Algorithmic Formulation for Network Resilience Enhancement by Optimal DER Hosting and Placement

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This work was supported in part by the National Science Foundation (NSF) under Grant 1553494, in part by the Department of Energy under Grant DE-EE0009349, and in part by the Florida International University Graduate School Dissertation Year Fellowship.

ABSTRACT This paper proposes an algorithmic formulation for optimal PV hosting and placement of distributed energy resources (DER) for network resiliency enhancement. The algorithm incorporates a unique critical infrastructure (CI) ranking scheme to prioritize the CI nodes for the DER placement while ensuring maximum hosting of the DER. The proposed multi-objective non linear programming formulation is validated on an IEEE 34 bus feeder with different outage scenarios caused by a hurricane event. The simulation has produced 18 Pareto Optimal Solutions showing several options of optimally locating the DERs in order to achieve a maximum DER hosting capacity, improve system’s resiliency and minimize the system’s active power loss while satisfying all network and power flow constraints. The results verify the effectiveness of the proposed algorithmic formulation which distribution planners and designers can apply directly to multitude of their network substations to improve the overall system’s resiliency through grid-scale situation awareness.

INDEX TERMS Critical infrastructure, optimal DER hosting capacity, resiliency, power distribution network, extreme events.

I. INTRODUCTION
There are several definitions of power system resilience, including those given by the U.S. Department of Energy (DOE), the Industrial Control Systems- Computer Emergency Readiness Team (ICS-CERT), and federal labs such as the National Renewable Energy Laboratory (NREL) and the Pacific Northwest National Laboratory (PNNL) [1]–[4]. In the context of the energy system, resilience indicates the strength of the system against high-impact, low-frequency events such as natural disasters like tornadoes, hurricanes, earthquakes, wild fires or cyber-attacks, human-physical activities. In this work, we refer to such events as extreme events. More explicitly, the resilience can be defined as system’s ability to anticipate, prepare for, and adapt to changing conditions and withstand, respond to, and recover rapidly from disruptions through sustainable, adaptable, and holistic planning and technical solutions [5]. The definition adopted in this paper measures resiliency of a distribution network as its ability to provide continuous power supply to at least one of its critical infrastructure (CI) nodes during the occurrence of an extreme event. Power system fails even during normal weather due to progressive degradation of system components, human factors amongst many others [6]. But the impact on power system due to extreme events is severe as it is mostly unpredictable, progresses so fast and can cause faults in several locations simultaneously. It also can be hard to physically access the fault locations in order to start the restoration process while the event progresses. The resilience topic has gained much attention in power systems area more than ever now due to frequent intensified extreme weather events, increasing digitization of society and shifting consumer expectations, increasing vulnerability to cyber attacks, vulnerability due to increased dependence on natural
gas for electric power etc [7]. Since the distributed energy resources (DERs) are dispersed across the power distribution network (PDN), grid-tied DER systems can island to form a microgrid during an extreme event consequently improving PDN’s resilience.

Several studies have been carried out on the use of microgrids for resilience enhancement in PDN. Most of these studies focus on developing system reconfiguration algorithms to form microgrids during an extreme event [8]–[10]. Some of these studies are discussed in section II. Optimal DER hosting and location for resilience enhancement is an important area of research but little of this concept have been studied and reported in literature. With increase in DER (PV) penetration [11], [12], the use of grid-forming technology of inverter-based DER can provide an effective way of improving PDN’s resilience. Optimal DER hosting (sizing) and location of the DER is typically constraint with by the PDN’s power flow, voltage measurements, cable ampacity, thermal limits as well power quality, however, this paper goes further by considering resilience measurements as part of the optimization formulation.

As previously mentioned, this paper defines the resilience of PDN by prioritizing the CI. During an extreme event it is important to prevent loss of critical services such as medical services, fire rescue etc. Therefore, it’s crucial to prioritize those CI nodes when enhancing PDN’s resiliency. The proposed algorithm in this paper prioritizes the CIs in the system when hosting the DERs. CI prioritization is mostly a cognitive decision in existing literature [13]. In contrast to that, this paper proposes a clear and consistent mathematically formulated ranking scheme for CIs and it is presented in section III. The proposed work aims to significantly enhance the resiliency of a distribution network by installing DER systems strategically with respect to the network’s CI nodes such that these DER systems and their corresponding local control systems can be treated as individual power plants. This concept illustrated in Figure 1. The lowest layer of the figure shows the entire PDN prior to identifying the CIs. The CI’s are identified and prioritized in the middle layer while the DER are optimally sized (based on maximum DER hosting) and strategically located to enhanced the PDN’s resiliency as defined in this paper.

II. RELATED WORK

Studies on the resilience of PDN have gained much attention recently, partly due to more frequent occurrence of extreme weather events. With the increasing number of grid-connected DERs on distribution feeders, there are studies focused on leveraging the DERs for grid resilience enhancement during extreme weather [14], [15]. These resilience enhancement methods can be divided into two, based on the time of action. They are hardening or preparation at pre-event and corrective actions or restoration at on-event. The articles [8], [9], [16] are focused on developing restoration and reconfiguration algorithms. Authors of [8] proposes a scheme to self-heal the system by sectionalizing the network into self-supplied microgrids. The development of impact assessment model and optimal restoration model for a PDN with DERs is done using non-sequential Monte Carlo simulation for a modeled probabilistic extreme event in [16]. In [9], an optimal scheduling model for microgrids to enhance resiliency during an outage is presented. Deployment of networked microgrids to achieve higher level of resilience is extensively analyzed in [10].

Proper DER placement can consider as a grid hardening technique at pre-event and there are only few previous studies carried out on strategical DER placement and sizing for resilience enhancement. An extensive review on different approaches of optimal energy storage and microgrid allocation to face extreme weather conditions is presented in [17]. The state-of-the-art on this regard is reviewed and a summary is tabulated in the Table 1. The general DER hosting calculations involve physical constraints of the system such as power flow voltage limits, generation limits and thermal limits of the PDN. One of the first papers that incorporates resilience constraints in to the DER hosting algorithms is [18] in which mixed-integer linear programming has used for optimal size and locate microgrids in the power transmission line to maximize the system resilience. Here, the objective function is defined to minimize the cost of unserved energy following hurricanes.

The paper [19] has also presented a strategy for optimal allocation of distributed generation to minimize the cost and emission and improve the transmission line resilience.
Optimal sizing and siting scheme for energy storage and PV is proposed in [20] to increase the reachability and accessibility of power in the face of an extreme event. Similar to previous studies the objective of the optimization includes the economic cost factor. Also a new parameter, the capacity accessibility is introduced there to represents the state of the resilience. The paper [21] has proposed an algorithm to identify the optimal microgrid placement to improve the resilience index of the system but doesn’t do the sizing. Diesel generators with fixed capacities are used as DERs here and the optimal locations are identified by simulating for all possible candidates rather than using any optimization technique.

None of the aforementioned articles have prioritized critical loads in their formulations of DER hosting. The only paper found in literature that have prioritized critical loads when placing DERs for resilience enhancement is [22]. There they have incorporated the unmet demand penalty costs of different load types in the objective function which prioritize them according to a ranking scheme. So, the power outage levels or the unmet demand is used here to represents the resilience measure. Further, they have performed a sensitivity analysis for different budget options. But, still this paper doesn’t do the optimal sizing and assumes the generation power and electricity outputs of DERs are known.

To the best of the authors knowledge, till date no paper has integrated PV hosting capacity problem as a holistic approach to distribution feeder resiliency improvement. Also several individual PV hosting algorithms have been proposed in literature [23]–[26] which are not formulated to improve distribution feeder’s resiliency. The PV hosting algorithms in literature usually iteratively or sequentially increases the sizes of PV on the nodes where the PVs are connected. This paper proposes a voltage sensitivity approach to increase the PV across the optimal PV nodes for maximum PV hosting capacity. In order to achieve this, voltages across all the nodes are monitored and the sizes of the PVs are increased based on their optimal locations up to the over-voltage limit according to the ANSI C84.1 standard. It is also worthy of note that most resiliency improvement algorithms in literature that integrates PVs, do not use the complete PV hosting capacity constraints which include the power flow, and the constraints of the legacy device operations.

A. PROPOSED CONTRIBUTIONS

Different to the discussed literature, this article presents an algorithm which optimizes the DER sizing and placement with the objective of improving the PDN resiliency prioritizing the CIs of the system incorporating system limitations as well. The key contributions of the paper are listed below.

1) Uniquely proposes an algorithmic formulation which leverages the benefits of DER sizing and placement to ensure continued power supply to the maximum possible number of CI nodes with minimum power losses during an extreme event.

2) Prioritizes the CIs in the network for PV sizing and placement with a developed ranking scheme.

3) Formulation of PV hosting capacity algorithm that is based on the feeder’s voltage sensitivity which allows more PV integration by pushing the maximum nodal voltages close to the overvoltage limit. Unlike other PV-integrated resiliency improvement algorithms, this algorithm applies complete power flow constraints including the operation of the voltage control legacy devices.

4) Application of probabilistic time series tools to emulate an extreme weather event to validate the proposed algorithm.

The article is structured as follows. Section I introduces the paper and the concepts of resiliency of PDNs; section II extensively reviews the existing research work that has been carried out in the same area. Section III presents the proposed identification and ranking scheme for CI nodes. The proposed algorithm for optimal DER hosting and location to improve PDN’s resiliency is presented in section IV and is followed by it’s validation through a test case in section V. Finally section VII concludes the article while also providing some future directions for this work.

III. IDENTIFYING AND RANKING THE CI NODES

A node within the grid whose loss or degradation poses a significant threat to the safety, health, environmental, economical, technological, or functional aspects of a society can be defined as a critical node. According to the U.S. Department of Homeland Security, these nodes are belong to one of the 16 CIs that include, but not limited to, energy, food and agriculture, emergency services, transportation systems, healthcare and public health, communications, government facilities, and water and wastewater systems [27]. But it is to be understood that this whole set of infrastructure does not have the same level of criticality when prioritizing the power continuity in the case of an extreme weather event.

During an extreme event it’s highly required to power up the CIs which are directly connected to the safety of human life. The ranking of infrastructure criticality is heavily dependent on that particular system. Some of the utility networks may have one or several critical loads such as hospitals, fire stations, police stations, air ports etc. and some may have none. Also, priorities change subjective to the extreme weather events frequent to that specific area. For an example hurricane is the most common extreme weather event in Florida while it is wildfires in California. During a wildfire, the electricity supply to the residential buildings in the affected area is cut off (public safety power shutoffs) while it’s the opposite for the hurricane. Unlike during a hurricane, transportation systems get a higher priority during a wildfire.

The approaches to identify and rank CI nodes involves risk assessment strategies that can be either qualitative or quantitative, and are typically bounded by the CI protection (CIP) guidelines of the North American Electric Reliability Corporation (NERC). Many methods exist in the literature to
### TABLE 1. A summary of state-of-the-art articles in DER locating and allocating for resilience enhancement.

| Author, Year | Technique | Highlights | Significance | Weaknesses |
|--------------|-----------|------------|--------------|------------|
| Eiskandarpour et al., 2016 [18] | Mixed-integer linear programming | • Microgrid optimal placement model that optimally size and locate microgrids to maximize system resilience.  
• Focused on transmission line resilience.  
• Resilience of the system is viewed as the cost of unserved energy. | Simulated hurricane passing through three hypothetical paths for validation. | Not clearly specified a methodology the microgrid sizing and placement has done and doesn’t do the sizing of DERs and doesn’t do critical load prioritization. |
| Shirazi et al., 2021 [19] | Multi-objective Gray Wolf optimization | • Objectives for optimization are minimizing the economic costs and greenhouse gas emissions, and maximize the system resilience.  
• Focused on transmission line resilience.  
• Resilience is viewed as the optimal resilience cost. | Considers reduction of greenhouse gas emissions as one of the objectives. | Doesn’t do the sizing of DERs and doesn’t do critical load prioritization. |
| Zhang et al., 2019 [20] | Multi-objective optimization | • Optimal sizing and siting scheme for battery storage and PV in the transmission network.  
• Objectives for optimization are investment and operation costs, capacity accessibility for demand and capacity accessibility for non-blackstart units. | Validated for events of different intensities. | Doesn’t do critical load prioritization. |
| Widiputra et al., 2019 [21] | By simulating each candidate DER placement. | • Resilience index is used to quantify the resilience.  
• Bus injection to bus current (BIBC) matrix is used to find the islanded buses due to the disaster. | Validated for three storm situations. | Doesn’t do the sizing of DERs and a fixed capacity diesel generators are used as DERs. |
| Kiritto et al., 2020 [22] | Single-source capacitated facility location coverage problem | • Resilience is viewed as power outage levels due to extreme event.  
• Objectives for optimization are minimize total investment costs, operation and maintenance cost, distance traveled for electricity distribution, power outage levels, and levels of excess renewable penetration. | • Sensitivity analysis is performed for different budget options.  
• Unmet demand penalty cost is arbitrarily assigned for each building type to prioritize the critical loads. | • DER sizing isn’t optimized.  
• Generation power is kept fixed for optimization.  
• Power flow conditions are not evaluated. |

rank CI systems and subsystems [28]–[33]. The work in [31] proposes a graph theory-based formulation to model the robustness of interdependent CI networks, where interdependencies were modeled as directed graphs, with critical nodes identified using graph centrality indices. Stochastic ordering techniques such as the Copeland scores have been used to rank CI nodes [30]. Economic impacts on CI nodes have been separately considered in [32], [33]. The work in [29] presents a development of a national CI priority inventory for Germany. They propose critical proportion, critical time and critical quality as properties of the criticality.

The work in [28] contrast the monocriteria and multicriteria techniques to rank CI nodes. The monocriteria model considers the interdependencies between CI nodes and evaluates the impacts of cascading failures. It creates a dependence matrix that represents the likelihood of each node in the network to be disrupted as a consequence of the disruption in another network. However, this model does not quantify the impacts and relies on the uncertainty of its decision-makers to rank the nodes. A multicriteria model, on the other hand, uses a scoring methodology where the net score depends on six specific criteria— the density of people and assets in the network, the financial impact, the nature of the CI sector, the degree of interdependency, the quickness of service delivery, and public confidence. This model, however, does not assign weights to these criteria, thereby giving them all equal importance, which is impractical. Almost all of these studies have focused on developing national CI priority schemes and they do not capture the specifics related to power system. Most of these studies measure the criticality based on the position of the node in the network and its likelihood to trigger cascaded failures. But, failure propagation due to the disruption of a node is most unlikely in the context of CI that we consider in this study. One among the very few studies found in literature which ranks CIs in distribution network resilience studies is [13]. Other than the CI ranking, this work introduces the term critical loads (CL) which represents the critical portion of a CI that needs emergency power supply. Although it has
proposed applying different weights for each customer type according to the criticality, it’s a random weight assignment and does not provide any exact methodology.

The cost of the power loss should be considered when ranking the CIs for power continuity. In this paper we consider three criteria that contribute to the cost of power loss. First one is the social importance of the infrastructure, $R_{SI}^i$. Ranking based on the social importance is more of a cognetic decision and is specific to the particular event and to the system. The simplest example is a hospital load which is essential to power up during a hurricane. This is because the cost of human life is invaluable and evaluated at the highest cost. Losing power of a bigger load creates a bigger economic loss as well as a higher impact to the stability of the grid. Therefore the next criteria is selected as the apparent power rating of the load, $S_{SL}^i$. During an extreme event the loads furthest away from the substation are more vulnerable as there is more chance they lose power due to damages to the incoming power line. Therefore, the proximity to the substation, $D_i$ is selected as a criteria for CI ranking.

As multiple criteria involved in decision making, analytic hierarchy process (AHP) is applied and the criteria are compared pairwise using the semantic scale of Saaty. The relative importance of criteria are obtained through pairwise comparison as 0.724, 0.193 and 0.083 for $R_{SI}^i$, $S_{SL}^i$ and $D_i$ respectively. Assuming $N_{CI}$ as the set of all CIs, $\forall i \in N_{CI}$, $R_{SI}^i$ is the normalized social importance ranking of each CI, $S_{SL}^i$ is the normalized apparent power rating of each CI, and $D_i$ is the normalized distance between each CI from the substation transformer. And then they can be expressed as (1), (2) and (3) respectively.

\[
R_{SI}^i = \frac{2}{|N_{CI}|} \left( 1 - \frac{R_{SI}^i}{|N_{CI}| + 1} \right)
\]

\[
S_{SL}^i = \frac{S_{SL}^i}{\sum_{i \in N_{CI}} S_{SL}^i}
\]

\[
D_i = \frac{D_i}{\sum_{i \in N_{CI}} D_i}
\]

Then, the net score (weight) for each node $i \in N_{CI}$ is expressed in (4).

\[
\omega_i = 0.724 \cdot R_{SI}^i + 0.193 \cdot S_{SL}^i + 0.083 \cdot D_i
\]

A set of weights are developed for the given network. The weights of CI nodes are arranged in descending order such that the node with the highest weight gets a rank of 1 (most critical), and the node with the least weight gets a rank of $|N_{CI}|$ (least critical) where $|N_{CI}|$ is the cardinality of $N_{CI}$.

**IV. PROPOSED NETWORK RESILIENCY ENHANCEMENT ALGORITHM**

The proposed optimal DER placement algorithm for network resiliency enhancement is illustrated in the Figure. 2. The DER considered in this paper is a photovoltaic (PV) system. The proposed algorithm is formulated as a multi-objective non-linear programming optimization problem in which three objectives are considered. Other than the optimal DER hosting and placement of DERs, maximizing the resilience and minimizing the overall power loss are formulated as the objective functions for the optimization problem. In order to measure the level of resilience, the resiliency metric used is expressed as (5) [13].

\[
OF_1 := \max |R_B| = \max \left\{ \sum_{i=1}^{N_{CI}} \omega_i (T_{U,i} + T_{D,i}) \right\}
\]
In this paper, a PV hosting algorithm based on the feeder’s voltage sensitivity at the point of common coupling is developed to ensure a high PV penetration in the distribution feeder. While optimally locating the PVs, proposed method tries to increase the size of the PV until the system reaches the overvoltage limit ($v_{max}$). Depending on the $r/t$ of the feeder at the point of interconnection (POI), more active power from the PV can be integrated into the feeder. The maximum voltage at the POI of a PV for $\Delta P_{1}^{pv, max}$ and $\Delta Q_{1}^{pv, max}$ injection can be expressed as (6).

$$v_{max} = v_{i} - \left\{ \frac{\Delta P_{1}^{pv, max} - j\Delta Q_{1}^{pv, max}}{v_{i}\delta_{i}} \right\} (R_{eq}^{i} + jX_{eq}^{i}), \forall i \in \mathcal{N}$$

where $R_{eq}^{i}$ and $Q_{eq}^{i}$ are the thevenin equivalent resistance and reactance at the POI of the PV, $v_{i}$ and $\delta_{i}$ are the voltage and voltage angle at the POI while $\mathcal{N}$ is the set containing all the nodes in the network.

In order to maximize the DER hosting capacity of the network, the second objective of the optimization problem is expressed as (7).

$$OF_{2} := \max|DER_{HC}| = \max \left\{ \sum_{i = N_{pv}}^{P_{i}^{pv}} \right\}$$

where $N_{pv}$ is the set containing all the PV systems used as DER in the network and $P_{i}^{pv}$ is the kW rating based on DER hosting capacity of the PV at node $i$.

The third objective of the problem formulation is to minimize the average hourly power loss as expressed in (8).

$$OF_{3} := \min \left\{ \frac{1}{T} \sum_{t = 1}^{T} P_{loss,t} \right\}$$

where

$$P_{loss,t} = \sum_{(i,j) \in \mathcal{L}} r_{ij} \times \frac{P_{ij}^{2} + Q_{ij}^{2}}{v_{i}} \forall t \in [1, \ldots, T], \mathcal{L} is the set of all branches in the network. \forall i \in \mathcal{N}, P_{ij} and Q_{ij} are the active and reactive power flow from node $i$ to $j$, $r_{ij}$ is the resistance between branch $ij$ while $v_{i}$ is the nodal voltage at node $i$.

The optimization constraints include the power flow constraints expressed in (9) and (10); the capacitor banks reactive power and voltage regulator tap constraints expressed in (11) and (12); and nodal voltage constraint is expressed as (13).

$$P_{i}^{eq} = P_{ij}^{eq} + v_{i}^{eq} \sum_{k = 1}^{n} \left( G_{ik} v_{k}^{eq} - B_{ik} v_{k}^{eq} \right)$$

$$+ v_{i}^{eq} \sum_{k = 1}^{n} \left( B_{ik} v_{k}^{eq} + G_{ik} v_{k}^{eq} \right) \forall i \in \mathcal{N}$$

(9)

$$Q_{i}^{eq} = Q_{ij}^{eq} + v_{i}^{eq} \sum_{k = 1}^{n} \left( -B_{ik} v_{k}^{eq} - G_{ik} v_{k}^{eq} \right)$$

$$+ v_{i}^{eq} \sum_{k = 1}^{n} \left( G_{ik} v_{k}^{eq} - B_{ik} v_{k}^{eq} \right) \forall i \in \mathcal{N}$$

(10)

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$$+ v_{i}^{eq} \sum_{k = 1}^{n} \left( B_{ik} v_{k}^{eq} + G_{ik} v_{k}^{eq} \right) \forall i \in \mathcal{N}$$

(9)

$$Q_{i}^{eq} = Q_{ij}^{eq} + v_{i}^{eq} \sum_{k = 1}^{n} \left( -B_{ik} v_{k}^{eq} - G_{ik} v_{k}^{eq} \right)$$

$$+ v_{i}^{eq} \sum_{k = 1}^{n} \left( G_{ik} v_{k}^{eq} - B_{ik} v_{k}^{eq} \right) \forall i \in \mathcal{N}$$

(10)

The algorithm starts by using the NSGA-II to generate the initial population of variables which is the set of nodes $N_{pv}$ from the candidates set of notes $M_{pv}$ (which are all three-phase nodes in the network) which are used to evaluate the fitness of the objective functions ($OF_{1}, OF_{2}$ and $OF_{3}$ as expressed in (5), (7), and (8) respectively). The DER considered in this algorithm is a photovoltaic (PV) system. In order to obtain the PV hosting capacity, $R_{B}$ and the average hourly power loss, based on the $N_{pv}$, algorithm starts by setting the PV kW rating to a minimum set value of $P_{ij}^{pv,min}$. The outage scenarios are simulated as explained in detail in the section V and the power loss and resilience metric are calculated for that particular scenario. Then the system nodes are checked for any voltage constraint violations and if the voltage stays within the limits the power level of each PV is increased by a factor $q$ for the next PV hosting capacity iteration. The kW rating of the PVs are increased and the outage scenarios are simulated as explained in detail in the section V and the power loss and resilience metric are calculated for that particular scenario. Then the system nodes are checked for any voltage constraint violations and if the voltage stays within the limits the power level of each PV is increased by a factor $q$ for the next PV hosting capacity iteration. The kW rating of the PVs are increased and the outage scenarios are simulated until the first nodal voltage violation occurs. The values of $OF_{1}, OF_{2}$ and $OF_{3}$ are computed while the NSGA-II generates the new set of off-springs and the process is continued until stop criteria is met and the Pareto Optimal Solutions (POS) are saved.

V. SIMULATION RESULTS AND ANALYSIS: A TEST CASE

When performing the resiliency study, it is required to simulate the extreme weather event over the PDN. In order to
Algorithm 1: Optimal DER Hosting and Placement
Algorithm for ResilienceEnhancement

Data: \( n \) = number of individuals in population,
\( \chi \) = fraction population to be replaced by crossover
\( \mu \) = mutation rate

Initialize generation:
\( k := 0 \);
Generate random population - size \( N^k \);
Evaluate \( OF_1, OF_2 \) and \( OF_3 \);
Assign rank (level) based on Pareto;
Generate child population;
Binary tournament selection;
Recombination and mutation;

while stopping criterion has not been met do
  for \( N^k_{pv} \) do
    \( P^v_i := p^v_{min} \);
    Simulate outage scenarios;
    Compute \( OF_1, OF_2 \) and \( OF_3 \);
    \( \forall i \in N^k \);
    if \( v_i < v_{max} \) then
      \( P^v_i := (1 + \chi) \times p^v_i \);
    Simulate outage scenarios
    else
      Compute updated \( OF_1, OF_2 \) and \( OF_3 \);
  end
Select points on the lower front with high crowding distance
Create new generation \( k + 1 \);
Select \( (1 - \chi) \times n \) members \( N^k_{pv} \) and insert into \( N^{k+1}_{pv} \);
Crossover: Select \( \chi \times n \) members of \( N^k_{pv} \);
Pair, produce offspring and insert into \( N^{k+1}_{pv} \);
Mutate: Select \( \mu \times n \) members of \( N^k_{pv} \);
Evaluate: Select \( \mu \times n \) members of \( N^k_{pv} \);
\( k := k + 1 \);
end

Select points on the lower front with high crowding distance
Create new generation \( k + 1 \);
Select \( (1 - \chi) \times n \) members \( N^k_{pv} \) and insert into \( N^{k+1}_{pv} \);
Crossover: Select \( \chi \times n \) members of \( N^k_{pv} \);
Pair, produce offspring and insert into \( N^{k+1}_{pv} \);
Mutate: Select \( \mu \times n \) members of \( N^k_{pv} \);
Evaluate: Select \( \mu \times n \) members of \( N^k_{pv} \);
\( k := k + 1 \);

In the considered test case, the wind storm progresses, reaching almost category-1 winds for that area. It is assumed that the damage assessments and line restorations begin as soon as the disastrous winds are over. The mean time for damage assessment and line restoration process is assumed as 12 hours and again this time is randomized for different lines by multiplying by a random number [36]. The obtained line failures are simulated at each simulation step and necessary measurements are obtained by performing the power flow analysis.

A. NETWORK DESCRIPTION

To validate the effectiveness of the proposed DER hosting and optimal placement algorithm for resiliency improvement, the IEEE 34 is modeled in the OpenDSS platform as a PDN as shown in Fig. 4. Five PVs are modeled as DERs and integrated into the PDN for the proposed algorithm. The global horizontal irradiance (GHI) profile and temperature (both ambient as well as module temperature) for the PV systems were collected from an actual 1.4 MW PV system located on the Engineering campus of Florida International University. Since the PVs are assumed to be utility scale PV, all the 3-phase nodes are selected as candidate nodes which means \( M_{pv} = 25 \) from which the optimal five locations for the PVs \( N_{pv} \) will be selected.

The nominal voltage rating of the feeder is 24.9kV. The feeder has two voltage regulators between nodes 814 – 850 and 852 – 832. The substation transformer upstream of node 850 is a 2.5MVA, 69/24.9 kV, \( \Delta Y \). The combined rating of the load (modified) on the feeder is approximately 3.1 MW (active) and 0.689 MVAR (reactive). Node 838 is the farthest distance and its approximately 59 km away from the substation transformer.

The IEEE feeder contains of 31 loads and 10 out of them are chosen as CI nodes for this study. Ten three-phase loads that are distributed across the network are randomly selected as the CI nodes as shown in the Figure.4. The chosen CIs are ranked according to the load prioritization scheme proposed in the Section III and is illustrated in the Table.2. RES1 and RES2 are residential loads on nodes mid858 and 850 respectively, HOS is a hospital load on node mid834, FR is fire rescue on node 860, CH is city hall on node 840, SM is shopping mall on node 844, SUP1 and SUP2 are supermarket loads on node 824 and 806 respectively, WPS is the water

emulate the failure bunching phenomenon due to extreme weather, [3] and [34] applied a sequential Monte-Carlo-based probabilistic tool. They have used a probability distribution of a wind profile and weather dependent fragility curves of the components to replicate the stochastic power system failure events across space and time during a hurricane. Adopting the same concept, this paper uses a fragility curve for power lines which is acquired from [35]. A wind profile of the hurricane Irma for the Fort Myers area in Florida is used for the analysis. The total simulation is done for a 48 hour time period starting at 12 am on 10th September 2017 with a 1-hour time resolution as shown in Figure.3. The wind speed is assumed to be constant during the one hour period. The probability of failure of lines during the event is not only dependent on the wind intensity but also on the age and wear of each of the line. Therefore, to provide this randomness in failure, the failure probability of line \( k \), \( P^k(\omega) \) is compared with a uniformly distributed random number, \( r \) at every simulation step. If \( P^k(\omega) > r \) then the line \( k \) will trip and otherwise the line will continue to operate. This method is implemented to provide different deterioration levels for different lines.
TABLE 2. Ranking of the CI nodes.

| I. Type | $R^{ci}$ | $R^{so}_{ci}$ | $S^{c}_{ci}$ | $S^{o}_{ci}$ | $D_{ci}$ | $D_{N,ci}$ | $\omega_i$ |
|---------|----------|-------------|-------------|-------------|--------|------------|--------|
| RES1 | 5 | 0.109 | 107.7 | 0.071 | 53.5 | 0.121 | 0.103 |
| HOS1 | 1 | 0.182 | 151.3 | 0.100 | 55.1 | 0.125 | 0.161 |
| FR1 | 2 | 0.164 | 76.8 | 0.051 | 56.6 | 0.128 | 0.139 |
| CH1 | 7 | 0.073 | 34.2 | 0.022 | 57.7 | 0.131 | 0.068 |
| SM1 | 10 | 0.018 | 513.1 | 0.397 | 55.6 | 0.128 | 0.089 |
| SUP9 | 9 | 0.036 | 76.8 | 0.051 | 34.8 | 0.079 | 0.043 |
| WPS4 | 4 | 0.127 | 458.9 | 0.302 | 52.7 | 0.119 | 0.160 |
| POL3 | 3 | 0.145 | 50.2 | 0.033 | 41.3 | 0.094 | 0.119 |
| R2 | 6 | 0.091 | 17.9 | 0.012 | 31.6 | 0.072 | 0.074 |
| SUP8 | 8 | 0.095 | 33.5 | 0.021 | 1.3 | 0.003 | 0.044 |

TABLE 3. POSs obtained for the test case.

| POS | DER placement ($N_{PV}$) | Objective function ($OF_1$, $OF_2$, $OF_3$) |
|-----|--------------------------|---------------------------------------------|
| 1   | 816 852 814 834 830      | 0.89 0.61 77.15                            |
| 2   | 832 828 860 816 834      | 0.94 1.91 136.83                           |
| 3   | 858 840 842 858 832      | 0.86 2.55 137.59                           |
| 4   | 834 844 854 814 812      | 0.86 0.98 104.79                           |
| 5   | 824 830 852 814 812      | 0.77 3.08 42.51                            |
| 6   | 824 848 816 834 830      | 0.84 1.58 121.84                           |
| 7   | 816 830 848 850 814      | 0.84 0.74 98.12                            |
| 8   | 816 852 814 834 830      | 0.89 0.61 77.15                            |
| 9   | 850 816 846 828 824      | 0.84 1.19 116.83                           |
| 10  | 846 840 842 858 832      | 0.87 2.32 143.50                           |
| 11  | 854 828 846 824 850      | 0.89 0.89 114.53                           |
| 12  | 806 828 812 830 854      | 0.72 4.10 61.72                            |
| 13  | 846 828 830 824 854      | 0.89 0.74 110.04                           |
| 14  | 824 848 850 858 830      | 0.88 1.31 125.78                           |
| 15  | 824 830 852 814 812      | 0.77 3.08 42.51                            |
| 16  | 832 830 860 850 834      | 0.94 1.74 134.96                           |
| 17  | 830 834 842 816 854      | 0.89 1.08 125.53                           |
| 18  | 848 844 814 806 832      | 0.86 1.44 129.68                           |

B. RESULTS AND ANALYSIS

The proposed algorithm as described in section IV is scripted in Matlab and coupled with OpenDSS through its COM interface. The simulation is run on a computing machine with Intel® Core i5-7400 @ 3.0GHz processor and 24GB RAM. The multi-objective optimization algorithm generated 18 Pareto optimal solutions (POS) for the considered test case as tabulated in Table 3. Each POS gives the nodes for optimal DER placement based on the set objectives ($OF_1$, $OF_2$, $OF_3$).

Based on the objective of highest priority, the corresponding set of nodes for optimal placement of the DER can be selected from the table.

The POS values (POS-2, POS-5 and POS-12) that produces the best of the three objectives is highlighted in gray as shown in Table 3. These solutions are selected for performance analysis of the proposed algorithm. The optimal DER locations and sizes achieved from POS-2 produces the highest resilience base ($OF_1$) of 0.94. The DER locations and sizes achieved from POS-5 has the least power loss ($OF_3$) of 42.51 kW while that achieved from POS-12 provides the highest DER hosting capacity ($OF_2$) of 4.10 MW. All the POS values can be used to size and site the DERs based in the priorities set by the distribution planning engineers. Trade-offs can be made in the selection of the DER sizes and location based on the objectives of priority. Rather than focusing only on maximizing a single objective, it is possible to select a POS in the middle ground according to the requirements of the distribution system. From the POS solution, Figure. 5 shows the 3-D plot the three set objectives. The plot clearly shows the interaction between the set optimization objectives.

Figure.6 shows the resilience trapezoids of the optimal DER (PV) placements and location for each of the POSs in contrast to the resilience trapezoid of without DER (PV) placement.

The plot (Figure.6) shows the percentage availabilities of CIs which are indicated as the measure of the network’s resilience. Typically, the resilience trapezoid provides information on the level of resilience degradation, the rate of system degradation, rate of restoration and the outage time. From the figure, we can see POS-12 (of all the POS solutions) has a steep resilience degradation, a long outage time and lowest resilience level of 0.3 (which is the lowest of the POS values). POS-12 has the largest trapezoid area. Compared to POS-12, the lowest resilience level which POS-2 dropped to is 0.8 and its area of the trapezoid the smallest of all.
the POS. This correlates with the values obtained from the POS which shows that POS-12 and POS-2 generates the lowest (0.72) and highest (0.94) $R_B$ values respectively (as seen from table 3). The resilience trapezoids also show that the trapezoid area without DERs (PV) is the largest compared to all the POS solutions with DERs integrated. The lowest value the resilience level drops is 0.1. For this scenario (without DER) the $R_B$ value is 0.51. This further shows the benefit of DER (PV) integration and further optimizing their location and sizes for improved PDN’s resiliency.

Figure 7 shows the voltage profile of the CI nodes without DER (PV) integration and it can be seen that nine out of ten CI nodes experiences outages during the hurricane. The zero voltage on the CI nodes during the simulated hurricane further highlights the importance of using DER to improve the availability of power to the CI nodes which is the measure of the network’s resiliency as defined in this paper. The sizing and locating the DER (PV) can be achieved by the POS in Table 3 as previously discussed.

Figures 8, 9 and 10 show the voltage profile of each of the critical node loads for POS-2, POS-5 and POS-12 respectively. The nodal voltages at a given time goes to zero whenever a power outage occurs due to the hurricane event. Comparing the voltage profiles of POS-2, POS-5, and POS-12, it can be seen that the higher base resilience value of POS-12 ($OF_1 = 0.94$) compared to POS-5 ($OF_1 = 0.77$) and POS-12 ($OF_1 = 0.72$) lead to lesser impact of the hurricane event on the outages on the critical infrastructure. This choice of POS-2 solution for the DER (PV) location and sizes gives the highest up time for the CI nodes and can be selected if the base resilience is of most importance to the distribution planning engineers. The trade-off of this solution (POS-2) is the lesser value of its DER (PV) hosting capacity value (1.91 MW) and higher active power loss value (138.83 kW) compared to that of POS-5 (DER (PV) hosting capacity value = 3.08 MW and active power loss = 42.51 kW) and POS-12 (DER (PV) hosting capacity value = 4.10 MW and active power loss = 61.72 kW).
We further investigated how the up times of the CI nodes are improved based on their level of criticality. The up times of the CI nodes for the selected POSs are analyzed in comparison to the priority weights applied to those CI nodes. This analysis is as shown in Figs. 11, 12 and 13. It can be seen that the three most critical CIs, water pumping station, hospital and fire station all have highest up times with POS-2 (which has the highest base resilience). This shows the effectiveness of the proposed ranking scheme. Although POS-5 and POS-12 generates the highest up time for water pumping station, the hospital and fire station CI loads have lower up time values. This is due to the fact that POS-5 and POS-12 achieves the least power losses and the most PV hosting capacity values respectively moreover does not achieve a higher base resilience value (compared to POS-2).

The proposed algorithm is further evaluated in comparison to a benchmark algorithm that has been created based on the existing studies presented in section II. Most of the studies don’t prioritize critical loads in their DER placement algorithms [18], [19], [21]. Also, these studies either don’t apply PV hosting as part of their algorithm for PV placement which evaluates the existing system’s capacities and capabilities ([22]) or they apply the system limits as constraints in the optimization algorithm [18], [19], [21]. Therefore, the benchmark algorithm was developed without critical load prioritization and without incorporating PV hosting. The Figure. 14 shows the up times of each critical load with the benchmark algorithm and it can be observed that the magnitudes of up times of the critical loads are not in priority order. When compared with Figure. 11, the FR which stands in second place of the priority order has a lower up time while low priority loads like CH and RES\textsubscript{1} have high up times. Furthermore, not incorporating the power flow and the legacy devices constraints in the PV hosting formulation for resiliency enhancement could result in practically infeasible solution. This further validates the superiority of the proposed algorithm compared to the benchmark models that exists in literature.

A sensitivity analysis has been carried out to see how the changes in the input parameters of the optimization problem, the PV placement and sizing would change the objectives of the optimization. First, the size of the PVs are kept constant and varied the placements. Since there are $25 \times 5 = 53130$ number of possibilities of PV placement in this test case, the analysis is carried out only for selected PV placements. To begin with, the placements and sizes of POS-2 which is the highest resilience POS has been selected and one out of five PV placements of it changed at a time. Figure. 15 displays the sensitivity of $R_B$ for those variations and $R_B$ at POS-2 is highlighted in yellow. It can be observed that $R_B$ is sensitive to the placements of PVs with an average change of 0.031 for a change in single placement. Similarly, the sensitivity of the power losses for PV placement is investigated using POS-5 placements. The obtained power loss variations for minimum changes to the placement is depicted in Figure. 16 and the average variation in there is 12.04 kW.

Then the sensitivity to the size of PVs is evaluated by keeping the placements constant at POS-2 and POS-5 and...
varying the sizes. As per the results obtained, the change in $R_B$ due to varying sizes is almost negligible. This might be due to composition of $R_B$ and the way it views the resilience. But, as given in Figure 17 the power losses vary with the sizes of PVs and can quantify it as 15 W of average change per 1 KW change in size.

VI. CONCLUSION AND FUTURE WORK

In this paper an optimal DER hosting algorithm to enhance the resilience of power distribution network is proposed. Here, the resilience of PDN is measured in the perspective of critical loads. Therefore, critical loads are prioritized according to a unique ranking scheme developed in this paper. The problem is formulated as a multi-objective optimization where NSGA-II is applied to obtain Pareto optimal solutions for the three objectives: enhance base resilience, maximize PV hosting capacity and minimize power losses.

The proposed algorithm is validated in a simulated environment in where a hurricane is emulated for two days time period applying probabilistic tools. The simulation results provide several options of DER (PV) sizes and placement which have different trade offs between the three objectives. The three dominated POSs are further analyzed for their impact on PDN. Conclusions can be drawn based on the results of the case study that:

1) critical load ranking scheme provides the required level of load prioritization in where hospital load ranked one and the water pumping station with the highest power consumption is ranked the second

2) the resilience of the PDN is enhanced by the optimal DER (PV) hosting and placement using the proposed algorithm from a minimum $R_B = 0.51$ to maximum $R_B = 0.94$

3) the algorithm was also able to maximize the DER (PV) hosting capacity from the least value of 0.61 MW to the highest value of 4.10 MW

Based on this study, following are identified as potential research directions to explore.

1) Incorporate appropriate smart inverter functionalities of DERs to enhance resiliency of PDN [37]–[39].
2) Improve the ranking scheme to dynamically change while event progress.
3) Consider the power transfer from neighbouring DERs through system reconfiguration strategies when constructing this optimization problem.
4) Incorporate the cost factor of DER installation to the objective function.
5) Combine the impact of two weather events simultaneously when emulating the extreme weather. For an example during a hurricane both the wind and the flooding affects the infrastructure.

REFERENCES

[1] J. D. Taft, “Electric grid resiliency and reliability for grid architecture,” Pacific Northwest Nat. Lab. (PNNL), Richland, WA, USA, Tech. Rep., Mar. 2018, pp. 2–5. [Online]. Available: https://gridarchitecture.pnl.gov/media/advanced/Electric_Grid_Resilience_and_Reliability_v4.pdf

[2] A. Clark-Ginsberg, “What’s the difference between reliability and resilience?” Stanford Univ., Stanford, CA, USA, Rep. ICS-CERT, Mar. 2016, pp. 1–3. [Online]. Available: https://ics-cs.gov/iocs-cert.gov/sites/default/files/ICSIWG-Archive/ONL_MAR_16/reliability%92and%92resilience%20pdf.pdf

[3] M. Panteli and P. Manarella, “Influence of extreme weather and climate change on the resilience of power systems: Impacts and possible mitigation strategies,” Electric Power Syst. Res., vol. 127, pp. 259–270, Oct. 2015.

[4] (Feb. 2016). Electric Power System Resiliency: Challenges and Opportunities. Electric Power Research Institute (EPRI). [Online]. Available: https://www.naseo.org/Data/Sites/1/resiliency-white-paper.pdf

[5] J. McLaren and S. Mullendore, “Valuing the resilience provided by solar and battery energy storage systems,” Nat. Renew. Energy Lab. (NREL), Golden, CO, USA, Tech. Rep., 2018, pp. 1–5.

[6] A. I. Sarwat, M. Amini, A. Domijan, Jr., A. Damnjanovic, and F. Kaleem, “Weather-based interruption prediction in the smart grid utilizing chronological data,” J. Mod. Power Syst. Clean Energy, vol. 4, no. 2, pp. 308–315, Apr. 2016, doi: 10.1007/s40565-015-0120-4.

[7] (2018). Fedcenter—EO 13693 (Archive)—Revoked by EO 13834 on May 17, 2018, Sec. 8. [Online]. Available: https://www.fedcenter.gov/programs/ees13693/

[8] Z. Wang and J. Wang, “Self-healing resilient distribution systems based on sectionalization into microgrids,” IEEE Trans. Power Syst., vol. 30, no. 6, pp. 3139–3149, Nov. 2015.

[9] A. Khodaei, “Resiliency-oriented microgrid optimal scheduling,” IEEE Trans. Smart Grid, vol. 5, no. 4, pp. 1584–1591, Jul. 2014.

[10] Z. Li, M. Shahidehpour, F. Aminifar, A. Alabdulwahab, and Y. Al-Turki, “Networked microgrids for enhancing the power system resilience,” Proc. IEEE, vol. 105, no. 7, pp. 1289–1310, Jul. 2017.

[11] T. O. Olowu, A. Sundararajan, M. Moghaddami, and A. Sarwat, “Future challenges and mitigation methods for high photovoltaic penetration: A survey,” Energies, vol. 11, no. 7, p. 1782, 2018.

[12] S. Dharmasena, T. O. Olowu, and A. I. Sarwat, “A low-complexity FSPMPPDC with extended voltage set for grid-connected converters,” IET Energy Syst. Integ., vol. 3, no. 4, pp. 413–425, 2021. [Online]. Available: https://ietresearch.onlinelibrary.wiley.com/doi/abs/10.1049/esi2.12109

[13] V. H. Chalishazar, S. Poudel, S. Hanif, and P. Thekkumpamath Mana. (Jan. 2021). Power System Resilience Metrics Augmentation for Critical Load Prioritization. [Online]. Available: https://www.osti.gov/biblio/1764623
[14] R. Arghandel, M. Brown, A. Del Rosso, G. Ghatikar, E. Stewart, A. Vojdani, and A. von Mieir, “The local team: Leveraging distributed resources to improve resilience,” IEEE Power Energy Mag., vol. 12, no. 5, pp. 76–83, Sep./Oct. 2014.

[15] A. Gholami, F. Aminifar, and M. Shahidehpour, “Front lines against the darkness: Enhancing the resilience of the electricity grid through microgrid facilities,” IEEE Electr. Mag., vol. 4, no. 1, pp. 18–24, Mar. 2016.

[16] P. Gahtam, P. Piya, and R. Karki, “Resilience assessment of distribution systems integrated with distributed energy resources,” IEEE Trans. Sustain. Energy, vol. 12, no. 1, pp. 338–348, Jan. 2021.

[17] V. B. Veskateswaran, D. K. Saini, and M. Sharma, “Approaches for optimal planning of energy storage units in distribution network and their impacts on system resiliency,” CSEE J. Power Energy Syst., vol. 6, no. 4, pp. 816–833, 2020.

[18] R. Eskandarpour, H. Lotfi, and A. Khodaee, “Optimal microgrid placement for enhancing power system resilience in response to weather events,” in Proc. North Amer. Power Symp. (NAPS), Sep. 2016, pp. 1–6.

[19] H. Shirazi, M. Ghasi, M. Dehghani, T. Niknam, M. G. Garpachi, and A. Ramezani, “Cost-emission control based physical-resilience oriented strategy for optimal allocation of distributed generation in smart microgrid,” in Proc. 7th Int. Conf. Control, Instrum. Autom. (ICICA), Feb. 2021, pp. 1–6.

[20] B. Zhang, P. Dehghanian, and M. Kezunovic, “Optimal allocation of PV generation and battery storage for enhanced resilience,” IEEE Trans. Smart Grid, vol. 10, no. 1, pp. 535–545, Jan. 2019.

[21] V. Widiputra, S. Oh, and J. Jang, “Optimal microgrid formation to improve the resilience of power system withstanding the storm,” in Proc. IEEE R10 Humanitarian Technol. Conf. (R10-HTC), Nov. 2019, pp. 228–233.

[22] R. Krizto, X. Li, K. Sun, and S. Li, “Optimal generator placement in utility-based microgrids during a large-scale grid disturbance,” IEEE Access, vol. 8, pp. 21333–21344, 2020.

[23] A. Arshad and M. Lehtonen, “A stochastic assessment of PV hosting capacity enhancement in distribution network utilizing voltage support technologies,” IEEE Access, vol. 7, pp. 46461–46471, 2019.

[24] S. Wang, Y. Dong, L. Wu, and B. Yan, “Interval overvoltage risk based PV hosting capacity evaluation considering PV and load uncertainties,” IEEE Trans. Smart Grid, vol. 11, no. 3, pp. 2709–2721, May 2020.

[25] T. Torquato, D. Salles, C. Oriente Pereira, P. C. M. Meira, and W. Freitas, “A comprehensive assessment of PV hosting capacity on low-voltage distribution systems,” IEEE Trans. Power Del., vol. 33, no. 2, pp. 1002–1012, Apr. 2018.

[26] F. Ding and B. Mather, “On distributed PV hosting capacity estimation, sensitivity study, and improvement,” IEEE Trans. Sustain. Energy, vol. 8, no. 3, pp. 1010–1017, Jul. 2017.

[27] (Nov. 2018). Critical Infrastructure Security and Resilience Month Toolkit,U.S. Department of Homeland Security (DHS) National Protection & Programs Directorate. [Online]. Available: https://www.dhs.gov/sites/default/files/publications/CISR-month-toolkit-10292018-508.pdf.

[28] A. Almeida, “A multi-criteria methodology for the identification and ranking of critical infrastructures,” Instituto Superior Técnico, Lisbon, Portugal, Tech. Rep., 2011, pp. 1–10.

[29] A. Fekete, “Common criteria for the assessment of critical infrastructures,” Int. J. Disaster Risk Sci., vol. 2, no. 1, pp. 15–24, Mar. 2011.

[30] K. Barker, J. E. Ramirez-Marquez, and C. M. Rocco, “Resilience simulation software: An 117-, pp. 89–97, Sep. 2013.

[31] S. Pimaka, R. Wylagadda, and E. K. Cetinkaya, “Modelling robustness of critical infrastructure networks,” in Proc. 11th Int. Conf. Design Reliable Commun. Netw. (DRCN), Mar. 2015, pp. 95–98.

[32] S. S. Chopra and V. Khanna, “Interconnectedness and interdependencies of critical infrastructures in the U.S. economy: Implications for resilience,” Phys. A, Stat. Mech. Appl., vol. 436, pp. 865–877, Oct. 2015.

[33] L. R. Duldsenberg and A. V. Outkin, “Modelling economic impacts to critical infrastructures in a system dynamics framework,” in Proc. 23rd Int. Conf. Syst. Dyn. Soc., 2005, p. 63.

[34] M. Pantel, D. N. Trakas, P. Mancarella, and N. D. Hatzigiargiou, “Power systems resilience assessment: Hardening and smart operational enhancement strategies,” Proc. IEEE, vol. 105, no. 7, pp. 1202–1213, Jul. 2017.

[35] R. Poudel, A. Dubey, and A. Bose, “Risk-based probabilistic quantification of power distribution system operational resilience,” IEEE Syst. J., vol. 14, no. 3, pp. 3506–3517, Sep. 2020.

[36] M. Pantel, P. Mancarella, D. N. Trakas, E. Kyriakides, and N. D. Hatzigiargiou, “Metrics and quantification of operational and infrastructure resilience in power systems,” IEEE Trans. Power Syst., vol. 32, no. 6, pp. 4732–4742, Nov. 2017.

[37] T. O. Olowu, A. Inaolajji, A. Sarwat, and S. Paulyal, “Optimal volt-VAR and volt-Var drop settings of smart inverters,” in Proc. IEEE Green Technol. Conf. (GreenTech), Apr. 2021, pp. 89–96.

[38] T. O. Olowu, S. Dharmasena, A. Debnath, and A. Sarwat, “Smart inverters’ functionalities and their impacts on distribution feeders at high photovoltaic penetration,” in Proc. IEEE Green Technol. Conf. (GreenTech), Apr. 2021, pp. 97–104.

[39] T. O. Olowu, J. Sarochar, and A. I. Sarwat, “Pareto optimal smart inverter curve selection for high photovoltaic penetration,” in Proc. IEEE Green Technol. Conf. (GreenTech), Apr. 2021, pp. 1–6.

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