Reliability Engineering and System Safety 237 (2023) 109395

Contents lists available at ScienceDirect

Reliability Engineering and System Safety

journal homepage: www.elsevier.com/locate/ress

# A stochastic investment decision making method for distribution system resilience enhancement considering automation, hardening and distributed energy resources

Puspendu Ghosh *, Mala De

*Department of Electrical Engineering, NIT Patna, India*

ARTICLE INFO

*Keywords:*
Resilience
Distribution system planning
Extreme weather event
Investment strategy
Microgrid
Distributed energy resources

ABSTRACT

Extreme weather events have always posed as a serious threat to the power system. In recent years the frequent occurrences of extreme events highlight the requirement for a resilient distribution system capable of maximizing load restoration under the most adverse situations. Because the requirement to reinforce the distribution system appears to be an expensive approach, it is crucial to make the proper investment decisions. In this regard, this article introduces a single-stage stochastic multi-criteria optimization method for maximizing network resilience over a series of investments while minimizing overall costs. This method conducts different categories of investments including the installation of sectionalizing switches, distributed energy resources, and hardening of overhead distribution lines. The optimization method is based on a genetic algorithm and can be used to address a large-scale network. Several numerical studies are tested on the IEEE 69-bus system to verify the effectiveness of the proposed method. The results of the investment decision-making method show the significance of combining planning and operational preparedness in distribution systems to respond to extreme weather events.

## 1. Introduction

Extreme weather events, such as earthquakes, floods, hurricanes/ tornadoes, ice storms, etc. can severely damage distribution networks, leading to large outages and economic losses [1]. Hence, distribution network infrastructure is required to be resilient in the face of severe disaster. According to [2], enhancing network response and load restoration after an extreme event can improve network resilience. Due to interruptions to distribution and transmission network components, it may be more challenging for utility power sources to address disrupted loads following the incidents. Multiple line faults may result from such extreme weather events, which might take many hours or maybe a few days to recover. In this stage, grid operators need to supply power as much as possible while minimizing load shedding penalties, which is an important parameter of distribution network resilience [3].

Consumers and power utilities looking for and contributing to resilience solutions have to be able to evaluate the cost-benefit analysis. Although the cost of a specific resilience strategy is generally acknowledged, determining the benefits is more challenging because there is insufficient data to justify them [4]. Various methods of assessing resilience have been proposed, such as the resilience analysis methods [5,6], and a matrix framework for evaluating energy resilience [7–9]. Even though several measures have been presented, there are currently no widely accepted resilience metrics. Moreover, no one metric is likely to be able to assess resilience because metrics are highly dependent upon weather severity factors and different objectives, and perceptions.

### 1.1. Background and existing works

In order to increase network resilience, two complementary solutions that are not incompatible with one another must be used. First, it is necessary to operate the network using backup plans developed especially for an extreme weather event. The second approach includes organizing the distribution system to build a reliable and adaptable infrastructure that can handle challenging conditions. The conventional deterministic method (such as undergrounding overhead distribution lines, and installing distributed generations without identifying the vulnerable branches) to improve the resilience of the distribution system to these extreme events is too costly. Numerous researchers suggest that a stochastic approach is more suitable and properly expresses the aspects of resilient planning [10–12]. The following dimensions have been identified as crucial for improving resilience: 1) the number of overhead distribution line required undergrounding; 2) level of

* Corresponding author.
*E-mail address:* puspendughosh92@gmail.com (P. Ghosh).

https://doi.org/10.1016/j.ress.2023.109395
Received 6 December 2022; Received in revised form 15 May 2023; Accepted 15 May 2023
Available online 19 May 2023

**Nomenclature**

*Abbreviations*

| | |
|---|---|
| SS | sectionalizing switch |
| RCS | remotely controlled switch |
| DER | distributed energy resource |
| MG | microgrid |
| OPF | optimal power flow |
| PV | photovoltaic |
| MT | micro-turbine |
| GA | genetic algorithm |
| SRM | system response method |
| OV | optimization variable |
| RAI | resilience assessment index |
| EENS | expected energy not served |
| MCS | Monte Carlo simulation |
| PDF | probability density function |

*Sets and Indices*

| | |
|---|---|
| $R$ | set of SRMs |
| $B$ | set of network buses |
| $L$ | set of network lines |
| $E$ | set of lines damaged by an event |
| $K$ | set of network lines with SS |
| $H$ | set of hardened lines |
| $MG^R$ | set of MGs included in the SRM $R$ |
| $C$ | set of scenarios |
| $I_{RA}$ | index of resilience assessment |

*Function and Variables*

| | |
|---|---|
| $OV_1^L$ | 1 if line $L$ has existed SS, 0 if not |
| $OV_2^L$ | 1 if line $L$ is hardened, 0 if not |
| $OV_3^L$ | ens in the MG belongs to line $L$ |
| $A(t)$ | expected performance curve |
| $A'(t)$ | actual performance curve |
| $N_1^R$ | number of MGs in the SRM $R$ |
| $P_{MG}^R$ | sum of the maximum demand of all customers within the MG |
| $D_{MG}^R$ | duration for yearly MG is out of service |
| $EENS^{MG}$ | EENS of MG |
| $EENS^R$ | EENS in the SRM $R$ |
| $AM_C^R$ | affectation matrix in the SRM $R$ and scenario $C$ |
| $I^{ws}$ | weather severity indicator |
| $I^i$ | intensity indicator |
| $P_f^{l^T}(I^{ws})$ | overhead distribution line failure probability with a total length of $l^T$ |
| $F_C^L(I^{ws})$ | 1 if line $L$ is damaged by an event in scenario $C$, 0 if not |
| $IC_{MT}^R$ | installation cost of MTs |
| $IC_{PV}^R$ | installation cost of PV systems |
| $IC_{SS}^R$ | installation cost of SSs |
| $IC_{LH}^R$ | installation cost of line hardening |
| $OMC_{MT}^R$ | operation and maintenance cost of MTs |
| $OMC_{PV}^R$ | operation and maintenance cost of PV systems |
| $OMC_{SS}^R$ | operation and maintenance cost of SSs |
| $OMC_{LH}^R$ | operation and maintenance cost of line hardening |
| $TYC_{DER}^R$ | total yearly cost of DERs |
| $TYC_{SS}^R$ | total yearly cost of SSs |
| $TYC_{LH}^R$ | total yearly cost of line hardening |

*Constants and Parameters*

| | |
|---|---|
| $t_1$ | time of event progress |
| $t_2$ | time of post-event |
| $t_3$ | time of restorative phase |
| $t_4$ | time of post-restoration phase |
| T | duration between the occurrence of an event and the restoration of the network |
| $M_B$ | maximum load demand at the bus $B$ |
| $X_E$ | length of damaged line impacted by an event in the MG |
| $T_E$ | damaged line repair time per unit length |
| $l$ | length of overhead distribution line between two poles |
| VoLL | Value of Lost Load |

distribution automation using sectionalizing switches (SSs) or remotely controlled switches (RCSs); and 3) the capability of distributed energy resources (DERs) to build microgrids (MGs) and hence maintain power supply to customers during an extreme event [13]. Although many researchers looking to enhance power system resilience assess the transmission network [14–16], many more are concentrating on the distribution network [3,5,8 – 11,17], since it provides the infrastructure for supplying electricity directly to the consumer and is more vulnerable to faults. This is mostly due to its structure, which is radial in nature and results in the loss of service to all downstream consumers in the case of a disaster. To enhance distribution system resilience, several planning strategies [7,18], and investment aspects [13,17], have been proposed.

Throughout the years, different solutions have been suggested for the issue of determining the appropriate size of a single MG. For instance, to reduce the overall cost of the network (initial investment and operating costs), an MG planning process for the selection of optimum size and combination of DER capacity is proposed in [19]. The optimum size issue of DER for a rural MG is addressed in [20] by the use of iterative “multi-year mixed-integer linear programming optimization”. To address the challenge of determining the optimal size of energy storage systems and photovoltaics (PVs) for a grid-connected MG, a multi-objective optimization method is proposed in [21] using the particle swarm optimization (PSO) algorithm. A linearized optimum sizing model is given in [22], with the goal of achieving optimal solutions for the implementation and operation of battery energy storage systems for isolated MGs. In [23], an AC optimal power flow (ACOPF)-based planning approach is designed to determine the optimum DER sizing for an isolated AC/DC MG.

However, the aforementioned works are primarily concerned with reducing network costs under normal operating circumstances. The impact of severe occurrences on decision-making in optimum sizing issues has not been addressed in the above-mentioned studies. When operating under uncertainty and contingency during extreme weather event, MGs may operate closer to their stability boundaries, which emphasizes the need to include these technical limitations in the optimization method being used. In normal operating conditions, MGs can be used to minimize network costs, while during severe occurrences, electricity sharing across MGs minimizes load shedding [24]. Using a heuristic approach, [25] provides a planning strategy for multi-MG networks that effectively addresses DER placement, DER size, and load allocation. A stochastic method is used to capture the uncertainties associated with the output of DER and the loads. However, power sharing amongst MGs is not addressed in this work. In [26], the optimum location and size of DER and the optimum position of sectionalizing switches are identified using a multi-objective PSO method. In addition, PSO is distinguished by its inefficiency when there are more than three factors that require to be sized optimally [23]. In conclusion, the aforementioned research only focuses on the internal concerns associated with generating resources and load characteristics.

### 1.2. Motivation

The analysis mentioned above overlooks external factors such as investment decision-making based on the inclusion of Value of Lost Load (VoLL), distribution system automation, line hardening, and DER integration, as well as the frequency of extreme weather events. Furthermore, these studies emphasize the sizing challenge of DER by selecting from a finite set of capacities instead of a continuous range, which may result in unnecessary costs. However, the research does not adequately address the planning issues of resilient networked MGs.

The probability of blackouts caused by severe occurrences may be reduced by a resilient design, as proposed in [27], which considers line hardening, networked MGs, and redundancy. Although this article considers the possibility of line failures, it does not deal with uncertainties and uses a finite set of capacities to size backup generators. Regarding the planning phase, there is a lack of research addressing the optimum sizing issue of networked MGs when considering both resilience and cost. Micro-turbines (MTs) and energy storage systems can be committed by distribution system operators during an event to mitigate the effects of a natural catastrophe [33]. Network hardening and the optimum DG allocation after a hurricane was coordinated using a two-stage robust optimization approach in [28]. However, the reconfiguration of network topologies was not employed as a preventive measure against natural catastrophes.

Additionally, the approaches presented in the literature usually focus on a specific source of investment to enhance network resilience, such as RCS/SS installations [29,34] DER integration [30,31] or distribution overhead line hardening [35]. While there is a single type of investment, a single-stage optimization strategy can frequently address the optimization problem. The optimization technique is divided into several subsequent phases of optimization due to the additional complexity that arises when there are several investment categories [10].

One major disadvantage is the capability to model a network only up to a specific size. Due to the stochastic and nonlinear characteristics of the planning concern, which leads to its difficulty, fixing it through an exhaustive approach demands a significant computing burden that is hard to achieve in large systems. In order to address this challenge, metaheuristic algorithms based on genetic algorithm (GA) is used in this work. These metaheuristic algorithms provide approaches accessible to a number of different scenarios to identify estimated solutions to issues where the exhaustive search or conventional optimization for numerical methods is not useful and GA-based metaheuristics are more commonly used in distribution system optimization due to their adaptable characteristics [36,37].

### 1.3. Contribution

The above discussion highlights the need of an appropriate investment decision making method that can overcome the drawbacks of existing approaches to provide realistic resilience-oriented planning for a large distribution network. The main contributions of this article are as follows:

- A novel stochastic investment decision making method is developed to perform multi-criteria optimization using metaheuristic algorithms with the purpose of maximizing system resilience and minimizing investment costs.
- An optimization method is presented for (a) optimal hardening planning; (b) optimal topology reconfiguration; and (c) optimal DER allocation to maintain a specific level of loads after an extreme weather event.
- Unlike previous research, this article considers three different types of investment and optimizes these investments simultaneously, eliminating optimizations over numerous phases that lead to sub-optimal outputs.

The three types of investment considered in this study include (a) hardening distribution lines; (b) installing SSs; and (c) installing DER (dispatchable DER, MTs, and non-dispatchable DER, PV systems) at specified network buses or branches (lines) that are optimally located. With the help of the proposed optimization method, we are able to understand and measure the interdependence and complementarity of these quite different types of system investment. Since extreme weather events usually have a significant influence across a wide geographic area, the solution approach has also been designed to enable working on a large system.

Table 1 provides comparisons between the proposed method and numerous previous planning methods for improving the resilience of distribution systems, such as optimization model, uncertainty modeling, network configuration, and investment strategies. In aspects of resilience-oriented investment planning, Table 1 shows that the proposed method is much preferable to previous research. However, compared to other resilience indices, this article has several differences and advantages, which are as follows:

- *Incorporation of automation, hardening, and DER*: This article considers the impact of automation, hardening, and DER on distribution system resilience. Most other resilience indices only focus on one or two of these factors and do not consider their combined impact.
- *Consideration of multiple scenarios*: The proposed method considers multiple scenarios, including different wind speed events, distribution system component failure, and frequency of extreme weather events. This allows decision-makers to evaluate the resilience of the system under different conditions and prioritize investments accordingly.
- *Investment decision-making*: The proposed method is designed to aid decision-makers in making investment decisions that will enhance the resilience of the distribution system. This is an advantage over other resilience indices that only provide a measure of resilience but do not suggest specific actions to improve it.
- *Incorporation of VoLL*: The proposed method incorporates VoLL in the decision-making process. This allows decision-makers to evaluate the economic impact of enhancing the resilience of the distribution system.

The rest of this article is organized as follows. The statement of the problem for this study is explained in Section 2. The objective function and constraints of the problem are described in Section 3. While Section 4 discusses how to evaluate the resilience and investment of the network, Section 5 presents the solution method. Furthermore, Section 6 shows and analyses the numerical studies. Finally, the conclusions of this research are summarized in the last Section.

## 2. Problem statement

The introduction section mentions an extreme weather event in the distribution system as a potential cause of an interruption in power supply for all consumers downstream to the fault occurrences. The radial structure of the distribution system, the limitation on network reconfiguration [29], and the fewer number of SSs are the major causes of this power outage. Different portions of the network could be damaged at the same time by an extreme incident, and their recovery would take more than a few hours to complete. The novel planning method that is presented in this work is based on developing MGs that maximize network resilience while requiring the least amount of investment. Along with the planning process, a prototype method for identifying catastrophic events that vary in effect and intensity has also been produced.

The problem statement is described using an example network for ease of understanding. Fig. 1 is an example of a base network. It shows that a fault in line $L3$ would result in the opening of the SS at line $L1$ and the interruption of power supply to all downstream consumers, keeping only consumers connected to buses $B1$, $B7$, $B8$, and $B9$ connected. The

**Table 1**
Comparisons of the proposed method with previous planning methods.

| Reference number | | [26] | [10] | [23] | [26] | [27] | [28] | [29] | [30] | [31] | [32] | This article |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Optimization model | Single-stage | × | × | × | × | × | × | × | ✓ | × | × | ✓ |
| | Two-stage | × | × | ✓ | × | ✓ | ✓ | × | × | ✓ | ✓ | × |
| | Multi-stage | ✓ | ✓ | × | ✓ | × | × | ✓ | × | × | × | × |
| Uncertainty modeling | Not Consider | × | × | ✓ | × | × | × | ✓ | ✓ | × | × | × |
| | Robust | ✓ | × | × | × | × | ✓ | × | × | × | × | × |
| | Stochastic | × | ✓ | × | ✓ | ✓ | × | × | × | ✓ | ✓ | ✓ |
| Network configuration | Initial | × | × | × | × | ✓ | ✓ | × | × | × | ✓ | × |
| | Optimal | ✓ | ✓ | ✓ | ✓ | × | × | ✓ | ✓ | ✓ | × | ✓ |
| Investment strategies | SS/RCS | × | × | × | ✓ | × | × | ✓ | × | × | × | ✓ |
| | DG/DER | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | ✓ |
| | Underground/Hardening | × | × | × | × | ✓ | ✓ | × | × | × | ✓ | ✓ |

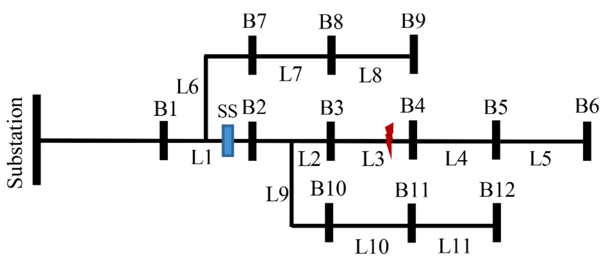

**Fig. 1.** Base network with one sectionalizing switches.

planning method includes hardening some overhead distribution lines to reduce their vulnerability to weather-related events and installing SSs and DER at selected buses to boost network automation and maintain power supply under isolated MGs. The concept of system response method (SRM) is introduced to make it easier to analyze various options available within the scope of potential solutions. The SRM consists of several planning options that include hardening specified lines, installing SSs on specified lines, and selecting the location and size of DER. The method proposed for identifying optimal SRMs is explained in the following section.

A SRM for the base network is shown in Fig. 2. One SS has been installed at $L3$, two DER have been installed at $B6$ and $B12$, and $L6$, $L7$ and $L8$ have been hardened. Through the hardening of these lines, the resilience of the network is aimed to be increased, particularly by preventing distribution lines from failing as a result of high wind events. In the event of a severe incident, the network division is made when the installed SS opens and enables the network to be reconfigured into three independent MGs. If a fault occurs in line $L1$, two SSs located at lines $L1$ and $L3$ should open, which leads to islanding of $MG^2$ and $MG^3$, with $MG^1$ continuing to receive power from the substation. It is important to mention that MGs only activate in islanded mode under severe conditions and only when they are unable to receive power from the substation.

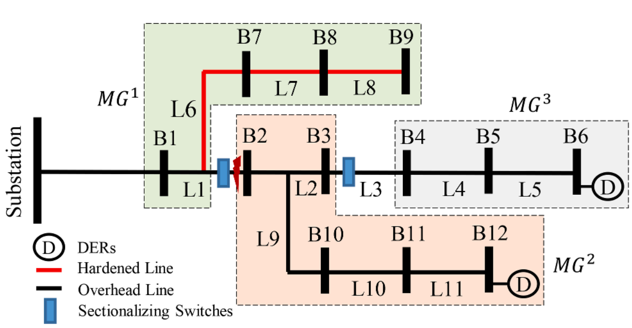

**Fig. 2.** Framework for the system response.

## 3. Problem formulation

The proposed optimization method initially searches to obtain a set of SRMs, $R$ and finds the optimal SRM that maximizes resilience and minimizes investment. Each SRM, $R$ is different and independent from one another and can choose from a number of different configurations according to the requirements of the network. The nonlinearity of the scenario adds to difficulty, as was already mentioned, necessitating the application of a suitable optimization for handling complex nonlinear problems than conventional techniques.

Based on a set of optimization variables (OVs) that achieves the highest ranking while assessing the objective function, a GA-based optimization attempts to determine the significance of decision variables in the optimization, subject to specific limitations. Both objective functions are used to assess these optimization variables, and the ones with the best results are used as the foundation for further iterations of OVs. The processes of recombination and modification are used to generate these further iterations of optimization variables.

The only condition where the different SRMs interact is when they are developing a new SRM. The different OVs are detailed below:

■ $\mathbf{OV_1^L}$

The binary variable represents the value 1 when an SS is installed in line $\boldsymbol{L}$, with as many $\boldsymbol{OV_1^L}$ as there are lines in the network. If there is no SS on that line $\boldsymbol{L}$, it will consider a value of 0. For example, according to Fig. 2, $\boldsymbol{OV_1^1} = 1$, and $\boldsymbol{OV_1^2} = 0$.

■ $\mathbf{OV_2^L}$

The binary variable equals 1 if line $\boldsymbol{L}$ in the SRM, $\boldsymbol{R}$ is hardened, and equals 0 if line $\boldsymbol{L}$ is not hardened. For example, based on Fig. 2, only three lines $\boldsymbol{L}6$, $\boldsymbol{L}7$, and $\boldsymbol{L}8$ are hardened which implies that $\boldsymbol{OV_2^6} = \boldsymbol{OV_2^7} = \boldsymbol{OV_2^8} = 1$ and the binary variable for the rest of the line will take a value of 0, e.g., $\boldsymbol{OV_2^1} = \boldsymbol{OV_2^2} = \boldsymbol{OV_2^3} = \boldsymbol{OV_2^4} = \boldsymbol{OV_2^5} = 0$.

■ $\mathbf{OV_3^L}$

The variable between 0 and 1 indicates an MG with expected energy not served (EENS) belongs to line $\boldsymbol{L}$ as a per-unit value. The MG to which the bus and the line both belong is indicated by this variable. The number of lines in the network is the same as the number of $\boldsymbol{OV_3^L}$. A set of optimal DER per MG is enabled to access a specific value of EENS. In the case of the location of DER, it is significant to recognize that selecting the MGs where DER will be placed is crucial for optimizing resilience. Although the bus in which the DER are installed within the specified MGs is irrelevant from the perspective of resilience. This is because the MG model presented in this article considers that no additional switching equipment is involved for network reconfiguration within the MG. To avoid overloads under MG operation and to do away with the requirement for operating power flows, it is considered that DER be installed at the MG's upstream bus, simulating a radial network operation. When the $OV_3^L$ value is 1, the MG has no DER. And when $OV_3^L$ equals 0, it means that all of the power required by the MG can be provided by the DER. If the value of $OV_3^L$ falls between 0 and 1, the presence of installed DERs can enhance the autonomy duration of the MG but cannot entirely prevent a partial supply loss. This variable offers the opportunity to subsequently find the set of optimal DER that satisfies the given EENS while requiring the least amount of investment.

$OV_1^L$, $OV_2^L$, and $OV_3^L$ incorporate the decision variables for the optimization because they together represent an SRM as a whole. In conclusion, $OV_1^L$ denotes the network split into MGs, $OV_3^L$ specifies the EENS of MGs which will eventually result in a set of DER, and $OV_2^L$ represents the hardened lines, which assist in enhancing the network's resilience. The decision variables for the corresponding SSs and hardened lines are fixed to 1 to specify as an input to the optimization problem. The location of the installing SSs and hardened line is specified by (1) and (2) respectively.

$$OV_1^L = 1 \forall L \in K \tag{1}$$

$$OV_2^L = 1 \forall L \in H \tag{2}$$

The set of network lines with SS is $K$, while the set of hardened lines is $H$. The ranges for the variables $OV_1^L$, $OV_2^L$, and $OV_3^L$ are defined by (3) and (4).

$$0 \leq OV_1^L, OV_2^L, OV_3^L \leq 1 \forall L \tag{3}$$

$$0 \leq OV_1^L, OV_2^L, OV_3^L \leq 1 \forall R \tag{4}$$

The proposed optimization includes the benefit of having just one constraint and being linear. According to this constraint, a set of optimal DER for each MG can be implemented over the whole network and is placed at the MG's upstream bus. This is obtained using (5) and (6), which demands that no DER be placed when $OV_1^L = 0$ and results in $OV_3^L = 0$.

$$OV_1^L + OV_3^L \geq 1 \forall L \tag{5}$$

$$OV_1^L + OV_3^L \geq 1 \forall R \tag{6}$$

Eqs. (1), (2), (5), and (6) are not expressed as constraints in the solution for scheduling concerns, but rather as a further process to find optimal SRM during the evaluation of the objective function. This is due to the challenge of finding random starting responses that satisfy the required constraints. After determining the investment cost and resilience of the network, we can decide which SRM reduces the investment and maximizes the resilience.

## 4. Assessment and maximization of network resilience

### 4.1. Index for resilience assessment

During an extreme weather event, the power supply might drop gradually because of line failures in the distribution network. As soon as the faults (line failures) have been repaired, the distribution system will keep providing electricity at a minimal level until the extreme event is over. After the extreme event, the operators will begin immediate repairs on the damaged components. Finally, distribution systems gradually return to normal operating conditions, and the power supply increases to its pre-outage levels. Fig. 3 shows the different phases of distribution systems represented by the performance index.

The duration when MG is out of service, the number of lines damaged, the intensity of the event, and the recovery time are considered in this article to assess the resilience of the distribution systems. The loss area of the performance curve under normal operating conditions (expected performance curve) and power outages (actual performance curve) represents EENS due to line failures during extreme events. The resilience assessment index (RAI), $I_{RA}$ is based on the amount of power supply during the event and is calculated as follows:

$$I_{RA} = \frac{\int_0^T A^{'(t)} dt}{\int_0^T A(t) dt} = \frac{\int_0^T A(t) dt - EENS^R}{\int_0^T A(t) dt} \tag{7}$$

where $T$ represents the duration from $t_1$ to $t_4$ in Fig. 3 that the distribution system is impacted by the extreme event, including the event progress times and the network recovery time; $A(t)$ is the expected performance curve of the distribution system under normal operating conditions; $A'(t)$ is the actual performance curve of distribution systems during the event; $EENS_C^R$ represents the EENS for an SRM, $R$ and scenario, $C$, which is the area between the expected and actual performance curves.

### 4.2. Resilience assessment method

The resilience index calculation provides a sample value for a specific SRM to enable a comparative comparison of alternative planning solutions. Following a detailed analysis of the previous literature, it has been shown in this case that the amount of EENS during severe events determines the system's resilience. A flowchart describing the proposed method for calculating the network's resilience for each SRM is shown in Fig. 4. After collecting the input data, the first stage in the method represented in Fig. 4 is to split the network into MGs ($N_1^R$) based on the locations of the SSs. Next, a simplified network topology is created by computing the maximum demand ($P_{MG}^R$), the yearly time out of service ($D_{MG}^R$), and the EENS ($EENS^{MG}$) of each MG. The final stage is to use the

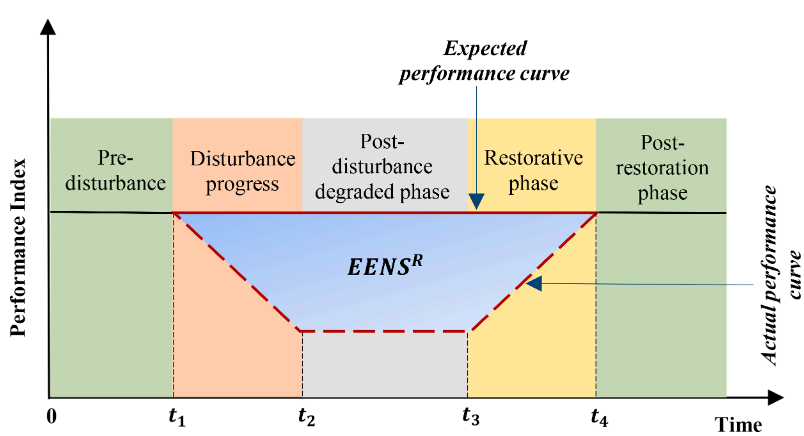


**Fig. 3.** The failure and response phase of distribution systems under extreme event.

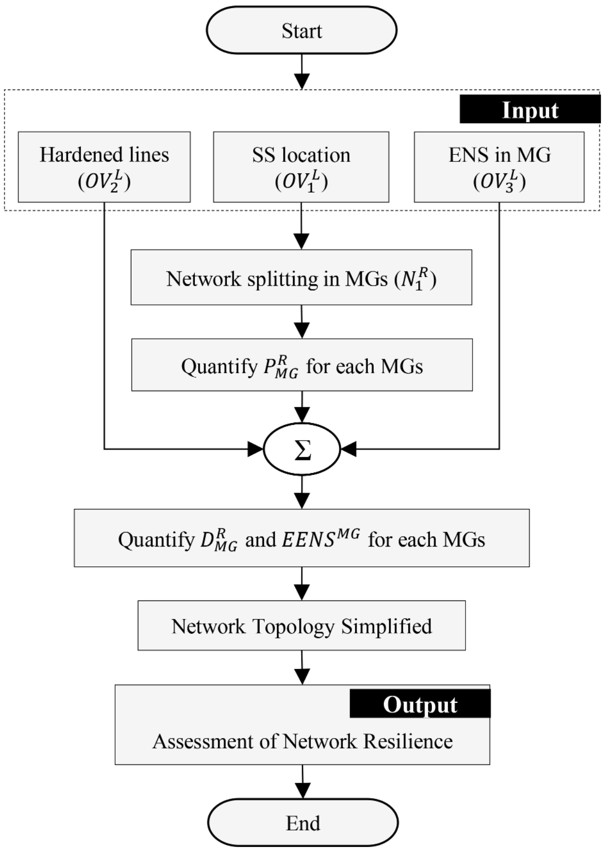


**Fig. 4.** Flowchart for assessing network resilience.

earlier estimated variables and the simplified network topology to determine the network's overall resilience. The method is described in detail below.

The locations of the SSs as identified by $OV_1^L$ are used to split the network into multiple isolated MGs for each SRM. This process enables accessing each MG's network components as well as all of the MGs accessible to deal with the effects of a certain occurrence. In an SRM, the number of MGs is represented by $N_1^R$, which is computed using (8). The variables needed to calculate the SRM's resilience are identified for all of the MGs that characterize the SRM. The sum of the maximum demand of all customers within the MG is calculated by (9). The duration when MG is out of service is determined by (10).

$$N_1^R = \sum_{L+1} OV_1^L \ \forall L \tag{8}$$

$$P_{MG}^R = \sum_B M_B \ \forall B \ \in MG^R \tag{9}$$

$$D_{MG}^R = \sum_E T_E * X_E \ \forall E \in MG^R \tag{10}$$

The set of network buses is $B$, and the set of lines damaged by an event is $E$. $M_B$ represented the maximum demand of the consumers located at the bus $B$. The set of MGs included in the SRM, $R$ is represented by $MG^R$. $T_E$ and $X_E$ define the recovery time and the length of the damaged line impacted by an event belonging to the considered MG. The value of $T_E$ is calculated by the intensity of the event and network parameters such as resource availability or structural characteristics, whereas the $X_E$ is based on the impact of the event.

The optimization variable $OV_3^L$ implies EENS throughout the analyzed time (i.e., from $t_1$ to $t_4$ in Fig. 3) for an MG. The availability of loops that enable network reconfiguration in the case of an extreme event is a factor to be considered. The value of $OV_3^L$ will be set to 0 if there is a loop in any of the analyzed buses of the MG, which is regarded as an external supply source capable of supplying the power of the MG. In urban networks with high demanding densities, the availability of loops is essential since they maximize service reliability. This study considers that there are no congestions that prevent these external supplies. We can obtain a smaller network by dividing it into the top bus and the buses downstream of the SSs. This simplification, seen in Fig. 5, enables the transition from massive networks with multiple buses to one in that each MG is characterized by a single point that receives all the necessary data while maintaining the topological features needed for the analysis of resilience.

To determine the resilience of an SRM, it is important to identify which MGs are impacted or faults that happen inside the MG by an extreme event. It is crucial to consider at this moment that multiple regions may be impacted simultaneously by the event, and the network structure defines which MGs can or cannot be serviced from the upstream substation. Due to this, an affectation matrix ($AM_C^R$) with the same number of components as MGs is immediately generated for each SRM, $R$ and scenario, $C$. Each $AM_C^R$ matrix component can be set to 0 if the MG is unaffected and the substation can supply power. If MG is impacted or lacks the generating capacity to offer a backup supply, and the network structure restricts it from receiving power from the upstream substation because of an intermediary event, then each component of the $AM_C^R$ matrix can take a value of 1. Each component of the $AM_C^R$ matrix can have a value between 0 and 1 if none of the distribution lines that make up the MG are disrupted, and it can no longer receive power from the upstream substation because of an intermediary event, but it can still receive power from the MG's generation sources. And the value of the $AM_C^R$ matrix components is equal to the ratio of the number of buses not satisfying demand power to the total number of buses in the MG. If three faults occur in lines $L1$, $L3$, and $L9$ in the base network shown in Fig. 5, in such a scenario, $B2$ and $B3$ in $MG^2$ do not receive power from any sources, while the other buses in the MG may receive the demand power. Therefore, the value of the $AM_C^R$ matrix component for $MG^2$ will be 2/5. The resilience of the network is finally assessed, which is represented in (11) for an SRM, $R$ as the average EENS for the different scenarios.

$$EENS^R = \sum_C \sum_{MG} P_{MG}^R * D_{MG}^R * AM_C^R \forall E \in MG^R \tag{11}$$

The EENS of the analyzed SRM, $R$ is calculated by multiplying the

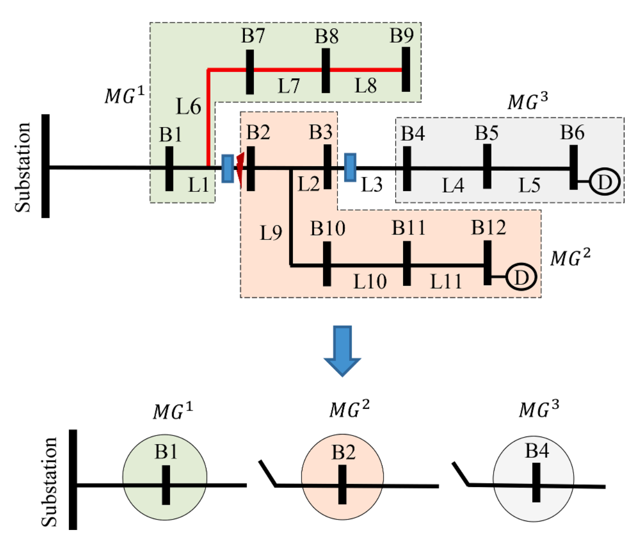


**Fig. 5.** An example of the network split in MGs for an SRM and its simplified network.

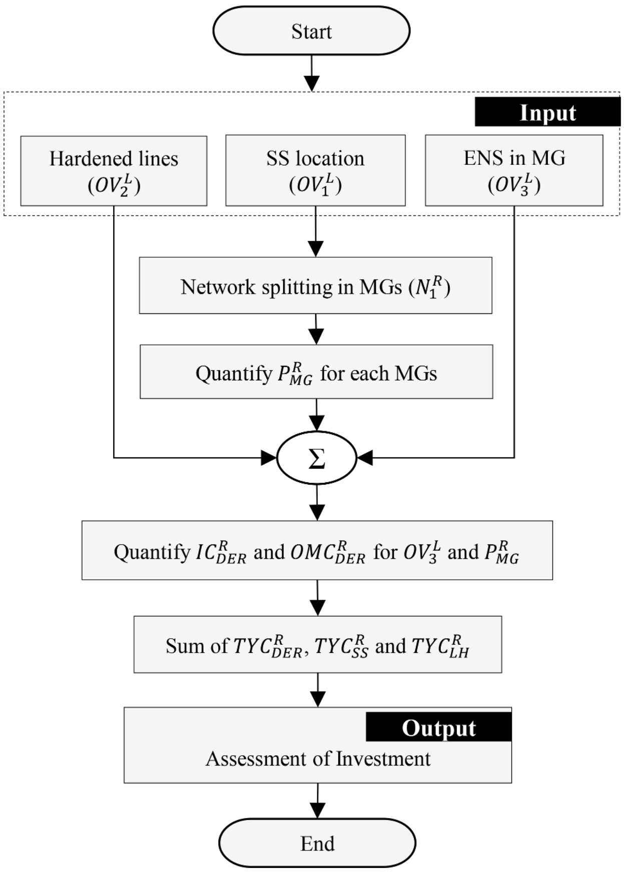


**Fig. 6.** Flowchart for assessing investments.

maximum power demand of the customers connected to the affected MGs ($\boldsymbol{P_{MG}^R}$), the yearly time out of service ($\boldsymbol{D_{MG}^R}$), and the affectation matrix ($\boldsymbol{AM_C^R}$).

### *4.3. Investment assessment method*

The methodology shown in Fig. 6 is used to quantify the overall investment of each analyzed SRM. As can be seen, we proceed with the variables $\boldsymbol{OV_1^L}$, $\boldsymbol{OV_2^L}$, and $\boldsymbol{OV_3^L}$ that the optimization algorithm provides. The network is then split into MGs based on where the SS is located, and the maximum demand power ($\boldsymbol{P_{MG}^R}$) of all MGs is determined using (9). We can identify which combinations of DER reduces the investment according to this network splitting and the optimization variable $\boldsymbol{OV_3^L}$. Finally, the amount of investment (AOI) is calculated by adding the total yearly investment in DER ($\boldsymbol{TYC_{DER}^R}$) to the total yearly investment in SSs ($\boldsymbol{TYC_{SS}^R}$) and total yearly investment in network hardening ($\boldsymbol{TYC_{LH}^R}$).

The total yearly cost (TYC) for each DER is the sum of the installation cost ($\boldsymbol{IC_{DER}^R}$), and the cost of operation and maintenance ($\boldsymbol{OMC_{DER}^R}$). The annualization process is required in order to do an appropriate comparison of the optimality of DER that have varying lifetimes. However, this process can be modeled for one or more DER. It should be noted that the costs associated with DER might vary based on their size and performance. Table 2 shows an assessment of the different types of investment.

The EENS of all MGs and power supplied by them are used as the input data for a lookup table that has been previously computed, and this lookup table is used to identify the optimal set of DER to all MGs. Before the optimization method starts, this lookup table is collected. As was already indicated, this enables an improvement in performance time since GAs operate effectively when the objective function is assessed quickly. To achieve this, we first estimate the load profiles of network customers to identify DER combinations that minimize investment for various quantities of power and EENS. The recovery period that DER can provide energy to customers is used to calculate the EENS.

## 5. Problem-solving method

The objective of this study is to provide a planning method to produce SRMs based on MGs that maximize network resilience while minimizing overall investment. The resilience of the network is evaluated in terms of EENS which means resilience is maximum when EENS is minimum. So, the objective function of the single-stage multi-criteria optimization can be defined as follow:

$$\boldsymbol{Max}\ (\boldsymbol{RAI}),\ \boldsymbol{Min}(\boldsymbol{AOI}) = \boldsymbol{Min}\left\{\sum_{i\in R}\boldsymbol{EENS}^{\boldsymbol{R}},\sum_{j\in R}\left(\boldsymbol{TYC}_{\boldsymbol{DER}}^{\boldsymbol{j}} + \boldsymbol{TYC}_{\boldsymbol{SS}}^{\boldsymbol{j}} + \boldsymbol{TYC}_{\boldsymbol{LH}}^{\boldsymbol{j}}\right)\right\} \tag{12}$$

Three key processes involved in this kind of SRM are: DER installations, boosting line hardening and enhancing network automation by adding SSs. Following an extreme event, the impacted network components will be separated, and all consumers who lost supply from upstream substations will be provided DER via different MGs generated using network reconfiguration. Utilizing a multi-criteria optimization method, several SRMs are performed and evaluated regarding the obtained resilience and desired investment. It is important to mention the requirement for combined optimization of the three planning steps under consideration, as these steps are utilized simultaneously to improve the resilience of the network. Hardened overhead lines reduce the failure probability of vulnerable lines that are impacted by high wind events [11], the SSs enable restructuring of the network after the event, and the DERs are supplying all customers who cannot receive power from the upstream substation. Because each of the three planning steps impacts how resilient the network is, it is ineffective to perform each step individually. Fig. 7 presents the overview of the proposed planning method.

The process starts with an input dataset that is used to generate the SRMs. The input datasets for the existing distribution system include the customer peak demand, SS locations, hardened overhead lines, and network configuration. The power rating for MTs and PV systems, and the yearly investment cost, operation costs, and maintenance costs, are all included in the input data for DER utilized in the network planning process. The costs of replacing an old SS with a new one and the average cost of hardening the overhead line are also included. The tested network is primarily normalized and represented as a graph network in order to apply complex network theory to the optimization process.

**Table 2**
Overall yearly investment assessment for an SRM, R.

| Investment | | Installation cost | Operation and maintenance cost | Total yearly cost (TYC) |
|---|---|---|---|---|
| DER | MTs | $\boldsymbol{IC_{MT}^R}$ | $\boldsymbol{OMC_{MT}^R}$ | $\boldsymbol{TYC_{MT}^R = IC_{MT}^R + OMC_{MT}^R}$ |
| | PV systems | $\boldsymbol{IC_{PV}^R}$ | $\boldsymbol{OMC_{PV}^R}$ | $\boldsymbol{TYC_{PV}^R = IC_{PV}^R + OMC_{PV}^R}$ |
| SS | | $\boldsymbol{IC_{SS}^R}$ | $\boldsymbol{OMC_{SS}^R}$ | $\boldsymbol{TYC_{SS}^R = IC_{SS}^R + OMC_{SS}^R}$ |
| Line hardening | | $\boldsymbol{IC_{LH}^R}$ | $\boldsymbol{OMC_{LH}^R}$ | $\boldsymbol{TYC_{LH}^R = IC_{LH}^R + OMC_{LH}^R}$ |
| Amount of investment (AOI) | | $\boldsymbol{TYC_{DER}^R + TYC_{SS}^R + TYC_{LH}^R}$; where, $\boldsymbol{TYC_{DER}^R = TYC_{MT}^R + TYC_{PV}^R}$ | | |

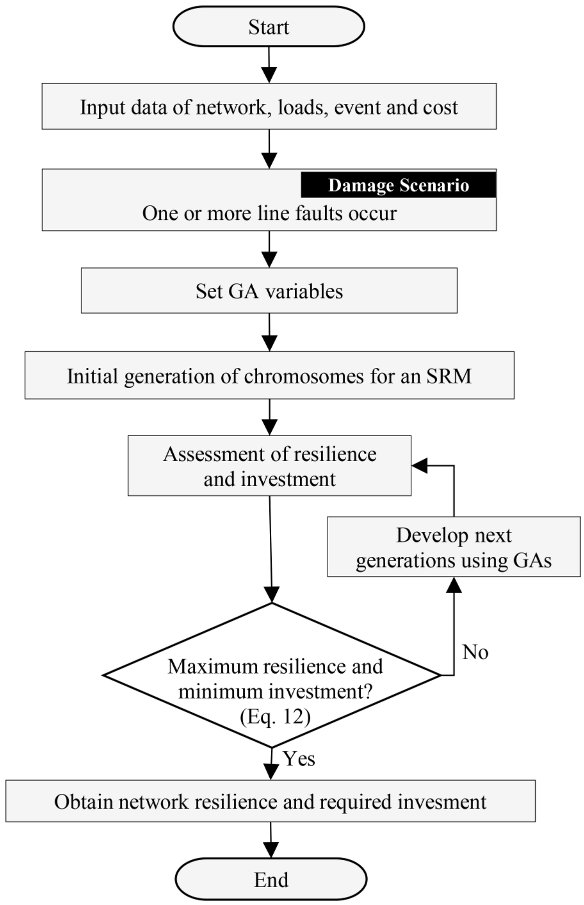


**Fig. 7.** Flowchart for the proposed methodology.

Then, in order to maximize network resilience and reduce investment, the optimization is employed. Because of nonlinearities, conventional mathematical programming-based optimization in large systems can be computationally infeasible. This indicates the requirement for optimization techniques, like metaheuristic algorithms, to deal with these nonlinearities. A multi-criteria GA is utilized in this scenario to maximize network resilience while minimizing investment by applying a multi-attribute optimal solution. The quick assessment of the objective function for the recommended solutions is one of the essential conditions for using GA [38]. As shown in Fig. 7, a number of early responses are assessed and updated based on their effectiveness to generate optimal solutions. The performance of assessing the objective function is a crucial feature in the structure of the model since this operation is conducted whenever solutions are evaluated. The application of complex network theory and GA in combination offers significant benefits for resolving this kind of issue and makes it analytically possible. Finally, the optimization method produces different optimum SRMs. All of these SRMs are formed by the three functions $OV_1^L$, $OV_2^L$, and $OV_3^L$, which represent the optimization variables of the problem.

### 5.1. Probability assessment for line failures

Additionally, a method is provided for generating various adverse weather conditions in order to analyze the resilience of the distribution system. This method is flexible enough to be able to describe different kinds of events depending on the requirements and threats that the network under analysis faces. A weather severity indicator, $I^{ws}$ is used to consider the different wind speeds and assist in predicting the probability of high-wind occurrences leading to the failure of overhead distribution lines. The probability of collapse to all distribution overhead line segments of length $l$ between two electric poles can be estimated from the fragility curve as a function of the wind speed as shown in Fig. 8 [39]. The fragility curve of resilience in distribution systems under extreme weather events is a mathematical model that describes the probability of a distribution system experiencing a certain level of damage or failure when subjected to an event of a given intensity. The following are some of the key assumptions underlying the fragility curve of resilience in distribution systems under extreme weather events:

- The probability of damage or failure of the distribution system can be estimated using a probabilistic model, such as the cumulative distribution function or the probability density function.
- The fragility curve is based on empirical data or analytical models calibrated using empirical data.
- The extreme weather event is considered to be the primary cause of damage or failure to the distribution system.
- The distribution system is assumed to be a linear, time-invariant system.
- The response of the power system to the cyclone can be described using a single or multiple performance metrics, such as outage duration, number of outages, or the percentage of customers affected.

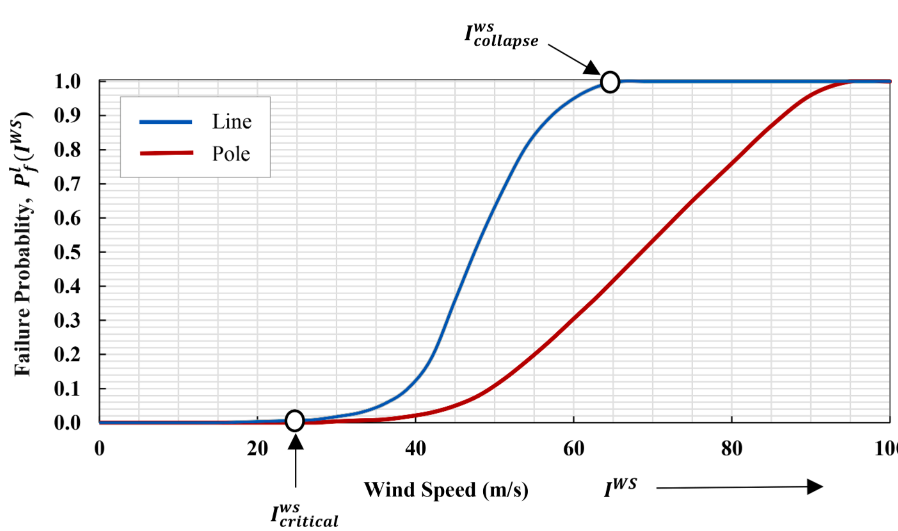


**Fig. 8.** Failure probability of overhead distribution line.

- The input event characteristics, such as wind speed, direction, and duration, are accurately modeled.
- The probability of failure of the components at low wind speeds, such as 15 m/s and 20 m/s, is assumed to be zero. However, there is a slight difference in their failure probability values, both of which are less than 1%. This similar assumption is also made for higher wind speeds (greater than 65 m/s).

At point, $\boldsymbol{I}^{ws}_{critical}$, the probability of failure increases exponentially, while at point $\boldsymbol{I}^{ws}_{collapse}$, the probability of surviving is very low. Therefore, the failure probability, $\boldsymbol{P}^{l}_{f}(\boldsymbol{I}^{ws})$ is zero when the $\boldsymbol{I}^{ws}$ is less than $\boldsymbol{I}^{ws}_{critical}$, and it is equal to one when $\boldsymbol{I}^{ws}$ is more than $\boldsymbol{I}^{ws}_{collapse}$. The failure probability of the overhead distribution line can be formulated as follow:

$$\boldsymbol{P}^{l}_{f}(\boldsymbol{I}^{ws}) = \begin{cases} 0, & if\ \boldsymbol{I}^{ws} < \boldsymbol{I}^{ws}_{critical} \\ \boldsymbol{P}^{l}_{f}(\boldsymbol{I}^{ws}), & if\ \boldsymbol{I}^{ws}_{critical} \le \boldsymbol{I}^{ws} < \boldsymbol{I}^{ws}_{collapse} \\ 1, & if\ \boldsymbol{I}^{ws} \ge \boldsymbol{I}^{ws}_{collapse} \end{cases} \quad (13)$$

The presented method is applicable to large systems that include all feeders of a substation. The weather severity indicator assists in determining the failure probability of the overhead lines that will be comparatively equivalent within the analyzed distribution network. This is particularly observable in the event of hurricanes when equivalent wind speeds have an impact across distances of large geographical areas. Thus, it can be considered that the wind speed will not change while simulating high-speed wind occurrences in the analyzed distribution networks. The line segment length between two poles in distribution systems i.e., the span is also quite similar as it depends on the voltage level of the distribution system and the height of the pole. Therefore, the Eq. (14) can be used to calculate the failure probability for an overhead distribution line with a total length of $\boldsymbol{l}^{T}$. This equation considers that the probable failures are independent of one another and that the probability of failure for the line between two poles is the same throughout the whole distribution system.

$$\boldsymbol{P}^{l^T}_{f}(\boldsymbol{I}^{ws}) = 1 - \left[1 - \boldsymbol{P}^{l}_{f}(\boldsymbol{I}^{ws})\right]^{\frac{l^T}{l}} \quad (14)$$

Another important factor in presenting the assessed high-speed event is the desired network recovery time. This calculation starts when the failure-causing event occurs until the network fully recovers. It extensively depends on several factors, such as the backup resources, capabilities of the repair staff, geographical location, and the intensity of the windstorm that will result in damage. Since the network recovery time varies and is dependent on each scenario, this emphasizes a requirement for comparative analysis. This study identifies the factor that determines the intensity indicator, $\boldsymbol{I}^{i}$ as the duration of time needed to repair 1 km of line damaged by the event. However, the weather severity indicator, $\boldsymbol{I}^{ws}$ and the intensity indicator, $\boldsymbol{I}^{i}$ are the two factors that characterize the simulation of an event.

In this article, the resilience enhancement by hardening is realized considering undergrounding the overhead distribution lines. Therefore, hardening of lines actually involves strengthening the line as well as the support structure as underground lines do not require any supports. Therefore, the work reported in this article considers that the failure probability of hardened lines is zero and the overall failure probability of an overhead distribution system (line and support tower together) to be same as that of the distribution line since the failure probability of a distribution line is relatively high compared to the supporting pole.

### 5.2. Generation of damage scenarios

The presented method utilizes a Monte Carlo simulation (MCS), in which several scenarios are produced to simulate every possible event. The MCS is an approach to estimating mathematical operations and simulating the functioning of complex systems by the use of statistical modeling and random sampling [40]. For complex problems that would be difficult to resolve by standard mathematical analysis, MCS can be utilized to find approximative answers straightforwardly. A random number generator, a programming language, and the ability to handle arrays are the minimum requirements for MCS. The majority of MCSs follow a sequence that entails modeling a system using probability density functions (PDF), repeatedly sampling (or scenarios) from the PDFs, and estimating the characteristics that are obtained as a consequence of the sampling (or scenarios). In all different scenarios, $\boldsymbol{C}$ keeps the weather intensity factor where the damaged lines can vary depending on the uniformly distributed random numbers, $\boldsymbol{r} \sim \mathscr{U}(0,1)$, generated in (15).

$$\boldsymbol{F}^{L}_{C}(\boldsymbol{I}^{ws}) = \begin{cases} 0, & if\ \boldsymbol{P}^{l}_{f}(\boldsymbol{I}^{ws}) < r \\ 1, & if\ \boldsymbol{P}^{l}_{f}(\boldsymbol{I}^{ws}) \ge r \end{cases} \quad (15)$$

This equation is used to determine if the occurrence in scenario, $\boldsymbol{C}$ had any impact on a distribution line, $\boldsymbol{L}$. The variable $\boldsymbol{F}^{L}_{C}$ will have a value of 1 if the event has an impact on a distribution line, and 0 otherwise. The probability of failure to all distribution lines is compared to random values between 0 and 1 to determine the operational status of the line. If the failure probability exceeds the random value, the overhead line is considered to be impacted by the event. The random number is used to generate each scenario in order to allow for variations in the effected lines. It is assumed that events with this type of extreme wind speed never impact hardened lines.

## 6. Numerical studies

The proposed method is tested on the IEEE 69-bus system impacted by extreme weather events. MCS is used to estimate the failure probability of each distribution line and generates 1000 different scenarios. The failure probability for each scenario is calculated by evaluating the status of each overhead distribution line. The status of each overhead distribution line can be verified by sampling the failure probability distribution of the overhead line. Each overhead line is considered to have an operational mode and a failure mode, and the failure of one line is assumed to be independent of the others. Hurricanes are used as a typical example of a severe interruption to assess the effectiveness of this method. The probability distribution of one or more-line failures at different wind speeds is shown in Fig. 9. We can observe that the failure probability is relatively low (6%) when five lines fail simultaneously. For a network size of 69 buses 6%-line failure probability yields very small number and is ignored, but for larger system size this 6% may be a very significant number and for those cases higher order failure need to be considered for calculations. Therefore, the present work emphasizes up to four lines of failure, high-order situations can also be represented in a similar manner whenever required.

### 6.1. Assumption

The structure of the network is shown in Fig. 10. The network has 68-line sections with a total load of 3800 kW and 2690 kVar. The network data is available in [41]. Consider that each line in the IEEE 69-bus system is 0.25 km long and that the event lasts for 5 h. In the base scenario, a wind speed of 35 m/s ($\boldsymbol{I}^{ws}$) and a repair time of 6 h ($\boldsymbol{I}^{i}$) are considered. It is also assumed that a maximum of 8% of the overall network length is hardened and that the network includes three SSs. However, when selecting a few lines for hardening, two aspects are taken into consideration. Firstly, Economic aspects: as hardening lines can be a costly process, it is necessary to harden the minimum number of lines required to achieve the desired level of resilience. Secondly, Resilience aspects: to maximize resilience through line hardening,

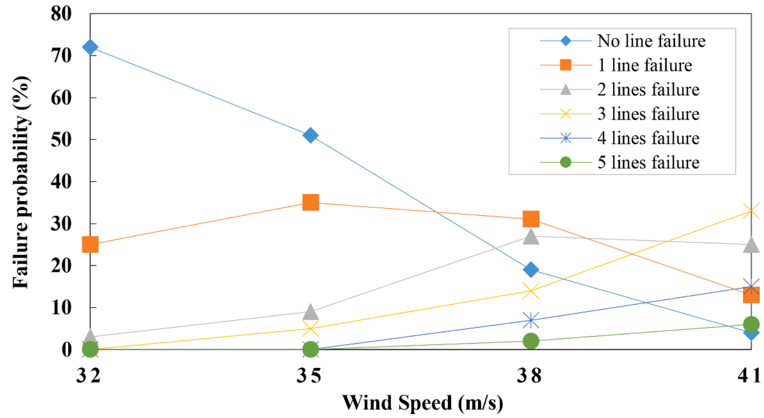


**Fig. 9.** Failure probability distribution at different wind speeds.

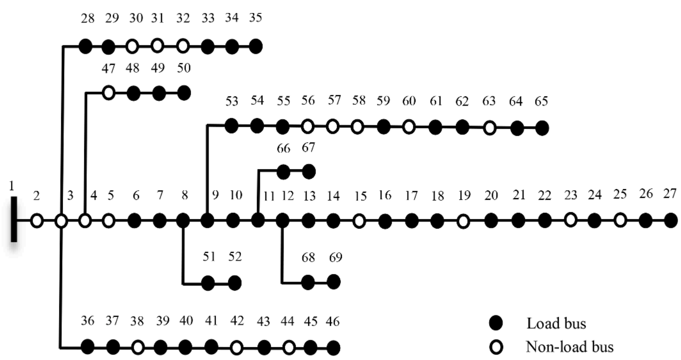


**Fig. 10.** Radial structure of IEEE 69-bus system.

priority should be given to hardening the lines in areas where no energy resources are available. The main parameters, including network peak load and installation costs, are shown in Table 3. To determine the operation and maintenance costs of network parameters, 2% of the installation cost has been assumed. Since the usable lifetimes of the installations vary, the costs have been annualized in order to be compared. For hardened lines, the usable lifetime is considered 35 years, although SSs and DER have been given a 15-year consideration. The following subsection discusses the results obtained from the proposed optimization method.

### *6.2. Results and comparative analysis*

The SRMs generated using the proposed method for the given scenario, concentrating mainly on SRMs with a reasonable investment, are shown in Fig. 11. This figure presents how the resilience of the network increases with increasing investments by comparing the required investment to achieve the related resilience. The EENS and RAI of the network due to a high wind-speed event are equal to 54.47 MWh and 19.64% respectively when no investment is made. By increasing investment amounts by 2.497 M$, it is possible to reduce the EENS by 1.513 MWh and enhance the RAI by 97.4%. Fig. 11 shows that when investment increases, the EENS decreases considerably for SRMs 2, 3, and 4. However, the amount of investment increased significantly between SRM 4 and 5, but the EENS decrease is not that significant. Furthermore, very small EENS reduction between SRM 5 and 6, despite a large increase in investment. It's important to note that the optimal network solution during extreme weather conditions can vary based on different factors such as the requirements of the system operator and the consumer's demands, critical loads of the network, economic perspective, etc. The resilience of the analyzed network concerning investment prospects may be optimally balanced between SRM 2 and around a maximum of 1 M$ of investment.

Fig. 12 represents the amount of investment required for different categories relevant to the outputs shown in Fig. 11 for different SRMs. As can be shown, installing SSs can reduce the EENS by almost 66%, while installing SSs, MTs, and PV systems can reduce the EENS by nearly 86%. Other solutions, such as line hardening, would need to be used to provide higher levels of resilience, although the investment required in this instance is significantly higher. It should be noted that there is no

**Table 3**
Parameters for the IEEE 69-bus Test System.

| Class | Parameter | Value | References for obtained value |
|---|---|---|---|
| System components | Peak load | 7.58 MW, 5.39 MVar | [29] |
| Investment | $IC^R_{SS}$ | $4700/SS | [42] |
| | $IC^R_{PV}$ | $1962/kW | [43] |
| | $IC^R_{MT}$ | $333/kW | [44] |
| | $IC^R_{LH}$ | $621,371/km | [45] |

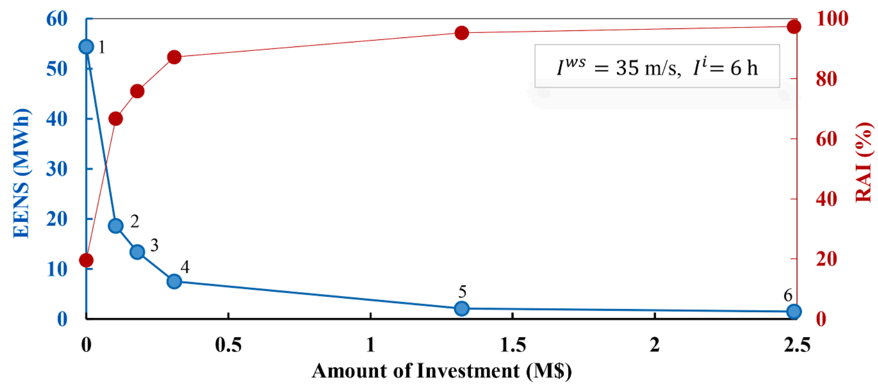


**Fig. 11.** EENS for various investment amounts in base case scenario.

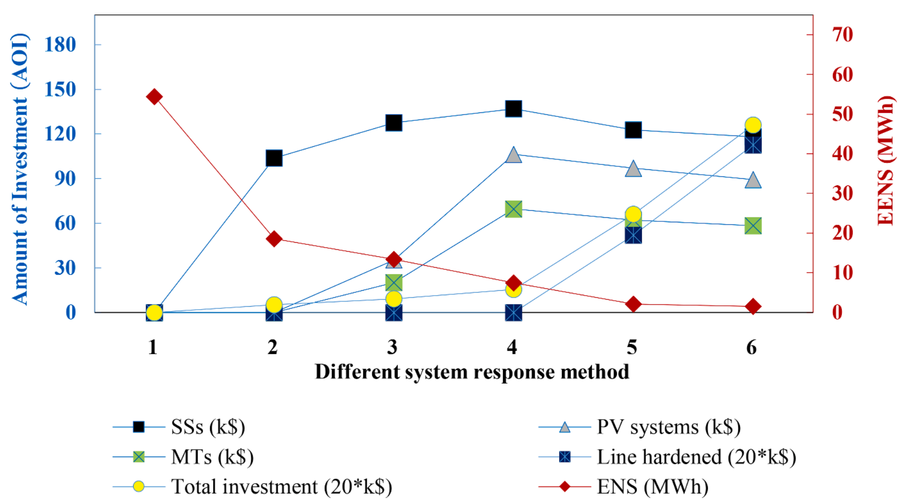


**Fig. 12.** EENS for different categories of investment in base case scenario.

question as to why simultaneous optimization for the different types of investment is preferable to sequential optimization. Sequential optimization is typically biased toward investing in one category of installation over the others, based on the sequence in which the phases are conducted and the stop limitations to move from one phase to another [46]. The example that follows shows how to analyze the profitability of investments as a post-processing of the obtained data to look into the economic effects of the network.

It is considered that EENS enhancements are evaluated in terms of the VoLL. The VoLL is the value of an energy unit that is not provided. Thus, it is desirable to find the minimal occurrence rate of the studied event at which the specified investments can remain economical for a certain VoLL, for example, 25 $/kWh. The profitable performance of SRMs varies based on the occurrence rate of the event, as shown in Fig. 13. When the VoLL reduction is greater than the amount of investment, it is considered to be profitable. If the event being considered occurs only once a year, the specified investments shown in Fig. 13 would result in a profit at the predefined VoLL. However, as predicted, the investment profitability reduces as the occurrence rate of the event drops. The SRMs become unprofitable at an occurrence rate of one event every ten years for higher investments or at an occurrence rate of one event every twenty years or more.

Finally, a comparative analysis of variations in the weather severity indicator ($\boldsymbol{I}^{ws}$) and intensity indicator ($\boldsymbol{I}^{i}$) is conducted. The results achieved by varying the wind speed are shown in Fig. 14, where the $\boldsymbol{I}^{ws}$ changes from 32 m/s to 41 m/s with an intensity indicator of 6 h. Although the starting EENS for the analyzed events is significantly diverse, the reliable responses of the network are all in a relatively similar range. Resilience limits between 4.5 to 20 MWh of EENS are estimated by the amount of investment between 0.5 to 1 M$.

Fig. 15 shows the results with adjustments in the $\boldsymbol{I}^{i}$, with a range of 4 h to 12 h needed to repair a km of damaged overhead distribution lines when the $\boldsymbol{I}^{ws}$ is fixed to 35 m/s. The results imply that the beginning EENS increases in direct proportion to the $\boldsymbol{I}^{i}$ increase without any additional investment. However, the reliable responses of the network are observed in an interval close to the results previously obtained for the different wind speed analyses.

The influence of the intensity indicator on the results is a crucial observation of this comparative analysis. In contrast to the weather severity indicator, which is dependent on the different weather circumstances, distribution utility management, and operational development procedures can significantly enhance the severity factor. This factor has a noticeable influence in the early network state prior to investment, where the EENS rises proportionally to it.

## 7. Conclusion

This article proposes a strategy for enhancing distribution system resilience through a stochastic investment decision-making method. Three approaches, including the installation of SSs and DER and hardening overhead lines, have been presented as potential methods for enhancing distribution system resilience. This proposed method aims to be applicable to large-scale distribution systems, and GA is utilized due to its ability to deal with highly nonlinear problems. The main contribution of this article is the proposed single-stage multi-criteria optimization method to simultaneously optimize the three different types of

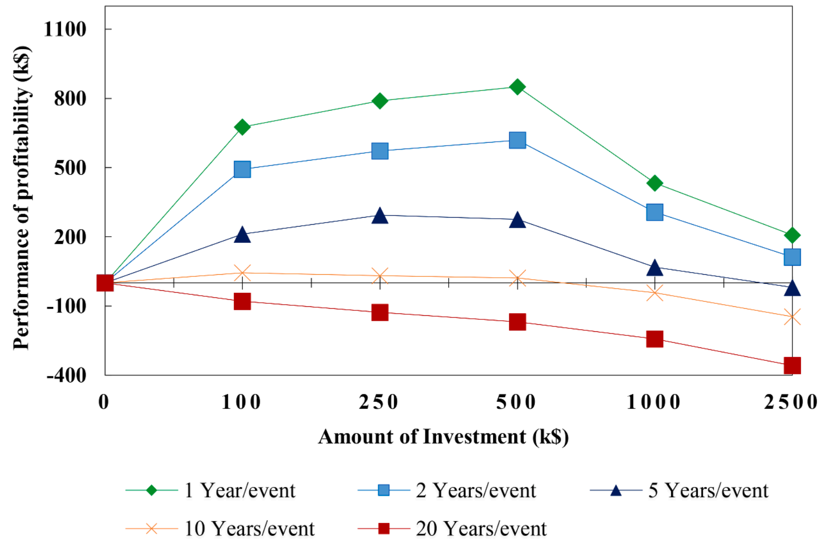


**Fig. 13.** Profitability performance based on the frequency of the event.

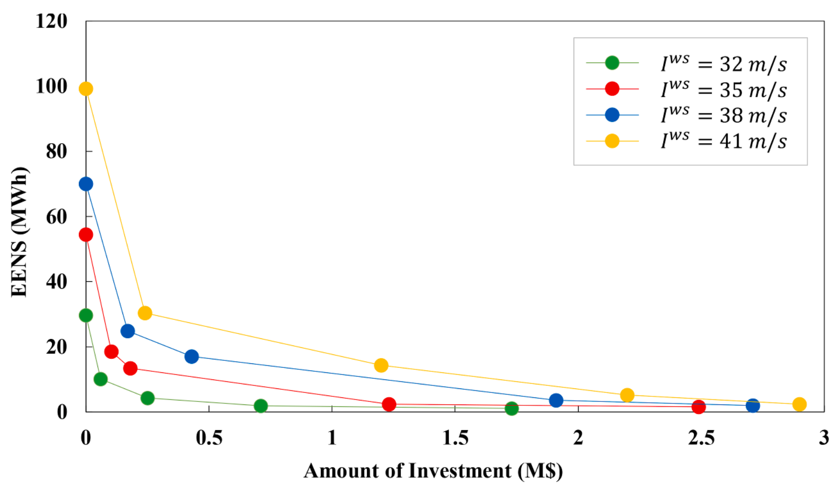


**Fig. 14.** Response from the system at different wind speed.

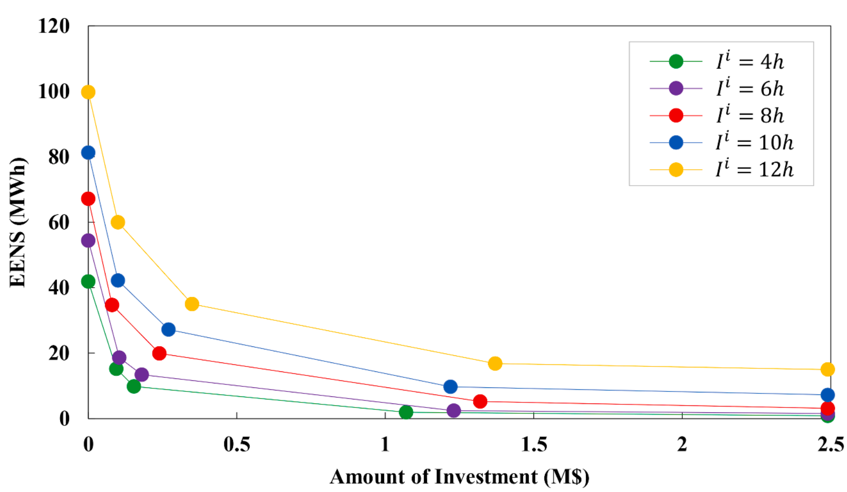


**Fig. 15.** Response from the system at different intensity indicators.

investments and maximize distribution system resilience. Unlike other research articles, this method provides an understanding of how different options interact and complement one another. The proposed method for evaluating the resilience of distribution systems has several distinctive features, including the incorporation of automation, hardening, and DER, consideration of multiple scenarios, support for investment decision-making to enhance resilience, and the inclusion of VoLL in the decision-making process. The results demonstrate how investment strategies are selected and quantify the economic benefits of enhancing network resilience.

Incorporating certain constraints as a post-processing stage in the assessment of the optimal solution has been shown to be essential to the operation of the optimization method. This technique avoids localized solutions to issues with a limited viable zone, which usually arise in the solutions found by the GA. However, the proposed method has a few limitations. Firstly, the proposed method assumes that the investment options are mutually exclusive and collectively exhaustive. Secondly, the method does not consider social and economic factors that may impact investment decisions related to distribution system resilience. Future research in this field should focus on addressing these limitations and further validating the effectiveness of the proposed optimization method. Overall, the proposed method in this article offers a comprehensive and practical approach for enhancing distribution system resilience through investment decision-making that considers the impact of automation, hardening, DER, multiple scenarios, and VoLL.

## CRediT authorship contribution statement

**Puspendu Ghosh:** Conceptualization, Investigation, Writing – original draft. **Mala De:** Conceptualization, Investigation, Supervision, Writing – review & editing, Investigation.

## Declaration of Competing Interest

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

## Data availability

Data will be made available on request.

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