Identification of Critical Nodes Using Granger Causality for Strengthening Network Resilience in Electrical Distribution System

Divyanshi Dwivedi, D. Maneesh Reddy, Pradeep Kumar Yemula, and Mayukha Pal

Abstract As countries around the world commit to reducing brownfield energy generation and shifting toward clean energy, the placement of renewable energy sources (RES) optimally in the electrical distribution system remains a strenuous issue. Improperly integrating RES could have a detrimental impact on the efficient operation of the grid. This study proposes a real-time data-driven approach for optimal DERs allocation and identification of critical nodes in the electrical distribution system. A community detection clustering is performed on the IEEE 123 node feeder system to optimally cluster the nodes into two regions. Then, the Granger causal analysis is used to identify critical nodes in the system that are susceptible to failure or extreme events which may interrupt the operation of the system. Hence, strategically allocating RES to these critical nodes enhances network resilience, as validated by the computation of the percolation threshold. The findings reveal an impressive 37% boost in the system's resilience attributed to the optimized deployment of RES.

Keywords Data-driven method · Renewable energy sources · Electrical distribution system · Granger causality · Percolation threshold · Resilience

1 Introduction

In 2018, a major power disruption took place in Puerto Rico when a tree fell on a crucial power line close to Cayey. This led to a significant outage, causing around 870,000 customers to lose access to electricity, making it the most severe power outage incident experienced by the territory of the USA [1]. Instances of cascading failures occur when a critical component in the electrical distribution system (EDS) faces disruption and subsequently affects other areas of the network, resulting in power outages for a large number of customers. To avoid such scenarios, identifying

D. Dwivedi · M. Pal (✉)
ABB Ability Innovation Center, Asea Brown Boveri, Hyderabad, India
e-mail: mayukha.pal@in.abb.com

D. Dwivedi · D. M. Reddy · P. K. Yemula
IIT Hyderabad, Hyderabad, India

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critical nodes and implementing necessary preventive measures may prove beneficial in preventing cascading failures [2]. Placing DERs at the identified critical nodes is a crucial precautionary measure that helps in maintaining continuous power flow and enhances the resilience of the system. "Resilience" refers to the ability to withstand, respond to, adapt to, and prevent disruptive events in the system during extreme events [3]. In a resilient EDS, residential solar PV panels and energy storage devices are commonly used for rapidly reconfiguring power flow and restoring electricity when extreme events happen [4]. Therefore, identifying these critical nodes and strategically placing RES in these locations could further improve the system's resilience. In the existing literature, the researchers have not thoroughly evaluated the real-time identification of these crucial nodes due to the complexities involved [5]. Rather critical nodes have been considered only for maintaining the certainty for the supply–demand [6] and in the presence of undetectable cyber-attacks [7]. However, the incorporation of distributed energy resources (DER) at the critical node for enhancing the system's resilience in real time was not performed.

In the distribution grid, the incorporation of RES is preferable for medium/low voltage levels as it causes reduction of system losses, and stress on generators and transmission system [8]. Various methods have been proposed for identifying optimal locations for DERs integration [9]. Placing DERs in inappropriate locations may lead to voltage deviations, power quality problems, increased power loss, and harmonic distortions. These issues have the potential to adversely impact system reliability and resilience. The current work only considers voltage stability margins and reduction in losses as key factors for optimal DER placement, without taking system reliability and resilience into account [10, 11]. Therefore, it is necessary to consider system resilience when optimally placing the DERs.

Quantifiable metrics are needed to measure the resilience of power distribution systems[12]. These metrics are based on the definition of resilience and include measures such as the aggregation of adaptive capacities of system assets, to assess the system's ability to withstand adverse conditions [13]. Additionally, a metric has been proposed for evaluating the influence of the short-term event on the long-term resilience of the system [14]. Another probabilistic metric has been developed to assess the resilience of EDS concerning extreme incidents [15]. While these metrics evaluate the operational resilience of the system, they do not provide a comprehensive perspective on the entire infrastructure as a single quantity [16]. The metrics discussed above do not consider the progression of events and how different characteristics of the system are impacted. As a result, the evaluation of resilience becomes inaccurate which may affect system operations. To address this issue, we use the percolation threshold as a metric to evaluate resilience in a more effective manner [4]. The percolation threshold is a statistical measure utilized to track system state transitions in response to extreme events, by monitoring the progress of such events. It is essential for energy resilience planning and operational decision-making, and the data-driven analysis can be integrated into any digital substation. Conversely, existing methods for identifying critical nodes and measuring system resilience are not feasible for real-world digital substations. For the identification of the optimal locations to integrate RES into the EDS, our study employs the Granger causality technique.

Granger causality was introduced by Granger in 1969 and is proven to be an effective statistical tool for analyzing time series data. This technique enables the identification of cause-and-effect relationships in an econometric model before the effect occurs. It involves using a multivariate regression model to examine the predictability of one signal's time-series data with the assistance of another signal's history [17, 18]. Granger causality has applications in multiple domains, including finance and neuroscience [19]. Furthermore, the principle of causal inference, which is based on information fusion, has the potential to aid in predicting electrical behavior resulting from shared causal dependencies [20]. By leveraging the efficacy of this technique, we were able to identify closely dependent and correlated nodes within the network that were appropriate for DER integration.

In this paper, we introduce a novel data-driven analysis that can be integrated into digital substations for optimizing the allocation of DERs. To test and validate our framework, we simulate the standard IEEE 123 node feeder system and obtained the time-series data of active power for analysis. By computing the Granger causality between the system's nodes, we identified the correlation between nodes. In cases where a node has high dependencies on other nodes, their failures could trigger cascading failures in EDS. Critical nodes in the network were identified and selected for the integration of RES for improving their self-sustainability. Our study further demonstrated that placing DER at the identified critical nodes improves the resilience of the system by the calculation of the system's percolation threshold.

The paper is structured as follows: Sect. 2 outlines the methodology utilized, and Sect. 3 provides information about the simulation and the steps taken for implementing the proposed framework. In Sect. 4, we analyze the results of the proposed framework on IEEE 123 test system and validate its performance. Finally, Sect. 5 concludes the study and summarizes our findings.

2 Materials and Methods

2.1 Discussion on Granger Causality

Granger causality referred to as G-causality is a statistical technique that determines how the past values of one time-series, T_2, could help for predicting the future values for another time series, T_1, such that T_2 Granger-causes (G-causes) T_1. This technique is established on the multivariate autoregressive model (AM) of a time-series process. Mathematically, to determine if T_2 G-causes T_1, a bivariate autoregressive (BVAR) model is constructed for both time series, with the same time length of both processes. In the context of electrical distribution system analysis, T_1 and T_2 represent the time-series data of power consumption recorded at 1-minute intervals.

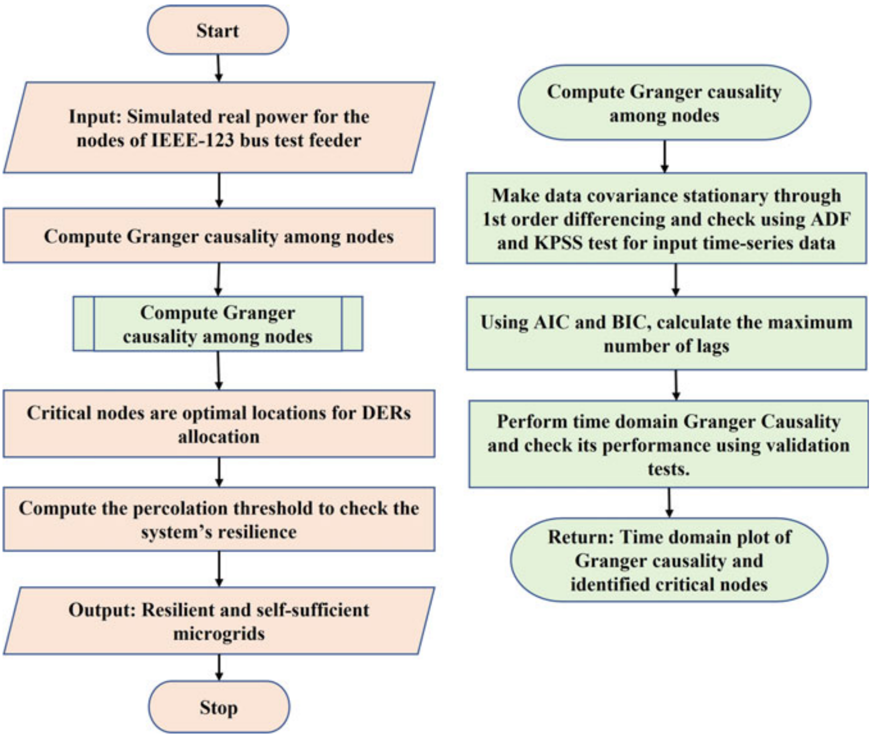

Fig. 1 Proposed framework put forward comprises distinct stages, including the application of Granger causality, the identifying critical nodes, and the assessment of the system's resilience

Model—1:

$$T_1(x) = \sum_{(i=1)}^{n} \alpha_{(11,i)} T_1(t-i) + \sum_{(i=1)}^{n} \alpha_{(12,i)} T_2(t-i) + \varepsilon_1(x) \tag{1}$$

$$T_2(x) = \sum_{(i=1)}^{n} \alpha_{(21,i)} T_1(t-i) + \sum_{(i=1)}^{n} \alpha_{(22,i)} T_2(t-i) + \varepsilon_1(x) \tag{2}$$

The value of n is the model order, representing the maximum lag integrated into our analysis to compute the Akaike Information Criterion (AIC) [21] and Bayesian Information Criterion (BIC) [22]. The Yule–Walker equations are utilized to determine the model parameters, represented by coefficient $\alpha_{(yz,)}$ ($i = 1, 2, \ldots, n$ and $y, z = 1, 2$). Furthermore, $\varepsilon_1(x)$ and $\varepsilon_2(x)$ are the error term used for loss of variances. Then, the univariate AM for T_1 and T_2 is computed by removing T_2 in Eq. (1) and T_1 in Eq. (2) in Model 2.

Model—2:

$$T_1(x) = \sum_{(i=1)}^{n} \alpha^*_{(11,i)} A_1(t-i) + \varepsilon_{11}(x) \tag{3}$$

$$T_2(x) = \sum_{(i=1)}^{n} \alpha^*_{(22,i)} A_2(t-i) + \varepsilon_{22}(x) \tag{4}$$

If the $\varepsilon_{11}, \varepsilon_{22}$ increases in comparison to error terms, $\varepsilon_1, \varepsilon_2$ then it means that T_2 G-causes T_1 and T_1 G-causes T_2 respectively. The magnitude of G-causality is determined by calculating the logarithmic ratio of the error terms. To illustrate, if T_2 G-causes T_1, then the magnitude of G-causality is expressed as:

$$\mathcal{F}_{2\to 1} = log \frac{\text{var}(\varepsilon_{11}(x))}{\text{var}(\varepsilon_1(x))} \tag{5}$$

When dealing with multiple time series processes, such as $T1$, $T2$, $T3$, $T4$, the process is the same as previously detailed, except the implementation of multivariate AM instead of BVAR, which is also known as conditional Granger-Causality [18]. An important presumption underlying models states that the time-series must exhibit covariance stationarity. Essentially, this means that the time series should possess consistent variance, mean, and covariance among two points based solely on their relative positions. The implementation of Granger causality with step-by-step instructions is depicted in Fig. 1. We use Granger causal analysis for identifying the nodes having high causal dependency in the distribution system. These nodes are recommended as the optimal allocation of RES.

2.2 Percolation for Evaluating Resilience

In order to evaluate the efficacy of the proposed approach in strengthening the electrical system's resilience at the designated DER placement, the percolation threshold is calculated as a resilience metric. The percolation threshold is a statistical tool used for the identification of variations in a system's operations. Percolation threshold offers both qualitative and quantitative measures of network resilience, making it an effective tool [4]. The percolation threshold is calculated by first determining the percolation strength, then evaluating susceptibility and estimating percolation threshold ρ_c at the point of maximum susceptibility [23].
Percolation Strength,

$$PS_\infty(p) = \frac{1}{NR} \cdot \sum_{q=1}^{R} SB_q(p) \tag{6}$$

Here, the function $SB(p)$ is dependent on the probability of bond occupation, defined as $p = v/V$, where V and v are the total edges and the edges that have been removed from the initial structure respectively. The total nodes are denoted by N. The susceptibility can be calculated as follows:

$$\chi(p) = \frac{(1/N^2R)\sum_{q=1}^{R}(SB_q(p))^2 - [PS_\infty(p)]^2}{P_\infty(p)} \tag{7}$$

$$\rho_c = \arg[\max \chi(p)] \tag{8}$$

We began by constructing a complex network for the distribution system with and without DER integration and used Eq. (6) to determine the bond occupation probability of the network. Next, we calculated the percolation strength of the network by removing edges/vertices, then evaluated the bond occupation probability at which susceptibility reaches its maximum; referring to it as the percolation threshold given in Eq. (8). It is considered as a quantifiable measure of resilience, where a higher value corresponds to a more resilient electrical system. This methodology was applied to validate the results obtained from Granger causality.

3 Data and Its Processing

The simulation was performed for the generation of the data and the proposed methodology. The IEEE 123 node test feeder is modeled in GridLAB-D which operates at 4.16 kV. The system comprises 84 constant loads and 36 other nodes (Meter nodes). The distribution system nodes were clustered into two regions using community detection clustering [24] and named them as Region-I and Region-II, as shown in Fig. 2.

Moreover, in order to determine the optimal locations for integrating DERs into the system, functional dependence between the nodes is identified using Granger causality. Nodes with high functional interdependence would significantly impact other nodes of the region and interruptions in these nodes could result in cascading failures or system outages. Therefore, identifying the highly dependent nodes and installing DERs (primarily 50 kW solar PV panels) in those locations would enhance the electrical distribution system's resilience and reliability.

In order to verify the efficacy of the optimal DER placement for enhancing system resilience, we calculated the percolation threshold for two regions under two conditions; integrated DERs and the absence of DERs. Initially, compute the Pearson correlation coefficient between the nodes, and apply a positive coefficient threshold for generating the adjacency matrix, and constructed a complex network. The percolation threshold was subsequently determined by applying the method described in Sect. 2.2 to the resulting complex networks. Figure 1 visually depicts the proposed methodology.

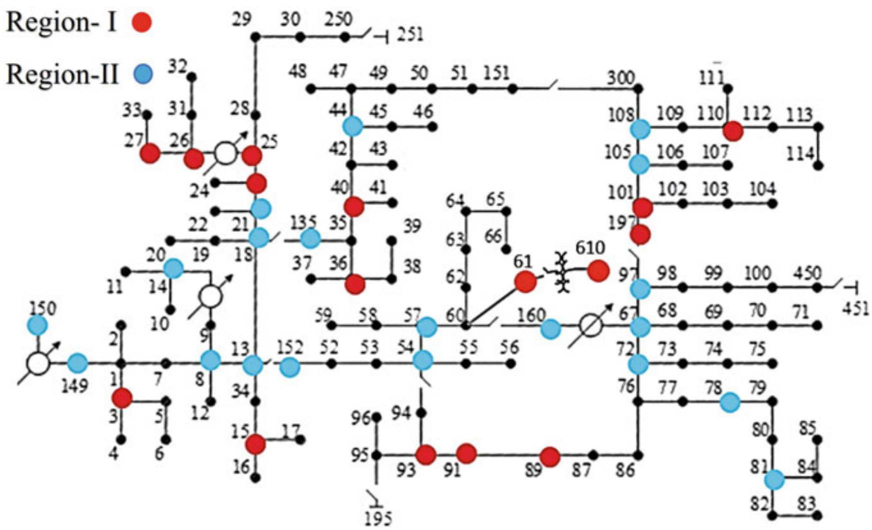

Fig. 2 IEEE-123 node test feeder clustered using community detection clustering algorithm as Region-I and Region-II

4 Results and Discussion

By implementing community detection clustering, the IEEE-123 node test feeder was optimally clustered into two regions, as depicted in Fig. 2. Granger causality was then utilized for determining the optimal locations for RES. We validated the incorporation of RES at the critical nodes in terms of the network's resilience and reliability by assessing the percolation threshold. The proposed methodology provides an end-to-end data-driven solution that provides a resilient and reliable system, with optimal DER placement by identifying the network's critical nodes.

4.1 *Critical Nodes Identification in Region-I*

Granger causality analysis is conducted on Region-I without integrating DER. As seen in Fig. 3, Region-I nodes are highly interconnected with significant magnitude. Among 16 nodes in Region-I, Meter-197, Meter-101, Meter-89, and Meter-26 were identified as critical nodes since they are strongly dependent on all other nodes in the region. Therefore, DERs such as solar panels were integrated into these nodes to enhance the system's resilience.

Initially, solar panels were incorporated at Meter-101, resulting in a prominent decrease in dependency and magnitude between the nodes, indicating that nodes became less dependent on each other as shown in Fig. 4a. Similarly, after

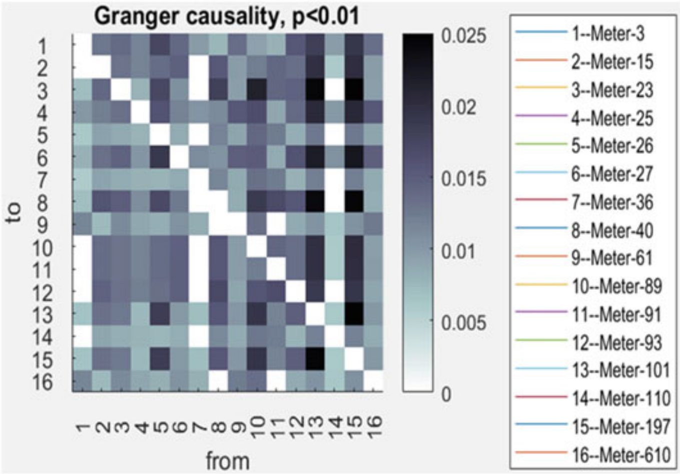

Fig. 3 Granger causality analysis for Region-I

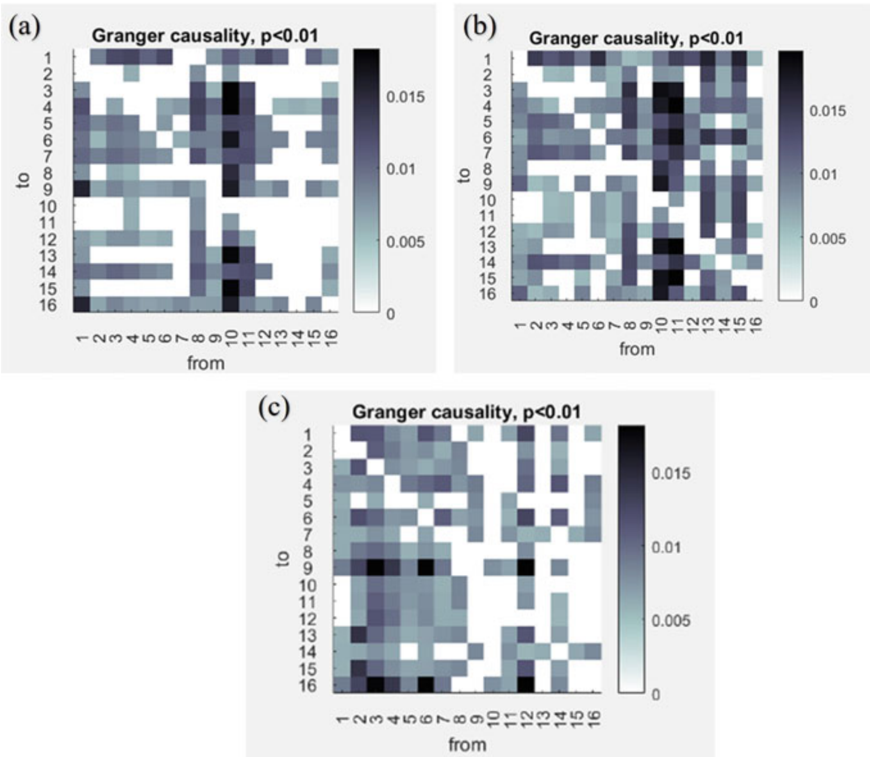

Fig. 4 Granger causal dependencies for Region-I with solar PV panels at **a** Meter-101, **b** Meter-197, **c** all critical nodes

incorporating solar panels at Meter-197, the causing magnitude and dependency have reduced in comparison to the Region-I operating without DERs, as seen in Fig. 4b. Finally, when solar panels were installed at all three critical nodes, the overall network dependencies were significantly reduced, as shown in Fig. 4c.

4.2 Critical Nodes Identification in Region-II

We performed the same analysis on Region-II as well. Figure 5 depicts the causal dependency between the nodes in the absence of DERs, revealing that the nodes causing effects are notably significant. Through the analysis, we were able to identify Meter-13, Meter-18, Meter-21, and Meter-44 as the critical nodes in Region-II that require the inclusion of solar PV panels to boost the region's reliability.

The inclusion of solar panels at Meter-21 showed a significant reduction in causing magnitude, as depicted in Fig. 6a, with Meter-57 and Meter-54 becoming independent on other system nodes. Similar to that the integration of solar PV panels at Meter-13, as shown in Fig. 6b, resulted in a slightly higher magnitude than Fig. 6a, but with reduced node dependencies. Finally, we integrated solar panels at all critical nodes as shown in Fig. 6c and observed a decrease in causing magnitude as compared to Fig. 5, along with an increase in the number of independent nodes. Thus, incorporating solar panels into the Region-II distribution microgrid has resulted in a more reliable and self-sufficient system that can efficiently maintain supply and demand.

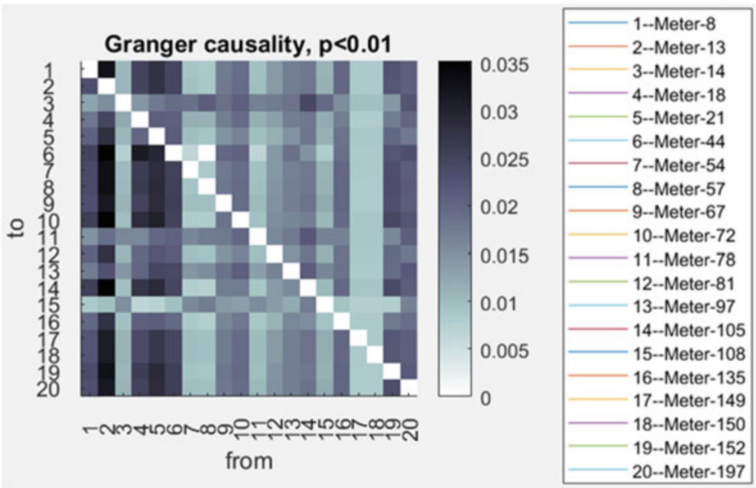

Fig. 5 Granger causality analysis for Region-II

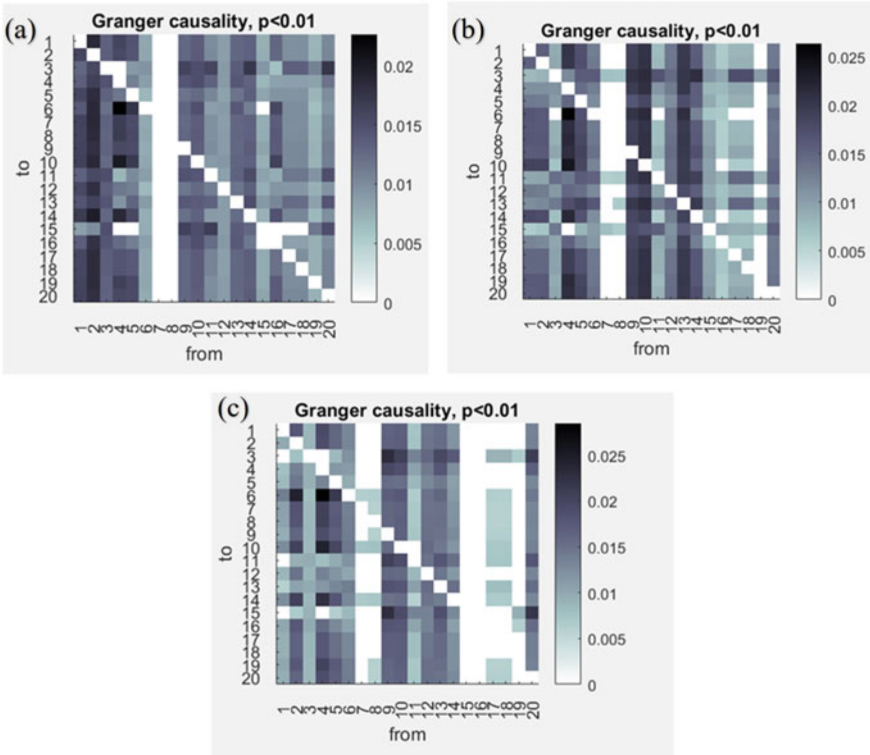

Fig. 6 Granger causal dependencies for Region-II with solar PV panels at **a** Meter-21, **b** Meter-13, **c** all critical nodes

4.3 *Evaluation of System's Resilience*

This section validates the reliable and resilient response of a system with RES incorporation at critical nodes. The network's resilience is determined by the computation of the percolation thresholds for the correlated network, for both regions under two conditions; integrated RES and the absence of RES. Higher percolation thresholds indicate greater network resilience. Results for Region-I and Region-II are shown in Table 1, the percolation threshold value increased with RES incorporation at critical nodes in both regions. Additionally, incorporating the same number of solar PV panels randomly in both regions showed less improvement in the percolation threshold when compared to RES placement at critical nodes. These findings demonstrate the effectiveness of the proposed methodology for the optimal allocation of RES, which enhances resilience and enables the system to sustain interruptions without a complete breakdown.

Table 1 Percolation threshold for both regions under various conditions for RESs integration

Region	RES placement	Percolation thresholds
Region-I	Without RES	0.06722
	With RES at RN	0.07733
	With RES at CN	0.09766
Region-II	Without RES	0.05263
	With RES at RN	0.05868
	With RES at CN	0.08349

*RN- Random Nodes, CN- Critical Nodes

5 Conclusion

The proposed methodology provides an effective approach for optimal DERs allocation in the electrical distribution grid and also quantifies and validates the system's resilience. We grouped the nodes of the IEEE-123 test feeder system into two clusters based on similarity using a community detection clustering algorithm. We further employed Granger causality to determine the critical nodes in the system that are strongly sensitive to disruptions and critical outages. We again performed Granger causality with solar panels integrated at these locations, and it is observed that there is a significant reduction in causal dependencies and magnitudes between nodes. To validate the proposed method, we calculated the percolation threshold for both regions under two conditions; integrated DERs and the absence of DERs. The results demonstrated a 31.17% increase in the percolation threshold for Region-I and a 37% increase for Region-II when the RES got integrated at critical nodes. These findings prove the effectiveness of our proposed methodology in developing a reliable and resilient distribution system with less node dependency, and nodes could maintain supply–demand independently.

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