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A Novel Approach for Enhanced Real-Time Event Diagnosis for Grid Connected Microgrid with Multiple Distributed Energy Resources (DERs)

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Abstract
Effective microgrid control for system recovery and restoring normal operation necessitates fast event detection and implementation of remedial action (if need arises). However, fast and reliable event detection in microgrids is challenging because of low observability and inconsistencies in measurements. A novel technique is proposed in the present work for the real-time event detection and to identify the various emerging abnormalities in the microgrid. The continuous energy signature using TKEO (Teager-Kaiser Energy Operator) of the continuous varying voltage and frequency signal are extracted through μPMU. REII (Robust Event Identification Index) is constructed from these energy signatures and based on its abrupt post-event deviation from the nominal values an event is flagged in the proposed method. The proposed method is data–driven and only depends on the real-time inputs through μPMUs thus it automatically adapts the uncertainties associated with the intermittent sources of energy in the microgrid under different operating conditions. The traditional event detection techniques fail in identification of abnormalities for a microgrid connected to the transmission systems and equipped with multiple DERs such as PVDG, WG etc. To address this challenge, an integrated microgrid with multiple DERs viz. PVDG, WG and a SG (Synchronous Generator) is first developed in this work. The complexity of simultaneous operation of a static generator i.e. PVDG along with a rotor-based generator such as WG and SG is handled by the modeling the dynamic controllers of PVDG and WG for their frequency and voltage control. The simulation results depict the efficiency, accuracy and robustness of the proposed technique in terms of estimation time, event accuracy and applicability in all types of events. Moreover, the presented methodology is also compared with the four AI/ML based methods to highlight the superiority of the method.

Keywords- Distributed generation, Microgrid protection, Event detection, Event diagnosis, Teager-Kaiser energy operator.

1. Introduction

Advancement and development in DG (distributed generation) is attracting the attention of both researchers and industries towards microgrids (Parhizi et al., 2015). The requirement of microgrids is increasing these days mainly due to the rise in demand and the increased attention towards the green and clean energy (Reddy et al., 2016). Microgrids are capable in both types of operations viz. islanded mode as well as when connected to the main grid (Salkuti, 2019a). The additional amount of the power requirement(s) is fulfilled by the transmission system for a grid–connected mode and remaining is supplied by the DGs. Moreover, if the main grid encounters any turbulence due to faults, voltage fluctuations and frequency deviations etc. then microgrid becomes an island and continues to operate independently. In islanded mode of microgrids, the critical loads can also be fulfilled without a utility grid by the contribution of DGs connected at the load–side (James et al., 2019; Ray and Salkuti, 2020). The security and reliability of the microgrid is improved by the sustainable and environment-friendly power generation through DGs (Colmenar-Santos et al., 2016; Mahmoud et al., 2015). However, besides the numerous benefits, protection due to high penetration of DGs remains one of the major challenges in microgrids. The bidirectional and dynamic fault currents are produced in the system based on the location, type, and penetration level of DGs (Telukunta et al., 2017). Nevertheless, the standard setting of protection systems based–on overcurrent relays have been affected significantly through topological transformations in microgrid operation such as islanding to grid–connected mode and vice-versa (Chandra et al., 2021; Nimpitiwan et al., 2007). Moreover, as the direct coupling of DGs is infeasible in microgrids hence, the synchronized integration of DGs in microgrids is achieved with the implementation of power electronics converters (Kroposki et al., 2010; Abdelgawad et al., 2019). However, severe protection challenges arise due to this interfacing mainly in IIDGs enabled microgrids. It is because the fault current is affected insignificantly due to the drop in the converter output current which emasculates the accuracy and feasibility of the microgrid protection based-on overcurrent relays (Chandra et al., 2021; Nimpitiwan et al., 2007). Therefore, to enhance the selectivity and to overcome the dynamic changes in the fault current, the directional and adaptive attributes have also been included in the overcurrent relay based conventional protection schemes (Coffele et al., 2015; Mahat et al., 2011; Ojaghi et al., 2013).

In literature various intelligent and fast event detection methods are proposed by the researchers to overcome the aforesaid challenges and issues associated with the microgrid operation. A decentralized energy scheduling mechanism is proposed for the various consumers and producers of energy that handles the trading of energy not only within a microgrid as well as through multiple microgrids (Meghana et al., 2022). A novel recursive matrix pencil method is proposed in (Deshmukh et al., 2023) based on a sliding window index for the fault detection in microgrids. It is well efficient in grid–connected as well as islanded mode however; HIFs must be taken into account for its successful operation. An event detection technique using secondary control for islanded microgrids is proposed in (Jamali et al., 2023) to enhance the communication efficiency of the microgrids connected to both DESSs and DERs. A controller for event detection in microgrids connected with DERs and batteries is proposed in (Irmak et al., 2023) to control the island operation of microgrids. An unsupervised event detection technique using Gaussian Process Regression tool is proposed in (Choi et al., 2023) that does not depends on the fixed threshold for the event detection.

Recently, data–driven based approaches are proposed by various researchers for phase and/or event detection in the microgrids. Random forest and decision tree are the most widely used methods for the event detection in islanded as well as grid–connected microgrids (Casagrande et al., 2013; Kar et al., 2017; Mishra et al., 2016). Other techniques such as k–nearest neighbors and support vector machines etc. are AI based ML approaches and have also been implemented to detect the events in microgrids (James et al., 2019; Casagrande et al., 2013). These data–driven approaches are capable of satisfactory event detection and classification due to their high computational speed in real–time. The relevant data about microgrid is required in these approaches for the examination of relation between input and output variables to identify an event. This required data is collected through PMU measurement points and it has to be processed through machine learning or signal processing approaches for the situational awareness of the events in the microgrids (Casagrande et al., 2014; Som et al., 2022). Moreover, extraction and analysis of time-frequency characteristics has been achieved by pre-processing the input signal with the adoption of DSP approaches viz. DFT and DWT etc. microgrids (Casagrande et al., 2013; James et al., 2019;). An unsupervised ML method is proposed in (Aligholian et al., 2021; Shahsavari et al., 2019) for clustering and event detection in microgrids. To detect and localize the multiple events in microgrids, a signal processing approach is proposed in (Negi et al., 2017; Yadav et al., 2019). The techniques proposed in (Aligholian et al., 2021; Negi et al., 2017; Shahsavari et al., 2019; Yadav et al., 2019) for event detection in microgrids need an exhaustive training of several PMU measurement factors as well as the situational awareness is essential for the events to achieve in the microgrids. However, only 0.04% of PMU based approaches are able to evidence any event in the microgrid as per the current studies, it is because the events generally occurs rarely (Aligholian et al., 2020). Also, the cases of identifying false events due the abnormalities in PMU factors are not addressed by any of these approaches proposed in (Aligholian et al., 2020; Aligholian et al., 2021; Negi et al., 2017; Shahsavari et al., 2019; Yadav et al., 2019).

The hierarchical control approach is proposed in (Guerrero et al., 2011) for the stand-alone microgrids with DERs. For optimal operation of microgrid and to alleviate steady–state errors, communication–based tertiary and secondary levels of hierarchical control are respectively essential. To improve the frequency regulation of microgrids in islanded mode, load fluctuations in the system are identified with the PMU based proposed schemes in (Rodrigues et al., 2019; Rodrigues et al., 2021). The secondary voltage and frequency fluctuations as per the IEEE standards (Generation and Storage, 2020) can only be achieved through accurate PMU and hence, the outliers of PMUs have to be identified and filtered out. To control reactive power sharing within DERs in a microgrid, an event-triggered-based (ETB) approach is developed in (Gupta et al., 2020). ETB based approach to control secondary frequency and voltage in a microgrid is discussed in (Ding et al., 2017; Khayat et al., 2020). The possibility of false measurements in PMUs must be identified, detected and replaced before utilization in ETB approaches for microgrid control as ETB schemes depend on accurate algorithms of event detection. A tertiary control technique is adopted in the schemes proposed in (Gao et al., 2018; Wang et al., 2020) to optimize the power flow in microgrids among multiple DERs. False measurements in PMUs may results in non–optimal power flow because the information about load and generation is collected through PMUs network by the microgrid energy management system for tertiary control. Recently, some researchers have considered the inaccuracies in PMU measurements and proposed the event detection techniques for microgrid systems with multiple DERs. The combination of network parameters and PMU measurements is utilized and the source of events in microgrids is localized in the approach presented in (Farajollahi et al., 2018). However, the approach is a combination of model-based and data-based methods. System behavior-based modelling-free analysis for event detection and for any variations in the topology of the network is proposed in (Mayo-Maldonado et al., 2020). The complete observability of the system is essential in the method proposed; however knowledge about the initial parameters of the system network is not required. The collective outlier detection approach is proposed through the techniques presented in (Zhou et al., 2019; Gholami et al., 2019) for the detection of events based on physics as well as for all types of PMU measurements outliers. To prevent the false event alarms due to the abnormalities in PMU measurements, a forest-based online isolation event detection method is proposed in (Wu et al., 2021). However, a huge number of set-points and one-time training is essential in the methods proposed in (Zhou et al., 2019; Gholami et al., 2019; Wu et al., 2021). Moreover, the impact of DGs is not considered with the capability of voltage control in any of these approaches for the detection of microgrid events and analysis.

It has been observed from the literature review that the event detection schemes in the microgrid require further improvements and there is a pressing need for a more feasible solution for the protection of microgrid under different events. Some recently developed and proposed schemes are not able to detect the type of event properly and its location hence, these methods cannot be adopted in real-time as it focuses only in the low-power applications. On the other hand, injection-based or travelling-wave techniques are well suitable to detect event type and/or location in AC microgrids (Che et al., 2014; Mohanty et al., 2015). However, they have their own challenges such as communication links of travelling-wave require synchronized data because it suffers from the discrimination and detection issues in reflected-wave. Hence, accurate event detection and its location are not achieved in islanded mode of microgrids operation. Meanwhile, some other techniques e.g. injection-based techniques are suitable for radial networks as they are only limited to line-to-ground faults (He et al., 2010; Jafarian and Sanaye-Pasand, 2010).

In this paper a microgrid consisting of PVDG, WG and SG connected to the main grid is considered for implementing the proposed methodology. The simultaneous operation of these energy sources is complicated and rarely implemented. The intermittent power is generated through the integration of PVDG and WG because both depend on the metrological and climatic conditions (Battula et al., 2021). Because of highly intermittent generated voltage through PVDG and WG, they cannot be connected directly to the main utility grid (Salkuti et al., 2019b). As a result, the simultaneous operation and control of grid–connected microgrid with PVDG, WG and SG is more complex and challenging (Salkuti, 2023). Therefore, firstly a static IIDG (inverter-interfaced DGs) such as PVDG along with a rotor-based generator such as WG and SG in the same microgrid is modelled. In the next stage, a new technique has been developed based on the TKEO (Teager-Kaiser Energy Operator) to identify the event in real-time. A novel index namely Robust Event Identification Index (REII) is developed to identify an emerging event in the developed microgrid. This new index developed is based on the real-time voltage and frequency signals available through μPMUs. The developed REII quantify the event signature by using TKEO and alerts the system operator during abrupt operating conditions. The major highlight of the proposed method is its dependence only upon the real-time voltage and frequency signals therefore it is essentially capturing the uncertainties associated with intermittent sources of energy in the microgrid. Moreover, it can identify the event immediately after the actual occurrence of the event. The presented methodology is also compared with the four Artificial Intelligence based methods viz. SVM, MLP, Random Forest and AdaBoost to highlight the superiority of the method.

The major contributions of the presented work include:

(i) The modeling of an eight bus, 60Hz microgrid system with three DGs viz. a PVDG, a SG and a WG in DIgSILENT PowerFactory® 2020. In which the successful simultaneous operation and control of grid–connected microgrid with multiple DERs is accomplished. All the eight buses are equipped with μPMU to capture the continuous real–time variations in the bus voltage and frequency signals.

(ii) A novel event detection technique based on the TKEO (Teager-Kaiser Energy Operator) is proposed for the real-time event detection in the microgrid under various operating conditions. The continuous real-time energy signatures are calculated using TKEO for the voltage and frequency signals received through μPMU. These signatures are used to construct proposed index i.e. REII (Robust Event Identification Index) and based on its abrupt post-event deviation from the nominal values an event is flagged.

(iii) The proposed event detection technique is a data–driven approach and will therefore work on real-time data extracted through μPMUs. The method will thus automatically capture the on-going system conditions i.e. sudden variations in the output of renewable energy sources under different operating conditions. Therefore, it is well efficient under uncertainties caused by the renewable energy sources.

(iv) Moreover, the presented methodology is also compared with the four Artificial Intelligence based methods viz. SVM, MLP, Random Forest and AdaBoost to highlight the superiority of the method. It has been observed that the efficiency of the proposed methodology meets expectations when compared with the efficiency of AI/ML based methods with 100% accuracy.

Simulation studies have been carried out under different events including faults in the system. These events include islanding operations due to outage of distribution line(s) or transformers(s) and non-islanding operations due to load change(s), outage of distribution line(s), outage of load(s) and short circuit fault at distribution line(s) etc. It has been observed that the frequency and voltage both varies non–linearly whenever an event occurred in the system. However, the magnitude of variation in both frequency and voltage w.r.t. time under the nominal variation in the system such as load change (increase or decrease) is minimal, and the system regains its stable operation within few cycles. Based-on the system response under nominal events viz. load change from ±10% to ±50% of the base load, the minimum and maximum threshold values for REII are estimated. It has been noticed in the simulation studies that REII violates the thresholds for either bus voltage or bus frequency only when there is an event occurred either at grid side or DG side and the thus event is successfully detected within first few cycles.

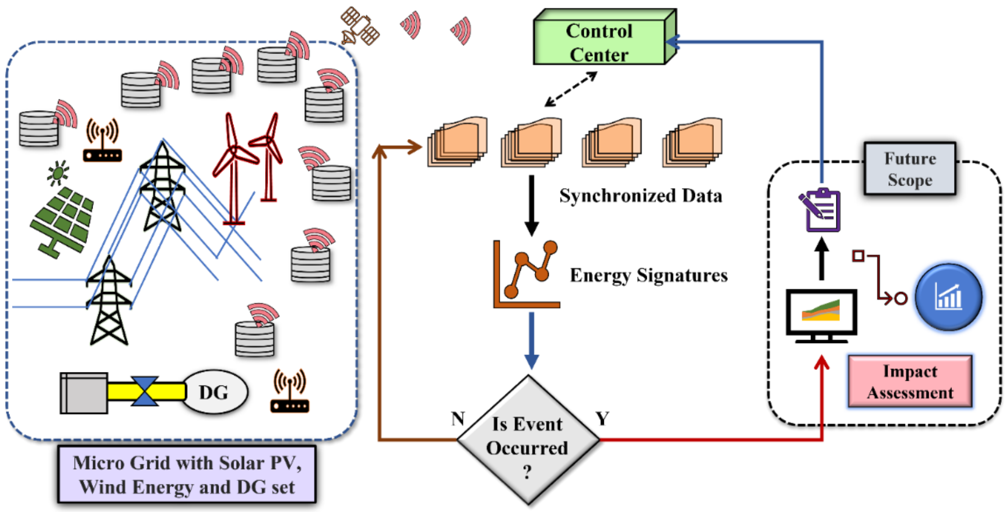


Figure 1. General outline of the proposed method.

The manuscript is organized as; literature review and major contributions of the proposed work are discussed in section 1. Section 2 illustrates the system modeling, wherein, proposed methodology for the detection of an event is explained in section 3. Section 4 is dedicated to the simulation results demonstration and analysis, whereas, performance and comparative analysis of the proposed methodology in different operating conditions is presented in section 5. The work is concluded in section 6 highlighting the efficacy of the proposed method. The block diagram representation of the proposed scheme is shown in Figure 1.

2. System Modeling

Single line diagram of balanced 8 Bus, 60Hz, 100MVA microgrid system with DERs is presented in Figure 2. A utility grid of 120kV is connected to a 25kV Bus with two parallel connected step-down transformers (TFR01 and TFR02) in the designed microgrid. DL01, DL02 and DL03 are the three distributed lines originate from the 25kV bus and load LD04 and C (2MVar capacitor) are also connected to 25kV bus. Three 25kv/575V delta–star step–down transformers (TFR03, TFR04 and TFR05) are used to connect DGs and loads (constant impedance loads) to the radial distribution network. It consists of three DGs viz. a PVDG, a WG and a SG.

The system in (Sankar and Sunita, 2021) has been modified and the details of the distribution lines, transformers, loads and DGs are given in Table 1. In the developed 8 Bus grid–integrated microgrid with DERs, the primary objective is successful operation of a static IIDG i.e. PVDG along with a WG and a SG.

It is challenging to integrate different DERs in the microgrid because WG and SG produce an inertia in the system due to their rotational mechanism for the power generation but PVDGs are static generators connected via inverter and do not produce an inertia. Therefore, the combination of these different types of generators leads to system instability as the frequency and voltage variations do not remain under control. The successful co-ordination between their operations is achieved by the dynamic modeling and implementation of PVDG’s controllers to control their frequency and voltage in RE integrated microgrids (Lammert et al., 2016). The dynamic modeling of controllers for PVDG and WG has also been developed in the designed microgrid test system as per the architecture proposed in (Lammert et al., 2016). The system has been tested and successful operation of all the DGs has been observed in the load flow analysis under steady state as well as various disturbances.

The circuit breaker relays at the event location acquires the current and voltage information at 64samples/s. DIgSILENT PowerFactory® 2020 software has been used to develop and simulate the system under different operating conditions and MATLAB ® 2020a software has been used for the analysis of simulation results.

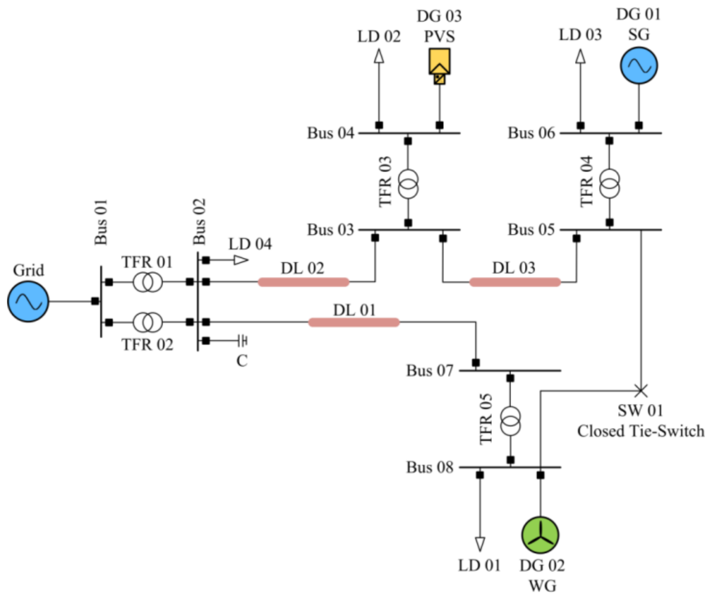


Figure 2. Simulated 8 bus grid integrated microgrid test system with DERs.

Table 1. Elements parameters/specifications of modified 8 bus system.

Sr. No.	Element	Parameters/Specifications
1.	Utility Grid	Rated short circuit MVA is 2500MVA, 60Hz, V_{grid} = 120kV and base power is 100MVA
2.	Distribution Lines: DL01, DL02 and DL03	22km, 60Hz, 3-ϕ, π–sections, C_1 = 10.1766nF/km, C_0 = 4.5nF/km, L_1 = 1.1mH/km, L_0 = 3.47mH/km, R_1 = 0.125Ω/km and R_0 = 0.447Ω/km
3.	Load: LD01 and LD03	60Hz, $V_{\phi-\phi}$ = 575V, 8MW and 1.75MVar linear constant impedance loads
4.	Load: LD02	60Hz, $V_{\phi-\phi}$ = 575V, 2.5MW and 0.75MVar linear constant impedance load
5.	Load: LD04	60Hz, $V_{\phi-\phi}$ = 25kV, 12MW and 2.8MVar linear constant impedance load
6.	Capacitor (C)	25kV and 2MVar
7.	Generator: DG01	SG of 9MVA, 60Hz and 575V
8.	Generator: DG02	WG of 9MW, 575V and 60Hz with 6 parallel units of 1.5MW DFIG (doubly fed induction generator)
9.	Generator: DG03	PVDG of 3.2MW, 60Hz and 575V.
10.	TFR01 and TFR02	32MVA, 60Hz, 120kv/25kV with $L_1 = L_2$ = 0.08pu, $R_1 = R_2$ = 0.0026pu, R_m = 1200pu and X_m = 600pu.
11.	TFR03	5MVA, 60Hz, 25kv/575V with $L_1 = L_2$ = 0.08pu, $R_1 = R_2$ = 0.0026pu, R_m = 1200pu and X_m = 600pu.
12.	TFR04 and TFR05	12MVA, 60Hz, 25kv/575V with $L_1 = L_2$ = 0.08pu, $R_1 = R_2$ = 0.0026pu, R_m = 1200pu and X_m = 600 pu.

3. Proposed Methodology

3.1 TKEO (Teager-Kaiser Energy Operator)

Kaiser in 1990 developed TKEO for the energy measurement of single continuous time-varying signal (Kaiser et al., 1990). To detect power supply oscillations by estimating the instantaneous frequency in the transient signals, TKEO has been applied to the electrical systems for the event(s) diagnosis (Rodriguez et al., 2013).

The TKEO energy signature [$\psi(f(t))$], for a time-varying continuous signal [$f(t)$] is given by Equation (1) as (Rodriguez et al., 2013):

$$\psi[f(t)] = \left[\dot{f}(t)\right]^2 - \dot{f}(t) \times \ddot{f}(t) \tag{1}$$

where, $\dot{f}(t) = \frac{df}{dt}$ is the first derivative and $\ddot{f}(t) = \frac{d^2 f}{dt^2}$ is the second derivative of $f(t)$. The discrete form of this signal which has been used in this work to calculate continuous time signals of frequency and voltage is given by Equation (2) as (Tran et al., 2014):

$$\psi[f(k)] = [f(k)]^2 - f(k-1) \times f(k+1) \tag{2}$$

Here in Equation (2), time derivatives of $f(t)$ are approximated and replaced by the time differences. In this technique, no band–pass filter is used to extract the TKEO of AM signal for the diagnosis of event (Li et al., 2009).

The TKEO can directly be applied to the raw vibration signal $f(t)$ i.e. in Equation (2) and can detect event(s) more effectively. Therefore, an effective discrimination in energy signature of $f(t)$ can be expected between the event bearing and normal conditions. The advantages of direct TKEO computation for $f(t)$ signal are as follows:

(i) Since, there is no band-pass filter used; hence, the estimation of an appropriate central frequency and band-width of band-pass filter is also not required.

(ii) The energy signatures using TKEO requires only three continuous adjacent samples at each time instant for the energy computation of the continuous time-varying signal hence, its implementation is computationally efficient and effortless.

Therefore, this method is easy to operate, time efficient with straightforward implementation and captures the information about the energy fluctuations directly.

3.2 Proposed Event Detection Technique

The manifestation of an event during time domain analysis is detected in the proposed methodology with REII indices of the energy signatures of bus voltage $\psi[V(t)]$ and bus frequency $\psi[f(t)]$ at all the 8 buses using TKEO. The buses in the developed system are equipped with µPMU which provides real–time variation of bus voltage and frequency signals. Moving sets of three continuous real–time samples in pu (per unit) for bus voltage and bus frequency are considered to compute energy signatures as shown in Equation (3) and Equation (4):

$$\psi_{B1}[f(t_1)] = [f(t_2)]^2 - f(t_1) \times f(t_3) \tag{3}$$

Here, $\psi_{B1}[f(t_1)]$ is the energy content of frequency for Bus 01 at time sample t_1 and $f(t_1)$, $f(t_2)$ and $f(t_3)$ are the bus frequencies of Bus 01 at time samples t_1, t_2, and t_3 respectively. The next energy content for bus frequency is given by Equation (4) as:

$$\psi_{B1}[f(t_2)] = [f(t_3)]^2 - f(t_2) \times f(t_4) \tag{4}$$

where, $\psi_{B1}[f(t_2)]$ is the energy content of frequency for Bus 01 at time sample t_2 and $f(t_2)$, $f(t_3)$ and $f(t_4)$ are the bus frequencies of Bus 01 at time samples t_2, t_3, and t_4 respectively. In this manner the REII indices are generated for the frequency signal of all eight buses.

The REII indices of bus voltages are also calculated using moving sets of three consecutive samples window of the µPMU output in real–time as represented in Equation (5) and Equation (6):

$$\psi_{B1}[V(t_1)] = [V(t_2)]^2 - V(t_1) \times V(t_3) \tag{5}$$

$$\psi_{B1}[V(t_2)] = [V(t_3)]^2 - V(t_2) \times V(t_4) \tag{6}$$

Here $\psi_{B1}[V(t_1)]$ and $\psi_{B1}[f(t_2)]$ are the energy content of voltage for Bus 01 at time sample t_1 and t_2 respectively. The real–time REII indices for bus frequency and voltages are computed under different events through µPMU output.

$$\psi[f(t)]B(k)[f(t_n)][f(t)]_{th\_max_{th\_min}} \tag{7}$$

$$\psi[V(t)]B(k)[V(t_n)][V(t)]_{th\_max_{th\_min}} \tag{8}$$

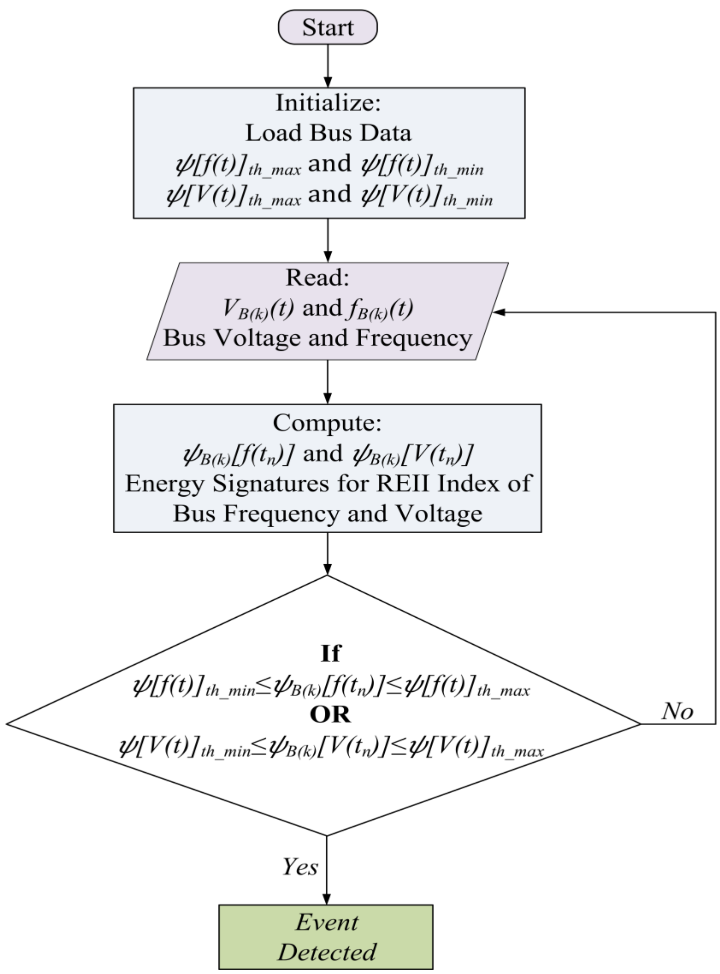


Figure 3. Flow chart of the proposed event detection methodology.

The real-time REII indices of bus frequency and voltage for all the 8 buses are then compared with the threshold energy signatures as given by Equation (7) and Equation (8) respectively and the event is detected eventually when the REII index violates the threshold limits. The threshold values for $\psi[V(t)]$ and $\psi[f(t)]$ are shown in Table 2 for different energy signatures.

Table 2. Threshold values of REII indices for $\psi[V(t)]$ and $\psi[f(t)]$.

Energy Signatures	Threshold Values (pu)
$\psi[f(t)]_{th\_max}$	0.0045
$\psi[f(t)]_{th\_min}$	-0.0118
$\psi[V(t)]_{th\_max}$	0.0238
$\psi[V(t)]_{th\_min}$	-0.0229

It has been observed under the various events that the REII indices varies with a small magnitude under the nominal events such as load change from ±10% to ±50% of the base load and system regain its stable operation within few cycles. Therefore, load change events are considered as the nominal operating conditions for the microgrid. The extremities of variation in REII indices for both frequency and voltage with ±50% load variation are considered as the threshold values for $\psi[V(t)]$ and $\psi[f(t)]$.

The flow chart of the proposed event detection methodology is shown in Figure 3. In implementing the proposed algorithm first step is to get the real-time bus data from the system viz. frequency $[f(t)]$ and voltage $[V(t)]$ variations using μPMU. The continuous energy signatures are then computed for both $[f(t)]$ and $[V(t)]$ simultaneously for each instant of time using TKEO to develop REII indices. The real-time REII indices are then compared with the threshold values as given in Table 2. If REII index violates the threshold limits then an event is flagged off or else, if the variation REII index is within the threshold limits then no event is detected.

4. Results Demonstration and Analysis

The simulation studies have been carried out using MATLAB® 2020a and DIgSILENT PowerFactory® 2020. The various events considered for non–islanding and islanding operations of the grid–connected microgrid system are given below:

(i) Islanding operation:
  - a) Islanding due to transformer switching of TFR01 and TFR02 together.
  - b) Islanding due to sudden outage of distribution lines DL01 and DL02 simultaneously.

(ii) Non–islanding operation:
  - a) Outage of DL01 or DL03.
  - b) Outage of DG01 or DG02.
  - c) Sudden load change of LD01 or LD02 up to ±50%.
  - d) Sudden outage of load LD01 or LD03.
  - e) Transformer switching of TFR01.
  - f) Short-circuit fault at distribution line (DL01 or DL02 or DL03) and cleared after 12 cycles.
  - g) Short-circuit fault at DL01 or DL02 and cleared after 12 cycles with a cascaded event of load outage LD01 or LD02 respectively.

Six different cases are presented in this section to examine robustness and effectiveness of the method proposed. These cases include severe as well as nominal events occurred in the microgrid including non-islanding and islanding operations. The details of the events are given below:

- **(i)** ***Case A*:** Islanding due to sudden outage of distribution lines DL01 and DL02 simultaneously at t=1.0s.
- **(ii)** ***Case B*:** Non–islanding due to short circuit fault at DL02 at t=1.0s and cleared at t=1.2s after 12 cycles with outage of DL02 from the microgrid.
- **(iii)** ***Case C*:** Load LD01 reduced to -50% of its rated load i.e. from 8MW to 4MW at t=1.0s.
- **(iv)** ***Case D*:** Load LD01 increased to +50% of its rated load i.e. from 8MW to 12MW at t=1.0s.
- **(v)** ***Case E*:** Load LD01 suddenly became out of service at t=1.0s and after 12 cycles synchronous generator DG01 also became out of service t=1.2s.

(vi) ***Case F*****:** Load LD01 reduced to **-**50% of its rated load i.e. from 8MW to 4MW at t=1.0s and load LD02 increased to +50% of its rated load i.e. from 2.5MW to 3.75MW after 12 cycles at t=1.2s.

The analysis of aforesaid cases is discussed briefly for highlighting the effectiveness of the presented methodology.

4.1 Case A (Sudden Outage)

In Case A, an islanding event occurred at t =1.0s with sudden outage (switching off) of distribution lines DL01 and DL02 simultaneously. The real–time variation of REII indices for frequency is presented in Figure 4(a) and voltage in Figure 4(b) for case A.

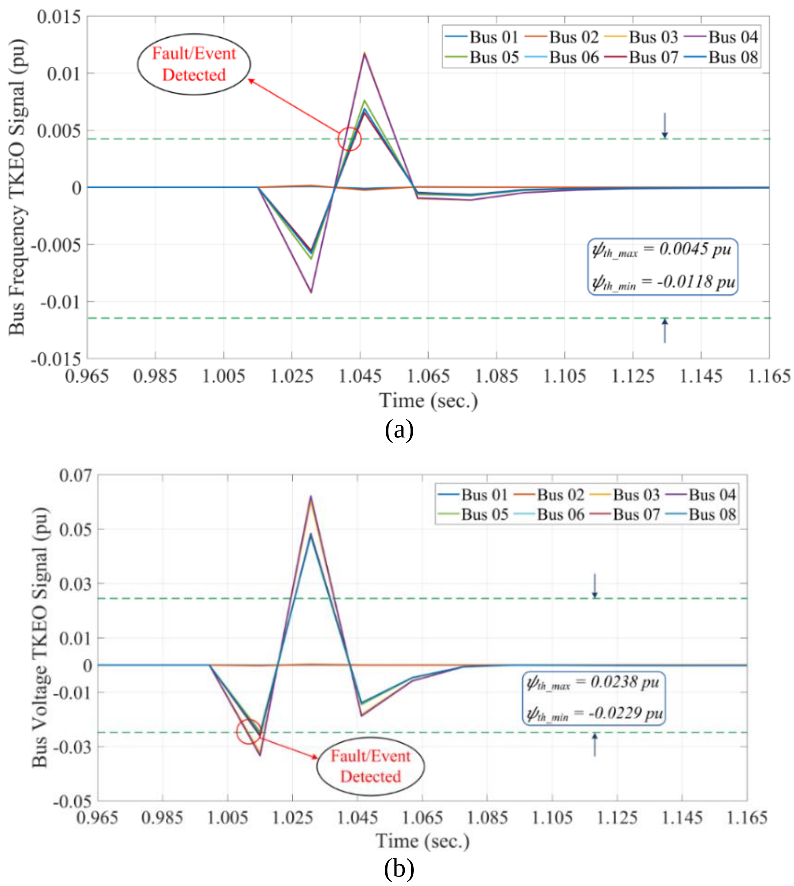


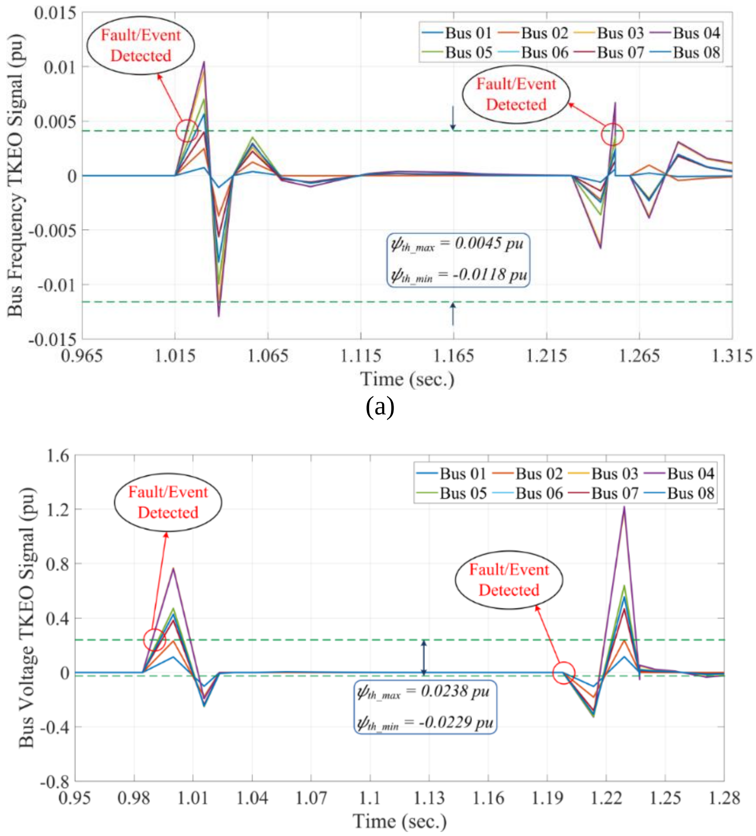
Figure 4. REII indices of (a) Bus frequency and (b) Bus voltage for case A.

The event occurred at t=1.0s and it has been noticed in Figure 4(a) that the REII index of bus frequency for bus 3 violated the maximum threshold at t=1.04s and the event is detected within 0.04s. Also, the REII index of bus voltage for bus 4 violated the minimum threshold at t=1.01s just after 0.01s from the event time in Figure 4(b).

So, the proposed technique is found well efficient in this case to detect the event with REII indices of bus voltage within 0.01s after the occurrence of an event.

4.2 Case B (with Severe Event of Cascaded Nature)

In Case B, more severe event of cascaded nature is studied i.e. a non-islanding event occurred at t=1.0s i.e. short-circuit fault at DL02 and cleared after 12 cycles at t=1.2s with DL02 switched off. One more event also occurred at t=1.2s i.e. LD02 switched off from the distribution network. The real–time variation of REII indices for frequency is presented in Figure 5(a) and voltage in Figure 5(b) for case B. Here, first event i.e. a short–circuit fault occurred at t=1.0s and cleared at t=1.2s with line outage.



(a) (b)

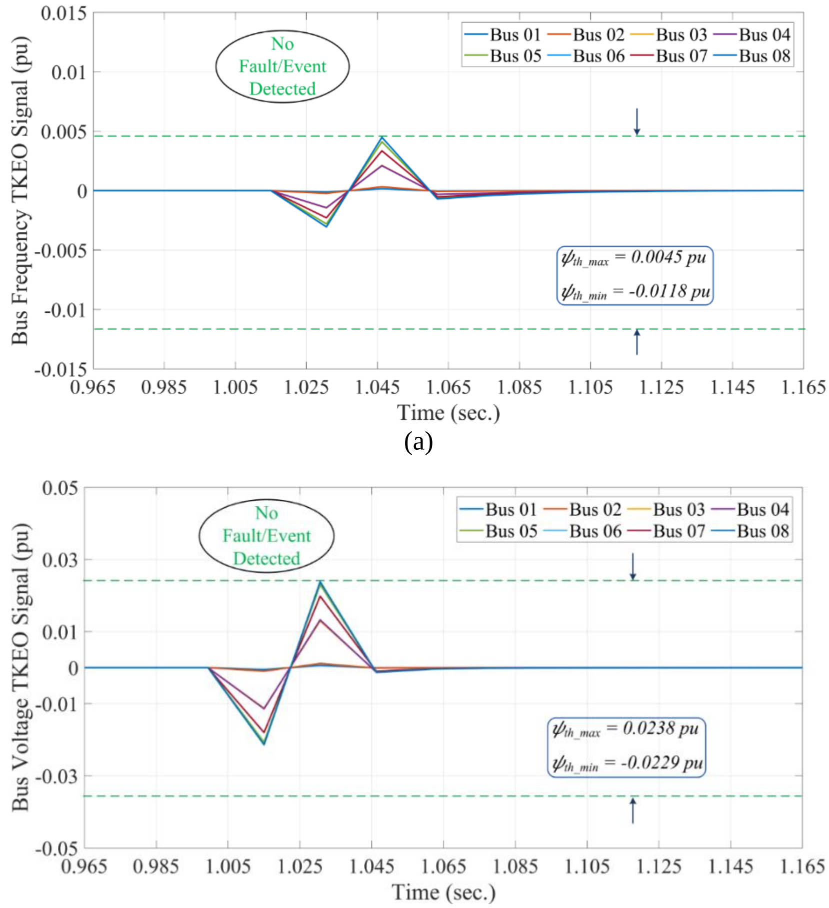
Figure 5. REII indices of (a) Bus frequency and (b) Bus voltage for case B.

It has been noticed in Figure 5(a) that the REII index of bus frequency for bus 4 violated the maximum threshold at t=1.02s and the fault has been detected within 0.02s. Also, the REII index of bus voltage for bus 4 violated the maximum threshold at t=1.01s and detected the fault just after 0.01s from the fault time as shown in Figure 5(b). Hence the short-circuit fault is identified with the REII index of bus voltage within 0.01s.

Second event occurred at t=1.2s in which line DL02 switched off and load LD02 disconnected from the network. In this event, it is noticed from Figure 5(a) that the REII index of bus frequency for bus 4 violated the maximum threshold at t=1.25s and identified the event after 0.05s. But, in case of bus voltage, REII index of bus voltage for bus 4 violated the minimum threshold at t=1.22s and detected the event just after 0.02s as shown in Figure 5(b). Hence, the clearance of fault and the second event are identified with the REII index of bus voltage within 0.02s. So, it can be concluded in this case that the fault and event in cascaded events are successfully detected with the proposed method.

4.3 Case C (Sudden Load Decrease of -50%)

In Case C, a sudden load variation of -50% from the rated load is considered. The real-time variation of REII indices for frequency is presented in Figure 6(a) and voltage in Figure 6(b) for case C. Here, load LD01 reduced to -50% of its rated value i.e. from 8MW to 4MW at t=1.0s.



(a)

(b)

Figure 6. REII indices of (a) Bus frequency and (b) Bus voltage for case C.

The REII indices for both bus frequency and bus voltage neither violated the maximum threshold nor the minimum threshold and the variation occurred within the threshold limits as seen in Figure 6. It is due to the fact that the load variation is not considered as an event in electrical power system, and it is a regular practice. Hence, the system regained its stable operation at t=1.065s just after 0.065s of the load change and status of the microgrid is predicted correctly by the presented method.

4.4 Case D (Sudden Load Increase of +50%)

In Case D, the load has suddenly increased by +50% from its rated load in LD01 (from 8MW to 12MW) at t=1.0s.

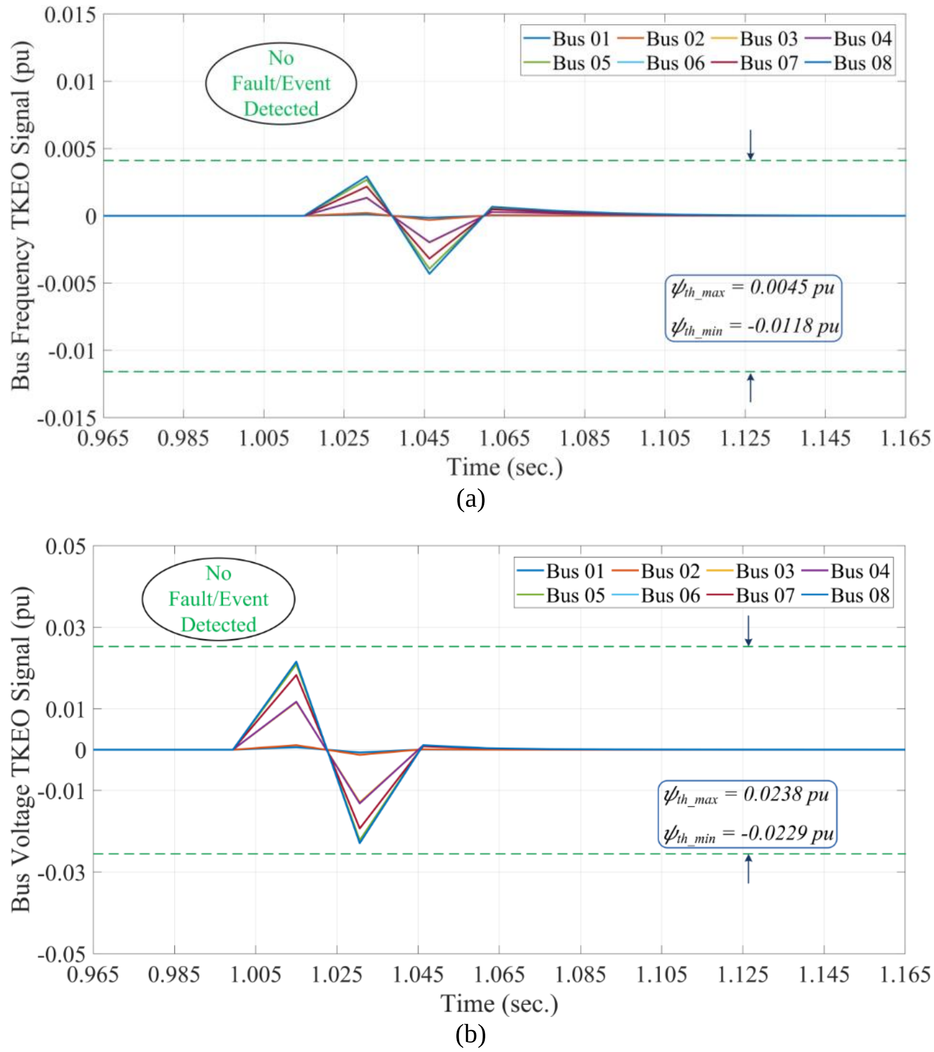


Figure 7. REII indices of (a) Bus frequency and (b) Bus voltage for case D.

The real–time variation of REII indices for frequency is presented in Figure 7(a) and voltage in Figure 7(b) for case D. The REII indices for both bus frequency and bus voltage are obtained and it is observed that these values neither violated the maximum threshold nor the minimum threshold as seen in Figure 7. The system regained its stable operation at t=1.065s just after 0.065s of the load change and no event is detected by the proposed method accurately.

4.5 Case E (Multiple Events of Cascaded Nature)

In Case E, events of cascaded nature are studied i.e. a non–islanding event occurred at t=1.0s i.e. load outage of LD03 and after 12 cycles at t=1.2s generation outage of DG01.

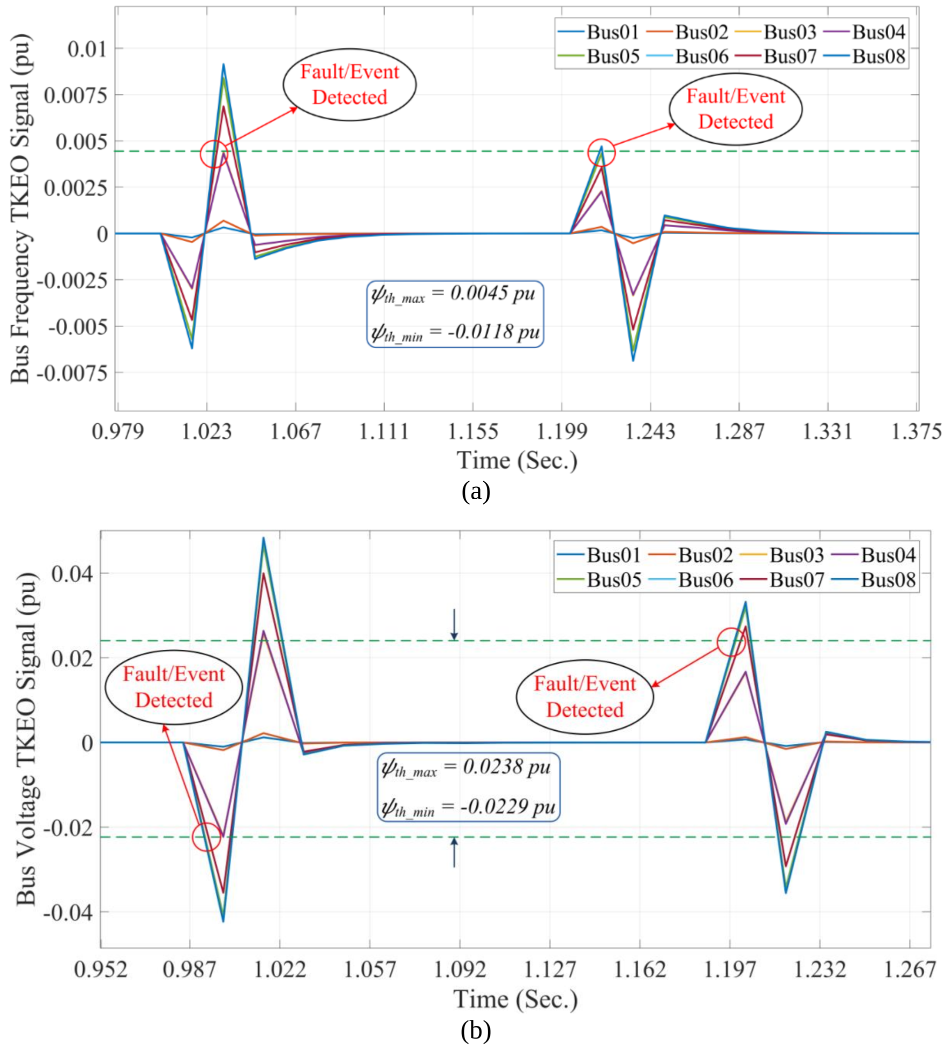


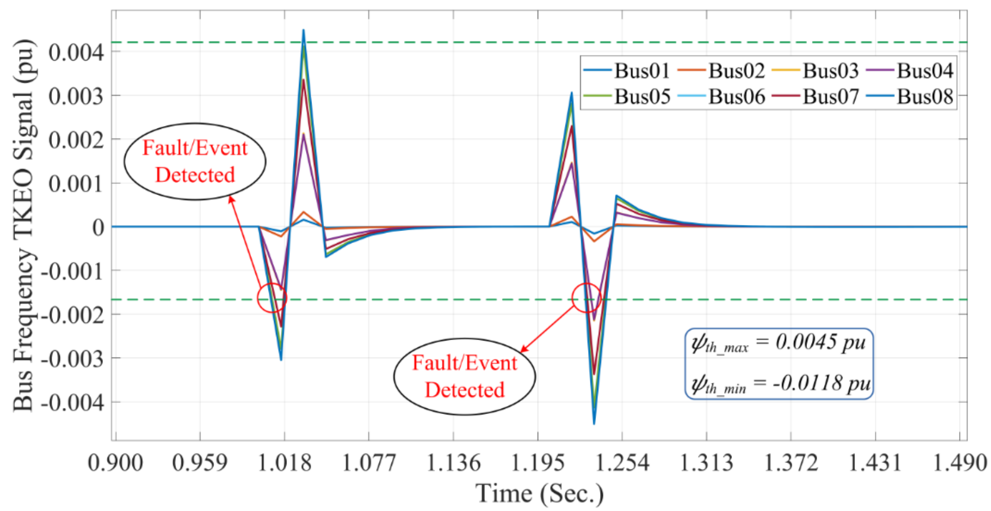
Figure 8. REII indices of (a) Bus frequency and (b) Bus voltage for case E.

The real-time variation of REII indices for frequency is presented in Figure 8(a) and voltage in Figure 8(b) for case E. Here, first event i.e. a load outage occurred at t=1.0s, it has been noticed in Figure 8(a) that the REII index of bus frequency for bus 6 violated the maximum threshold at t=1.023s and the fault has been detected within 0.023s. Also, the REII index of bus voltage for bus 6 violated the minimum threshold at t=1.01s and detected the event just after 0.01s from the event time as shown in Figure 8(b). Hence the load outage event is identified with the REII index of bus voltage within 0.01s.

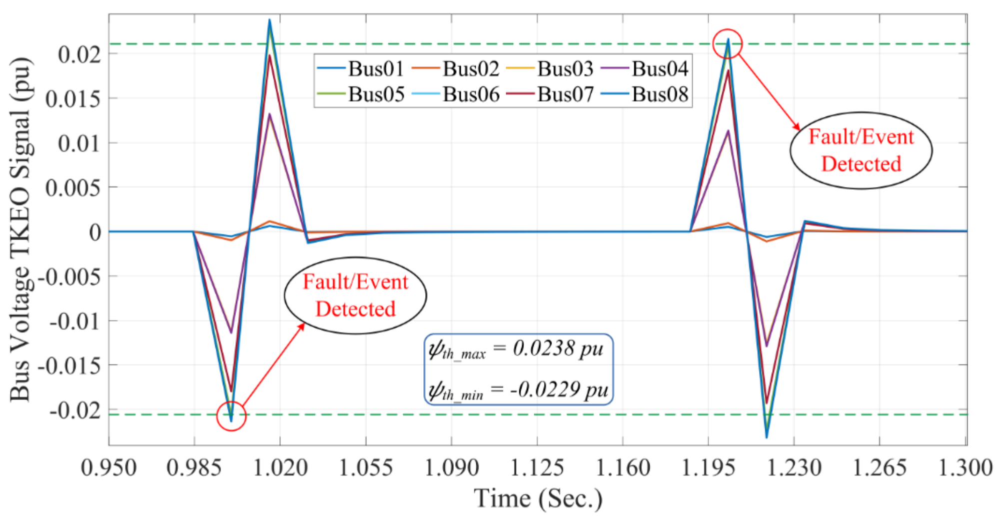
Second event occurred at t=1.2s in which line DG001 switched off from the network. In this event, it is noticed from Figure 8(a) that the REII index of bus frequency for bus 6 violated the maximum threshold at t=1.22s and identified the event after 0.02s. But, in case of bus voltage, REII index of bus voltage for bus 6 violated the maximum threshold at t=1.21s and detected the event just after 0.01s as shown in Figure 8(b). Hence, the second event is identified with the REII index of bus voltage within 0.01s. So, it can be concluded in this case that the events in cascaded event are successfully detected with the proposed method.

4.6 Case F (Multiple Events of Cascaded Nature)

In Case F, events of cascaded nature are studied i.e. a non–islanding event of load change occurred at t=1.0s in which LD01 reduced suddenly reduced to 50% of its rated demand and after 12 cycles at t=1.2s another load change event occurred in which LD03 suddenly increased to 150% of its rated demand. The real–time variation of REII indices for frequency is presented in Figure 9(a) and voltage in Figure 9(b) for case F.



(a)



(b)

Figure 9. REII indices of (a) Bus frequency and (b) Bus voltage for case F.

Here, first event i.e. a load variation occurred at t=1.0s and it has been noticed in Figure 9(a) that the REII index of bus frequency for bus 8 violated the minimum threshold at t=1.01s and the event has been detected within 0.01s. Also, the REII index of bus voltage for bus 8 violated the minimum threshold at t=1.01s and detected the event just after 0.01s from the event occurrence time as shown in Figure 9(b). Hence the load variation event is successfully identified by both the signatures i.e. frequency and voltage within the same duration of time i.e. 0.01s.

The second event occurred at t=1.2s in which line LD03 suddenly increased to 150% of its rated demand. In this event, it is noticed from Figure 9(a) that the REII index of bus frequency for bus 6 violated the minimum threshold at t=1.215s and identified the event after 0.015s. But, in case of bus voltage, REII index of bus voltage for bus 6 violated the maximum threshold at t=1.21s and detected the event just after 0.01s from Figure 9(b). Hence, the second event is successfully identified with the REII index of bus voltage within 0.01s. So, it can be concluded in this case that the events in cascaded event are successfully detected with the proposed method.

5. Performance Analysis of Proposed Method Under Different Operating Conditions

The study of different types of events to identify the robustness of the proposed technique is also performed under different operating conditions. There are 21 different types of events considered that include islanding as well as non–islanding operations as discussed above. It has been assumed that the time of occurrence for all the events in the system is identical i.e. t=1.0s and in the cases when there is a fault, the respective fault is cleared after 12 cycles. The analysis and discussion of all these events are presented in Table 3 which shows the event detection through the proposed method in different operating conditions.

Table 3. Analysis of the proposed method under different operating conditions.

Operating Conditions.	**Case Details**	**Event Occurred**	
		Actual	**Estimated**
Condition# 01	Steady State Analysis without any Disturbance	No	No
Condition# 02	Islanding: DL01 and DL02 out of service at 1s	Yes	Yes
Condition# 03	Islanding: DL01 and DL03 out of service at 1s	Yes	Yes
Condition# 04	TFR01 out of service	Yes	Yes
Condition# 05	DL01 out of service	Yes	Yes
Condition# 06	DL03 out of service	Yes	Yes
Condition# 07	DG01 out of service	Yes	Yes
Condition# 08	DG02 out of service	Yes	Yes
Condition# 09	LD01 reduced to 50% of rated load(8MW)	No	No
Condition# 10	LD02 reduced to 50% of rated load(2.5MW)	No	No
Condition# 11	LD01 increased to 150% of rated load(8MW)	No	No
Condition# 12	LD02 increased to 150% of rated load(2.5MW)	No	No
Condition# 13	S/C at DL01 at 1.0s, cleared at 1.2s with DL01 out of service	Yes	Yes
Condition# 14	S/C at DL02 at 1.0s, cleared at 1.2s with DL02 out of service	Yes	Yes
Condition# 15	S/C at DL03 at 1.0s, cleared at 1.2s with DL03 out of service	Yes	Yes
Condition# 16	LD01 out of service at 1.0s and DG02 out of service at 1.2s	Yes	Yes
Condition# 17	LD03 out of service at 1.0s and DG01 out of service at 1.2s	Yes	Yes
Condition# 18	S/C at DL02 at 1.0s, cleared at 1.2s with DL02 and LD02 out of service	Yes	Yes
Condition# 19	S/C at DL01 at 1.0s, cleared at 1.2s with DL01 and LD01 out of service	Yes	Yes
Condition# 20	LD01 reduced to 50% at 1.0s and LD03 increased to 150% at 1.2s	Yes	Yes
Condition# 21	LD04 reduced to 50% at 1.0s and LD02 increased to 150% at 1.2s	Yes	Yes

It is observed that in five cases for a nominal variation of frequency/voltage due to normal variation in the load (±20%-±30%) proposed method correctly classifies these changes as a normal operation. However, in all other cases when an actual event occurred in the system then the proposed method efficiently detected the event and estimated the event time.

The proposed methodology has been found robust and well efficient as per the studies performed in all types of events under different operating conditions in the microgrid system connected to the main grid with different DERs. Moreover, the comparative analysis is presented in Table 4 to validate that the proposed method is also well efficient when compared with the available well established event detection approaches (Sankar and Sunita, 2021).

Table 4. Comparative analysis of various event detection techniques.

Technique	Time for Event Detection	Benefits	Limitations	Reference
ANFIS and Passive Technique	0.045s	Good accuracy and lesser NDZ	Training time	Mlakic et al. (2019)
SVM	0.04s	Least false event detection	Significant NDZ	Baghaee et al. (2020)
Moving Window PCA	Under 2s	Relevant for dynamic variables	Significant NDZ, false detections and Short circuit faults not analysed	Rafferty et al. (2016)
PCA	Under 2s	Detection of islanding location	Not efficient under incomplete outliers, significant NDZ and false detections	Liu et al. (2015)
Linear PCA	Under 2s	Event type detection using fault reconstruction vector	High false detections and only suitable for linear and static data	Guo et al. (2013)
Recursive PCA and Approximate linear dependence condition	Under 2s	Detection of islanding location	High false detections and Short circuit faults not analysed	Guo et al. (2015)
PCA	20 ms	Lesser NDZ	Well suitable for linear variables	Muda and Jena (2018)
Moving window kernel PCA	Under 2s	Well suitable for the non-linear voltage characteristics	Significant NDZ, false detections and Short circuit faults not analysed	Liu et al. (2016)
Proposed REII Technique	Under 0.02s	100% efficient with great accuracy. Applicable under various operating conditions with zero false alarms	Event location not identified (future scope)	"NA"

5.1 Performance Analysis with State of Art Using Machine Learning Models

The proposed method works on TKEO based energy signatures of buses voltage and frequency to identify the occurrence of an event in the microgrid connected with multiple DERs. In this method the REII indices of buses voltage and frequency are calculated in pu and the event is flagged whenever the signatures in REII violates either minimum or maximum threshold. This approach makes the proposed method heuristic in nature however; the efficiency of the method under different operating conditions and multiple scenarios has been found 100%. Therefore, the results obtained for methodology proposed in this work are also compared with the results obtained through AI based Machine Learning Models to examine the robustness and effectiveness. Four Machine Learning Models are used to compare the results viz.

a. Support Vector Classifier (SVC) (Perez et al., 2023)
b. Multi–Layer Perceptron (MLP) (Mandal and Chanda, 2023)
c. Random Forest (Hola and Czarnecki, 2023)
d. AdaBoost (Belghit et al., 2023)

The data set of total 200 cases is utilized to assess the efficiency of event identification. The data is first shuffled thoroughly and then 80% of the dataset is used for training and rest 20% is utilized for testing the trained data mining tools.

The assessment results obtained are presented in Table 5. It has been observed in the assessment results that the efficiency through one of the methods i.e. SVC is 90% but through other three machine learning methods viz. MLP, Random Forest and AdaBoost is 100% that matches the efficiency and accuracy of the methodology proposed in the present work.

Table 5. Assessment results of AI/ML tools and proposed method.

Methods	Accuracy/Efficiency
Proposed Method	100%
Support Vector Classifier	90%
Multi–Layer Perceptron	100%
Random Forest	100%
AdaBoost	100%

However, the continuous update of data is essential in AI/ML tools for the assessment which may increase the response time which is not required in the proposed methodology. Therefore, the response time is very less in the proposed method as it assesses the event through the energy signatures directly that is an advantage over AI/ML tools.

6. Conclusion

In this work successful operation of the gird connected microgrid with multiple DERs has been accomplished by the dynamic modeling of controllers for PVDG and WG. The system has been tested for successful operation of DERs by performing dynamic simulation under different operating conditions as well as under steady–state condition. A novel event detection technique for abnormalities in the microgrid operation is also proposed in this paper using TKEO based REII indices. The major highlight of the proposed method is its dependence only upon the real-time voltage and frequency signals therefore it is essentially capturing the uncertainties associated with intermittent sources of energy in the microgrid. Moreover, it can identify the event immediately after the actual occurrence of the event. Simulation studies of the proposed method on the designed system have been performed under different operating conditions. In the proposed method, a continuous real–time REII index is computed through μPMU output for both bus frequency and bus voltage signals using TKEO. Based–on the system response under nominal changes viz. load variation from ±10% to ±50% of the rated load, a threshold window for energy signatures is estimated. It has been observed in the simulation studies that REII violates the threshold window only when there is a severe event occurred either at grid side or DG side and the event is successfully detected within few cycles. Different types of operating conditions with various events have been considered to examine the efficacy and robustness of the technique proposed. It is found that in case of an actual event only the proposed algorithm flagged the event whereas for all other variations REII never violates the threshold boundaries. The simulation results depict the robustness and effectiveness of the technique proposed in terms of event estimation time which is 0.01s to 0.02s, event accuracy and applicability in all types of events as the system is found able to regain its stable operation within 0.5s to 0.65s. Moreover, the presented methodology is also compared with the four Artificial Intelligence based methods viz. SVM, MLP, Random Forest and AdaBoost and it has been found that it is 100% efficient and accurate. Therefore, it can be concluded that the proposed methodology is robust in all types of events under different operating conditions for a microgrid connected to the main grid with multiple DERs. The proposed method is well efficient for event detection in a balanced microgrid system. This study can be extended for identifying the event location and type for the balanced and unbalanced system in the future work.

Nomenclature

DER	Distributed Energy Resources
DG	Distributed Generation
TKEO	Teager–Kaiser Energy Operator
μPMU	Micro-Phasor Measurement Unit
REII	Robust Event Identification Index
PVDG	Photovoltaic Distributed Generator
WG	Wind Farm Generators
SG	Synchronous Generator
HIF	High Impedance Fault
DESS	Distributed Energy Storage System
DWT	Discrete Wavelet Transform
DFT	Discrete Fourier Transform
IIDG	Inverter Interfaced DG
AI	Artificial Intelligence
ML	Machine Learning

Conflict of Interest

The authors declare no conflicts of interest regarding this article.

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