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Evaluation of operational resilience in electrical distribution systems

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ABSTRACT

Resilience evaluation is a crucial aspect of operation and planning in electrical distribution systems (EDS). Resilience refers to the system's ability to effectively respond to and recover from highly impactful, low-probability (HILP) events. Recent advancements in renewable energy technologies have paved the way to build and significantly enhance the resilience of EDS under extreme events. This paper introduces the percolation threshold (PT) as a quantifiable measure for analyzing the operational and planning resilience of the system. PT helps in measuring the resilience of EDS in an instantaneous time-based environment with consideration of different fault conditions. This study compares PT values at various nodes of the distribution system with and without extreme events. The fault time and restoration time of the system are analyzed for various events. To evaluate the performance of PT, it is compared with other electrical-based resilience measures. The analysis is extended to a larger system considering longer time frames and integration of distributed energy resources (DER). Additionally, we employ a machine learning-based feature importance algorithm to identify the important nodes of the EDS that significantly characterize the system's resilience. Furthermore, we use Gaussian Process Regression (GPR) for the prediction of PT values, offering a proactive approach to understanding and managing system resilience. The developed framework provides a valuable method for analyzing and enhancing the resilience of EDS that enables utilities and system operators to make informed decisions and implement robust strategies to ensure resilient power system operation.

1. Introduction

The distribution grid in various regions around the world has become more vulnerable due to the deteriorating infrastructure, particularly in places where investment in grid modernization has not kept pace with growing demands and technological advancements [1]. This deterioration could be attributed to several factors, including but not limited to aging infrastructure, financial constraints, regulatory and logistical challenges, increased demand, and environmental factors. The continuous maintenance of EDS encounters difficulties due to a combination of financial, regulatory, and logistical issues, which would further be compounded by a lack of skilled workforce [2]. The EDS is also coupled with adverse varying weather conditions such as lightning strikes, hurricanes, and storms with strong winds causing severe damage to overhead lines [3,4]. In the United States, approximately 50% to 60% of power interruptions are attributed due to extreme weather events [5], leading to annual economic losses ranging from $20 to $55 billion [6]. The increase in such incidents has emphasized the need for a resilient distribution grid. The importance of resilience in the electrical distribution system became evident after the impact of Superstorm Sandy in 2012, which exposed the vulnerability of the power grid's reliability [7]. To minimize the adverse impacts of extreme weather events on the power grid infrastructure, significant efforts have been made to propose the need for resilience.

It is found that there is a lack of clear definitions and quantifiable measures for resilience in EDS that hampers the practical implementation of resilience strategies. Resilience in EDS could be referred to the network's ability to withstand power supply disruptions during challenging operating conditions and to recover from damages caused by such events as shown in Fig. 1 [8–10]. In recent years, there has been a significant research focus on the resilience of distribution grids, and the study has been approached in two ways. The first approach involves developing qualitative frameworks to analyze grid resilience and identify policies that can enhance it. The second approach focuses on the creation of measures that quantitatively measure grid resilience,

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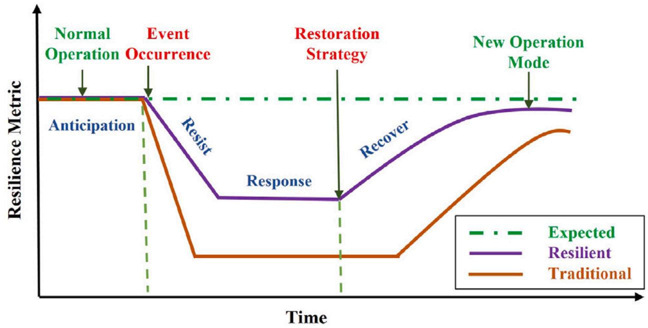


Fig. 1. The typical system performance curve in case of extreme events.

aiding to improve the response in adverse situations [11]. Resilience analysis encompasses various aspects, including adaptation and recovery strategies, as well as guidelines for designing resilient grids. For instance, researchers have explored the relationship between power grid resilience and power generation, particularly distributed generation, with a focus on designing resilient distribution grids. Studies have shown that optimized allocation and operation of renewable energy sources in microgrids enhances grid resilience, benefiting planning, response, and grid restoration efforts [12–16]. Furthermore, the potential impact of peer-to-peer energy trading on microgrids has been examined on system resilience in the literature [17–21]. National government organizations are also actively involved in enhancing power grid resilience. For instance, the Power Grid Corporation of India Limited (PGCIL) released a report in 2021, outlining measures to enhance the resilience of the electricity infrastructure in response to climate change and extreme weather events [22]. In 2018, the United States Department of Energy announced funding of up to $7.5 million to support research and development aimed at strengthening the resilience of the U.S. power grid [23]. Additionally, in 2019, the department published the North American Energy Resilience Model to aid in the development of solutions that effectively safeguard the country's energy infrastructure [24]. Thus, extensive literature already exists on system restoration and optimal recovery strategies for infrastructure networks following catastrophic events. However, these discussions primarily focus on techniques for restoring affected power systems, and they often lack the quantification of system resilience in situations where networks have been damaged by severe weather conditions. Understanding the readiness of an existing infrastructure to handle unexpected disruptions is crucial, and this necessitates the use of resilience measures to inform operators. Resilience itself is a subjective concept, but quantifying it is essential because, without measurement, it becomes challenging to enhance the existing level of resilience within a system. Developing robust resilience measures for EDS is crucial for two reasons: firstly, for planning, to justify investments in infrastructure upgrades aimed at improving resilience, and secondly, for operation, to assess the effectiveness of specific approaches employed by operators to enhance resilience during contingencies or attacks [11].

The operational resilience of power distribution systems refers to their ability to effectively respond to and recover from highly impactful, low-probability (HILP) events. Traditionally, the performance of power distribution systems has been assessed using reliability measures such as SAIFI (System Average Interruption Frequency Index), SAIDI (System Average Interruption Duration Index), and MAIFI (Momentary Average Interruption Frequency Index), which provide evidence-based insights into how well a distribution grid handles normal failure events and outages [25]. However, anticipation and response to HILP events are intrinsically challenging due to their rare occurrence. Reliability measures are inadequate for quantifying the impacts of HILP events, highlighting the need for a broader perspective on resilience [26]. However, there are limited indicators available for comparing the impact of various proactive approaches on enhancing EDS resilience. There are approaches that quantify resilience based on factors such as accessibility of power resources to cater to the interrupted loads post an extreme event [27]. Furthermore, it examines the system's capability to provide critical loads with constrained resources [28], or the satisfaction level of customers in terms of power availability [29]. However, these methods are not explicitly modeling the probabilistic nature of HILP events. There are numerous optimization-based restoration methods have been proposed to quantify resilience based on the amount and duration of critical loads restored [29–31]. Moreover, they are specific to particular systems and scenarios; therefore, they do not provide explicit assessments of system performance as per the expectation during HILP events. Additional resilience metrics, such as expected energy not served (EENS) and loss of load expected, have been presented in prior studies [32,33]. However, these metrics primarily focus on reliability aspects and do not specifically consider the consequences of HILP events. Although certain frameworks have been put forth to evaluate the resilience of distribution networks during disasters, they tend to overlook the specific impacts of HILP events and lack the ability to assess system performance for potential future extreme events in a generalized manner [34].

Although there is significant literature on quantifying EDS resilience, there is currently no universally accepted resilience measure. Some authors have proposed resilience measures that gauge the mitigated effects of failures or the deviation in system performance [35,36]. However, these measures have limitations and do not provide insights into potential future impacts, specifically when measuring the impacts of HILP events. It lacks a comprehensive framework to universally assess the impact of planning measures on system resilience. Some researchers have put forward the idea of employing risk-based approaches to characterize resilience [37]. For example, a method for risk-based resource planning has been proposed to evaluate the resilience of EDS [38]. Additionally, there are probabilistic methods available to assess the time-dependent resilience of electric power transmission systems.

Probabilistic measures suggested in [39], evaluate the resilience of the EDS but there exhibit a limitation by not considering the entire system. On the other hand, Ref. [40] introduces performance measures that focus on specific aspects of resilience, such as anticipate, endure, and recover capability. However, these measures do not provide a comprehensive view of the entire system's infrastructure. Moreover, there have been proposals for measures that consider the system's versatility, agility, durability, and flexibility [41,42]. However, they do not adequately integrate the system's progression of events, leading to an incomplete evaluation of resilience to impact the system's operations. Another framework utilizes geographic information systems (GIS) to predict the risk levels of distribution networks [43], but this study does not effectively measure how well the system can bounce back and continue providing power after a major event.

To address the mentioned concerns, we propose to use the percolation threshold as an evaluation measure that takes into account the sequence of events and facilitates a robust assessment of resilience. The percolation threshold, based on complex network theory, captures the system's state change in the face of extreme events, making it a relevant measure for energy resilience. Recent research has demonstrated that complex network theory is well-suited for modeling the system, and the percolation threshold provides us with the likelihood of failure of critical nodes and their connecting lines [44]. The percolation threshold is used for disrupted traffic systems under natural hazards in terms of both local traffic performance and percolation-based robustness at the network scale [45]. A framework for studying the resilience of networks with a community structure is proposed [46]. The application of percolation theory in measuring network resilience is elucidated, emphasizing its role in addressing various types of network failures. In addition to measuring fault tolerance, this approach introduced the measurement of adaptability and recoverability for quantifying network resilience using percolation theory [47].

Here, we propose a novel approach for quantifying the resilience of an electrical distribution system. Our method involves the development of a novel measure that draws upon percolation theory, providing a comprehensive assessment of system resilience. The quantification of resilience involves evaluating the system's ability to withstand a threat, which is represented by the probability of a node being damaged due to an unfavorable event. By employing the percolation theory, it becomes feasible to identify a specific threshold probability known as the percolation threshold. For the computation of the percolation threshold of EDS, a network needs to be created, and therefore we employ a visibility graph method which is a geometric data structure used in computational geometry [48]. It represents the visibility relationships between a set of points in a given space. The graph connects the points with edges, i.e., lines connecting two data points, if there is a clear line of sight or visibility between them. This means that no other point obstructs the direct line between the two connected points. Visibility graphs are commonly used in various applications, such as robotics, computer graphics, and path-planning algorithms. They could be used to determine the visibility of an object from a particular viewpoint, find the shortest paths between points while considering visibility constraints, or perform visibility-based spatial analysis [49].

This work also proposes a technique to predict the systems' resilience over a time period using Gaussian Process Regression. It is a probabilistic machine-learning technique used for regression tasks based on the principles of Gaussian processes, which are a collection of random variables, any finite number of which have a joint Gaussian distribution. It has been used to develop a model that accurately predicts the electricity consumption of buildings based on various input variables [50], for the detection of faults in the microgrid and accurately predicts the location of the fault based on real-time data [51] and predicts the electricity load of residential buildings based on various input variables [52].

In this study, we present a novel measurable approach to assess the resilience of the electrical distribution system, both in terms of operational and planning aspects. The proposed framework introduces a novel quantifiable measure that incorporates a visibility graph computation to analyze the network, followed by an assessment of the percolation threshold. This threshold serves as a quantifiable indicator of system resilience. To demonstrate the effectiveness of our proposed approach, we conducted a resilience evaluation of the IEEE 13-bus distribution test system, within an instantaneous time-based environment. We considered various conditions and events occurring at different locations to comprehensively evaluate the system's resilience. Furthermore, we applied the proposed measure to calculate the resilience of a larger system, such as the IEEE 123-node test feeder system. We consider the resilience measured at a few identified important nodes in the system and used GPR for predicting the resilience of the entire system. By employing this comprehensive methodology, we offer a robust and practical framework for quantifying and evaluating the resilience of electrical distribution systems. The key contributions of this work are as follows:

1. A quantifiable measure for evaluating the resilience of a distribution system in an instantaneous time-based environment is proposed.
2. The resilience measurements obtained through the proposed percolation threshold approach are compared with electrical-based resilience measures to highlight the effectiveness and advantages of the proposed quantifiable measure in assessing system resilience.
3. The evaluation of system resilience is extended to a larger system for a longer time frame to provide a more comprehensive analysis.
4. Important key nodes which are responsible for contributing to the overall system resilience are identified within the distribution system based on their corresponding percolation threshold values using a machine learning model.
5. Gaussian process regression is used to predict the percolation threshold values. By leveraging machine learning techniques, the study enhances the accuracy of resilience predictions and offers a valuable tool for estimating the resilience of distribution systems based on the identified key nodes.

Overall, these contributions provide valuable insights and methodologies for measuring, comparing, and predicting the resilience of distribution systems, paving the way for effective planning and operation of electrical distribution networks. In Section 2, we outline the methodologies employed to measure resilience, including the utilization of a visibility graph to create a network and the prediction of system resilience using GPR. In Section 3, we present the results obtained from a simulation study conducted in an instantaneous time-based environment. The study encompasses various cases and analyses performed on a larger system. In Section 4, we summarize our findings and draw conclusions based on the research conducted.

2. Materials and methods

2.1. Resilience measure from percolation threshold

From complex network theory, a significant statistical tool known as the percolation threshold has proven to be useful when assessing the resilience of electrical distribution systems, as it captures a critical phase transition point within any given network [25]. The percolation threshold serves as an essential measure of a system's ability to endure and recover from extreme events without experiencing interruptions in the power supply. It represents a crucial point that, once surpassed, indicates a transition in the system's behavior and functionality. At this threshold, the network undergoes a phase transition, transitioning from a state of efficient operation to one where cascading failures and disruptions are likely to occur. To evaluate the resilience of an electrical distribution system, the network's percolation strength is quantified, and then the percolation threshold is computed. This process involves assessing the network's ability to maintain connectivity and deliver power to critical components even under highly challenging circumstances. By measuring the percolation strength, we gain valuable insights into the system's robustness and its capacity to withstand extreme events.

To obtain the most accurate estimation of the true percolation threshold, direct numerical simulations are conducted using the Monte Carlo method proposed by Newman and Ziff [53]. This method is particularly suitable for undirected and unweighted networks consisting of N nodes and E edges. The simulation process involves sequentially removing edges in random order and observing the evolution of the size of the largest cluster, i.e., nodes in close proximity, in the network, denoted as $S(p)$. The bond occupation probability, denoted as p, is defined as the ratio of the number of edges removed, represented by e, to the total number of edges E in the initial configuration. Initially, $S(p)$ corresponds to the probability of the smallest cluster in the network. To obtain a reliable estimation of the percolation threshold, the entire process is repeated T independent times. Through these repetitions, statistical variations and fluctuations could be taken into account, leading to a more robust estimate of the percolation strength using [54]:

$$P_{\infty}(p) = \frac{1}{NT} \cdot \sum_{i=1}^{T} S(p) \tag{1}$$

The computed percolation strength refers to the extent of connectivity in a network as characterized by the largest cluster's size during the percolation process. It is a measure of the network's ability to maintain connectivity under varying degrees of edge removal. This

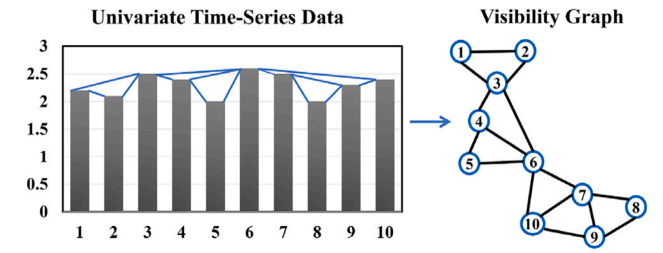


Fig. 2. A visual representation of constructing a complex network from univariate time-series data through the application of a visibility graph.

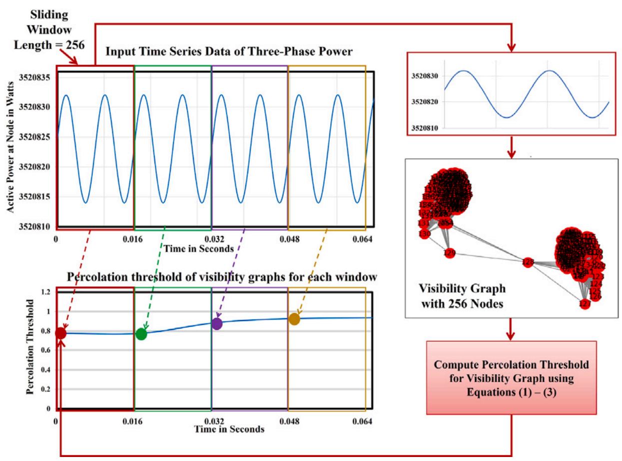


Fig. 3. Process for measurement of the system's resilience using the proposed approach. The measured time-series data of three-phase power is passed through a sliding window of length 256 without overlap. For each window, a visibility graph is created (having nodes equivalent to the number of data points), and then the percolation threshold is computed.

conceptually signifies the point at which the network undergoes a critical transition from a fragmented to a connected state. Further, the network's susceptibility is evaluated through a specific calculation process given as [54]:

$$\chi(p) = \frac{\frac{1}{N^2 T}\sum_{i=1}^{T}[S(p)]^2 - [P_\infty(p)]^2}{P_\infty(p)} \tag{2}$$

Susceptibility measures the network's sensitivity to changes in the bond occupation probability, denoted as p. It provides insights into how the network responds to alterations in connectivity and captures the degree of fluctuation in the size of the largest cluster as the percolation process unfolds. Further, the percolation threshold, denoted as p_m, is determined by identifying the critical value of p at which the susceptibility reaches its maximum. In this context, the significant value of p corresponds to the threshold that signifies a crucial transition in the network's behavior. Percolation Threshold is defined as,

$$p_m = \arg\{\max_p \chi(p)\} \tag{3}$$

In the context of an electrical network, a higher value of the percolation threshold is anticipated, indicating a network with greater resilience [55]. To compute the percolation threshold for the distribution system, a complex network needs to be constructed using a visibility graph [48] based on univariate data [56]. A visibility graph is an innovative method for converting time series data into a complex network, which then allows for an analysis of the data's structural properties through network theory [48]. This method represents each point in a time series as a node in a network and establishes links between nodes if they are visible to each other; a straight line can be drawn between any two points without intersecting any intermediate

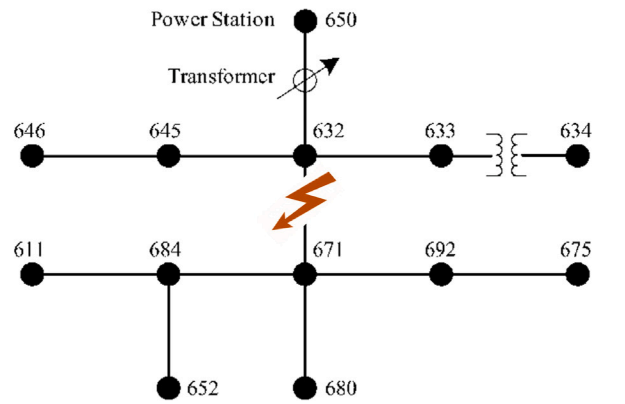


Fig. 4. Single-line diagram of IEEE 13-bus distribution test system with fault between 632 and 671.

data points. This transformation of time series data into a visibility graph provides the application of complex network analysis techniques to study time series data in a new way. The visibility graph method has been applied across various disciplines, including finance, meteorology, and neuroscience, providing valuable insights into the structural characteristics of time series data. By bridging the gap between time series analysis and graph theory, visibility graphs offer a unique and powerful tool for uncovering hidden relationships and patterns in data, which enhances the understanding of complex systems and their behavior over time.

In the construction of the network, consecutive time series data points are associated if the visibility between the corresponding data point and the connection line does not intersect any other data height as shown in Fig. 2. This visibility relationship is used to establish links between two data points (u_m, v_m) and (u_n, v_n) in the network [48]. To determine if a visibility link exists between two data points, an additional data point (u_p, v_p) needs to satisfy a specific condition given as:

$$v_p < v_n + (v_m - v_n)\frac{(u_n - u_p)}{(u_n - u_m)} \tag{4}$$

These criteria help determine the connections and linkages within the network, which ultimately contribute to the computation of the percolation threshold. By constructing the visibility graph, we could quantify the percolation threshold and gain insights into the network's resilience. The measurement process of the proposed approach is illustrated in Fig. 3.

2.2. Resilience measures from electrical parameters

In terms of power loss in an electrical system, resilience is defined as [57]:

$$Resilience = \frac{1}{Loss} \tag{5}$$

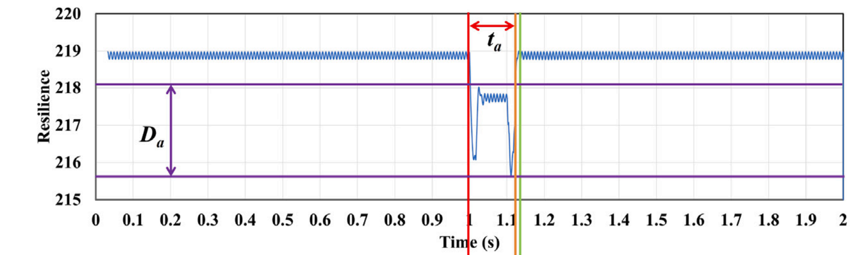
Resilience is computed for a particular extreme event, that could be effectively illustrated by analyzing changes in system performance. The power loss is the amount of power that is unavailable to the system and is represented as [58]:

$$Loss = \frac{P_0 - P_m}{P_m} \tag{6}$$

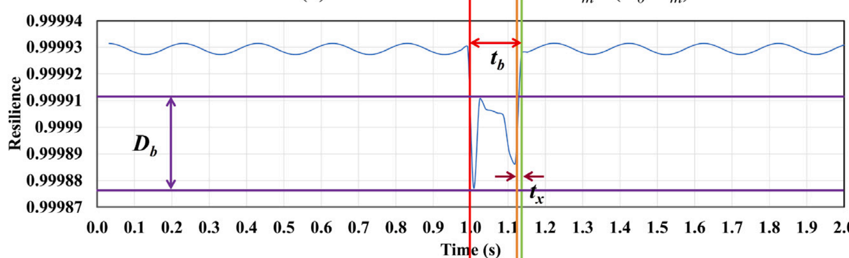
where P_0 and P_m are the total and instantaneous power in the system, respectively.

Another resilience measure is defined in terms of the ratio of instantaneous power and total power, represented as [59]:

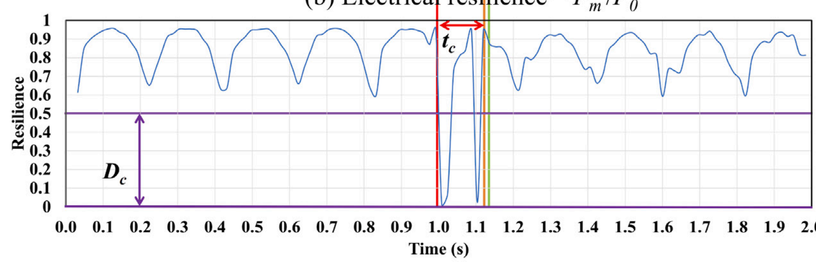
$$Resilience = \frac{P_m}{P_0} \tag{7}$$



(a) Electrical resilience – $P_m / (P_0 - P_m)$

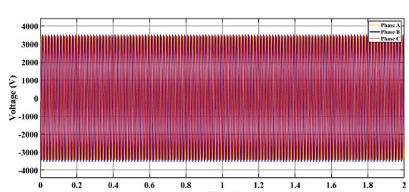


(b) Electrical resilience – P_m / P_0

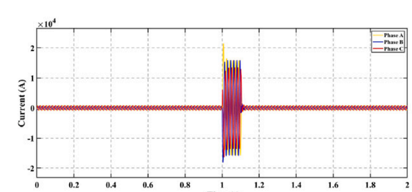


(c) Electrical resilience – Percolation threshold

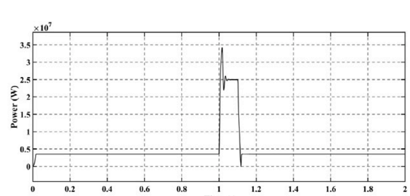
Fig. 5. Comparison of percolation threshold with electrical parameter-based resilience measures. D_a, D_b, and D_c indicate the variation in the resilience magnitude during fault and t_a, t_b, and t_c indicate the duration from fault instant to restoration for all three cases, respectively. D_a, D_b vary for each data and fault type, whereas D_c is same for all data and fault type. For the second compared electrical resilience measure (P_m/P_0), the restoration time is delayed by a time t_x.



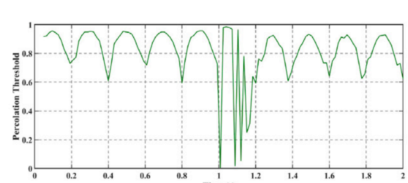
(a) Three-phase voltage measurement at 632.



(b) Three-phase current measurement at 632.



(c) Computed three-phase power at 632.



(d) Computed percolation threshold at 632.

Fig. 6. PT calculation from voltage and current measurements at source node (632) for TLG fault at 671.

Resilience is measured on a scale from zero (indicating no resilience) to infinity (representing maximum resilience). Zero resilience signifies a system that lacks the ability to recover from events, resulting in a complete collapse where the system fails to restore the load. Conversely, infinite resilience characterizes a system capable of fully recovering all loads following an event, demonstrating its exceptional ability to bounce back from disruptions [58]. In this study, we have performed a comparison between the outcomes obtained through our

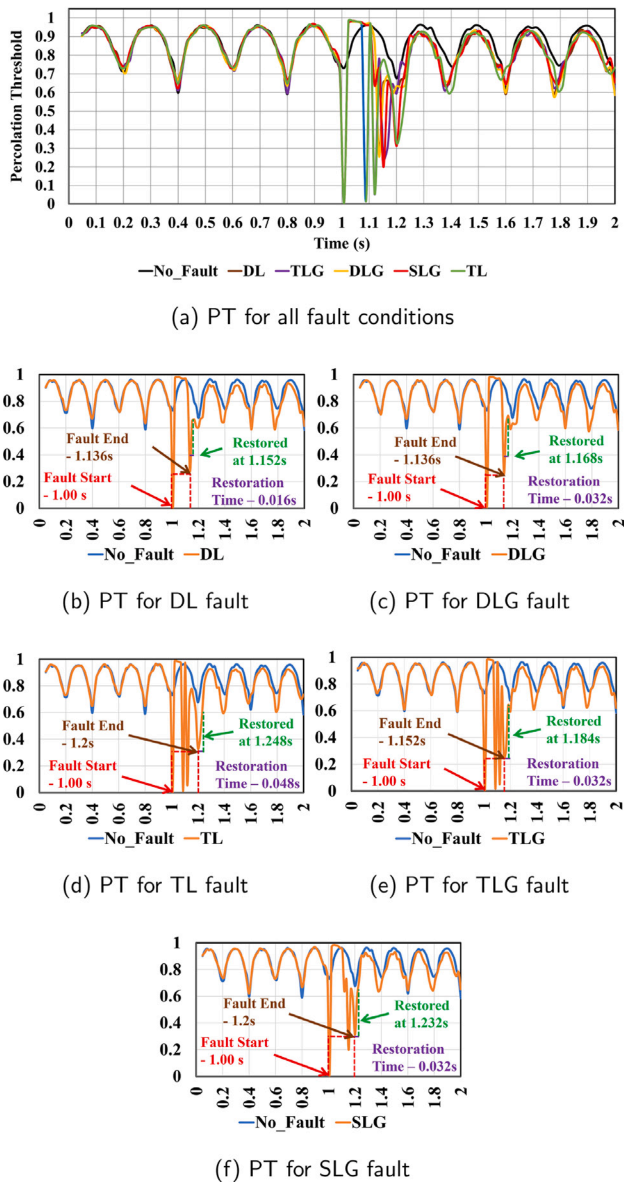


Fig. 7. PT at node 632 for various fault conditions at fault node 671.

proposed quantifiable measure utilizing the percolation threshold and the other two electrical resilience measures discussed in this section.

2.3. Gaussian process regression for time series resilience prediction

Gaussian process regression is a non-parametric method used for regression tasks. In the context of univariate time series prediction, it is used to estimate the underlying function from the given input–output pairs, i.e., the timestamps and corresponding values.

A Gaussian process (GP) is a collection of random variables, any finite number of which have a joint Gaussian distribution. It is completely specified by its mean function $m(x)$ and covariance function (or kernel) $k(x, x')$. The mean function $m(x)$ represents the expected value of the GP at a particular point x, and the covariance function $k(x, x')$ indicates the expected covariance between the function values at two different points x and x'. Assuming the noise in the observations to be Gaussian with variance σ^2, the prior over the function values is represented as:

$$f(x) \sim \mathcal{GP}(m(x), k(x, x') + \sigma^2 I) \tag{8}$$

The predictions $\hat{y}$ is obtained by conditioning the GP on the observed data $D = \{(x_i, y_i)\}_{i=1}^{N}$:

$$\hat{y}|x, D \sim \mathcal{GP}(\mu_{post}(x), \Sigma_{post}(x, x')) \tag{9}$$

where $\mu_{post}(x)$ and $\Sigma_{post}(x, x')$ are the posterior mean and covariance, and computed using the prior mean and covariance, and the observed data.

By adjusting the parameters of the mean function and covariance function, we tune the GP to fit the time series data, effectively capturing the temporal dependencies in the data. This methodology predicts future points in univariate time series data by understanding the underlying trend, seasonality, and other time-dependent structures present in the data.

3. Simulation study, result analysis and discussion

3.1. Resilience evaluation during fault conditions

The simulation model of the IEEE 13-bus distribution test system [60] is developed in MATLAB\SIMULINK [61] and provides a platform for analyzing fault conditions and performing time-series analysis in a distribution system as shown Fig. 4. The considered test system has a system voltage of 4.16 kV and consists of 12 nodes with eight spot loads and one distributed load.

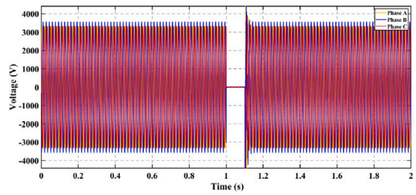
The percolation threshold is compared with other electrical parameter-based resilience measures, illustrated in Fig. 5. Resilience defined in (5) and (6) is shown in Fig. 5a, where the values are not varying between 0 and 1, which indicates that this parameter value varies for different measurements and cannot be compared accurately. The resilience defined in (7) is shown in Fig. 5b, where the value varies between 0 and 1, which indicates that this parameter value is consistent for different measurements and can be compared accurately. However, we can observe that the resilience value varies only in the third decimal when a fault occurs, which is not a proper indication of fault. In contrast to these two parameters, the proposed percolation threshold for resilience evaluation varies from 0 to 1 for all data is shown in Fig. 5c. When a fault occurs, there is a significant observable difference between normal and fault operations. When a fault occurs, the PT reaches a value of zero and close to zero values several times (depending on the type and magnitude of fault) before recovering back to normal condition. It is observed that under normal operating conditions of the system, the variation in PT values is between 0.6 to 1. This variation is dependent on the data but provides a consistent range of values for normal operations. Therefore, PT values below 0.5 are considered to be fault conditions.

We evaluate the proposed resilience measure using the percolation threshold for three cases; evaluating resilience at the system source node, evaluating resilience at the fault node, and evaluating resilience at one node for faults occurring at different nodes.

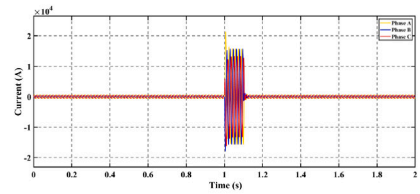
3.1.1. Case A - Resilience evaluation at system source node

Resilience at the source node of the system is evaluated for different fault conditions. Three-phase voltage and current measurements could be collected using measurement devices as shown in Figs. 6(a) and 6(b), respectively. The three-phase power is computed as shown in Fig. 6(c), which is used to compute the percolation threshold for every 256 samples, i.e., 0.016 s (1 cycle for 60 Hz) as shown in Fig. 6(c). In Fig. 6, the triple-line-to-ground (TLG) fault is considered for 100 ms from 1.0 s to 1.1 s. All faults are considered at 1.0 s and simulated with 100 ms fault duration.

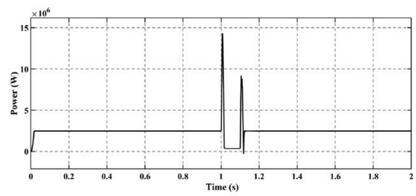
We considered all types of faults, such as single-line-to-ground (SLG) fault, double-line-to-ground (DLG) fault, TLG fault, double-line (DL) fault, and triple-line (TL) fault. Though the fault is simulated for 100 ms, the system takes time to return back to its operational state. Thus the fault time is considered from 1.0 to the instant of the last negative peak of the percolation threshold. Therefore restoration time



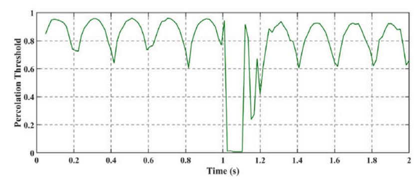
(a) Three-phase voltage measurement at 671.



(b) Three-phase current measurement at 671.



(c) Computed three-phase power at 671.



(d) Computed percolation threshold at 671.

Fig. 8. PT calculation from voltage and current measurements at fault node (671) for TLG fault at 671.

Table 1
Fault time and restoration time analysis for all cases.

Cases	Fault type	Measurement node	Fault node	Fault time (s)	Restoration time (s)
Case A	SLG (Phase A)	632	671	0.2	0.032
	DL (Phase C & A)	632	671	0.136	0.016
	DLG (Phase C & A)	632	671	0.136	0.032
	TL	632	671	0.152	0.032
	TLG	632	671	0.2	0.048
Case B	SLG (Phase A)	671	671	0.152	0.048
	DL (Phase C & A)	671	671	0.136	0.032
	DLG (Phase C & A)	671	671	0.184	0.032
	TL	671	671	0.2	0.032
	TLG	671	671	0.216	0.032
Case C	SLG (Phase C)	632	671	0.2	0.016
	SLG (Phase A)	632	652	0.152	0.016
	SLG (Phase C)	632	632	0.136	0.016
	SLG (Phase A)	632	680	0.104	0.016
	SLG (Phase A)	632	692	0.104	0.016
	SLG (Phase C)	632	611	0.072	0.016
	SLG (Phase A)	632	675	0.072	0.016
	SLG (Phase C)	632	633	0.056	0.016
	SLG (Phase C)	632	684	0.052	0.016
	SLG (Phase C)	632	634	0.04	0.016
	SLG (Phase C)	632	645	0.04	0.016
	SLG (Phase C)	632	646	0.04	0.016

is therefore considered from the last negative peak to the next positive peak.

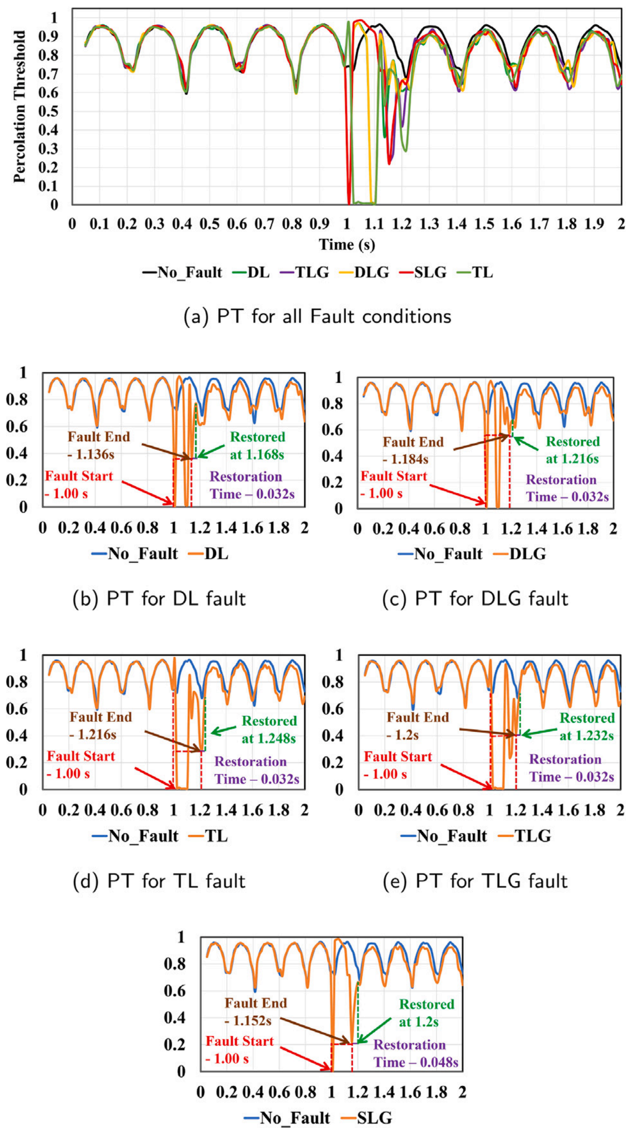
In Fig. 7, we compare and analyze the percolation threshold at the system source node 632 for all fault conditions occurring at fault node 671. For each fault condition, the resilience first drops to zero at 1.0 s and then may have one or more negative peaks before reverting back to the original state after the fault is cleared. The fault time is 0.136 s for DL and DLG, 0.2 s for TL and SLG, and 0.152 s for TLG. The restoration time is 0.032 s for DLG, TLG, and SLG, 0.016 s for DL, and 0.048 s for TL.

3.1.2. Case B - Resilience evaluation at system fault node

Resilience at the fault node is evaluated for different fault conditions. Three-phase voltage and current measurements are shown in Figs. 8(a) and 8(b), respectively. The computed three-phase power is shown in Fig. 8(c), this is used to compute the percolation threshold for every 1 cycle as shown in Fig. 8(d). Similarly, the TLG fault is considered for 100 ms from 1.0 s to 1.1 s in Fig. 8. We compare and analyze the PT at fault node 671 for all fault conditions as shown in Fig. 9. It is observed that the impact of fault at the fault node is more than at the source node. For instance, during TL and TLG faults, the PT value at fault node remains zero for the entire duration of 1.0 to 1.1 s as shown in Figs. 9(d) and 9(e). Whereas, the PT value at the source oscillates for the entire fault duration as shown in Figs. 7(d) and 7(e).

3.1.3. Case C - Resilience evaluation at a single node for faults at various nodes

We compare and analyze the percolation threshold at the system source node 632 for all single-line-to-ground faults occurring at different nodes across the system. The analysis is graphically shown in Fig. 10 for real-time visualization, and observations are tabulated in Table 1. Phase C to ground fault is considered as most nodes have phase C otherwise phase A to ground fault is considered. When observing at the source node for SLG faults occurring at 12 different nodes, the



(a) PT for all Fault conditions

(b) PT for DL fault

(c) PT for DLG fault

(d) PT for TL fault

(e) PT for TLG fault

(f) PT for SLG fault

Fig. 9. PT at node 671 for various fault conditions at fault node 671.

restoration time is the same, i.e., 0.016 s but fault time varies from 0.04 s to 0.2 s. It is worth emphasizing that the fault time observed at the source node is less than the actual fault duration of 0.1 s for faults at nodes 634, 645, 646, 684, 633, 611, and 675. For faults at the rest of the nodes, it is greater than 0.1 s and reaches a highest of 0.2 s for SLG at 671. From case A and case B, it is observed that the SLG fault at phase A of 671 has a higher impact with longer restoration time and fault time when compared to the SLG faults observed in case C.

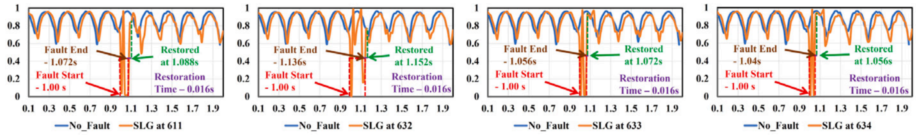
Though Table 1 gives a good observation of the restoration and fault times; the impact of instantaneous changes in the resilience are more observable in the time-series based resilience shown in Figs. 6, 8, and 10. It is observed that TLG has more impact on the system resilience when compared to SLGs and DLGs, which is in-line with the intuition. Also, faults observed at the source node have less impact than those observed at the fault nodes. Thus, the time-based resilience evaluation gives more information when compared to aggregated resilience for a longer duration. Also, the resilience evaluation using the percolation threshold, when compared to other electrical-based resilience parameters, is significantly more accurate and consistent with the type of faults and the measurement nodes.

3.2. Resilience evaluation with renewable energy systems

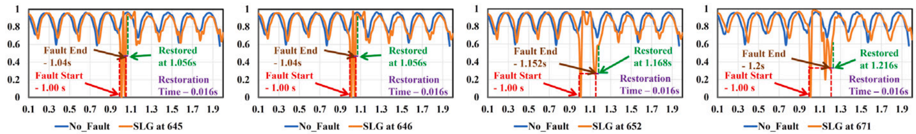
The proposed framework is extended for a larger system with renewable energy sources to evaluate the resilience of the distribution system. We have considered an IEEE 123-node test feeder [60] with solar integration as shown in Fig. 11.

3.2.1. Resilience evaluation with DERs

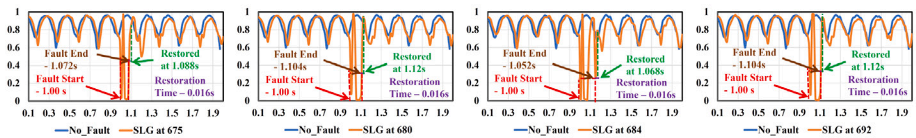
We performed the simulation in GridLAB-D for the IEEE 123-node test feeder. In this system, we considered a total of 85 constant loads, which collectively require 3620.5 kW of real power. Each node of the system has a unique load profile and is equipped with solar PV panels considering the climate conditions of Bakersfield, California [62]. Our simulation spanned for seven months (January-July), with data collected at one-hour intervals. Throughout the simulation, we gathered valuable time-series data of active power, energy consumption, and generation for each node. To evaluate the system's resilience for a particular day, we obtained 24 data points (recorded for each hour) representing the energy consumption at each node with and without DERs.



(a) PT for SLG at 611(b) PT for SLG at 632(c) PT for SLG at 633(d) PT for SLG at 634



(e) PT for SLG at 645(f) PT for SLG at 646(g) PT for SLG at 652(h) PT for SLG at 671



(i) PT for SLG at 675(j) PT for SLG at 680(k) PT for SLG at 684(l) PT for SLG at 692

Fig. 10. PT at source node for SLG at different nodes.

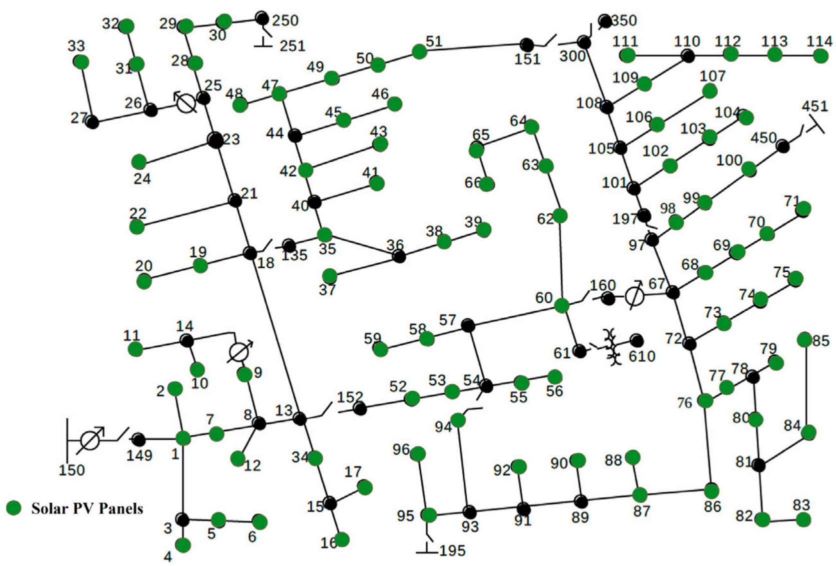


Fig. 11. IEEE 123-node test feeder with RES.

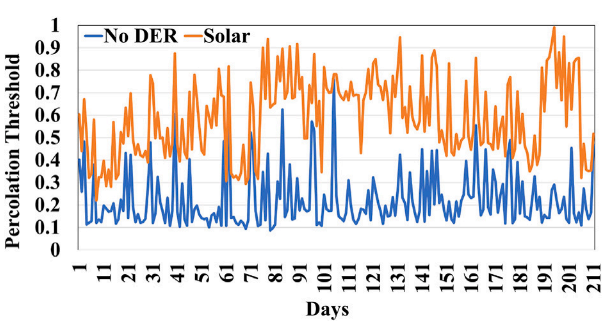


Fig. 12. System resilience with and without DER.

To analyze the resilience of the system, we created a visibility graph using the 24 data points. By constructing the visibility graph, we computed the percolation threshold at various nodes which provide insights into the resilience of the system and its ability to withstand disruptions or failures at the supply end. From Fig. 12, it is shown that the overall resilience of the system improves with the integration of DERs. It shows that for 211 days the percolation threshold values got increased when DERs are integrated. Also, we evaluated the resilience improvement of individual nodes with DERs integration as shown in Fig. 13. The improvement in resilience is shown for node-001 and node-002 of the considered IEEE 123-node test feeder system. Thus, the obtained results provide an understanding of resilience dynamics, accommodating a larger-scale system and longer-term effects.

3.2.2. Feature importance based on PT at different nodes

The random forest regression model is a valuable tool for anticipating the overall resilience of a system by identifying crucial nodes that make substantial contributions to the system's resilience. This identification process enables service providers and decision-makers to

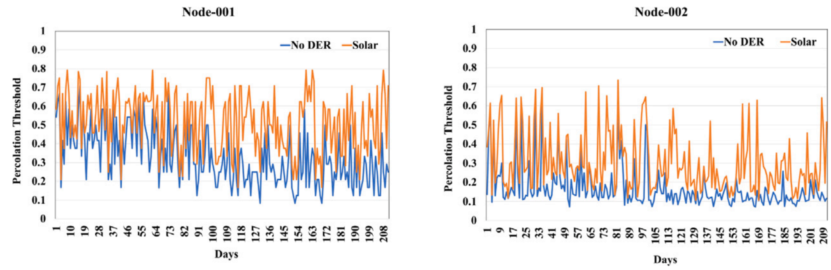


Fig. 13. Resilience at individual nodes (Node 1 & 2) with and without DER.

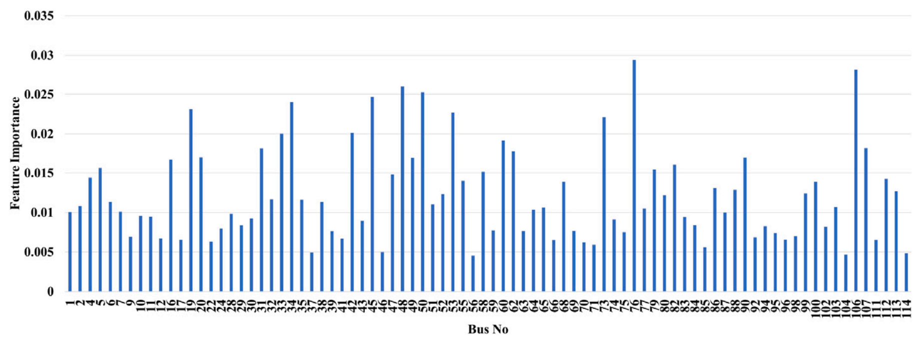


Fig. 14. Identification of important nodes which are highly responsible for determining the overall resilience of the system using random forest regression model.

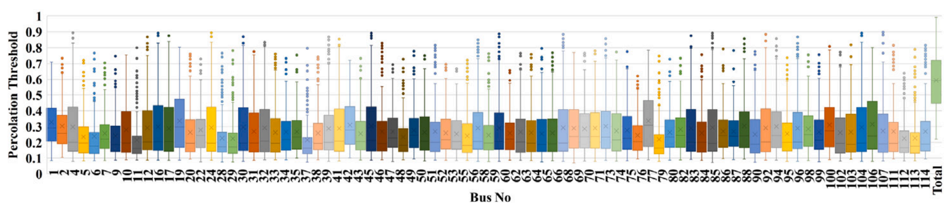


Fig. 15. Box plot of PT for all nodes and total system.

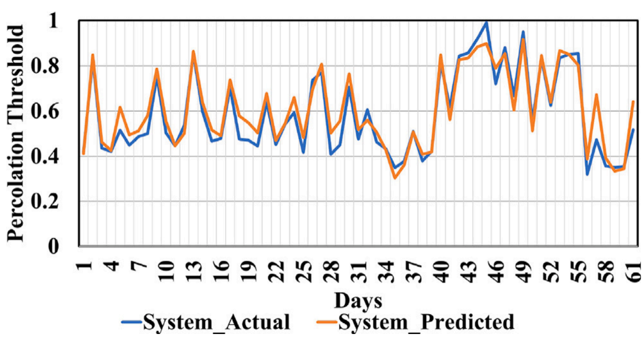


Fig. 16. Prediction of system resilience for 61 days using Gaussian process regression.

focus their efforts on protecting these nodes, thereby enhancing the system's overall resilience. We fed 211 days of computed resilience of all nodes as input to the random forest regression model and calculate the contribution of each node in determining the system's resilience as shown in Fig. 14. It is observed that nodes 19, 33, 45, 48, 50, 53, 73, 76, and 106 have high feature importance scores among all the present nodes and are suitable to anticipate the overall resilience of the system. The box plot of the computed percolation threshold of all 85 nodes and the overall system for 211 days is shown in Fig. 15.

3.2.3. Prediction of PT using Gaussian process regression GPR

For the prediction of system resilience, we used percolation threshold values of 10 nodes with high feature importance scores for 150 days to train the GPR model. Further, the model performance is tested for the remaining 61 days and compared with actual values as shown in Fig. 16. We evaluated the performance of the prediction model using metrics mentioned in Table 2; it is observed that the prediction using GPR is reliable and effective. Thus, the proposed model is effective and reliable for analyzing and improving the resilience of the system through proper planning.

Table 2
Prediction scores.

Scores	Values
R^2 Score	0.90646
Mean absolute error	0.04296
Explained variance score	0.92013
RMSE	0.05559

4. Conclusion

In this work, we proposed an operational and planning measure for resilience in an electrical distribution system in an instantaneous time-based environment. The proposed resilience evaluation method is fundamentally data-driven, relying on the continuous monitoring of three-phase current and voltage measurements to calculate the percolation threshold using visibility graphs. This threshold is a real-time, quantitative indicator of the system's resilience is found to be an effective tool for evaluating resilience in EDS by considering the system complexities under all conditions. We compared the PT values at different nodes with and without faults, as well as analyzed the impact of various fault locations when observing PT values from a single node. With the presence of faults, the PT values exhibited a significant decrease indicating an accurate reduction in the system's resilience when compared to other electrical-based resilience measures. Moreover, the study explored the fault time and restoration time of the distribution system, providing insights into the system's recovery capabilities.

We have also extended our analysis to a larger system with longer time durations. This analysis provided a broader perspective on the system's behavior and resilience while considering the integration of PV sources. We have examined the nodes which significantly contribute to the system's resilience using the random forest regression model. The PT measured at these selected nodes is used for predictive modeling of the entire system's resilience using the Gaussian process regression. This offers valuable insights into the system's behavior, enabling proactive measures to be taken to mitigate potential issues and improve overall resilience. The proposed method is suitable for developing a real-time monitoring system that continuously measures and evaluates the distribution system's resilience to detect anomalous events, predict potential system failures, and trigger proactive resilience-enhancing actions for decision-makers and system operators.

CRediT authorship contribution statement

Divyanshi Dwivedi: Writing – original draft, Validation, Software, Methodology, Formal analysis, Data curation. **K. Victor Sam Moses Babu:** Writing – original draft, Visualization, Validation, Software, Methodology, Formal analysis, Data curation. **Pradeep Kumar Yemula:** Writing – review & editing, Supervision. **Pratyush Chakraborty:** Writing – review & editing, Supervision. **Mayukha Pal:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interest or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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