the grid returns to normal operating conditions. The schematic of the MG under consideration is shown in Figure 1. The islanding detection technique implemented in the control circuitry of the inverter helps in disconnecting the MG from the main grid throughout abnormal operating conditions, and the MG is operated in stand-alone mode. For simulating grid behaviour in MATLAB/ Simulink, a modified IEEE 6-Bus system model is used (as shown in Figure 2). This configuration gives a balance between compactness and complexity for a realistic power system analysis. Islanding is the state in which an MG keeps a site powered by local DGs, even when there is no longer any main grid power available. In the event of an islanding, all utilities must comply with IEEE standards by disconnecting DGs from the grid as quickly as feasible. Unintentional islanding poses significant risks to both utility personnel and sensitive equipment, prompting strict regulatory measures.

According to IEEE 929-2000 and the more recent IEEE 1547-2018 standard, DGs must disconnect from the grid within two seconds of detecting the islanding condition. When the MG is linked to the grid, it is regulated to supply a certain amount of power. In this paper, focus is given on the efficient operation of Voltage Source Inverter (VSI) interfaced DGs forming an MG. Here, the MG system's VSI operates in current-controlled mode while the system is in grid-tied operation, since the grid determines the system voltage. Power supply to the essential loads is not anticipated to be disrupted in the event of a grid breakdown. Accordingly, the inverter control strategy is modified to enable standalone operation, ensuring that the output voltage of the inverter remains constant and matches the rated voltage of the connected load. In this case, MG can operate in standalone mode to feed the local/critical load demand. Accurate detection of islanding determines the efficiency of seamless transition.

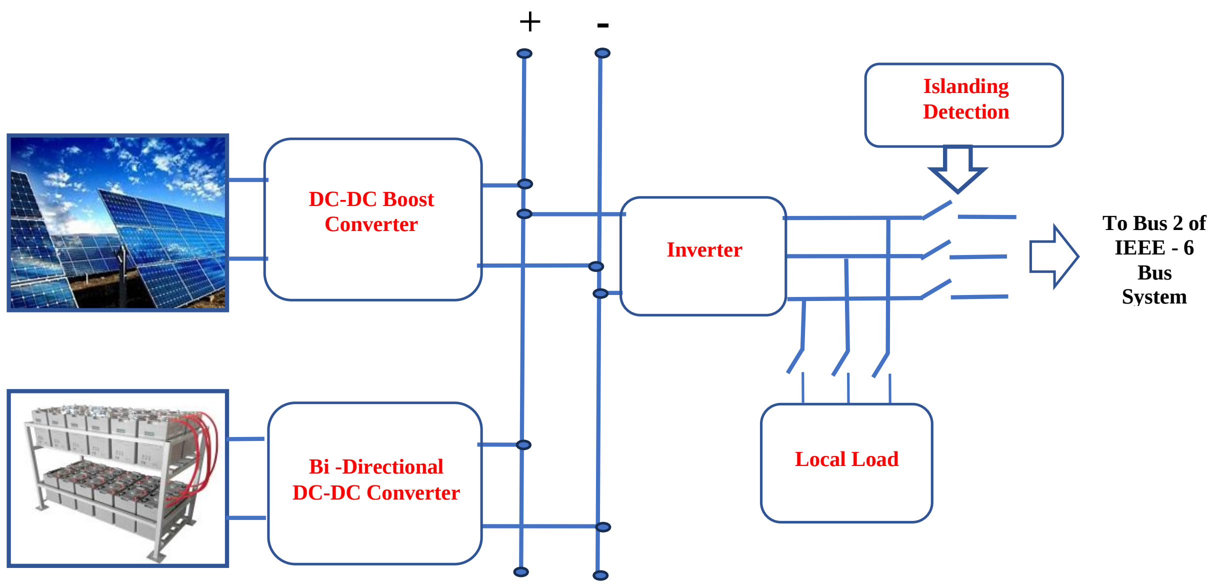

Fig. 1 Grid-Integrated Microgrid system schematic

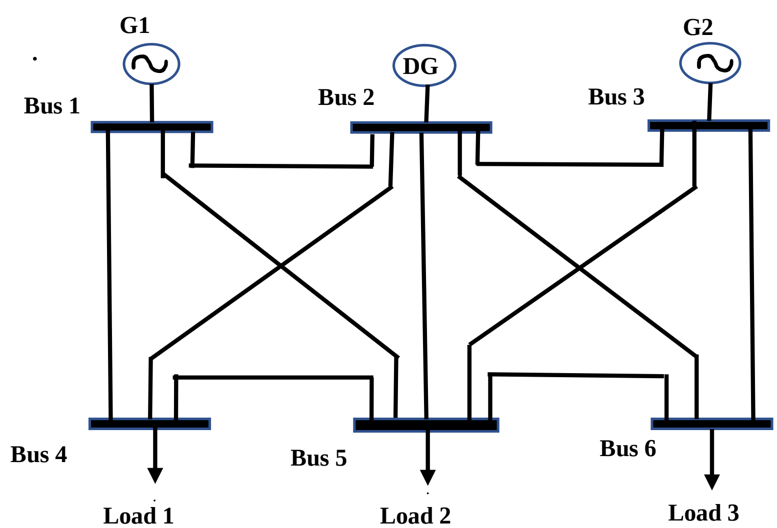

Fig. 2 Configuration of the modified IEEE 6-Bus Network

1.1. Literature Review

Islanding Detection Schemes (IDSs) are broadly categorized into remote, local, and intelligent-classifier-based methods. Remote IDSs rely on communication infrastructure-such as SCADA systems, Power Line Carrier Communication (PLCC), and Direct Transfer Trip (DTT) protocols-to detect islanding events from the utility side. Low Non-Detection Zone (NDZ) and fast response are the main advantages of these methods, which make them reliable [1-3]. But the high implementation cost and complex coordination between DGs and utility control centres make them less acceptable. The functioning of Local IDSs is either by continuously monitoring the important electrical parameters like voltage, current, frequency, and phase angle, or by injecting disturbances at the PCC and analysing the parameters. Local IDSs are more cost-effective and easier to implement than remote methods. Based on the principle of operation, local IDSs are classified as active methods, Passive methods, and hybrid methods. Passive IDSs detect islanding through parameter thresholds by measuring key parameters at the PCC (Figure 3).

Active IDSs [4] inject a disturbance signal at PCC, which introduces variations in system parameters. Here, islanding is detected by comparing these parameters with previously defined thresholds. Active IDSs reduce the NDZ compared to passive IDSs, but may adversely affect the power quality. These intentionally injected disturbances can distort the waveforms, which leads to increased Total Harmonic Distortion (THD).

Passive methods are generally simpler, cost-effective, and non-intrusive, but they suffer from larger NDZs and may fail to detect islanding under balanced load-generation conditions [4, 5]. Protective relays then operate by comparing these variations with predefined threshold values. They do not introduce any changes to the system characteristics. They are simple and economical but suffer from a large NDZ, especially when local generation closely matches local load. Hybrid IDSs combine elements of both active and passive methods. So, they can address the PQ problems of active IDSs and the large NDZ of passive IDSs [6].

Intelligent classifier-based IDSs have attracted considerable interest owing to their advanced capabilities and enhanced performance when compared to conventional techniques. They leverage advancements in artificial intelligence and machine learning theories. The working principle involves deriving features from obtained signals, forming a feature vector, and feeding it as input to an intelligent classifier that makes decisions based on these features (Figure 4).

Utilizing the DG system's capacity even under unfavorable grid circumstances can be made feasible by the transfer of mode [7-12]. Based on the real data, a supervised Machine Learning (ML) system with a classification learner is presented in [13] for the intentional islanding of MGs. Frequency fluctuations and transient disturbances in the signal can be extracted using designated basis functions, facilitating accurate identification of islanding conditions. This technique, as demonstrated by [13], proves effective in reliably detecting islanding events. Additionally, Ensemble learning is carried out, which aims to enhance predictive performance by merging predictions from many models. The main disadvantage here is the delay in prediction, which affects the performance of the system. Instantaneous values of the voltage and current waveforms are processed after being measured at the PCC using Instrument Transformers in [14].

Islanding status is predicted by feeding these characteristics into Support Vector Machine (SVM) models that are created offline. With the help of IOT and ML, Islanding detection is done, and the system is brought to a stable state within 50ms, which is to be reduced to improve the performance in [15]. A method for island detection is created by fusing machine learning and signal processing methods in [16]. The method for signal processing is variational mode decomposition, and the ML methodology employed is the ensemble bagged-trees method. Prediction time increases in ensemble methods, as multiple models are being trained. The Reinforcement Learning approach, a methodology for teaching computers to learn by reinforcing positive behavior with rewards and/or imposing consequences for wrong behavior, was employed in [17].

ANN-based techniques for islanding identification are presented [18, 19], where the patterns in voltage waveforms are identified. Here, the time required for accurate identification of islanding will increase compared to ML-based methods. Simulink/PSB is used to represent and simulate a real-world situation. By doing sensitivity analysis, it is possible to confirm how various sample rates affect the effectiveness of the suggested approach. SVM classifier-based islanding detection, along with grid fault detection, is studied in [20], but the transition between islanding and grid-connected modes is not discussed.

A Large-scale Support Vector Machine (LaSVM)-based online learning method was used to accomplish an online islanding detection strategy [21]. The approach takes into account a collection of independent variables and unknown variables, adopting a classification issue for islanding identification in grid-connected systems. The known islanding occurrences in the grid-connected system are tied to the independent variables, while the real-time grid dynamics are related to the unknown variables. KNN classifier-based islanding detection [22-24] identifies the islanding scenarios in case of small data sets, but the speed of prediction decreases as data samples increase. The performance is improved when an SVM classifier is used for the prediction of islanding [25, 26], which improves the response time for synchronous DGs.

A multistage passive islanding detection method, employing a classification algorithm similar to a Decision Tree (DT), is presented in [27]. This approach enhances the reliability of islanding identification by systematically analysing signal features across multiple stages. The main innovation of the suggested approach lies in how characteristics are transferred to the later stages of the DT. A sequence of steps in the tree receives feature sets that were extracted using various time frames. In this approach, events that can be promptly classified as islanding or non-islanding are detected early, without requiring the full feature set to be processed. This algorithm utilizes the time windows, which vary during run time, that align with the temporally evolved patterns. So the speed of detection is comparatively reduced.

This paper introduces a supervised machine learning framework for islanding detection, utilizing classification algorithms to accurately distinguish islanding events from normal operating conditions. For training, data is generated under several scenarios, including different kinds of faults, load switching, and capacitor switching at different locations of an IEEE 6-bus system. An MG consisting of PV and a battery bank is islanded from bus-2 of the grid system, and the stand-alone mode is activated in case of detection of a fault in the grid. Various ML techniques (Decision Tree, KNN, and Logistic regression Classifier) are examined, and the SVM classifier is determined to be the most effective one, which is utilized in the simulation.

A key challenge in achieving seamless transfer lies in the accuracy and speed of detecting unintentional islanding. The proposed islanding detection method significantly reduces the transition time between grid-tied and islanded operation with high accuracy.

2. Description of the System and Proposed Method

The system under study is an MG interfaced with a single bus of a standardized 6-bus test network.DC-DC converters are connected to the DG outputs to maintain the voltage output equal to the DC bus voltage. Various islanding scenarios are simulated in the test system, and the resulting datasets are used to train classification algorithms for increasing the accuracy of islanding detection. Different classifiers are trained using the data generated, and performance is assessed based on the accuracy and detection speed.

2.1. Smooth Switch Between Grid-Connected and Stand-alone Operation

One of the main challenges in the optimal utilization of DG systems like solar and wind is the complexity of the transition between stand-alone and grid-connected modes. For achieving reliable mode shift, IDS implemented in the inverter control should be able to distinguish and identify each operational condition [28]. The inverter in islanded mode uses the voltage and frequency requirements of the local load as a guide for switching. Here, the inverter monitors the power consumption of the local load.

In the case of a grid fault, the inverter can continue supplying local loads by switching to stand-alone mode [29, 30]. To facilitate this operational transition, an effective islanding detection mechanism is essential. The time required for this transition to islanding mode should be as small as possible for the smooth operation of critical loads. The power delivered by the inverter in stand-alone mode will be determined by the requirements of the local load.

2.2 Control of Inverter while Connected to Grid

Here, Real-time monitoring of grid voltage, phase angle, and frequency is done for the detection of possible islanding conditions. When the grid health is detected as normal by the IDS, dq-axis control is employed by the inverter controller to calculate reference values for voltage and phase, enabling synchronized operation of the inverter to the grid [31]. In Voltage Oriented Control (VOC), the d-axis of the rotating reference frame is aligned with the grid voltage vector, so that effective current regulation is done within the synchronous dq reference frame. The advantage of this configuration is that the d-axis current governs active power transfer, while the q-axis current manages reactive power, enabling accurate control of power exchange between the inverter and the grid.

In VOC, the active and reactive power of the inverter are regulated by adjusting the current components along the corresponding axes. The d-axis reference current ($I_{D(ref)}$) controls the active power.

The reactive power is governed by q-axis reference current $I_{Q(ref)}$, whereas the voltage control loop dynamically sets the $I_{D(ref)}$ to keep the DC-link voltage constant at the inverter input.

$$V_d = L\frac{di_d}{dt} + R\,i_d - L\omega i_q + e_d \tag{1}$$

$$V_q = L\frac{di_q}{dt} + R\,i_q - L\omega i_d + e_q \tag{2}$$

The inverter output voltages $\boldsymbol{V}_d$ and $\boldsymbol{V}_q$ represent the direct and quadrature components obtained through the Park transformation. Similarly, the grid voltage components at the input side under steady-state conditions are denoted by e_d and e_q corresponding to the dq-axis representation of the grid voltage. The magnitude and phase information obtained from the VOC is utilized to generate PWM signals for controlling switches of the inverter. This control strategy of the current controller ensures accurate active and reactive power delivery to the grid at given reference levels.

2.3. Control of Inverter in Standalone Mode

When a grid fault is detected by the islanding detection algorithm, the DG must be disconnected from the grid and should be switched to standalone operation. In stand-alone mode, the inverter continues to power locally connected loads in the microgrid (MG), functioning as a voltage-controlled source. The inverter maintains stable operation of the local load by regulating output voltage and frequency according to predefined reference values corresponding to the load requirements.

2.4. Microgrid System

The MG system configuration under consideration contains a PV system interfaced with the DC bus through a boost converter and a battery energy storage unit, through a bidirectional converter. When the battery voltage drops below a specified reference level, charging is initiated using either grid power or PV output. Battery energy storage systems serve a critical function in MGs by enhancing energy reliability and supporting seamless operation during both grid-connected and islanded conditions.

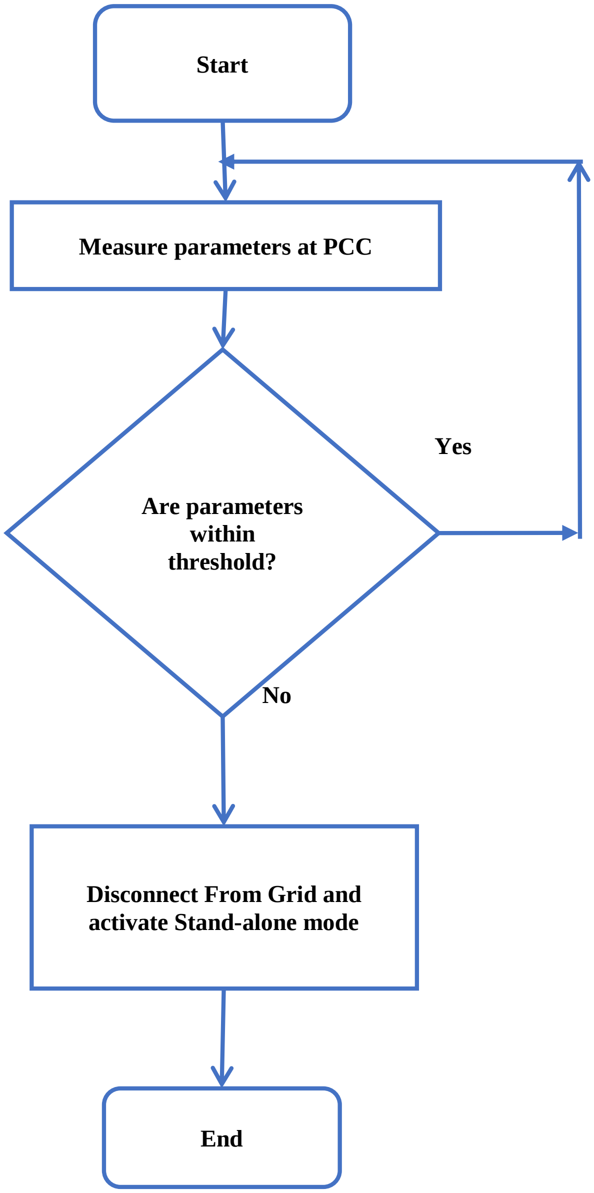

Fig. 3 Flowchart for passive islanding detection

2.5. Control Schemes

In grid-tied operation, voltage control is used, while in islanding operation, current control is used. The islanding detection technique produces a mode selection signal. The inverter switches to voltage control mode and operates in islanding mode if it is 0. When the signal is 1, the system operates in grid-linked mode. Here, the inverter operates in the mode of current control.

2.5.1. Current Control

In this operational mode, the current control block utilizes grid voltage and current measurements to regulate the active as well as reactive components of power supplied to the grid. In this operational mode, effective power exchange between the inverter and grid is governed by the current control block.

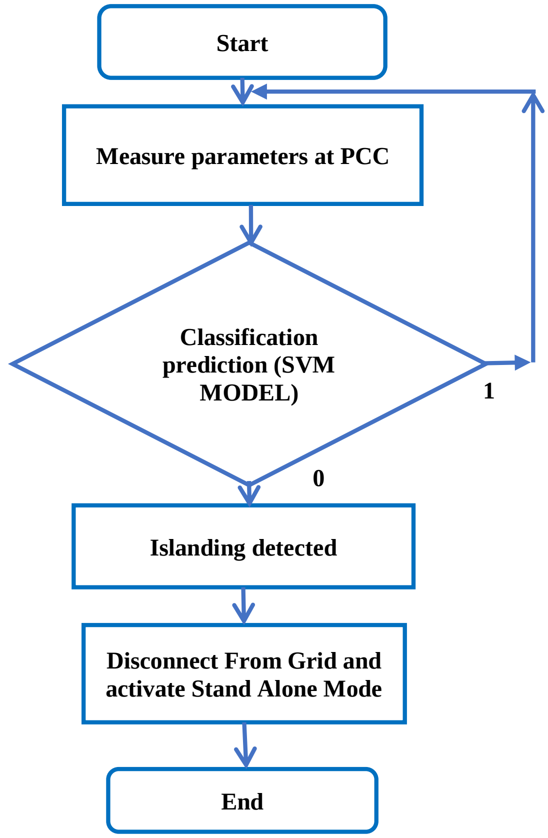

Fig. 4 Flowchart for machine learning based islanding

It continuously monitors the grid's voltage and current waveforms to compute the instantaneous active and reactive power. These measurements are processed within the synchronous dq reference frame, allowing precise independent regulation of the direct-axis and quadrature-axis current components (Figure 5). Active power flow is controlled by modulating the direct-axis current (i_d), whereas the quadrature-axis current (i_q) governs the reactive power exchange through injection or absorption. By adjusting these current references, the inverter ensures compliance with grid codes, maintains power quality, and supports voltage stability at the PCC. This control strategy is especially effective during dynamic grid conditions, enabling fast response and robust performance in both grid-connected and transition modes.

2.5.2. Voltage Control

If the islanding detection algorithm identifies abnormal grid conditions, the inverter must cease operating in current-regulated mode. Critical loads linked to the DG should be able to get enough power from its output. In order to supply the critical load with a known voltage and frequency, a voltage control method is used here. The rated voltage of the critical load is compared to the peak value of the output voltage of the inverter. The reference for the PWM inverter is created by multiplying the difference by this amount. Figure 6 provides a good explanation of voltage regulation.

Table 1. System details

Parameters	Values
Grid Frequency	50 Hz
Grid Voltage	110 V
Filter Inductance	360 µH
Filter Capacitance	950 µF
PV voltage	218.4 V

The peak output voltage of the inverter is continuously monitored and measured to ensure accurate regulation and stability. This real-time tracking enables the control system to respond promptly to variations in operating conditions, thereby maintaining optimal performance across both grid-connected and islanded modes. The reference voltage Vref can be changed to adjust the voltage magnitude if it varies as a result of the DG output or a change in load.

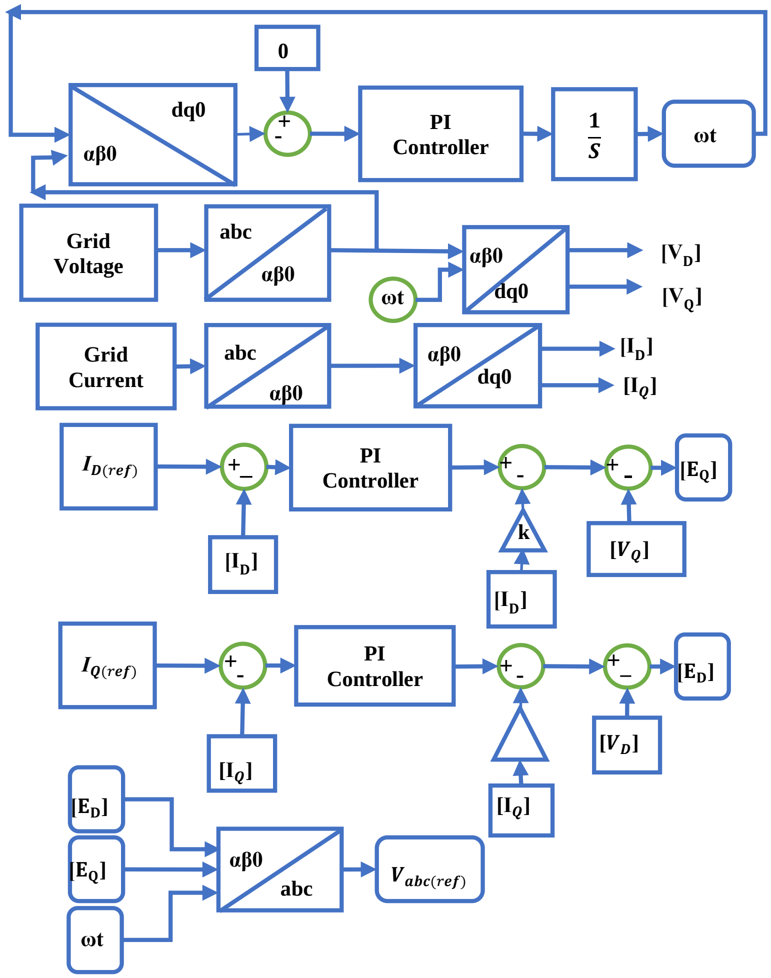

Fig. 5 Current control strategy implemented during grid-interfaced operation

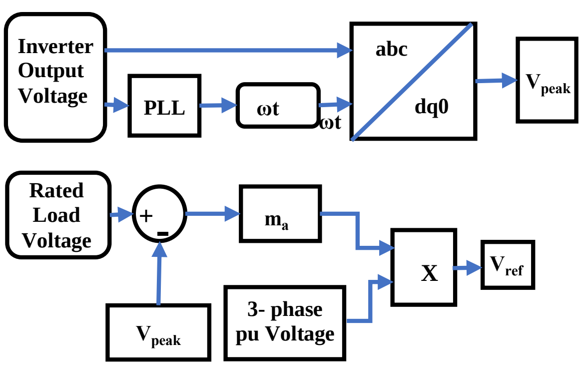

Fig. 6 Voltage control strategy applied during islanded mode

2.5.3. ML-based Islanding Detection Method

This study presents a comparative analysis of four machine learning-based islanding detection techniques. ML methods are broadly categorized into supervised and unsupervised approaches. In unsupervised learning, the datasets do not have labelled outputs. The learning happens through the insights extracted from the datasets. In a supervised learning method, each input has a labelled output. The two main branches of supervised learning are regression and classification. Here, after training with the required dataset, the model can predict the output for an unseen input. The classification algorithms employed in this study are SVMs, DTs, KNN, and logistic regression classifiers [32, 33].

The dataset is generated from measurements of voltage, frequency, THD, and active power at the PCC, Feature selection and extraction are performed with that data. These parameters show notable variations during islanding, making them suitable for islanding detection.Data collection for training ML models is done with various events of islanding and non-islanding cases, including different fault conditions, load switching, capacitor switching, voltage sag, and swell. The selection of the most suitable ML method is done based on a comparative evaluation of the performance metrics of different models.

The model selected for training the collected dataset is Optimizable SVM, as it gives high accuracy with the highest speed of prediction. In MATLAB/Simulink, Optimizable SVM model's hyperparameters are tuned automatically to improve classification performance. Bayesian optimization is employed to automatically fine-tune hyperparameters to achieve minimal classification error. The dataset is partitioned into training and validation subsets to evaluate the performance of the model. Cross-validation proves that the model can be generalized to unseen data effectively, which ensures the reliability of the model. Figure 10 presents the comparative performance of the four machine learning models, trained with the same dataset, illustrated using their respective confusion matrices. The trained model, SVM, is integrated in the controller of a MATLAB/Simulink-based MG-grid integration framework to enable accurate islanding detection. In case of identifying an islanding event, the circuit breaker disconnects the MG from the faulty grid, and the stand-alone mode is activated to continue supplying power to the local load independently.

3. Results and Discussion

The grid-connected inverter-based MG and its control architecture have been simulated in MATLAB/Simulink. The DG components within the MG are modeled as a PV system and a battery energy storage unit. An IEEE 6-bus test system is modified to serve as the primary grid in the simulation. The voltage source inverter's output is connected to Bus 2 of the modified IEEE 6-bus model through a circuit breaker. The signal that selects the mode of operation identifies the suitable reference input for the inverter, guided by the output of the block that identifies islanding. When operating in grid-interfaced mode, a dq-axis current controller is utilized to manage the injection of both active and reactive power into the grid. In case of standalone operation, the inverter's output voltage is regulated by a voltage control block to match the rated voltage required by the connected load.

The system details used in the simulation are given in Table 1. Conventional passive islanding detection techniques are characterized by a large Non-Detection Zone (NDZ), which limits their effectiveness in reliably identifying islanding events. Determining the threshold value of parameters at the PCC for accurate detection. In machine learning-based islanding detection, high accuracy is achieved when the model is trained on a well-curated and representative dataset. The details of the data collected are given in Table 2.

A line-to-ground fault at Bus 5 in the main grid triggers islanding detection, causing the MG system to transition to standalone operation. The signal that selects mode shifts from 1 to 0, initiating the disconnection of the breaker on the grid side. Upon restoration of grid power, the signal reverts from 0 to 1, and the circuit breaker reconnects following the reactivation of the inverter's current control mode. At 0.4 seconds into the simulation of the MG integrated IEEE 6-Bus system, a fault at Bus 5 triggers an immediate disconnection of the MG from Bus 2. Figure 7 illustrates the inverter's voltage at PCC, inverter current, and the mode selection signal, indicating whether the system is grid-connected or operating in stand-alone mode. On the occurrence of a capacitor switching at bus 4, the islanding detection method worked successfully and was not misinterpreted as islanding (Figure 8). The voltage sag caused by load switching at Bus-1 was not classified as an islanding event by the SVM-based detection method, as illustrated in Figure 9. In ML based islanding detection method, the data for training the model is generated from the Simulink model in various fault conditions and load switching conditions. The trained model is then integrated into the control system of the connected MG system. Different scenarios, including capacitor switching, load switching, and line-to-ground faults, are generated in the modified IEEE 6 bus system, in which the MG is connected. When islanding is detected by the SVM model, a signal is given to the Circuit breaker, and the MG system will switch to standalone mode. The training accuracies, prediction speed, training time, and model size of different classifier models are tabulated in Table 3. The MG is integrated with the IEEE 13-bus system, where identical scenarios (line-to-ground fault, capacitor switching, and load switching) were simulated. The results obtained were successfully validated. The prediction speed of the KNN classifier decreases as the number of data samples increases, due to its reliance on exhaustive distance computations. However, for accurate islanding detection, a large data set is essential for training. In contrast, the performance of the SVM classifier remains relatively unaffected by the growth in sample size, making it more scalable for larger datasets. Table 4 compares the accuracy and prediction speed with the existing research findings. Compared to the studies in [33-35], the proposed method is fast with high accuracy. Speed of detection is a very important aspect in seamless transition between modes.

Table 2. Data generated for training the SVM classifier

Sl No	Scenario	No. of data samples
1	Grid Connected	500
2	Stand-alone mode	100
3	L-G fault	120
4	Capacitor switching	100
5	Load switching	129

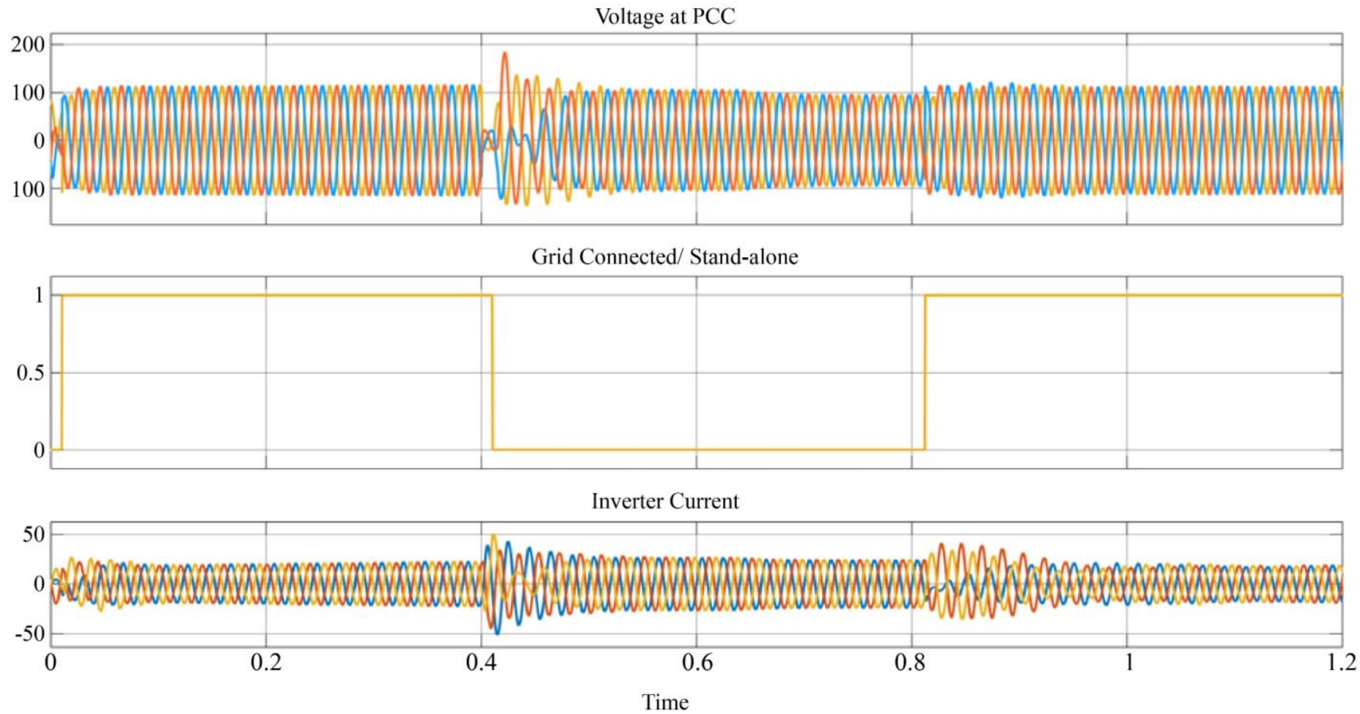

Fig. 7 Voltage at PCC and inverter current for SVM-based islanding detection

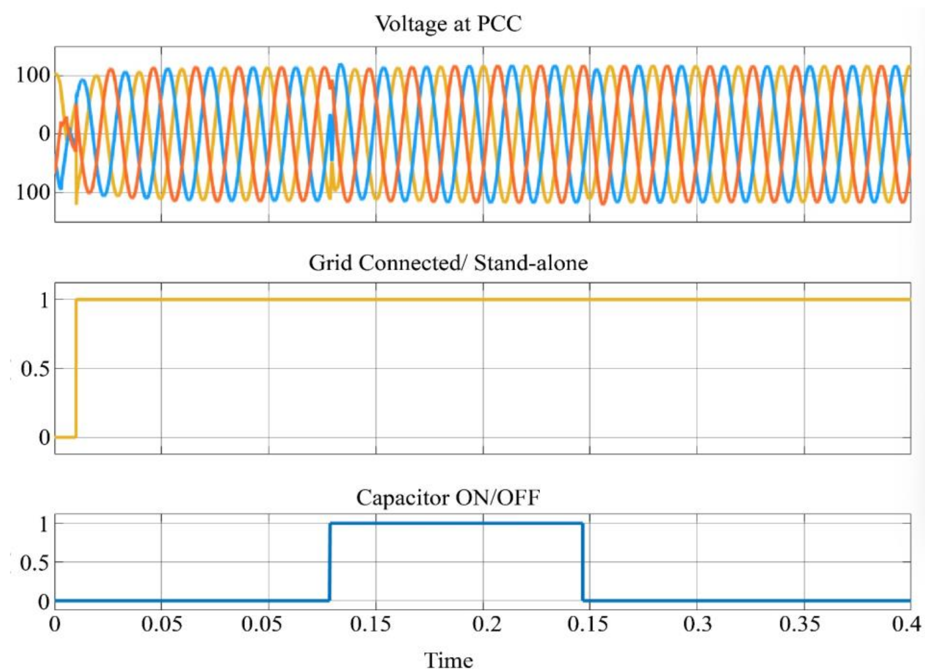

Fig. 8 Effect of capacitor switching on Bus-4

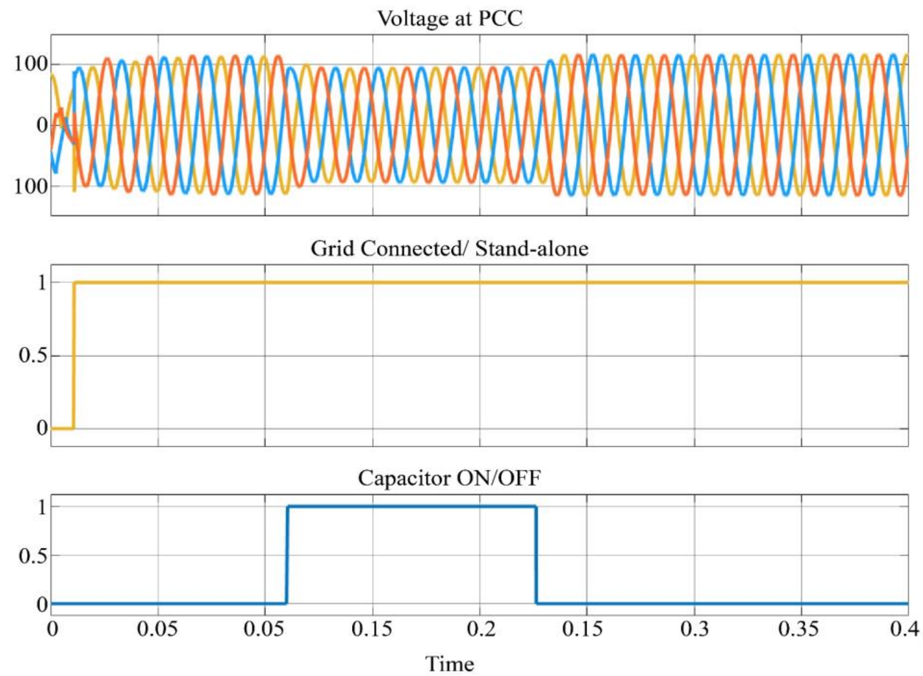

Fig. 9 Effect of load switching on bus-1

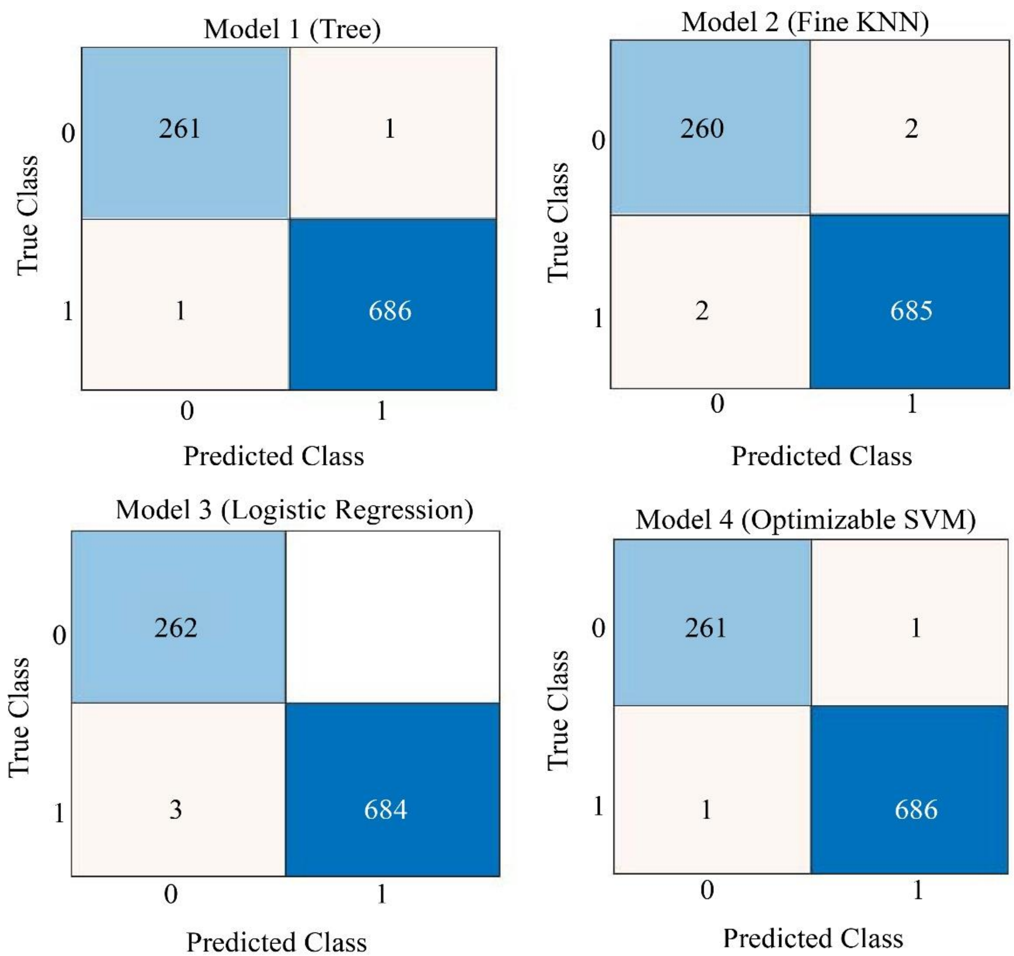

Fig. 10 Confusion matrix illustrating the classification performance of different models

Table 3. Comparison of different ML methods

Model Type	Accuracy % (Validation)	Speed of prediction (obs/sec)	Size of model (bytes)
Tree	99.79	31209	3393
KNN	99.58	12034	59352
Logistic Regression	99.68	38870	11008
SVM	99.79	62880	4014

Table 4. Comparison with existing research findings

Reference	Method of Detection	Prediction Accuracy	Detection time(ms)
[33]	SCHO-NN	97.11	169
[34]	KNN	100	156
[35]	ANFIS	78.71	40
Proposed method	SVM	99.79	20

4. Conclusion

A machine learning based approach for islanding detection is presented in this study. Performance of different models is evaluated, and SVM showed the best overall performance. SVM has the highest prediction speed with excellent detection accuracy. The MATLAB/Simulink model of a grid-connected DG system can switch to stand-alone mode seamlessly, employing SVM based islanding detection model. This ensures an uninterrupted supply to the critical load. If a grid fault occurs, the MG is instantaneously isolated from the grid and switches to stand-alone mode, ensuring an uninterrupted power supply. When the normal grid conditions are retained, MG is synchronised back to the grid utilizing SRF-PLL, which monitors the grid parameters. The voltage source inverter functions in current-regulated mode while grid-tied and transitions to voltage-regulated mode during islanding operation. Despite isolating from the main grid, the MG seamlessly transitions to islanded mode and continues supplying power to its connected local loads.

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