Original Article

Optimal placement of distributed generation for enhancing resiliency in single and multiple fault scenarios using grey wolf optimization algorithm

Hamid Reza Amin Saremi[1]*, Seyyed Mehdi Hosseini[2]

[1]Electrical Engineering, Noushirvani Industrial University of Babol, Iran. [2]Faculty of Electrical Engineering, Noushirvani Industrial University of Babol, Iran.

Correspondence: Hamidreza Aminsaremi, Electrical Engineering, Noushirvani Industrial University of Babol, Iran. aminsaremi.h.r@gmail.com

ABSTRACT

Due to extensive outages occurring in recent decades, coupled with the impacts of climate change, the number and types of non-forecasted faults are on the rise. This paper investigates the impact of the type and capacity of distributed generation resources on the resiliency of distribution networks. Genetic and Grey Wolf Optimization algorithms are employed for simulation to address the problem of optimal distributed generation resource allocation to enhance system resiliency. The results obtained by implementing the proposed model on a real-world sample network, demonstrate that network resilience depends on the type and capacity of distributed generation resources used in the network. When appropriately placed, Distributed Generations (DGs) can enhance network resiliency. The resilience index increases significantly at first with an increase in the capacity of distributed generation resources and then decreases beyond a certain point and Increasing the budget to a certain extent improves resilience, but allocating more budget does not necessarily lead to changes in the resilience index.

Keywords: Distribution network resilience, Distributed generation placement, Optimization, Non-forecasted faults, Grey Wolf Optimization algorithm

Introduction

In recent decades, extensive power outages have occurred, primarily due to climate change, increasing the number and severity of non-forecasted faults. To ensure an uninterrupted power supply to consumers, it is essential to consider reliability criteria alongside traditional metrics. Faults with low probability but high impact, causing significant annual losses, pose a threat to the health of distribution networks, highlighting the necessity of network expansion for improved resilience. [1]

Continuous and uninterrupted electricity delivery to consumers is crucial for maintaining resilience and the reliability of the power system. In recent decades, electricity consumption has seen a substantial increase, transforming electrical energy into an essential element for industrial production, national security, commerce, public transportation, healthcare, and communications. Power interruptions and outages can occur due to natural phenomena (e.g., storms, earthquakes, floods) or physical and cyber-related issues (e.g., malicious cyber-attacks, communication signal interference). Such undesirable events can be highly hazardous, endangering billions of dollars and human lives.

Various studies' data estimate the economic costs of power interruptions resulting from faults in the global economy to be in the hundreds of billions of dollars. For instance, Hurricane Sandy in 2012 caused $71 billion in damages, Hurricane Maria in 2017 resulted in $90 billion in losses, and Hurricane Harvey in 2017 led to $125 billion in damages. Following the Great East Japan Earthquake in 2011, more than 24,000 people were reported as killed or missing.

The most vulnerable part of the power systems in dealing with faults is distribution networks. Nearly 90% of all power outages associated with various types of faults occur in distribution networks.

Many researchers are striving to find efficient ways to enhance resilience in distribution networks against faults, with a focus on recovery methods. This work is concentrated on addressing threats related to weather conditions and enhancing flexibility using Distributed Generation (DG) resources. [2]

The integration of distributed generation (DG) resources into the network introduces various challenges such as network loading, voltage control, stability, network protection, and more. This research delves into the role of DG in enhancing the resilience of distribution networks.

Section Two focuses on the assessment of resilience in distribution networks, introducing various measurement metrics, comparing them, and delineating different types of faults. It subsequently introduces various methods for improving network resilience and investigates the enhancement of system resilience through the introduction of the best approach.

Section Three deals with the definition of distributed generation resources, highlighting their advantages and disadvantages within the network, and studies the role of these resources in enhancing system resilience. It proceeds to model distributed generation resources and present mathematical formulations of their resilience. It evaluates their placement within the network.

Section Four compares various resilience methods, examines the results, and, by introducing a case study network, attempts to calculate the location, capacity, and type of DG resources. Subsequently, it endeavors to improve network resilience by measuring the resilience index. Lastly, it compares different simulation algorithms to obtain the best resilience index in the system.

Definition of Resilience in Distribution Systems

Resilience is defined as the ability of a system to maintain an acceptable level of performance in the face of a severe fault and to recover within an appropriate period. In recent decades, the increase in widespread outages caused by non-forecasted faults, including floods, storms, and network failures, has doubled the importance of resilience studies in distribution networks. Furthermore, it is expected that due to climate change, the number and severity of non-forecasted faults will increase in the future. Globally, the need to focus on network resilience and ensure continuous load supply, considering the various consequences of outages on social, political, and economic levels, is more significant than ever.

Under normal circumstances, when a fault occurs in distribution networks, maximum load is typically ensured by isolating the fault location using manual or automatic switches and changing the distribution network's configuration by maneuvering the lines. However, when an unforeseen event occurs, distribution substations and the main network may be without power, making it impossible to supply the load through the network, or isolated areas may be created within the network due to equipment damage. In such cases, traditional resilience methods cannot guarantee consumer energy supply after the fault occurs.

Resilience is a new concept in the field of power systems, and most studies in this area have introduced the concept of resilience, explored its impact on system operation, provided formulations for its indicators, measured and improved it, and quantified it using distributed generation resources. [3]

System Resilience Assessment

Resilience assessment can be categorized into two forms:

1. Qualitative Resilience Assessment
2. Quantitative Resilience Assessment

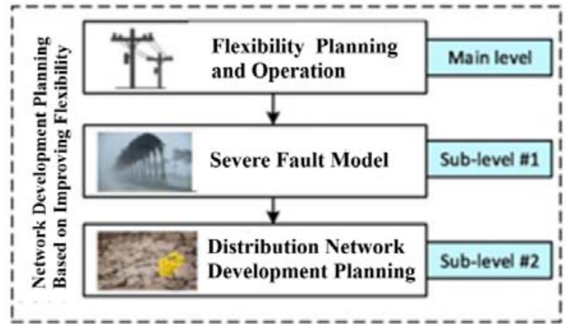


Figure 1. Distribution Network Resilience Development Planning

Qualitative assessment is defined as a method that does not involve mathematical calculations to compute resilience. However quantitative assessment is a method that involves mathematical computations, domain modeling, or agnostic measurements for evaluation [4,5].

Enhancing Resilience in Distribution Systems

Resilience against severe events relies on prior knowledge of the system's behavior and its capability to recover from faults without performance degradation. As depicted in Figure (1), network identification is the first step in achieving system resilience, encompassing system topology, operational constraints, physical characteristics, and distributed generation capacity. Once network identification is accomplished, the second phase involves the analysis of network vulnerability. The occurrence and recovery speed of disturbances resulting from faults depends on network vulnerability. Vulnerability analysis can be performed by considering the system's response under normal conditions, during, and after a fault. A flexible system aims to maintain its functionality after a fault, demonstrating the system's ability to preserve, adapt to severe events, and rapidly recover the system to mitigate disturbances caused by various faults.

In this section, the DRI (Distribution Risk Index) is utilized to assess resilience in distribution networks. The key feature of this index is its consideration of the resilience of distributed generation resources alongside the load resilience index to determine the overall network resilience. Given that the use of distributed generation resources is indispensable for enhancing network resilience, it is essential to prioritize the availability of these resources during and after severe events.

(1)

$$- GRI_{DG}\ DRI_{load} = DRI$$

In equation (1), DRI_{load} represents the network's risk in providing load supply. This index indicates the amount of lost load in the distribution network during unforeseen events. The lower the value of this index, the higher the network's resilience in ensuring load supply.

Considering the presence of distributed generation resources in the distribution network, which act as the main power source during unforeseen events, the availability of these resources during such events is of paramount importance and has a significant impact on network resilience. Therefore, the GRIDG index is defined to account for this. To calculate the DRI_{load} index, equation (2) can be utilized [33]:

$$DRI_{load} = \sum_{sec=1}^{k} LS_{sec} \times P_{sec}(W,F) \times S_{sec} \quad (2)$$

$$LS_{sec} = \frac{\sum_{t=1}^{T} \sum_{l=1}^{n} \text{Load}(t)_{l,sec}}{T} \quad (3)$$

In this equation, $P_{sec}(W, F)$ represents the probability of section failure due to an error, LS_{sec} is the amount of lost load in case of section failure, S_{sec} is the sensitivity coefficient given to the section based on the value or priority of the load, and K is the total number of sections in the studied distribution network.

This article utilizes the Grey Wolf Optimization (GWO) algorithm to address the problem of locating DG in the distribution network. Grey wolves belong to the mammal family and are positioned at the top of the food chain, signifying that they are predators. Grey wolves prefer to live in groups, with the average group size ranging from 5 to 12 members. The leaders of the group consist of one male and one female, referred to as the alphas. Alphas are primarily responsible for making decisions regarding hunting, sleeping locations, wake times, and more. Alpha decisions are imposed on the group, and a form of democratic behavior is observed where one alpha follows another within the group. In group gatherings, the entire group acknowledges the alphas by lowering their tails. Since alpha commands must be followed by the group, alpha wolves are referred to as the dominant wolves, and alpha wolves are only allowed to choose a mate within the group. Alphas are not necessarily the strongest members of the group but are the best at managing the group. This illustrates that organization and order within a group are more important than raw power. Subsequently, the results of optimizing with the Grey Wolf Optimization algorithm are provided, and a comparison with the genetic algorithm is presented.

Improving Resilience and Reliability Using ENS Index

To present the importance of system interruption, the Energy Not Supplied (ENS) index is introduced. The ENS value of the consumer is calculated as follows [28]:

(4)

In equation (4), I_{kp} represents the line current, λ_k is the fault rate for the K^{th} branch, and V_{rated} is the rated voltage of the system. α and d are the load factor and repair time, respectively. In this article, the value of ENS (Expected Network State) is calculated after the placement of DGs, and the improvement of resilience and reliability is studied using this index.

Algorithm Implementation and Numerical Studies

Numerical Studies

In the previous section, we explained the algorithm for locating DGs and studying resilience in the distribution network. Now, using these algorithms and the required parameter values, as described in this section, we will solve the problem of determining the optimal number, location, and capacity of distributed generations in networks labeled "44 Shin" and "RBTS-BUS2". In this section, besides improving network resilience, other research aspects will also be examined, such as the impact of the presence or absence of renewable distributed generation units and the effect of their placement on network resilience and reliability indices.

Research Result Validation

In this section, the results of reference [33] are used as a benchmark for comparing the results of this research. Due to the random nature of DG sources, optimal locations have not been considered. However, the DRI index, DG capacities, and network loss values are implemented according to the Grey Wolf Optimization algorithm. As observed, the results of this research are similar and, in some cases, better than the reference [33].

Table 1. Results of Reference [33] and Validation

Budget	DRI index	DGs capacity	Amount of losses (KW)

$$\text{ENS} = \alpha d \sum_{k=1}^{N_{\text{br}}} \lambda_k \left| I_{kp} \right| \times V_{\text{rated}}$$

B1	111.3	2121	4.65
B2=3B1	92	2420	4.93
B3=6B1	83.4	2980	6.65
B4=15B1	70.5	5520	6.72

Determination of the DRI Index and Isolated Areas in the Network

In this section, a two-stage problem of improving distribution network resilience using different optimization algorithms has been addressed. Network resilience is studied over 24 hours following a fault using the proposed model. The optimal solutions are obtained after 50 iterations in the algorithm with an initial population of 180 and a mutation rate of 0.3. It is assumed that some DG units with sizes in multiples of 100 kVA and a maximum of 1 MVA can be installed at candidate sites.

In the first stage, the capacities of DG units are determined simultaneously. Four budget levels, from B1 to B4, are considered. The value of B1 is equal to 100,000. The second budget level (B2) is three times B1, the third budget level (B3) is six times B1, and the fourth budget level (B4) is fifteen times B1. The B4 level is assumed to cover all loads in the distribution network after a fault. In this stage, to optimize the DRI index and not exceed the budget level, the capacities of DGs for each budget level are obtained. The maximum DG capacities for each region at different budget levels are determined according to the load that needs to be supplied in the isolated area, and the minimum DG capacity for network stability. The results of the first stage are presented in Table 2. Figure 2 shows the trend of changes in DRI with changing budget levels.

Table 2. DRI value and DG unit capacities in Stage 1

Budget Level	Maximum capacity DG(KW)	DRI
B1	No DG	142
B1	2226	111
B2=3B1	2429	92
B3=6B1	3099	83
B4=15B1	5013	70

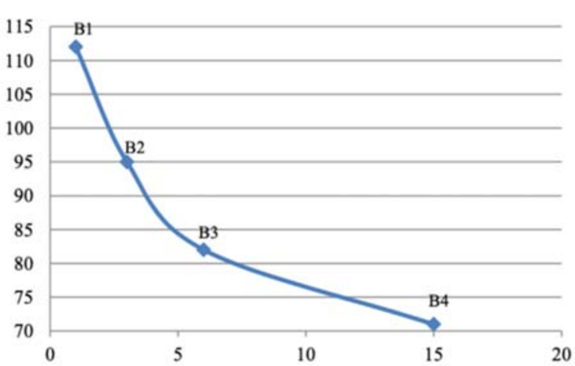
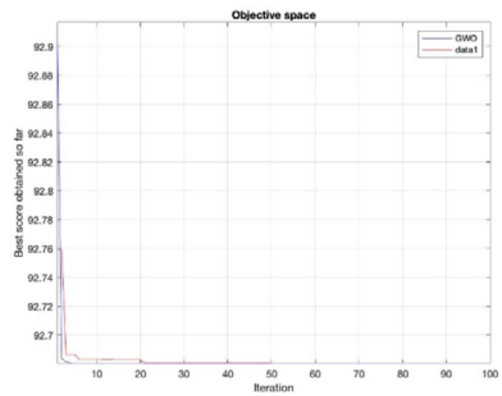


Figure 2. DRI value at different budgets

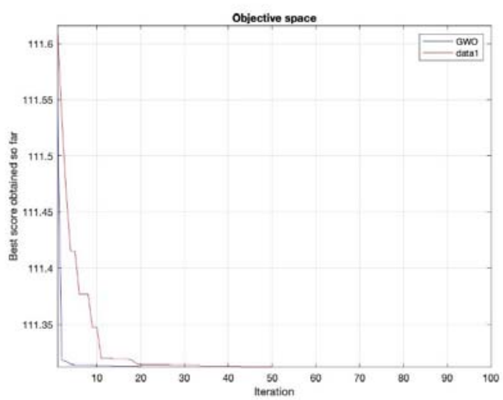
Comparison of Genetic Algorithm and Grey Wolf Optimization after the First Stage

The genetic algorithm, inspired by biological evolution, has been used in many optimization problems and seeks the best or the closest solution to the best answer by searching through possible solutions based on the principle of survival. On the other hand, in Grey Wolf Optimization (GWO), to model the hierarchical social structure of wolf packs, the best solution is considered as the alpha (α). Among the best solutions, the second and third best are named beta (β) and delta (δ). The remaining candidate solutions are designated as omega (ω). In this study, after optimization with the genetic algorithm (GA), the solutions were further optimized using the Grey Wolf Optimization algorithm. As observed, the results calculated by the Grey Wolf Optimization algorithm at different budget levels have improved compared to the genetic algorithm, indicating the superiority of this algorithm over the genetic algorithm in this objective function.

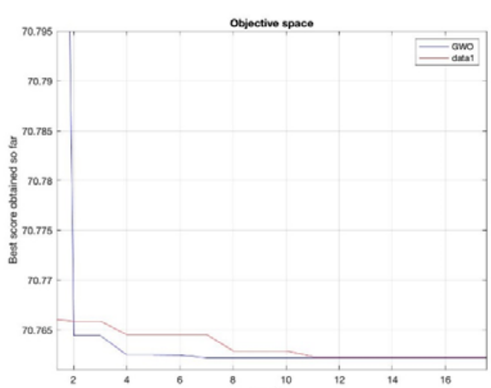
A)B1



B)B2



C) B3



D) B4

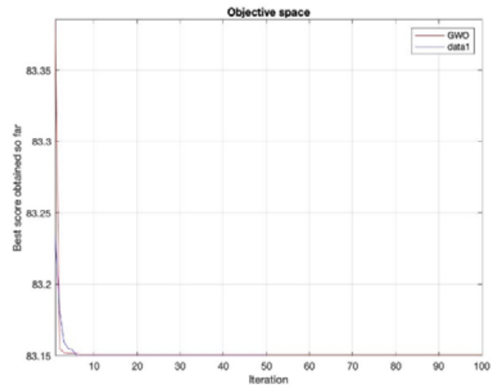


Figure 3. Comparison of genetic and grey wolf algorithms in Stage 1

Determination of Optimal Locations and Capacities for Distributed Generation

In the second stage of the problem, optimal locations for DG units in the network have been identified to minimize network losses, based on the regions identified in the first stage, for four budget levels. The results of this stage are presented in Table 3, and Figure 4 shows the optimal designs obtained at the end of the second stage at different budget levels. By running the Grey Wolf Optimization algorithm multiple times for each case and obtaining the best results, confidence in the optimality of the obtained results is ensured.

The results show that at budget level B1, an allocation of three DG units with a total capacity of 1300 kW is made. At this level, DGs are allocated based on priority load areas due to limited costs and have the most significant impact on network resilience. For budget level B2, four DG units with a total capacity of 1700 kW are allocated. At budget level B3, seven DGs with a total capacity of 3100 kW are allocated. Finally, for budget level B4, which is considered to supply all loads, seven DG units with a total capacity of 4800 kW are allocated. With the increase in budget levels at the initial stages, priority loads are supplied, and network flexibility increases significantly. However, with the continuous increase in budget levels to some extent, the increase in resilience decreases significantly. From budget level B3 to B4, despite the substantial increase in the budget level and the use of more DGs, the DRI does not change significantly. The ENS index, representing the absence of load supply in the network, decreases after the presence of DG units in the network. This can lead to improved network resilience and reliability.

As observed, the presence of DG units in the distribution network enhances network resilience. To achieve the highest redundancy level and obtain an optimal structure with minimal losses, a two-stage DG planning approach is essential. In this study, this approach has been utilized.

Table 3. DG unit allocation and system losses in stage 2

Maximum capacity DG(KW)	Optimal location	Budget Level	Amount of losses (KW)	IndexENS	error mode
550 250 400	A5 A8 A12	B1	4.63	4.5038×10^7	single Fault
350 750 350 100	A7 A11 A14 A5	B2=3B1	4.93	4.5034×10^7	single Fault
500 900 300 300 400 204 400	A11 A13 A19 A15 A22 A21 A17	B3=6B1	6.54	3.0626×10^7	Multiple Faults
700 600 900 900 600 237 800	A7 A9 A11 A15 A5 A13 A16	B4=15B1	6.65	2.8824×10^7	single Fault

Conclusion

In this research, an attempt has been made to introduce the concept of distribution network resilience in the presence of distributed generation resources and model common natural disasters such as floods and hurricanes. New resilience indices have been presented to study the impact of these resources on the network's resilience in terms of load supply and the resilience of distributed generation resources (solar cells and conventional gas resources) independently. Furthermore, the mathematical formulation of improving system resilience was addressed. The study also examined the impact of different types and capacities of solar power plants and conventional gas resources on the resilience of the distribution network. The optimization problem of locating distributed generation resources to improve system resilience was solved using genetic and grey wolf optimization algorithms. The results obtained from implementing the proposed model on a real-world sample network show that the network's resilience depends on the type and capacity of the distributed generation resources used in the network. Using DG units at appropriate locations and sizes increases the network's resilience. The magnitude of the increase in the resilience index is initially significant and decreases after a certain budget threshold. To achieve the highest level of resilience in the distribution network and make optimal use of the available capacity of distributed generation resources, it is recommended to focus on the optimal design of the type and location of these resources in network design and development statistics. In future studies, the presented model can be used to address comprehensive distribution network design issues, including the design of each existing component. It is worth noting that with limited budgets, transitioning towards a distribution network is possible.

Acknowledgments: **Acknowledgements** We extend our heartfelt gratitude to Dr. Seyyed Mahdi Hosseini from the Noshirvani University of Technology, Babol, Iran, for his invaluable assistance and guidance throughout this project.\

Conflict of interest: The authors declare no competing interests.

Financial support: There is no funding source for this research.

Ethics statement: There was no need for ethics approval or ethical state- ments.

References

[1] joan giang "Resilient distribution system leveraging distributed generation and microgrids: a review", November 2020

[2] Illia Diahovchenko. Gowtham Kandaperumal "Distribution Power System Resiliency Improvement Using Distributed Generation and Automated Switching" June. 2019

[3] Davoud Baghbanzadeh, Javad Salehi "Resilience improvement of multi-microgrid distribution networks using distributed generation" Jun. 2021

[4] Kumari Sandhya, Kalyan Chatterjee, "A Review on the state of the art of Proliferating Abilities of Distributed Generation deployment for achieving Resilient Distribution System " , November 2020

[5] M.H. Amirioun ''Metrics and quantitative framework for assessing microgrid resilienceagainst windstorms ''July 2018

[6] Akhtar Hussain, Syed Danial Ali Shah, Syed Muhammad Arif, "Heuristic optimisation-based sizing and siting of DGs for enhancing resiliency of autonomous microgrid networks" July, 2019.

[7] Prabodh Bajpai, Senior Member ''A Novel Metric to Quantify and Enable Resilient Distribution System using Graph Theory and Choquet Integral ''November 2016

[8] Prithwiraj Roy Chowdhury, Somasundaram Essakiappan, "Optimized Dispatch of Distributed Energy Resources for Resiliency and Power Quality Improvements at the Grid-Edge", March 2021

[9] Atwa, Y. M., El-Saadany, E. F. 2011. "Probabilistic Approach for Optimal Allocation of Wind-Based Distributed Generation in Distribution Systems." June 2011

[10] Georgilakis, P. S., and Hatziargyriou"Optimal Distributed Generation Placement in Power Distribution Networks: Models, Methods, and Future Research." March 2013

[11] Injeti, S. K., Prema "A Novel Approach to Identify Optimal Access Point and Capacity of Multiple DGs in a Small, Medium and Large Scale Radial Distribution Systems." May 2013

[12] Mistry, K. D., Roy, R "Enhancement of Loading Capacity of Distribution System through Distributed Generator Placement Considering Techno-Economic Benefits with Load Growth." May 2014

[13] El-Khattam, W., Hegazy, Y .G., and Salama, "An Integrated Distributed Generation Optimization Model for Distribution System Planning." June 2005

[14] Phung Dang Huy , Vigna K. Ramachandaramurthy ''Optimal Placement, Sizing and Power Factor of Distributed Generation: A Comprehensive Study Spanning from the Planning Stage to the Operation Stage ''january 2020

[15] Energy Nexus Group, "Technology characterization–microturbine," USA Environmental Protection Agency, 2002.

[16] Wang, Jing, Wangda Zuo, Landolf Rhode-barbarigos, Xing Lu, Jianhui Wang, and Yanling Lin. "Literature Review on Modeling and Simulation of Energy Infrastructures from a Resilience Perspective." May 2018

[17] Ullah, Zia, Shaorong Wang, and Jordan Radosavljevi. "A Novel Method Based on PPSO for Optimal Placement and Sizing of Distributed Generation." July 2019

[18] Kumar, Sajjan, Kamal K Mandal, and Niladri Chakraborty. "A Novel Opposition-Based Tuned-Chaotic Differential Evolution Technique for Techno- Economic Analysis by Optimal Placement of Distributed Generation." May 2019

[19] Gao, Haixiang, Ying Chen, Shengwei Mei, Shaowei Huang, and Yin Xu. "Resilience-Oriented Pre-Hurricane Resource Allocation in Distribution Systems Considering Electric Buses." April 2017

[20] Zhang, Bei, Payman Dehghanian, and Mladen Kezunovic. "Optimal Allocation of PV Generation and Battery Storage for Enhanced Resilience." August 2019

[21] Yao, Shuhan, Peng Wang, and Tianyang Zhao. "Transportable Energy Storage for More Resilient Distribution Systems with Multiple Microgrids." December 2018

[22] Kavousi-fard, Abdollah, and Mengqi Wang. "Stochastic Resilient Post-Hurricane Power System Recovery Based on Mobile Emergency Resources and Reconfigurable Networked Microgrids" March 2018

[23] Nikkhah, Saman, Kamran Jalilpoor, Ehsan Kianmehr, and Gevork B. Gharehpetian. "Optimal Wind Turbine Allocation and Network Reconfiguration for Enhancing Resiliency of System after Major Faults Caused by Natural Disaster Considering Uncertainty." April 2007

[24] Sedzro, Kwami Senam A, Alberto J Lamadrid, Senior Member, and Luis F Zuluaga. "Allocation of Resources Using a Microgrid Formation Approach for Resilient Electric Grids." September 2018

[25] Abedi, Amin, Ludovic Gaudard, Franco Romerio, Ludovic Gaudard, and Franco Romerio. "Review of Major Approaches to Analyze Vulnerability in Power System." October 2018

[26] Lei, S, J Wang, and Y Hou Chen, C. "Mobile Emergency Generator Pre-Positioning and Real-Time Allocation for Resilient Response to Natural Disasters." August 2016

[27] E. Abbaspour, B. Fani, E. H. Forushani. "A Bi-Level Multi Agent Based Protection Scheme for Distribution Networks with Distributed Generation." May 2019

[28] Bahramipanah, Maryam, Dimitri Torregrossa, Rachid Cherkaoui, and Mario Paolone. "A Decentralized Adaptive Model-Based Real-Time Control for Active Distribution Networks Using Battery Energy Storage Systems." January 2018

[29] Haixiang, Gao, Chen Ying, Xu Yin, and Liu Chen-Ching. "Resilience-Oriented Critical Load Restoration Using Microgrids in Distribution Systems." June 2016

[30] Chen, Xin, Wenchuan Wu, Boming Zhang, and Chenhui Lin. "Data-Driven DG Capacity Assessment Method for Active Distribution Networks." November 2017

[31] Li, Z, M Shahidehpour, … F Aminifar - Proceedings of the, and Undefined 2017. 2017. "Networked Microgrids for Enhancing the Power System Resilience." May 2017

[32] Rigo-mariani, Rémy, Keck Voon, and Jan Maciejowski. 2019. "A Clusterized Energy Management with Linearized

Losses in the Presence of Multiple Types of Distributed Generation." July 2019

[33] REZA SABERI, HAMID FALAGHI, "A two-stage approach to enhance distribution network resilience against natural disasters" August, 2020