A Bi-Level Security Constrained Model for Optimal Flexibility Operation

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Abstract—Aggregated distributed energy resources (DER) units in the distribution networks are utilized to support flexibility services in modern grids. To ensure modern grid security, active and reactive flexibility operation must not increase the risk index at the transmission-distribution (T-D) network boundary and the distribution network nodes. This paper assesses the impact of aggregated DER units on the distribution networks and proposes a bilevel optimization approach to mitigate the impact on the grid's security. The bilevel optimization approach involves distribution network reconfiguration and flexibility quantity estimation. Many existing flexibility operation models in recent literature are developed based on economic objectives and constraints rather than security constraints. Also, the existing flexibility operating models do not account for probabilistic scenarios, leading to security issues during flexibility operations. The probabilistic risk index and hosting capacity are included as security objectives in the reconfiguration problem formulation to minimize the total distribution network power loss. A decision tree classification approach is proposed to estimate the minimum flexibility MVA to achieve a desired voltage deviation reduction. The proposed approach was tested on IEEE 33- and 69-node distribution networks. Under a 100% increase in load at specific nodes, the proposed technique achieved a significant improvement of 16.67% in the voltage deviation of the worst nodes in both the IEEE 33- and 69-node test networks. The results show that the proposed bilevel technique optimally reconfigures the network and effectively estimates the flexibility support required to ensure the grid's security during disturbances. The proposed model will enhance the interaction between the transmission and distribution network operators.

Keywords: Distributed energy resources, Flexibility, Integrated grid, Network reconfiguration, System operators

1 INTRODUCTION

1.1 Background and motivation

High penetration of variable energy generation source units into the modern power grid will provide technical merits when optimally planned and efficiently operated. A major requirement of modern transmission system operators (TSO) is to mitigate security challenges associated with the modern power grid. The grid's security can be ensured through enhanced interaction between the TSOs and the distribution system operators (DSO) [1]. The existing interaction includes congestion management and flexibility services. The process of achieving enhanced interaction involves the ability to perform quasi-real-time network assessments using varying grid measurements. The process also ensures the grid's security when several ancillary services are simultaneously involved under dynamic conditions and constraints. Since the modern grid's security depends on the level of coordination between the TSO and DSO, it is essential to develop approaches that integrate local solutions at the transmission-distribution (T-D) network boundaries [2]. Flexibility refers to a grid's ability to manage the unpredictability of demand and supply reliably and cost-effectively across all relevant timescales. The operational flexibilities estimate the rate, duration, and capacity of the services required to absorb steady and transient disturbances to secure the operation of the grid [3]. Demand-side services, including real-time balance of frequency and voltage management previously provided by centralized generators, have been replaced by new market structures supported by aggregators. Therefore, the distribution networks hosting the variable energy generation source units will have an active role in controlling and managing every market participant connected to them. The flexibility operation may include a change in network topology, deployment of reserves, and demand-side participation. Flexibility planning and operation problems for modern grids are multi-objective problems that require all-inclusive formulation, which may best be solved using new computational methods and artificial intelligence techniques [4].

For enhanced interaction between the transmission and distribution network operators, specifically during flexibility services for disturbances, the combinations of considered parameters under the prevailing constraints will increase the complexity of the flexibility operation and the computational requirements for the employed tools [5]. The operational flexibility estimation techniques must be extended beyond the planning horizon to include estimations for operations in the short-term ahead under both steady and transient state constraints. Existing flexibility operation models are focused on economic considerations to minimize the cost and duration of flexibility operations without considering the impact of flexibility operation on the distribution networks. Consequently, new flexibility operation techniques should consider approaches combining economic and technical considerations with probabilistic security constraints.

Flexibility services involve properly shaping injected active and reactive power from controlled and aggregated power sources connected to the distribution networks. The increasing penetration level of variable energy generation sources into the grid also requires new regulations concerning power reserve and flexibility services. With the new regulations, aggregated DER units may participate in the voltage support of the grid during disturbances. Aggregated DER units and their interactions have to be well coordinated. The aggregated DER units with well-coordinated control can significantly improve the grid's local and area-wide voltage stability [6, 7]. Using dispatchable power from aggregated DER units for voltage support services presents a new challenge. The challenge is associated with controlling a large, distributed load, the configuration of the distribution network, and the impact of the aggregated DER units' operations on the distribution network. Control of large, distributed loads includes the charging pattern of electric vehicles and other power electronics-based loads. The constraints associated with the configuration are due to the load distribution, size, and network configuration type. Consequently, the methods for optimal operations of the aggregated DER units for optimal voltage support should consider some of these constraints [8].

1.1.1 Network Configuration and flexibility services

The configuration of the distribution network influences the voltage response of the network. Therefore, developing a specific numerical measure for any configuration is crucial to evaluate it against other configurations. In recent research, the number of node connections, total branch impedance, and the electrical distance between the node where the disturbance occurs and other nodes have been considered to distinguish each configuration [9]. Using the system impedance matrix, the impedance as viewed from the disturbance node is given by (1), where k is the network node, Z is the total impedance, Z_{ii} is the self-impedance in the node where the disturbance occurs and Z_{ij} refers to the connection impedance between the node where the disturbance occurs and the node where the aggregated DER unit is connected. The summation of the impedances creates the overall topology measure ($\boldsymbol{\lambda}$) given in (2), which indicates the electrical distance between the areas. A high value of $\boldsymbol{\lambda}$ implies high impedance. The network configuration largely impacts the system voltage angles and magnitudes, which define the subsequent generator pick up and post disturbance power flow. A node with a high electrical distance from the rest of the system will experience a larger voltage angle than the rest of the network. When subjected to a large and sudden load increase, such nodes experience voltage deviations beyond the security limits [10]**.** A high electrical distance can result in a highly localized voltage response. As the magnitude of the voltage deviation continues to increase, it is imperative to activate nearby flexibility services to prevent the grid from progressing into an insecure state during the disturbance window.

$$Z = \sum_{j=1}^{N-1} (Z_{ii} + Z_{jj} + 2Z_{ij}) \tag{1}$$

$$\lambda = \frac{Z}{k} \tag{2}$$

The location and magnitude of the generation and load determine the power flow, voltage magnitudes, and angles in a network. The voltage stability and response of different networks with different penetration levels of variable energy generation source units will differ depending on the network generation and load points. The power flow into the area of the disturbance can be used as a quantity to indicate the voltage angle differences with respect to the location of the disturbance. It is anticipated that the voltage angle differences will increase as the power flow into the disturbance area increases. This resultant larger angle difference due to a greater power transfer into the disturbance area is expected to have a detrimental impact on voltage stability and lead to larger voltage deviations [11].

1.1.2 Distribution Network Voltage Support

Reconfiguration is an important technique for improving distribution networks' performance under normal and recovery conditions. The increasing penetration of variable energy generation source units and variable loads introduce significant variation in the distribution networks' operation, rendering the common reconfiguration objectives inadequate. Improper distribution network configuration may lead to increased power losses, bad voltage profile, low power factor, high reverse current, and high short circuit current contribution considering the high penetration of variable energy generation sources into the distribution network [12]. The hosting capacity and risk index are terms associated with the security condition of the modern distribution network with variable energy generation sources penetration. The hosting capacity represents the amount of variable energy generation sources that can penetrate the distribution network securely. Adequate hosting capacity is important for aggregated DER units and energy storage systems in the distribution network to ensure the network's security under varying generation conditions [13]. The risk associated with undervoltages and overvoltages at the network nodes due to the impact of the variabilities in the power generation from variable energy generation sources units is modeled by the risk index. The utilization of the distribution network flexibilities during grid contingencies necessitates the modern reconfiguration techniques to be adaptive to achieve effective voltage support. The common reconfiguration objectives in the literature are minimizing power loss and enhancing voltage profile [14]. However, there is a need to include more security objectives in the reconfiguration problem formulation due to the increased penetration of variable energy generation sources into the distribution network. Therefore, this paper proposes a network reconfiguration technique that maximizes the hosting capacity and minimizes the risk index to achieve an effective voltage response support from aggregated DER units during network disturbances.

1.2 Review of Relevant Literature

The functioning of the grid at different levels becomes more challenging when the responsibilities of managing grid contingencies are transferred to the DSO [2]. Therefore, developing new structures and models that enhance the coordination between the TSO and DSO is important to ensure secure and reliable grid operation. Many literature on active distribution network planning and optimal operations focused on interaction and coordination between transmission and distribution network operations related to dynamic distribution network reconfiguration has been published. The literature already contains many methods for reconfiguring distribution networks to meet various objectives. The majority of the prior research on network reconfiguration may be broken down into three main classifications: heuristics [15-17], mixed approaches [18, 19], and evolutionary and knowledge-based strategies [20, 21]. Although techniques based on evolution and knowledge may handle more complex goals, they have relatively large computing runtimes and are consequently less suited for online distribution automation. To reduce computing runtime without compromising solution quality, hybrid reconfiguration approaches are mixed solutions that incorporate evolutionary and heuristic methodologies. They nonetheless require more processing power than heuristics, although having runtimes that are often shorter than those of evolutionary approaches. It has been demonstrated that heuristic algorithms provide great outcomes with noticeably shorter runtimes. Considering loss minimization objectives, heuristic algorithms are among the most acceptable algorithms for real-time distribution system reconfiguration [15, 22].

Ref. [14] reviews recent literature's common network reconfiguration objectives and optimization techniques. Multi-objective optimization techniques are more common compared to single-objective techniques. In numerous studies, the objective of minimizing power loss appears alongside other objectives. In addition to the reduction of power loss, voltage profile improvement [23], reliability improvement [24],[25], service restoration [26], resiliency improvement [27],[28], and operation cost reduction [29] are some of the objectives that have been proposed in multi-objective studies. The choice of the algorithm used to solve the generated multi-objective problems determines the global and/or local optima and the convergence time, both of which are critical in achieving a good reconfiguration scheme. The reconfiguration problem is a complex multi-constraint problem. Therefore, metaheuristic optimization approaches are widely used due to their ability to achieve convergence with complex and non-linear problems. Although literature concludes that metaheuristic approaches perform better for complex problems, conventional optimization methods can be used for problems with small networks and problems with fewer constraints as shown in [30]. Compared to evolutionary algorithms, swarm intelligence-based algorithms are more extensively used under the metaheuristic approaches [14]. The extensive use of swarm intelligence-based algorithms is due to the emergence of collective swarm behaviour to achieve a global optimal despite the environmental constraints of the individual swarm entities [31].

Many literature on active distribution network planning and optimal operations focused on interaction and coordination between transmission and distribution network operations related to flexibility modeling and operations in a distribution network have been published. A linearized model was proposed in [32] for the aggregation of active and reactive power at TSO-DSO connection points. The interaction between the TSO and DSO regarding optimal flexibility operation has been studied under a game theory approach [33]. A method for estimating the quantity of time-varying ancillary services of a distribution network to the transmission grid is proposed in [34]. Many papers have discussed and proposed methods for estimating the flexibility operating regions under various components like market parameters, generation types, and energy storage systems. Ref. [35] presents reviews on issues ranging from quantifying flexibilities and modeling flexibility boundaries to procurement and management services from the energy components in the distribution network. Techniques based on optimal power flow [36, 37] and economical generation dispatch [38, 39] are commonly used in literature to estimate the flexibility operating region for different generation scenarios. The optimal power flow techniques are straightforward, and their results are reliable under stated conditions and operational constraints. The economic dispatch-based models are typically used to manage the flexibilities based on demands from the transmission system. A multi-objective genetic algorithm optimization approach to minimize the cost and power losses during flexibility operation was proposed in [36]. In [40, 41], analytical models based on the active power injection technique optimization at the transmission-distribution network boundary were proposed to estimate the flexibility ramping for generation, loading, and contingencies scenarios.

Considering that variable energy generation sources and energy storage systems are becoming more widely implemented, recent literature has presented approaches for maximizing distribution system flexibility. The common flexibility supports in literature are the voltage and frequency support from the DG [42], [43]. Ref. [44] proposed a weighted analytical hierarchy process for the operation of vehicle to grid (V2G) systems to achieve optimal flexibility services. A non-linear optimization technique for power loss and hosting capacity optimization is proposed in [44] to achieve effective load shifting within the distribution network. A network reduction technique for microgrids was also proposed in [45] to enhance the frequency response of the grid. A technique based on adapted optimal power flow (AOPF) was proposed in [46] to achieve flexible interaction at the transmission and distribution network interface. With the AOPF technique, the operating area at the interface can be roughly modeled in real time, considering the system operator's constraints.

The review shows that the impact of voltage support units connected to the distribution networks has not been investigated. Furthermore, many of the techniques focus only on economic considerations to minimize the cost of flexibility operation. Likewise, there are no security constraints in the optimization problem formulation to mitigate the negative impact on the grid's security during flexibility activation. The existing models focus on the distribution networks and do not consider interaction and coordination between the transmission and distribution network operators.

1.3 Contribution and Organisation

This research aims to study the impact of voltage support unit operation on the distribution network during flexibility operation and to propose a method to mitigate such impact to achieve optimal voltage support. A probabilistic risk index is proposed to assess the impact of aggregated DER unit operation of the network. The probabilistic risk index is the probability that the voltage at the aggregated DER units' connection points as well as the neighboring nodes will exist outside the security limits. A bi-level model consisting of network reconfiguration and flexibility value estimation is proposed to achieve optimal voltage support. The probabilistic risk index is included as a constraint alongside the hosting capacity for the distribution network reconfiguration problem formulation. An improved decision tree classification technique is developed to estimate the active power from aggregated DER units to minimize voltage deviations during disturbances. The proposed classification technique consists of attributes obtained from the interaction between the transmission and distribution system operators (TSOs and DSOs). Therefore, the proposed bi-level optimal flexibility operation technique will be suitable for enhanced interaction between the transmission and distribution network operators. The review shows the need for more research to include probabilistic and security constraints in the reconfiguration problem formulation for optimal flexibility support from the distribution network. Also, there is a need to enhance the interaction between the transmission and distribution network operators for effective voltage support from aggregated DER units. Based on the above explanations, the contributions of this paper can be summarized as follows:

1. proposing a probabilistic risk index to examining the impact of aggregated DER units operation on the distribution network,
2. including the probabilistic risk index and the hosting capacity as variables for optimal network reconfiguration and
3. proposing an improved decision tree classification-based model to estimate optimal flexibility value from aggregated DER units for optimal voltage support.

The rest of this paper is organized as follows. Section 2 discusses modern distribution network operations, focusing on the interaction between the transmission and distribution networks and flexibility for voltage management. The proposed approach for optimal flexibility operation is presented in Section 3. The results of testing the proposed approach on IEEE 33 and 69 node networks are presented and discussed in Section 4. Lastly, the conclusions of this research are presented in Section 5.

2 MODERN DISTRIBUTION NETWORK OPERATION

2.1 TSO and DSO Interaction

Enhanced interaction between the transmission system operators (TSO) and distribution system operators (DSO) is a key to ensuring the security of the modern grid. Several control techniques have been proposed to achieve optimal interaction considering available technologies and emerging markets [47]. The distributed control technique is feasible and most applicable for systems with high penetration of distributed generation (DG) and electric vehicles (EVs). Aggregated DER units for demand-side participation in real-time active and reactive power balancing corresponding to frequency and voltage control from distributed systems have been explored as a solution to local and grid-wide voltage control during disturbances. The solution will involve real-time voltage trackers at the TSO/DSO boundary. In addition, DER units can be employed to provide frequency and voltage support for load peak shaving, valley filling, and shifting.

The concern, however, is how to ensure the grid's security during flexibility exchange from the DER units in the distressed transmission network regions. The flexibility operating region for the active and reactive power transfer from the distribution network under security constraints is one of the proposed approaches to ensure the grid's security during flexibility operations [12]. Figure 1 illustrates the interaction between the TSO and DSO for optimal flexibility operation in the modern grid. The interaction is established through coordinated real-time data exchange at the phasor measurement unit (PMU) hub. The flexibility operating region is subsequently established using appropriate optimization techniques considering required constraints at the T-D network boundary. The DER units within the distribution network is aggregated and dispatched following successful negotiations. The aggregator uses real-time synchronized data to achieve flexibility activation from the VPPs at the optimal cost.

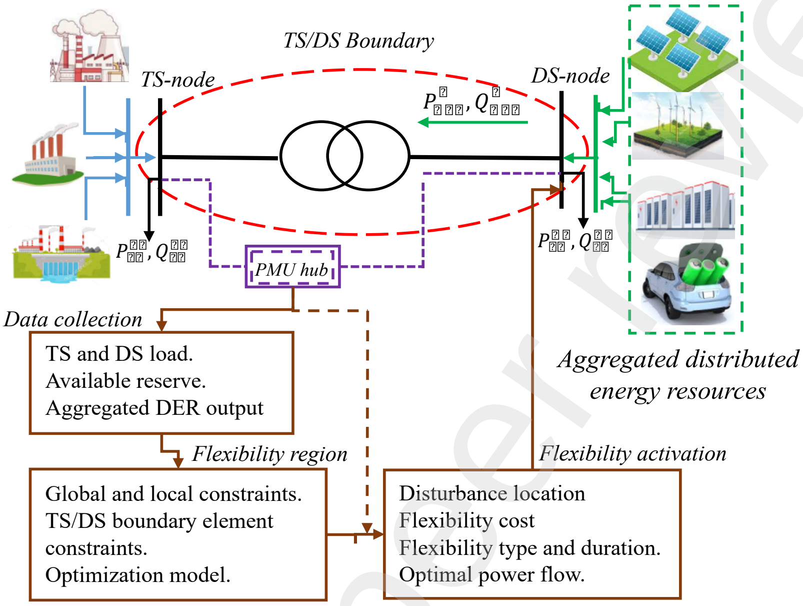


Figure 1. Interaction illustration between the TSO and DSO

Aggregated distributed energy resources (DERs) units operate similarly to conventional power plants when participating in the energy market as a unit [48]. A major component of the aggregated DER units is an efficient energy management system that can schedule and control the individual power generation sources in the aggregated units. Depending on the need of the grid for voltage regulation, DER unit proprietors may act as load or generators accordingly. Efficient operation of the aggregated DER units can minimize reliance on fossil fuels generation units, reduce the cost of voltage control and significantly reduce carbon emissions caused by power generation. Aggregating DER units also reduces the impact of unstable output from individual DER units on the grid. A major drawback of aggregated DER units is that the units are installed at different locations within the distribution network. Also, the interaction between the transmission and distribution network operator for efficient control of aggregated DER units during flexibility operation requires complex algorithms [49].

Assuming a balanced distribution network, the operational constraints of aggregated DER units are formulated as shown in (3) to (5). The active and reactive power injection into the network branches is given in (3) and (4), where B is the vector of possible active and reactive dispatch from the aggregated DER units. The security with respect to the distribution network branch (i,j) where the aggregated DER units are connected is constrained by (5). The active and reactive power balance at each node is constrained by (6). The voltage magnitude limit at each network node during DER unit operation is enforced by the inequality constraint in (7). The aggregated DER units operating limits are represented by (8), where R is the set of active and reactive power that can be activated securely by the distribution network operators.

$$P_{DER}^{f(i,j)} = F_{i,j}(v, \theta) \qquad \forall_{ij} \in B \tag{3}$$

$$Q_{VPP}^{f(i,j)} = F_{i,j}(v, \theta) \qquad \forall_{ij} \in B \tag{4}$$

$$P_{VPP}^{f(i,j)} + Q_{VPP}^{f(i,j)} \leq S_{VPP}^{ij} \ \forall_{ij} \in B \tag{5}$$

$$P_g^i - P_d^i = \sum P_\ell^{ij},\ Q_g^i - Q_d^i = \sum Q_\ell^{ij} \qquad \forall \in N \tag{6}$$

$$V_{min}^{\ i} \leq V^i \leq V_{max}^{\ i} \qquad \forall \in N \tag{7}$$

$$(P_{DER}, Q_{DER}) \in R \qquad \forall \in N \tag{8}$$

2.2 *Flexibility for voltage management*

The increased penetration of variable energy generation sources units into the distribution network will increase the responsibilities of the network operators, from ensuring the secured network operation to managing flexibility services. Excess power generation, overvoltage, and reverse power flow are some challenges to consider during network planning and operation. Energy storage systems and power flow redirection effectively mitigate the challenges. While energy storage systems can only store a limited amount of power, power flow redirection achieved by network reconfiguration can transfer the excess power to areas at lesser losses and without violating security constraints. One of the objectives of the grid operators is to maximize the flexibilities of the modern distribution network to enhance the performance of the grid. Integrating tie-lines for possible network reconfiguration in responding to changes in generation and load within the distribution network is one way to achieve this objective. Also, in the event of planned or unplanned outages, tie-lines are employed to ensure network reliability and resilience [50]. Conclusively, the use of network reconfiguration in the modern distribution network is associated with the distribution network's flexibility services.

Utilizing the substantial potential of variable energy generation sources to provide regulation power and voltage control supports is essential for a secured and reliable power grid with high penetration of variable energy generation sources. Recent studies have demonstrated the capability of these variable energy generation sources of modern grids to contribute to the grid's localized and area-wide voltage control. Modern operators are revising their grid codes to create more effective voltage controllers for control support from variable energy generation sources [51]. Modern power grid management and control face major challenges, including planning the necessary power reserve in light of the rapidly increasing variable energy generation sources and their effects on power grid performance. A suitable approach can be seen in the contribution of variable energy generation sources to the provision of a regulated power reserve. Currently, in some cases, the design and functionalities of variable energy generation sources are comparable to conventional SGs [51]. For example, the time required for a conventional generating unit to ramp up power generation to the desired level is significantly larger than the time required by the variable energy generation sources. The variable generation resources can therefore be configured to perform grid regulation tasks, as traditional generators. The variable generation resources can receive the desired voltage set-points and other required operation/control commands from the distribution network operators to produce the required voltage regulation support. These commands are distributed between the aggregator to determine the contribution amount for each participant aggregated DER units in the grid voltage regulation. The required amount of active and reactive power from the aggregated DER units will be determined through the hosting capacity of the distribution network.

3 PROPOSED APPROACH

The reconfiguration of the distribution network considering the operations of variable energy generation sources is a probabilistic planning and operation problem that must account for uncertainties. Possible contingencies and variations in the output of the variable energy generation sources units and node loads are among the uncertainties that must be considered for modern distribution network reconfiguration. The variations in the node load are modeled using probability distribution functions. However, given that the distribution network's topology remains constant before and after implementing reconfiguration schemes, both deterministic and stochastic variables can be considered in the reconfiguration problem formulation. This paper, therefore, seeks to propose a technique to mitigate the impact of voltage support unit operations such as aggregated DER units on the distribution network through network reconfiguration and flexibility quantity estimation.

The bilevel process of the proposed technique in this paper is shown in Figure 2. The first stage involves economic consideration, achieved through reconfiguration problem modeling. The objective is to minimize the cost of flexibility operations through reduced net power loss after network reconfiguration. The variables and the constraints considered are the probabilistic risk index and the network hosting capacity. The developed multi-variable optimization problem is solved using the constrained fmincon optimizer. The fmincon optimizer starts from an initial estimate and finds a constrained minimum of a scalar function of several variables. The fmincon optimizer supports linear and non-linear constraints while performing non-linear constrained optimization. The solver configuration includes settings for convergence criteria, maximum iterations, and the calculation of gradients. The second stage involves technical considerations, which involve estimating the flexibility required to achieve specific voltage support during disturbances. The machine learning classification technique is applied to the developed dataset from several Quasi-dynamic state simulations with specific attributes.

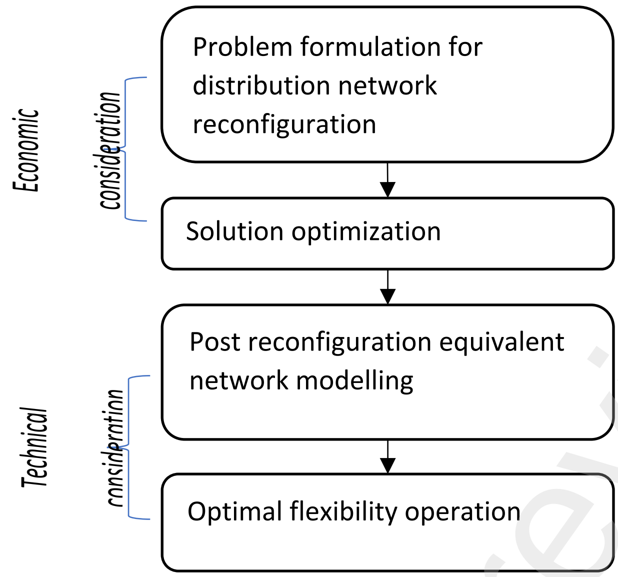


Figure. 2. Hosting capacity approach

3.1 Network reconfiguration problem formulation

Radial distribution network reconfiguration is a practical method for enhancing distribution network performance. Changes in configurations can be made to ensure load supply, power loss reduction, system security improvement, and power quality enhancement. Additionally, the reconfiguration lessens the network components' overload. Switching operations for reconfiguration action can be either manual or automatic. The reconfiguration also relieves the overloading of the network components [22]. The goal of distribution network reconfiguration is to reduce net power loss (PL) while considering the distribution network's suggested deterministic and probabilistic factors. To achieve this goal, the network's switches' states must be changed while adhering to equality and inequality requirements. The distribution network reconfiguration problem is formulated as (9) subject to the power flow (PF), probabilistic risk index (x),hosting capacity (y), and radiality constraints in (10) to (14).

$$\min PL = f(x,y) \tag{9}$$

$$PF(P_j,Q_j,V_i,\theta_i) = 0 \tag{10}$$

Subject to:

$$x_1 \leq x \geq x_2 \tag{11}$$

$$y \geq y_1 \tag{12}$$

$$PL = \sum_{j=1}^{m}. I^2(j)R(j) \tag{13}$$

$$m = n - 1 \tag{14}$$

where n is the number of nodes, m is the number of branches, I is the current, R is the resistance of the line, and Q_j are the active and reactive power flow on the branch j, respectively.

3.1.1 Hosting Capacity

IEEE 1547.1 standard must be followed in designing and managing a distribution network using variable generation resources. This standard provides crucial variable generation resource penetration conditions for safe network operations. The hosting capacity (HC) is an index that determines how much power generated by variable generation resource units can reach the distribution network while maintaining the grid's security within acceptable parameters, given the limits and limitations of the current network setup. After a change in network configuration via reconfiguration, enlargement, and reinforcement, the network's new hosting capacity must be established. With the ability to estimate hosting capacity, distribution operators now have a new security-based index to measure how variable generation resources have affected the functioning of the distribution network and the grid as a whole. Hosting capacity values may be assigned to network nodes while considering nodal restrictions. It is possible to obtain the hosting capacity values for each node and for the entire distribution network. The nodal hosting capacity is preferable and common in the literature because it is a function of the distance between the network substation and each distribution network node. The nodal hosting capacity is expressed as the ratio of the total power generation from the variable generation resources units (S_{vr}) to the total load (S_{ld}) connected to the node. Constraints selection, definition, hosting capacity estimation, and verification of security limit violations are the major steps in establishing a network's hosting capacity. If i and j represent the node and branches, respectively, then the current (I) which represents thermal, voltage (V), voltage harmonics (V_{thd}) and fault current (I_f) constraints used to evaluate the distribution network nodal hosting capacities in this paper are defined in (15) to (18).

$$I_i \leq I_{i,max} \tag{15}$$

$$V_{j,min} \leq V_j \leq V_{j,\,max} \tag{16}$$

$$V_{thd,i} \leq V_{thd,i,max} \tag{17}$$

$$I_{f,i} \leq I_{f,i,max}, \tag{18}$$

3.1.2 Distribution Network Probabilistic Risk Assessment

This study models the network nodes' probabilistic risk index before and after changes in the network configuration using the risk related to node voltage. The probabilistic risk index measures the likelihood that the voltage at the distribution network nodes will exceed predetermined security thresholds. The nodal probabilistic risk index (PRI) can be estimated using (19), where the voltage probability (P_v) and the severity (A) can be derived using (20) and (21), respectively. Using the Monte-Carlo simulation-based probabilistic load flow (MCSPLF) approach, the overvoltage or undervoltage probabilities are determined. The probability distribution function used to simulate changes in the loads and power generation under the assumption of a constant power factor is shown in (22).

$$RI(i) = P_v(i) * A(i) \tag{19}$$

$$P_v(i) = \lim_{N\to\infty} \frac{(n_1)}{N} + \lim_{N\to\infty} \frac{(n_2)}{N} \tag{20}$$

$$A(i) = |1 - \overline{V}(i)| \tag{21}$$

$$f(P_s,Q_s{:}P_l,Q_l) = \frac{1}{\sqrt{2\pi\sigma(P,Q)}} exp\left(- \frac{((P,Q) - \mu(P,Q))^2}{2\sigma_{P,Q}^2} \right) \tag{22}$$

where N is the number of simulations, $\overline{V}$ is the average voltage for N sample of instances, n_1 is the total number of $\overline{V}$ lesser than 0.95 pu, n_2 is the total number of $\overline{V}$ greater than 1.05 pu, P_s is the active power supply, Q_s is the reactive power supply, P_l is the active load, Q_l is the reactive load, while μ and σ are the expected mean value and standard deviations, respectively.

3.2 A Random tree classification algorithm

A random tree is constructed randomly from a set of possible trees with K random features at each node. Each tree is assigned an equal sampling probability in the set of trees. Random trees (RT) provide simple human-readable rules and are effective for classification optimization problems. The model of the RT is from the physical tree structure consisting of roots, nodes, and branches. A RT is constructed from nodes and edges that are arranged in a hierarchical pattern [52]. The RT node represents specific characteristics and attributes of the dataset, while the branches represent the values of the attributes. The attribute's range of values impacts the attributes' partitioning points. To create the RT structure, a data instance is classified based on predefined conditions and characteristics that best divide the dataset. The classification progresses from top to bottom, and the dataset instances are split according to the values of the attributes until a terminal node representing the objective is obtained. The classification process is applied to each split subset of the dataset recursively. The process terminates when all the dataset instances in a current subset belong to the same class. The RT algorithm was adopted in this paper because of its flexibility, capability to handle numerical and categorical data, and excellent performance with small and large datasets. Random trees can be generated efficiently, and combining large sets of random trees generally leads to accurate models [53]. The generic structure of a RT is shown in Figure 4. The three major steps to developing a RT classification model are attribute selection for the root node, splitting instances into subsets, and recursive repetition for each RT node.

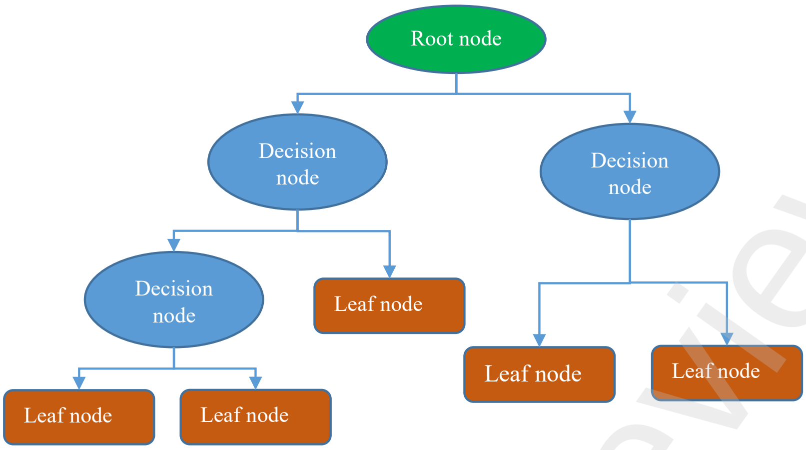


Figure. 4: Decision tree model

The Gini index measures the integrity of the attributes on which the splitting action is performed. Since the Gini index measures the impurity of the dataset, the dataset attributes with the highest Gini index are chosen as the best split for that node [4]. The Gini index can be calculated using (23).

$$Gini(n) = \frac{1}{2} - \left[1 - \Sigma_i p(\omega_i)^2\right] \tag{23}$$

where $p(\omega_i)$ is the relative frequency of class ω_i at node n. The impurity in the attribute is zero if the samples are in the same group; otherwise, (23) returns a positive value. The classification outcome is impacted by the predictive power of the developed dataset. The predictive power can be estimated using the entropy-based information gain model. The entropy-based information gain is a feature selection method used to calculate the loss in entropy, representing the impurity level in a given dataset [17]. The information of the attributes with an information gain value higher than the average represents the predictive power of the dataset. For example, given a dataset N containing instances with each of k outcomes, the entropy of N is given in (24), where $p(I)$ is a portion of N belonging to class I. If the value of the entropy is k, then all instances of N belong to the same class. For an attribute x of sample set N, the information gain $G\ (N,x)$ is defined as (25).

$$E(N) =- \Sigma_{I \in k} p(I) \log_2 p(I) \tag{24}$$

$$G((N,x) = E(N) - \Sigma_{j \in x} \left(\frac{|N_j|}{N}\right) \tag{25}$$

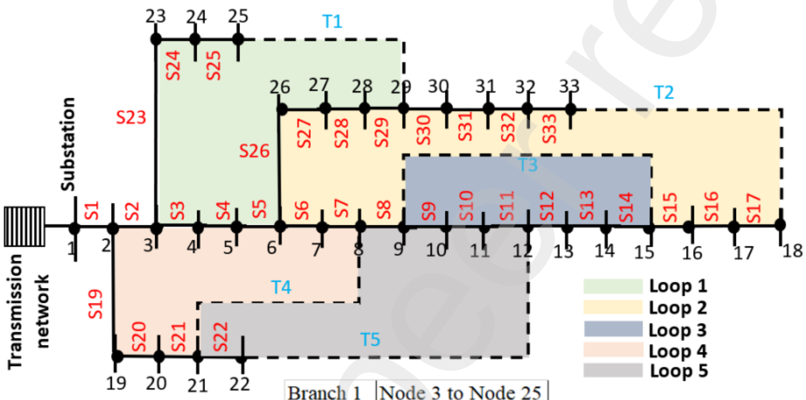
4 RESULTS AND DISCUSSION

4.1 IEEE 33 node Distribution network

4.1.1 Base network result

This section presents the results of testing the proposed technique on the IEEE 33-nodes distribution network. The test distribution network with the identified loops generated from the tie lines (T) and section line switches (S) is shown in Figure 3. The substation represents the interface between the transmission and the distribution networks. The normal load flow result shows that 18 nodes out of 33 nodes are outside the security limit. Also, under probabilistic load flow analysis, 72% of the node exist out of the security limit with the mean voltage and standard deviation of 0.89 and 0.009, respectively. The total normal state power loss is 212.4 kW, with nodes 1 to 6 accounting for about 68.6% of the total loss. Figure 4 shows the probabilistic risk index (PRI) of the IEEE 33-node network when the aggregated DER unit is connected to branch 1. The PRI is proportional to the total branch load and the distance of the connecting node from the substation. The values of the PRI for the base network are considerably high due to constant variations of loads on the branches. The connection and operation of aggregated DER units will understandably increase the PRI value due to variations in the output levels of the generations. At certain periods of the day, undervoltages and overvoltages may be experienced around the nodes with connected DER units due to undergeneration and overgeneration of power, respectively. Branch 4 has the highest branch contribution to the network average risk index, at 9.24%, accounting for 42% of the network's PRI.

The technique proposed in this paper will enable distribution network operators and aggregators to securely operate aggregated DER units, thereby promoting more penetration of DER units in the distribution network. Branches 4 and 2 have the highest and lowest average hosting capacities of 5.56 MVA and 0.57 MVA, respectively. Figure 5 shows the probabilistic line loading of the network with and without the operation of aggregated DER unit on the first node of the network branches. In consistency with the advantage of the DER's optimal operation, the network's line loading under probabilistic loading is considerably reduced for each branch. The branch loading and the distance of the branch from the substation impact the percentage line loading reduction obtainable under constant network parameters. The highest reduction of 55.1% was obtained from branch 4. The probabilistic power loss reduction obtained for branch one is inconsiderable due to the number of load points connected and the size of the load connected. The power loss reduction of 140 MVA was obtained after connecting the aggregated DER unit on the first nodes on branches 2 and 3, shown in Figure 6. The best hosting capacity conservation of 90.7% was obtained when the aggregated DER unit was connected to branch 4. An average percentage reduction of 39.42% in the hosting capacity was recorded after connecting the DER unit to the distribution network.



Branch 1	Node 3 to Node 25
Branch 2	Node 6 to Node 33
Branch 3	Node 7 to Node 18
Branch 4	Node 2 to Node 22

Figure 3: Initial networks showing the loops

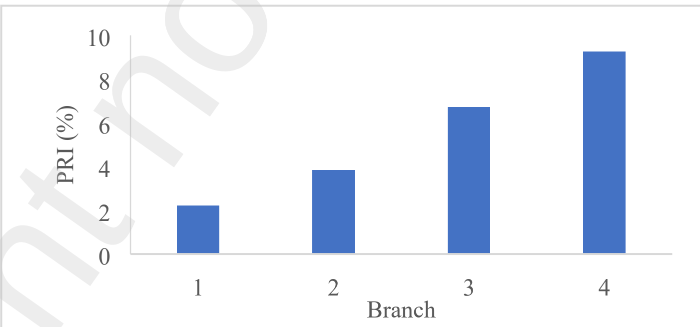


Figure 4: Network hosting capacity and risk index

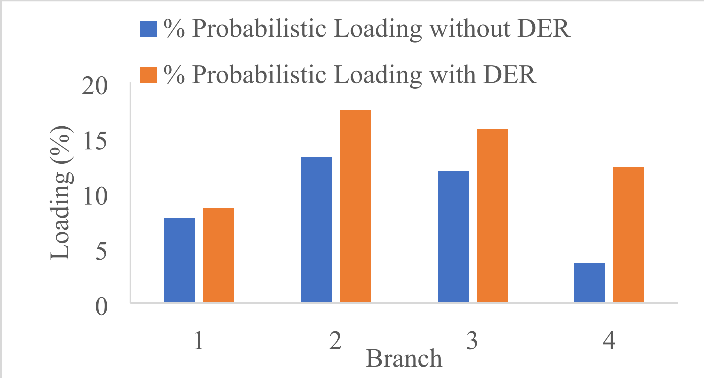


Figure 5: Probabilistic line loading with and without aggregated DERs

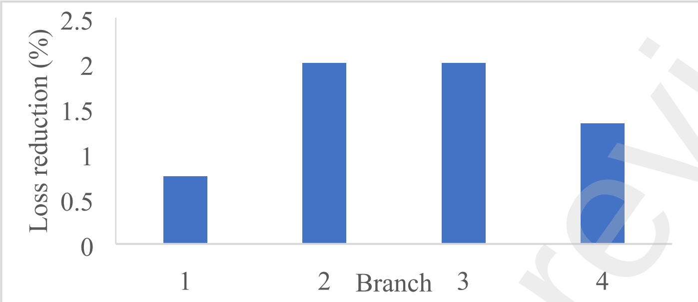


Figure 6: Percentage power loss reduction with DER units operations

4.1.2 Optimization results

This section presents the solution to the distribution network reconfiguration optimization problem. The fitness functions in this paper are developed to achieve a configuration that minimizes the network power loss considering the risk index and hosting capacity variables presented in section III. The opening operations of the section switches (S) and the tie switches (T) for the loop under consideration achieve the desired configuration. Also, the fitness functions are derived such that there is no mesh network within the distribution network, thereby ensuring the radiality constraint of distribution network reconfiguration. The radiality constraint ensures that no node is left unserved after network reconfiguration. The fitness functions are developed for each loop within the distribution network. Figure 7 shows the global optimal values after 20 iterations for the loops obtained using the fmincon optimization algorithm. The lowest and highest standard deviations of 0.032 and 0.0779 from the optimal values were obtained from loop 1 after 20 iterations. The x and y values corresponding to the PRI and the hosting capacity values for the optimal power loss values for each loop are shown in Table 1. The section line switch to achieve the required reconfiguration is indicated in Table 1

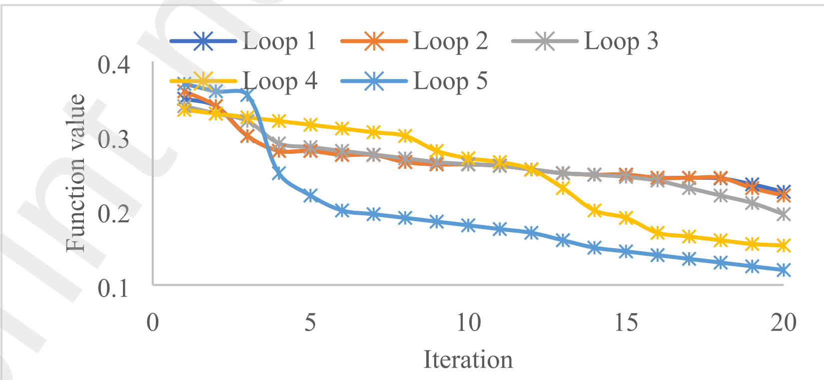


Figure 7: Loop optimization objective values

Table 1: Optimal solutions for reconfiguration

Loop	PLI	HC	Section line switch (S)
1	8.95	2.32	S29
2	8.56	2.16	S11

3	10.76	2.3	S12
4	7.22	2.28	S6
5	6.64	2.32	S8

4.1.3 Reconfigured network results

The reconfigured network models and the optimization variables' results are presented in this section. Figure 8 shows the reconfigured networks for each loop. The highest probabilistic risk index reduction is obtained from the reconfigured network for loop 1, as shown in Figure 9. The average network PRI was reduced by 41.8%, with the highest reduction of 94.6% from loop 4. The maximum and average hosting capacity was increased by 62.5% and 13.36% for loop 1 network reconfiguration. Figures 10 and 11 show the power loss and line loading reduction of the network with aggregated DER unit operation before and after network reconfiguration. Considerable reductions of 25% and 22% were achieved for the power loss and line loading, respectively, by connecting the aggregated DER units to branch 1 on node 23 of the reconfigured network considering loop 1.

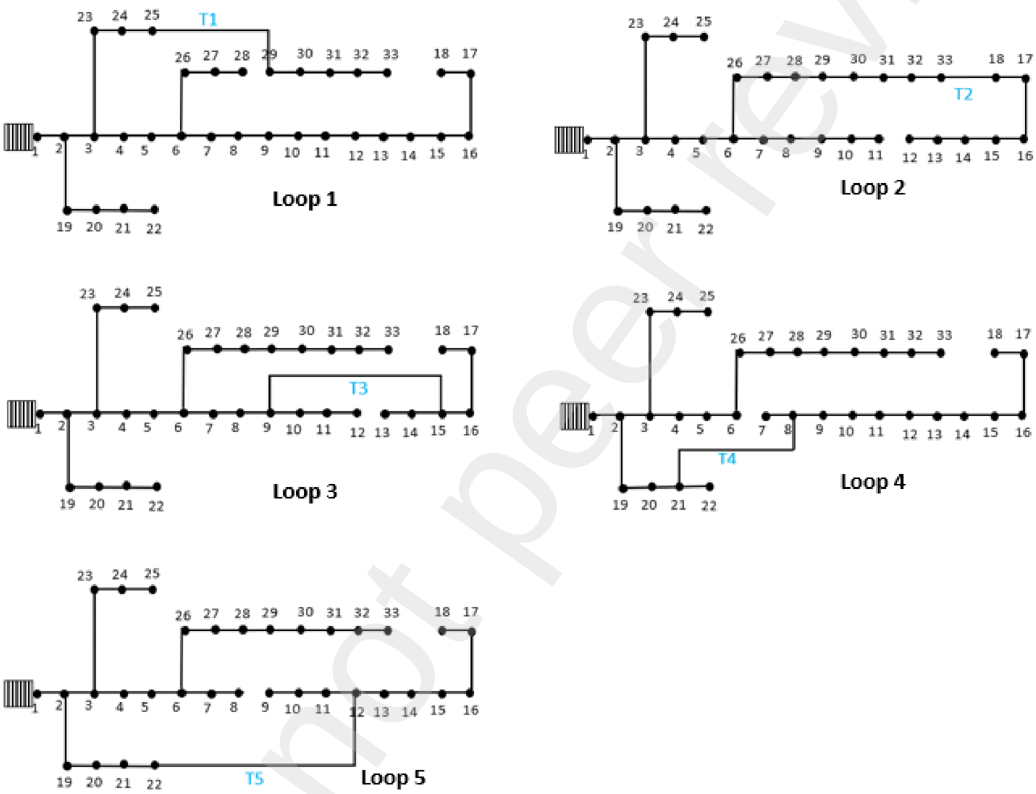


Figure 8: Reconfigured network for each loop

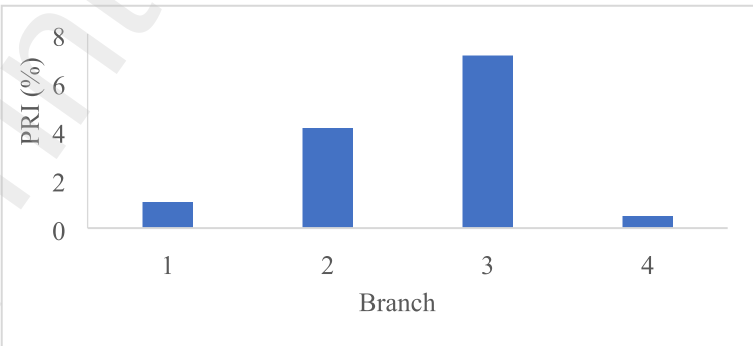


Figure 9: Probabilistic risk index of branch with aggregated DERs

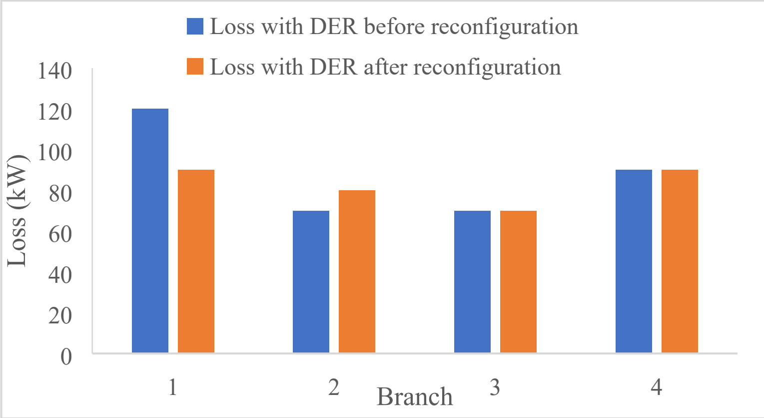


Figure 10: Power loss change with DER units' operations

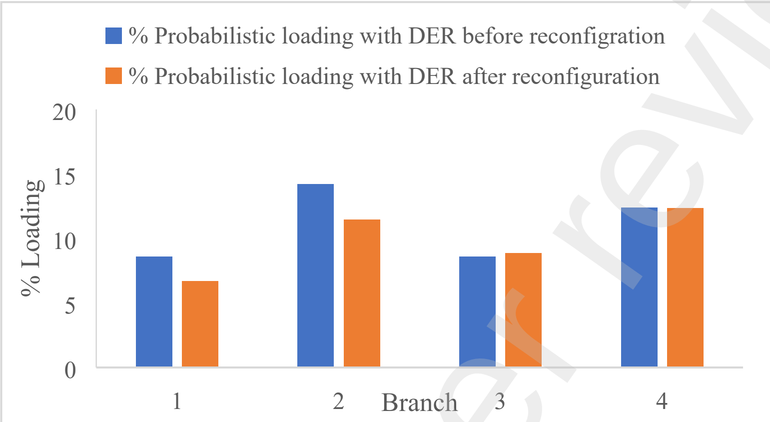


Figure 11: Probabilistic line loading with DER units

Figure 13 shows the voltage response of the reconfigured networks under the step load changes in the load profile shown in Figure 12 with and without the operation of the aggregated DER units. The operation of the aggregated DER unit is implemented through the dispatch and switch events. The sudden increase in load is activated on the node with the highest load on the branch at 4.00 pm. The flexibility from the aggregated DER unit is also activated on the first node on the branch and activated at 4.00 pm and deactivated through the switch event at 6.00 pm. The minimum voltage obtained from branch 3 due to the 100% load increase from the average network load was improved by 5.05%. More voltage deviation reductions are obtained through the minimum generation of 3 MW and power factor of 0.85 from the aggregated DER units.

Figure 14 shows the improvement in the voltage deviations obtained in loop 1 for branches 2, 3, and 4. The highest improvements of 8.99% and 5.87% were obtained when the aggregated DER unit was connected to branches 4 and 3, respectively. The minimum voltage is greater for low impedance branches and large load change events. Figure 15 shows the voltage deviation improvements for the loops and branches of the network load changes. The voltage deviation improvements are greater for branches with lower impedance values. Branch 1 presents a uniform average improvement of 3.8% in the minimum voltage during the load change event across the network loops. Reconfigured network with loop 3 generates the highest minimum voltage improvement with DER unit operation.

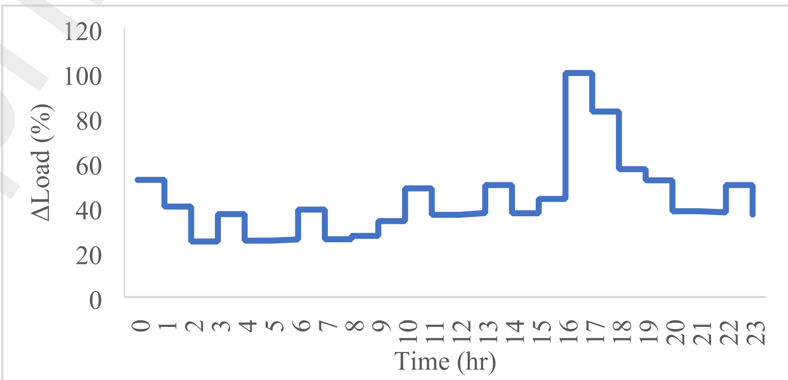


Figure 12: Load change event profile

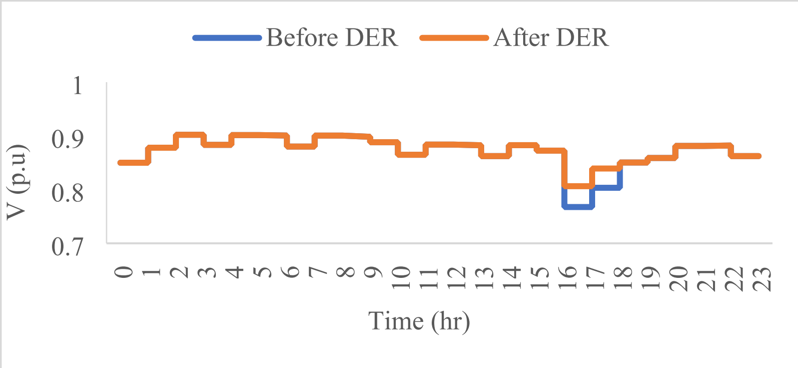


Figure 13: Voltage support from the DER units on Branch 1 from loop 1

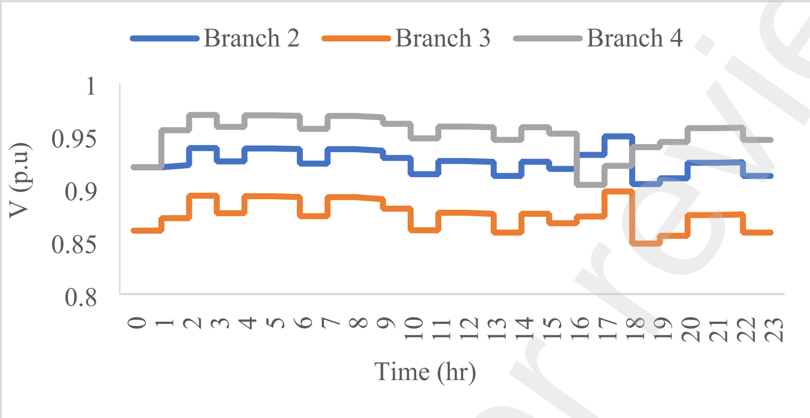


Figure 14: Voltage support from DER units for branches 2, 3 and 4

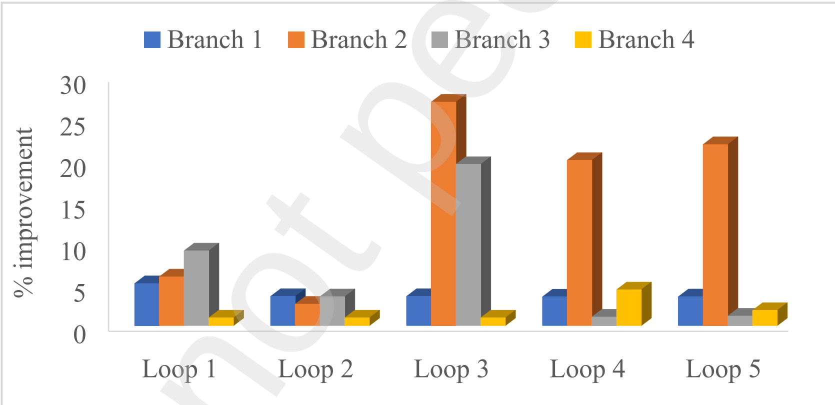


Figure 15: Percentage improvement from DER units for each loop and branch

4.2 IEEE 69 node distribution network

4.2.1 Base network results

This section presents the results of testing the proposed technique on the IEEE 69 nodes distribution network. The test distribution network with the identified loops generated from the tie lines (T) and section line switches (S) is shown in Figure 16. The normal load flow result shows 47 out of 69 nodes are outside the security limit. Also, under probabilistic load flow analysis, 80% of the node exist out of the security limit with the mean voltage and standard deviation of 0.88 and 0.0163, respectively. The normal state power loss is 210.8 kW, with branch 6 accounting for about 56.17%. Figure 17 shows the probabilistic risk index of the IEEE 69 node network. The values of the PRI for the base network are considerably high due to constant variations of loads on the branches. Like the IEEE 33-node test network, the connection and operation of aggregated DER units predictably increase the PRI value due to variations in the output levels of the generations. Branches 7 and 8 have the highest and lowest average hosting capacities of 3.01 MVA and 2.24 MVA, respectively. The average hosting capacity conservation of 93.3% was obtained when the aggregated DER unit was connected to branch 1 of the distribution network. Branch 4 has the highest branch contribution to the network average risk index at 22.76 %. The risk index contribution of branches 1 and 7 are insignificant since the least probabilistic voltage of its nodes is within the voltage security limit.

Figure 18 shows the probabilistic line loading of the network with and without the operation of aggregated DER unit on the first node of the network branches. In consistency with the advantage of the DER's unit optimal operation, the network's line loading under probabilistic loading is reduced for each branch. The branch loading and the distance of the branch from the substation impact the percentage line loading reduction obtainable under constant network parameters. The highest line loading reduction of 99.83% was obtained from branch 2. The probabilistic line loading reduction obtained for branch 6 is inconsiderable due to the number of load points connected and the size of the load connected. The percentage power loss reduction obtained after the connection of the aggregated DER unit is shown in Figure 19. An average power loss reduction of 77.4 MVA was obtained after connecting the aggregated DER unit to the distribution network. The voltage responses of the reconfigured network for several scenarios are afterward determined.

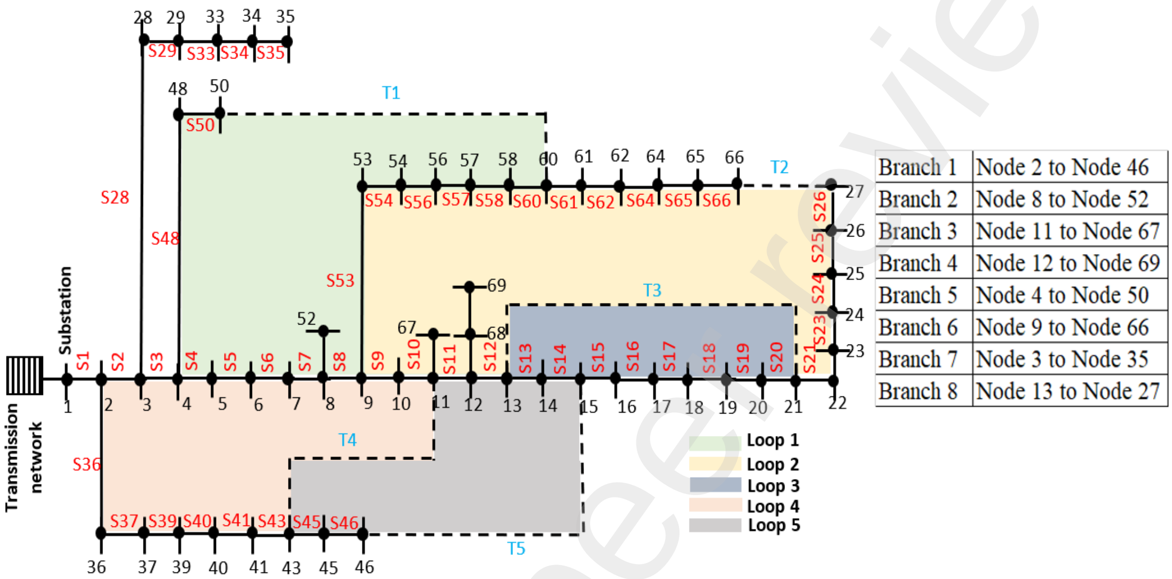


Figure 16: Initial networks showing the loops

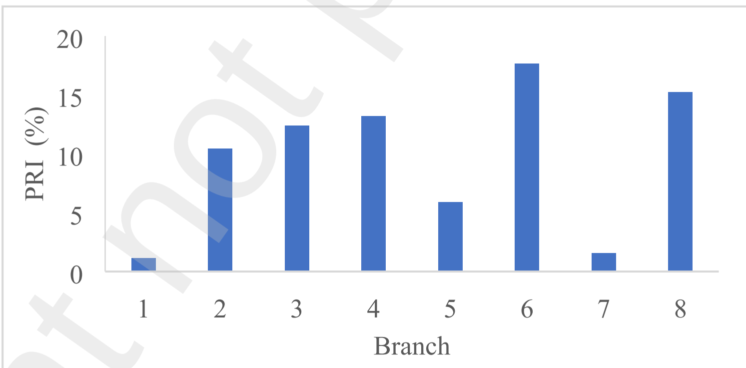


Figure 17: Probabilistic risk index of branches with aggregated DER units

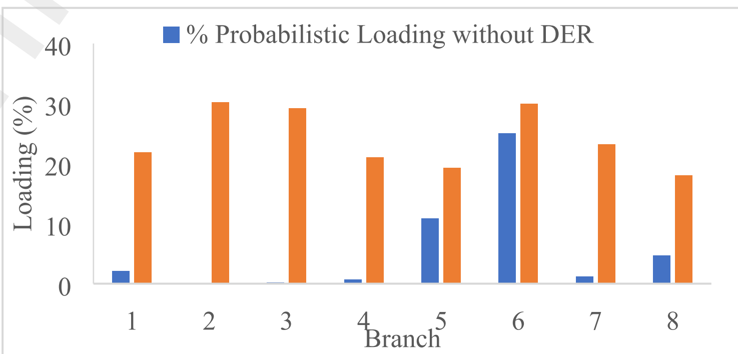


Figure 18: Probabilistic line loading with and without aggregated DER units

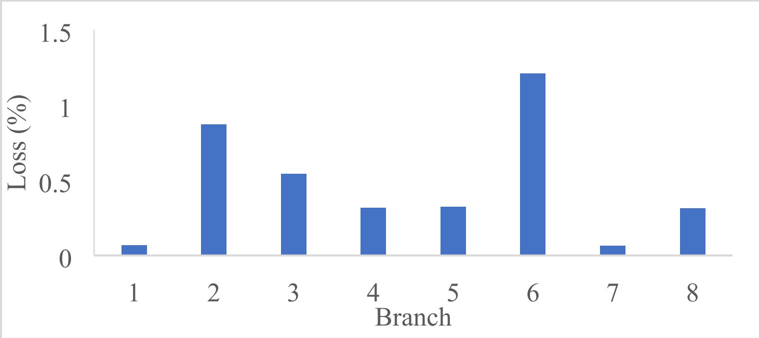


Figure 19: Percentage power loss change with DER unit operations

4.2.2 Optimization results

The fitness functions for the IEEE 69-node test network are also developed for each loop within the distribution network. The fitness functions are developed to achieve a network configuration that minimizes the network power loss considering the risk index and hosting capacity variables through operations of the section switches (S) and the tie switches (T). Figure 20 shows the global optimal values after 20 iterations for the loops. The lowest and highest standard deviations of 0.018 and 0.032 from the optimal values were obtained from loop 1 after 20 iterations. The x and y values corresponding to the PRI and hosting capacity values for the optimal power loss values and the section line switch (S) to achieve the required reconfiguration for each loop are shown in Table 2. The fitness function is also derived such that there is no mesh network within the distribution network, thereby ensuring the radiality constraint of distribution network reconfiguration.

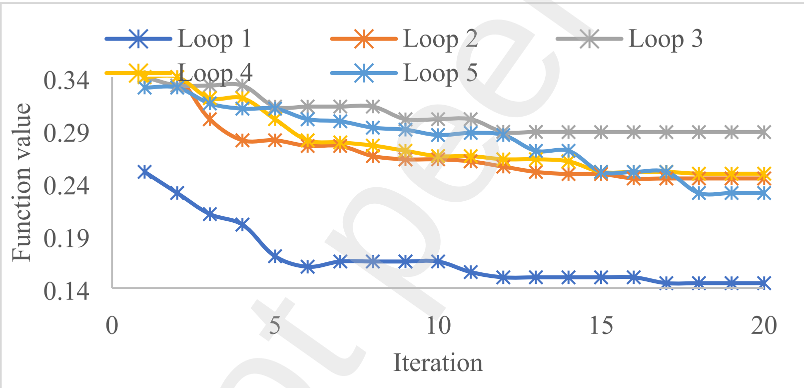


Figure 20: Loop optimization objective values

Table 2: Optimal solutions for reconfiguration

Loop	PLI	HC	Section line
1	8.012	3.1	S56
2	12	3.01	S64
3	11.05	3.05	S20
4	9.5	2.95	S41
5	8.68	2.98	S12

4.2.3 Reconfigured network results

The reconfigured network models and the optimization variables' results are presented in this section. Figures 21 shows the reconfigured networks for each loop. The highest probabilistic risk index reduction is obtained from the reconfigured network for loop 2, as shown in Figure 22. The average network PRI was reduced by 92.7%, with the highest reduction of 99.2% from loop 2. The minimum and maximum hosting capacity were increased by 16.7% and 2% for loop 1 network reconfiguration. Figures 23 and 24 show the power loss and line loading reduction of the network with aggregated DER unit operation before and after network reconfiguration.

Considerable reductions of 31.7% and 17.58% were achieved for the power loss and line loading, respectively, by connecting the DER unit to branch 1 of the reconfigured networks considering loop 1.

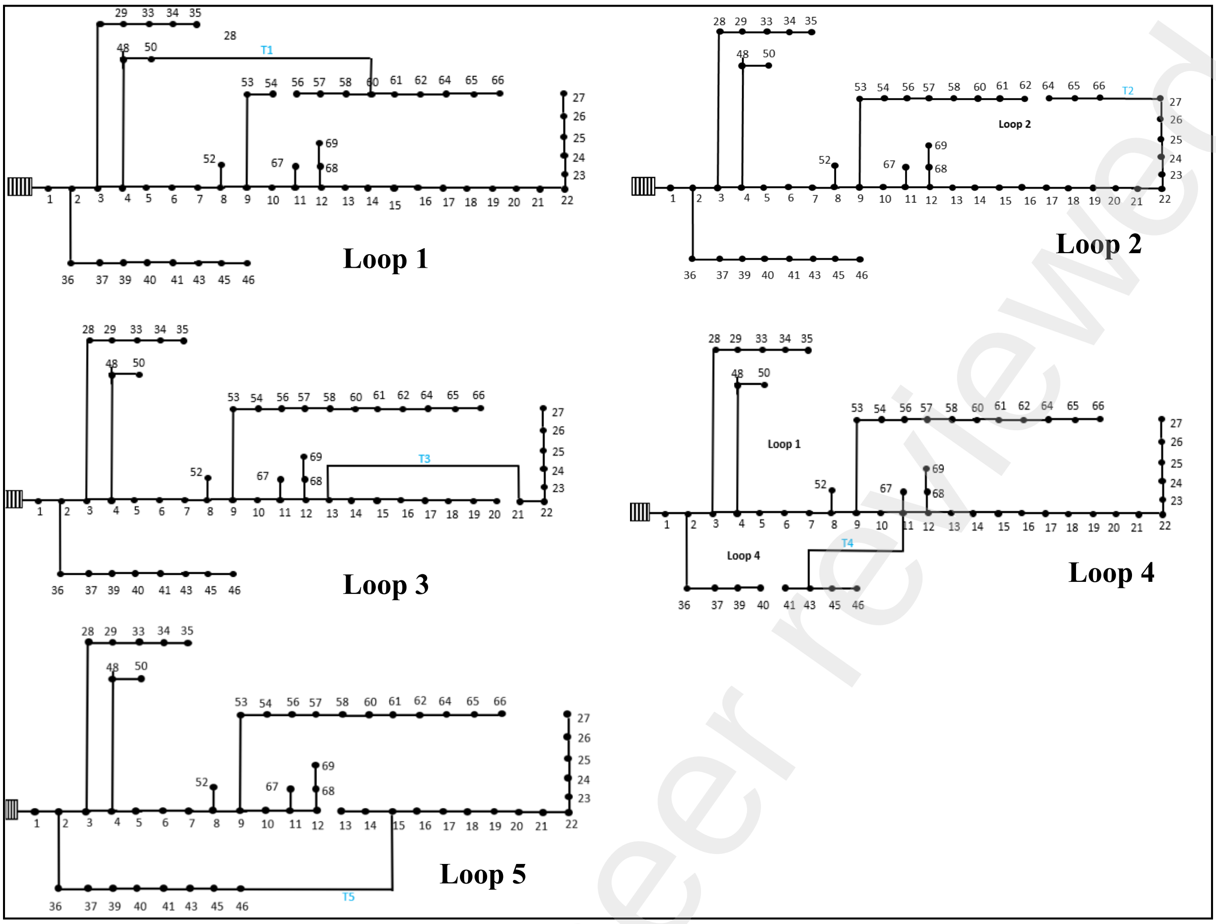


Figure 21: Reconfigured network for each loop

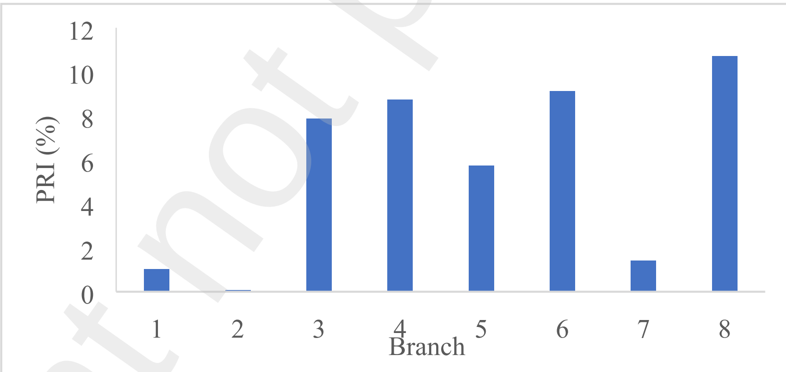


Figure 22: Probabilistic risk index of branches with aggregated DERs

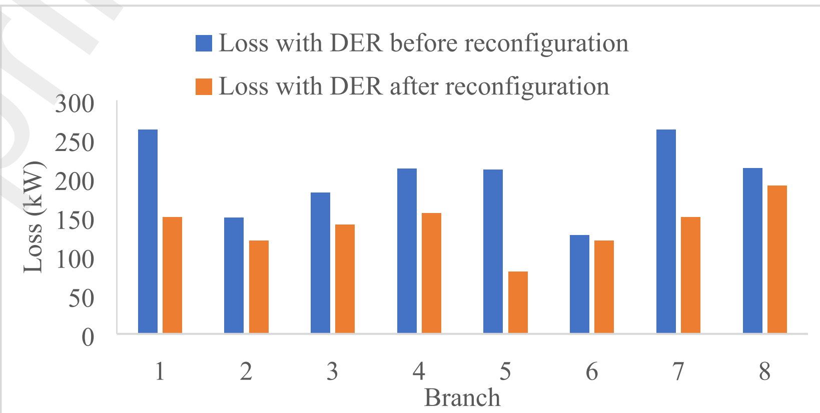


Figure 23: Power loss change with DER unit operations

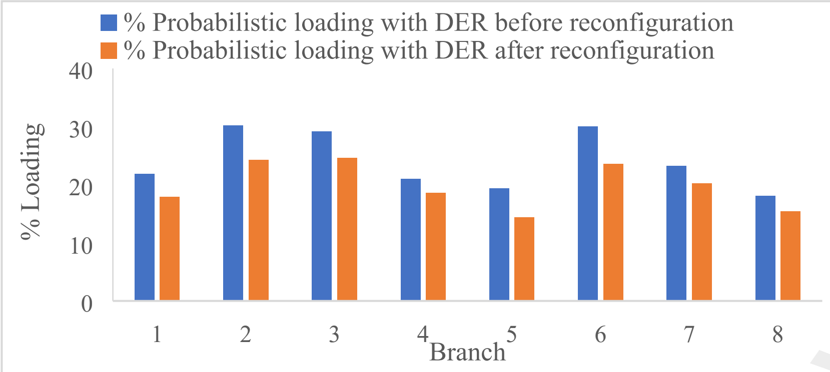


Figure 24: Probabilistic line loading with DER units

Figure 25 shows the voltage response of reconfigured networks under the step load changes in the load profile shown in Figure 12 with and without the operation of the aggregated DER unit. The operations of the aggregated DER unit and the activation of the load and switch events are the same as in section 4.1. The highest minimum voltage improvement of 2.3% was obtained from branch 8. More voltage deviation improvements are obtained through the minimum generation of 3 MW and power factor of 0.85 from the aggregated DER unit. Figure 26 shows the improvement in the voltage deviations obtained in loop 1 for branches 5, 7, and 8. The highest improvements of 0.32% and 0.58% were obtained when the aggregated DER unit was connected to branches 5 and 8, respectively. The minimum voltage is greater for low impedance branches and large load change events. Figure 27 shows the voltage deviation improvements for the loops and branches of the network load changes. The voltage deviation improvements are greater for branches with lower impedance values. Branch 2 presents the highest average improvement of 15.4% in the minimum voltage during the load change event across the network loops. The reconfigured network with loop 3 for branch 2 generates the highest minimum voltage improvement of 26.8% with aggregated DER unit operation.

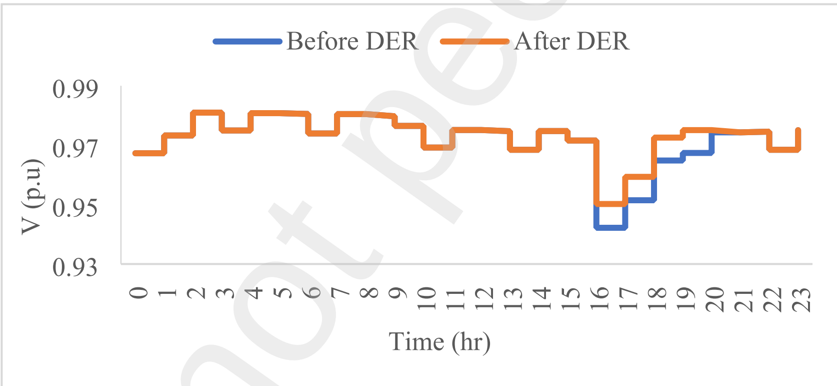


Figure 25: Voltage support from the DER unit on Branch 1 from loop 1

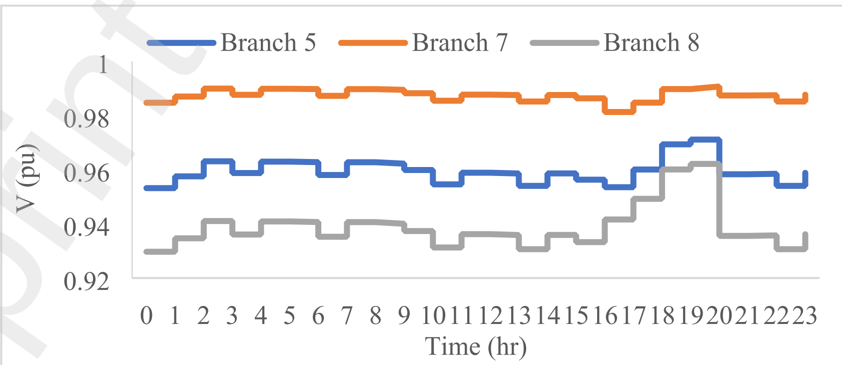


Figure 26: Voltage support from DER unit for branches 5, 7 and 8

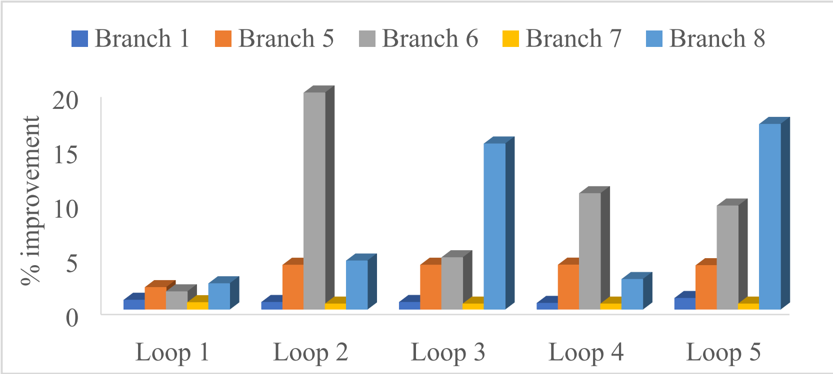


Figure 27: Percentage improvement from DER unit for each loop and branches

4.3 Flexibility quantity estimation

This section presents the results of simulations and machine learning model training to estimate the required flexibility quantity to achieve a desired voltage deviation improvement considering the reconfigured distribution network for loop 1. The approach proposed in this paper considers the impedance (Z) between the node where the aggregated DER unit is connected and the node where the load change disturbance occurs. The voltage deviation is monitored at the last node of the branch. The impedance between the node where the aggregated DER unit is connected is clustered into low, medium, and high impedances. Figure 28 shows the estimated flexibility dispatch from the aggregated DER unit considering the step load change and the branch impedance clusters. The required aggregated DER unit dispatch to obtain the maximum voltage deviation improvement (21.95% to 24.32%) is 3MW for the medium and high impedance connections and 2.5MW for the low impedance connection. With the highest average load change of 3390 MW and the medium impedance connection, the average voltage deviation is improved by 13.46%. Figure 29 shows the estimated flexibility dispatch from the aggregated DER units considering the step load change and the expected voltage deviation improvement during the disturbance. Notwithstanding the level of load change disturbance on the network, the highest voltage deviation improvement is generally recorded with DER units' dispatch values between 2.25 MW to 3 MW. The average voltage deviation improvement of 13.58% with a deviation of 3.46% was obtained with 2.15 MW average dispatch from the aggregated DER units during the 100 load change events simulated in the grid. The medium connection impedance generates the highest voltage deviation improvement of 36.46 % greater than the mean of 13.5%.

A dataset with four attributes and 100 instances was developed with quasi-dynamic simulations with several possible operation states. The results of training the decision tree model to estimate the quantity of flexibility needed to achieve the desired outcome voltage deviation support are shown in Figure 30. The developed dataset is divided into five data batches of 20 instances each. The average model build time for all five models is 4s. The average correlation coefficient and RMSE from all the batches are 0.957 and 0.187, respectively. The minimum model build time of 3s and RMSE of 0.161 was achieved with Batch 5. The constructed tree model obtained during the model's classification process with batch 5 is shown in Figure 31. The root node represents the voltage deviation improvement attributes, while the load change and connection impedance are considered at the decision nodes. The decision rules are generated from the leaf nodes on a root node's path in the decision tree. The classification obtained from each leaf node from the path of a root node forms the rule, while the leaf nodes represent the estimated flexibility quantity. Thirty-one classification rules were extracted from the RT model. The rules serve as a condition for the considered attributes that, when met, return an estimated flexibility quantity predicted grade. Figure 32 shows the actual and estimated flexibility quantities obtained from the developed random tree model using a different dataset with twenty instances. The estimation model is effective as only 35% of the estimations exceed the average estimation error of 0.1725. The estimated flexibility quantity will ensure the anticipated voltage support is obtained during load change disturbances within the distribution network.

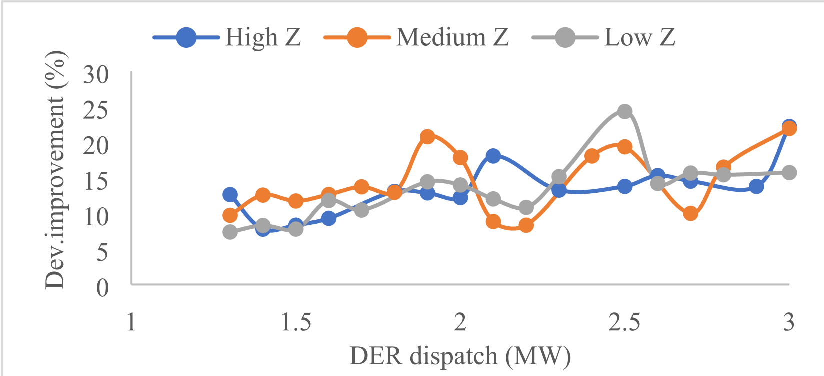


Figure 28: DER units dispatch level, connection impedance and voltage deviation improvement

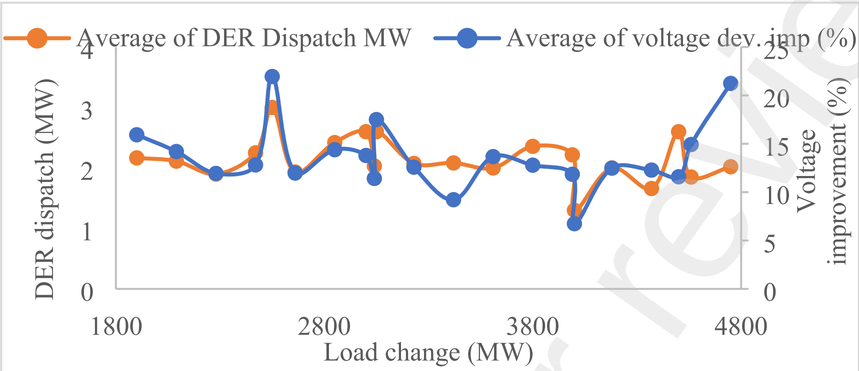


Figure 29: DER unit dispatch level, load change and voltage deviation improvement

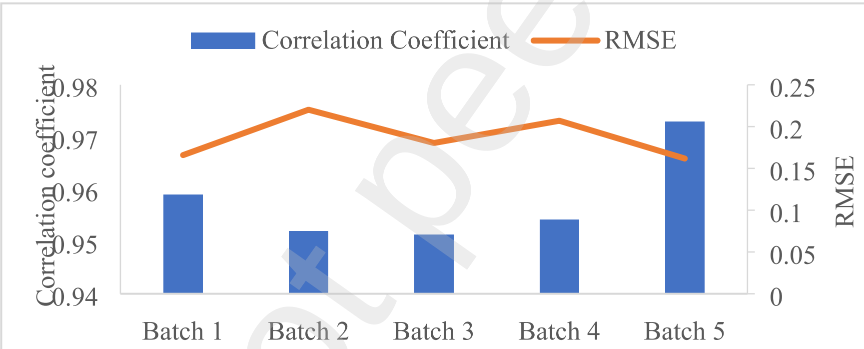


Figure 30: Flexibility quantity classification performance

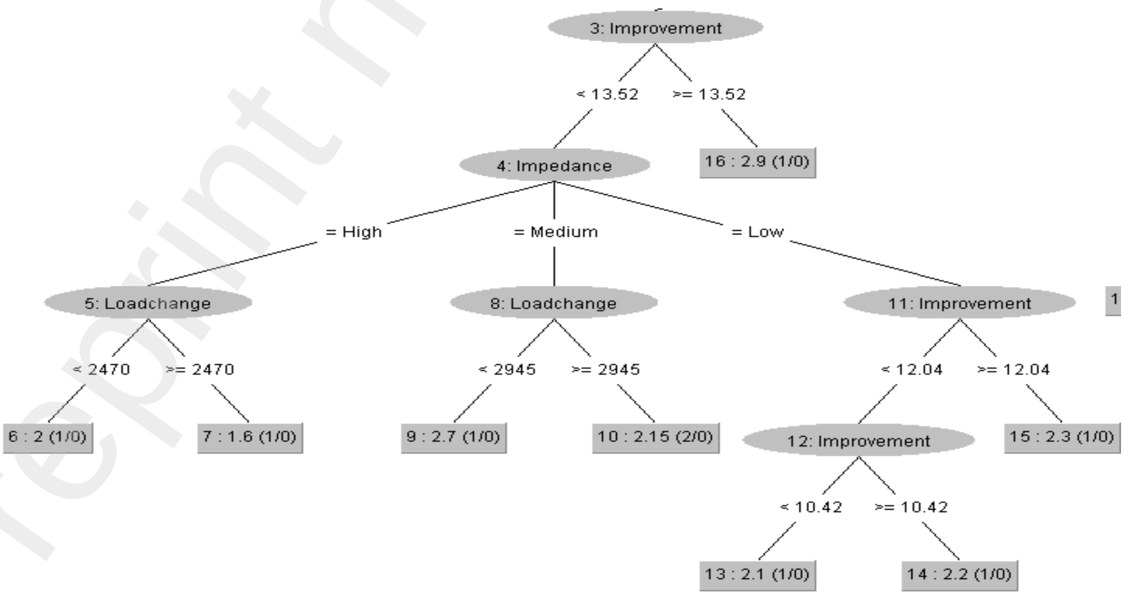


Figure 31: Random tree flexibility estimation model

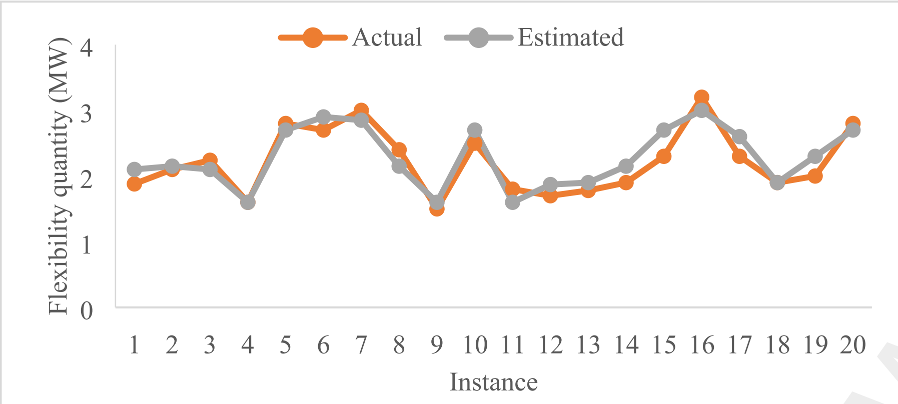


Figure 32: Flexibility quantity actual and estimated

5 CONCLUSIONS

This paper proposes a technique for optimal distribution network reconfiguring using the probabilistic risk index and hosting capacity variables. An effective voltage response support method during grid disturbance using estimated flexibility from aggregated DER units is also presented. The proposed techniques were implemented and simulated on the IEEE 33 and 69 nodes test distribution networks. The results show that the probabilistic risk index was reduced by 0.05% and 0.083%, respectively, by the optimal loop for the IEEE 33 and 69 nodes networks, respectively. The power loss reduction and the hosting capacity conservation of 25% and 5.6%, 31.7%, and 51.9% were obtained with the IEEE 33 and 69 node networks. Under a 100% increase in load, the proposed technique achieved a significant improvement of 16.67% in the voltage deviation of the worst nodes in both the IEEE 33 and 69 nodes test networks. The results show that the approach can achieve network reconfiguration to minimize the distribution network power loss and the probabilistic risk index and maximize the hosting capacity to accommodate more penetration of aggregated DER units. The proposed optimal distribution network reconfiguration approach can also achieve effective voltage support under sudden load change contingency, considering the estimated flexibility dispatch from aggregated DER units after the reconfiguration.

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