



Providing a preventive maintenance strategy for enhancing distribution network resilience based on cost–benefit analysis

Ebrahim Ghorbani¹ · Mohammad Ebrahim Hajiabadi¹ · Mahdi Samadi¹ · Hossein Lotfi¹

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Abstract

Today, with the increasing electricity consumption and human needs for this energy, the availability of electricity has received more attention than before. Natural disasters, especially hurricanes, cause great damage to the power systems, leading to economic and social disruptions and public discontent. In general, reliability issues are not the perfect answer for evaluating the distribution network in the face of extreme events and the need for distribution network resilience studies. Resilience is the ability of the power system to withstand disruptions and rapid reconstruction against events that are unlikely to occur but have a high impact. In this paper, the preventive maintenance strategy is used for cost–benefit analysis of the objective function, which includes the cost of preventive maintenance, cost of resilience, and cost of reliability. In addition to cost analysis, reliability and resilience indicators in implementing various scenarios are analyzed. Finally, the system resilience diagrams for the severity of different accidents are presented. Based on the simulation results for several scenarios, the best preventive maintenance scenario is selected to improve the resilience level and reliability of the distribution network after the incident. The proposed strategy is implemented on the part of the standard test system to show the justification of the proposed approach.

Keywords Resilience · Cost–benefit analysis · Reliability · Preventive maintenance · Reconstruction

Abbreviations

ENS	Energy not supplied
EENS	Expected energy not supplied
PM	Preventive maintenance
VOLL	Value of lost load
USE	Unserviced energy (EUSE)
EUSE	Expected unserved energy (EUSE)
RBTS	Roy Billinton Test System

1 Introduction

1.1 Motivation

Today, the status of electrical energy is extremely important in human life, so uninterrupted power outages or unintended blackouts in power grids cause damage and sometimes irreparable damage. In recent decades, with climate change, we have witnessed severe incidents and storms worldwide which cause widespread outages in electricity distribution and transmission networks, which sometimes take a long time to repair and eliminate network damage. More than 80 percent of power outages in the USA between 2003 and 2012 were caused by weather hazards such as hurricanes [1]. For example, Hurricane Sandy caused power outages for more than 8.66 million customers in 2012 [2]. In 2017, Hurricane Irma caused damage to 2,900 power poles and power outages for 62% of Florida customers [2]. Therefore, to deal with such widespread outages, it is necessary to adopt measures and activities, referred to as preventive maintenance (PM), to improve resilience. Planned preventive maintenance

✉ Mohammad Ebrahim Hajiabadi
Me.hajiabadi@hsu.ac.ir

¹ Department of Electrical and Computer Engineering, Hakim Sabzevari University, Sabzevar, Iran

to improve resilience helps us reduce damage, costs, and subscriber outages time by identifying accident-prone areas and making them more resilient to natural disasters.

1.2 Literature review

Abnormal natural phenomena or natural disasters such as storms, snow, earthquakes, and floods can occasionally severely damage power grids. Assessing the state of the network against these phenomena cannot be done with classical reliability studies, and the need for different studies called resilience studies. Studies related to improving the reliability and resilience of the power system with the help of maintenance strategy are reviewed in two separate sections, respectively.

- *Reliability concerns*

In [3], the maintenance strategy is proposed for overhead power lines based on monitoring the status and reliability of the network. This study determines the relationship between the status monitoring data and the failure of the overhead line rate. It then calculates the expected energy not supplied (EENS) index using the new overhead lines failure rate. A new method is introduced for scheduling maintenance of transmission equipment. This method focuses on failure mode analysis. Also, different programs are introduced for maintenance based on the Markov model in each failure mode [4]. In [5], a model is provided to determine the schedule maintenance of the reclosers in the distribution network based on the importance of reliability. A method is provided for selecting critical components from the point of view of system reliability and reliability-based maintenance of all equipment in the distribution network [6, 7]. In [8], the inspection-based model is used to determine the inspection rate of distribution network feeders. The variable failure rate with long-term time in this model is modeled by several Markov models in consecutive years. The total cost, including maintenance, inspection, and the disconnection of feeders, is minimized. A preventive maintenance (PM) strategy is presented on a set of feeders of the distribution network to minimize the outage time of users [9]. A novel probabilistic maintenance approach is proposed in which the reliability level of the distribution network components is evaluated according to the three-state Markov model [10]. In [11], a method is presented for managing the assets of transformers in the distribution network by calculating the crisis index. A zone-based strategy is introduced for inspecting transformers and distribution network breakers [12]. An inspection-based model combines equipment failure due to aging equipment and repairable failure to achieve the optimal equipment inspection rate in each area. An approach for technically and economically adapting the reliability of

power distribution networks through an optimization method consisting of a mathematical model and a meta-heuristic solution method to obtain an optimal program for efficiently managing maintenance tasks is presented. [13]. In [14], a two-objective mathematical model is presented for energy hub planning, considering preventive maintenance policy to minimize costs and maximize system reliability. A new short-term preventive maintenance method is proposed that considers the potential support of distributed generators and batteries as well as the uncertainty in power generated by DGs [15].

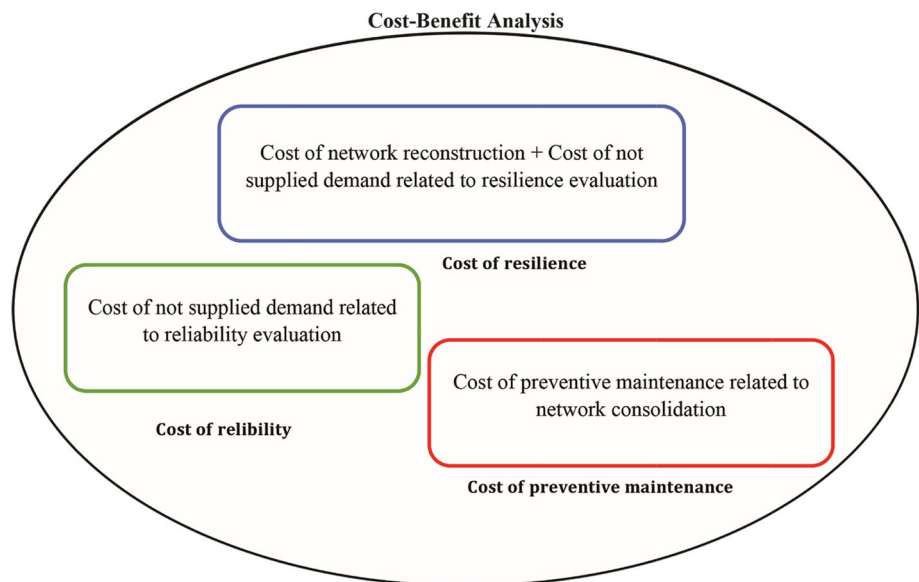
- *Resilience concerns*

Arab et al. [16] propose a comprehensive framework and supportive theory to enhance the resilience of the distribution grid against storms and other natural disasters. This study aims to accelerate recovery and minimize related economic, social, and physical disorders. In [17], a mathematical program is proposed to repair a transmission system's equipment after a significant disturbance (e.g., storm). The transmission system repair problem involves dispatching crews to repair damaged electrical components to minimize blackout [17]. Aref et al. [18] propose a two-stage stochastic mixed-integer linear program to optimize the routing of repair crews in the distribution grid after natural disasters. The first step is to dispatch the repair team to the damaged parts. The second step is to rebuild the distribution system using distributed generators and reconfigure it [18]. In [19], a three-step method is proposed to control integrated, flexible home appliances to change load demand at the distribution network level to improve service restoration against natural disasters. Moreover, uncertainties related to loading and solar generation are considered in the proposed framework. In [20], a two-stage optimization model is presented to increase the resilience of distribution grids subjected to extreme weather events. However, they showed damage uncertainty through a multifaceted set. Me et al. [21] performed a two-stage random optimization to select the optimal preventive maintenance of the distribution grid exposed to severe natural disasters (e.g., storm). They looked at increasing resilience by minimizing expected costs. In [2], a mixed-integer nonlinear programming model is presented to enhance the resilience of obsolete distribution grids in multiple storm events using risk-based optimal maintenance scheduling. A general outline of these references has been organized and presented in Table 1 to ease access to essential information of the research, such as merits and demerits.

Table 1 Some of recent literature about considered problem

References	Type of study perspective		Type of repairs	
	Reliability	Resilience	Preventive	Corrective
[3]	✓			✓
[4]	✓			✓
[5]	✓			✓
[8]	✓			✓
[9]	✓			✓
[10]	✓			✓
[16]		✓		✓
[17]		✓		✓
[18]		✓		✓
[19]		✓		✓
[20]		✓		✓
Our research	✓	✓	✓	

Fig. 1 Graphical representation of the proposed scheme



1.3 Contributions

A review of previous studies shows that the maintenance strategy is used to improve the reliability or enhance the distribution system’s resilience. In contrast, neither study has attempted to improve both functions simultaneously. Moreover, the above studies have not examined the planning of pre-disaster maintenance strategies to increase the resilience of power distribution systems. Repair and maintenance operations are performed in the network after the incident. In this study, a preventive maintenance (PM) strategy is presented to improve the resilience and reliability of the distribution network against the severe incident. For this purpose, to investigate the improvement in the level of resilience, after

obtaining geographical information of parts of the distribution network at risk of natural disasters such as floods and storms, four PM scenarios are performed in these areas. By performing these scenarios, the PM strategy’s role in improving the distribution network’s resilience level is determined, and its importance becomes increasingly obvious. Also, the proposed objective function minimizes the sum of the costs of resilience, reliability and preventive maintenance. The cost–benefit analysis is proposed to implement different scenarios to evaluate the considered approach from an economic and technical point of view. In this analysis, the cost is related to implementing different scenarios in the test network. The benefit is related to improving the level of resilience and reliability. The proposed scheme for the considered problem in this study is shown in Fig. 1

1.3.1 Research structure

The problem formulation is introduced in the second part, along with the problem constraints. In the third section, simulation and review of the resilience index in four scenarios are presented along with graphs and their analysis. The conclusion is also presented in the fourth section.

2 Problem formulation

In the proposed PM strategy, we seek to reduce the cost of damage caused by the severe incident. Therefore, to achieve a complete objective function in this field, Eq. (1) is proposed in this study. In this section, the objective functions and constraints of the problem are presented as follows:

2.1 Objective function

In general, the considered objective function minimizes the sum of the cost of resilience, cost of reliability, and cost of preventive maintenance (PM), as we understand it from the equation.

$$\begin{aligned} \text{Min (OF)} &= \text{Cost}_{\text{PM}} + \text{Cost}_{\text{rel}} + \text{Cost}_{\text{res}} \\ &= \underbrace{\sum_a \sum_f (L_f \times C_{af} \times X_{af})}_{\text{Cost of Preventive maintenance}} + \underbrace{(\text{EENS} \times \text{VOLL})}_{\text{Cost of reliability}} + \underbrace{((\text{EUSE} \times \text{VOLL}) + (L \times C \times K \times P))}_{\text{Cost of resilience}} \end{aligned} \tag{1}$$

2.1.1 Modeling the cost of resilience

The cost of network resilience, according to Eq. (2), consists of two parts:

$$\begin{aligned} \text{Cost}_{\text{res}} &= C_{\text{EUSE}} + C_{rb} \\ &= ((\text{EUSE} \times \text{VOLL}) + (L \times C \times K \times P)) \end{aligned} \tag{2}$$

The first part of the above equation is the cost of expected unserved energy (EUSE) to users, and the second part is the cost of network reconstruction.

- *Network reconstruction cost*

In this study, the cost of network reconstruction is considered relative to the cost of implementing the distribution network. In other words, with the occurrence of the incident, the distribution network is destroyed, so after the incident, the network must be rebuilt. C is the cost of network reconstruction per kilometer. Certainly, after the incident and depending

on the severity of the incident, which in this study is modeled with K ($0 < K < 1$), the cost of network reconstruction is different. In addition, the cost of network reconstruction depends on the length of the damaged network. Equation (3) shows the cost of network reconstruction after the incident.

$$C_{rb} = L \times C \times K \times p \tag{3}$$

where p indicates the probability of an incident. Therefore, C_{rb} is the expected cost of network reconstruction. One of the main reasons for prolonging outage after the incident is the long network reconstruction time. In this study, it is assumed that the time of network reconstruction is relative to the time of network construction. This ratio is completely dependent on the severity of the incident. The network reconstruction time can be calculated as follows:

$$T_i = L \times T_b \times K \tag{4}$$

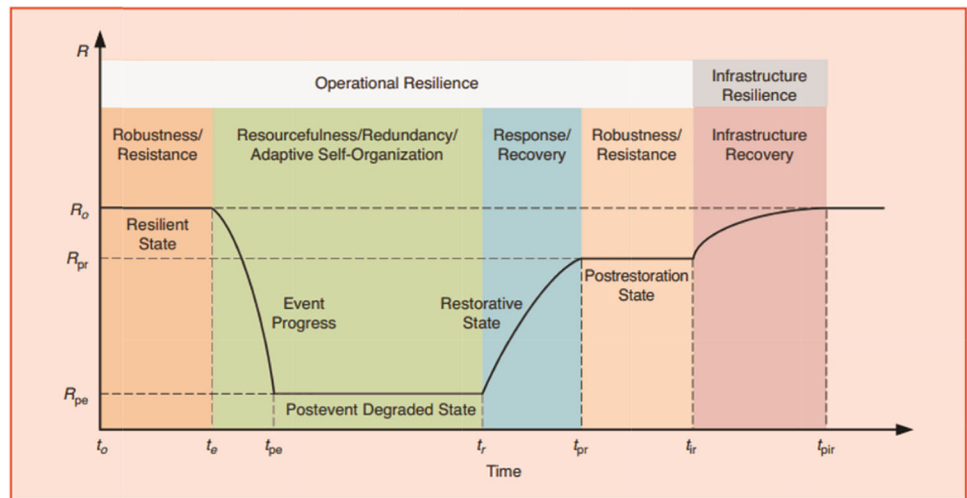
where T_i is the time of network reconstruction, which begins after the incident and continues until the end of the network reconstruction. L is the damaged network line length, T_b is the time of construction of medium voltage network in cri-

sis conditions, the average time of construction of medium voltage network is one week. K is the incident intensity coefficient, considered between zero and one. Certainly, a set of PM strategies aimed at strengthening the network structure can reduce physical damage to the network due to an incident. Reducing the damage to network equipment will reduce network reconstruction costs, and speed up network recovery after an accident. Equation (5) is used to model the effect of maintenance activities on improving the level of resilience.

$$K = K_b - K_A \tag{5}$$

In this regard, it is assumed that the A th preventive maintenance reduces the amount of incidents as much as K_A . In Eq. (5), K_b indicates the severity of the incident without considering the PM, and K indicates the severity of the incident after the A th preventive maintenance. By reducing the level of K in Eq. (4), the cost of network reconstruction and network reconstruction time is reduced according to Eqs. (3) and (4).

Fig. 2 Network resilience diagram after the incident [22]



- *Unservd energy after fault related to the resilience study* value.

It should be noted that unserved energy (USE) after fault is considered a resilience index in this study, which is presented in Eq. (6). Expected unserved energy (EUSE) is one of the important indicators of resilience obtained by multiplying the unserved energy caused by the incident into the probability (p) of an incident. The USE can be formulated as follows, according to Fig. 2.

$$USE = \int_{T_0}^{T_f} (L_b - R) dt \tag{6}$$

where L_b is the base load, T_0 is at the time of the accident, T_f is the network reconstruction time and R is the function of the load restored after the incident. The expected unserved energy (EUSE) is given in Eq. (7).

$$EUSE = USE \times p \tag{7}$$

In this study, the value of lost load (VOLL) in a major incident is assumed to be the same as the value lost in the reliability studies. Therefore, the $Cost_{EUSE}$ is formulated in Eq. (8).

$$Cost_{EUSE} = EUSE \times VOLL \tag{8}$$

2.1.2 Modeling the cost of reliability

The cost of reliability is obtained from Eq. (9).

$$Cost_{rel} = EENS \times VOLL \tag{9}$$

where expected energy not supplied (EENS) is the reliability index in times of crisis and VOLL is the cost of the lost load

$$EENS = \sum_{i=1}^N L_{ai} \times U_i \times p \tag{10}$$

where L_{ai} and N are the annual load and number of all nodes, respectively. U_i is the average duration of a permanent blackout at point i .

2.1.3 Preventive maintenance cost modeling

The cost of preventive maintenance (PM) can be modeled as follows:

$$Cost_{PM} = \sum_a \sum_f (L_f \times C_{af} \times X_{af}) \tag{11}$$

where C_{af} is the cost per kilometer of PM to improve the resilience of the A th activity in the f th feeder. This cost is per kilometer. L_f is the length of the f th feeder exposed to the incident, and preventive maintenance is performed on it. For X_{af} , there are two cases as follows:

In the first case, no PM is done, so $X_{af} = 0$, and if PM are done, $X_{af} = 1$ is considered.

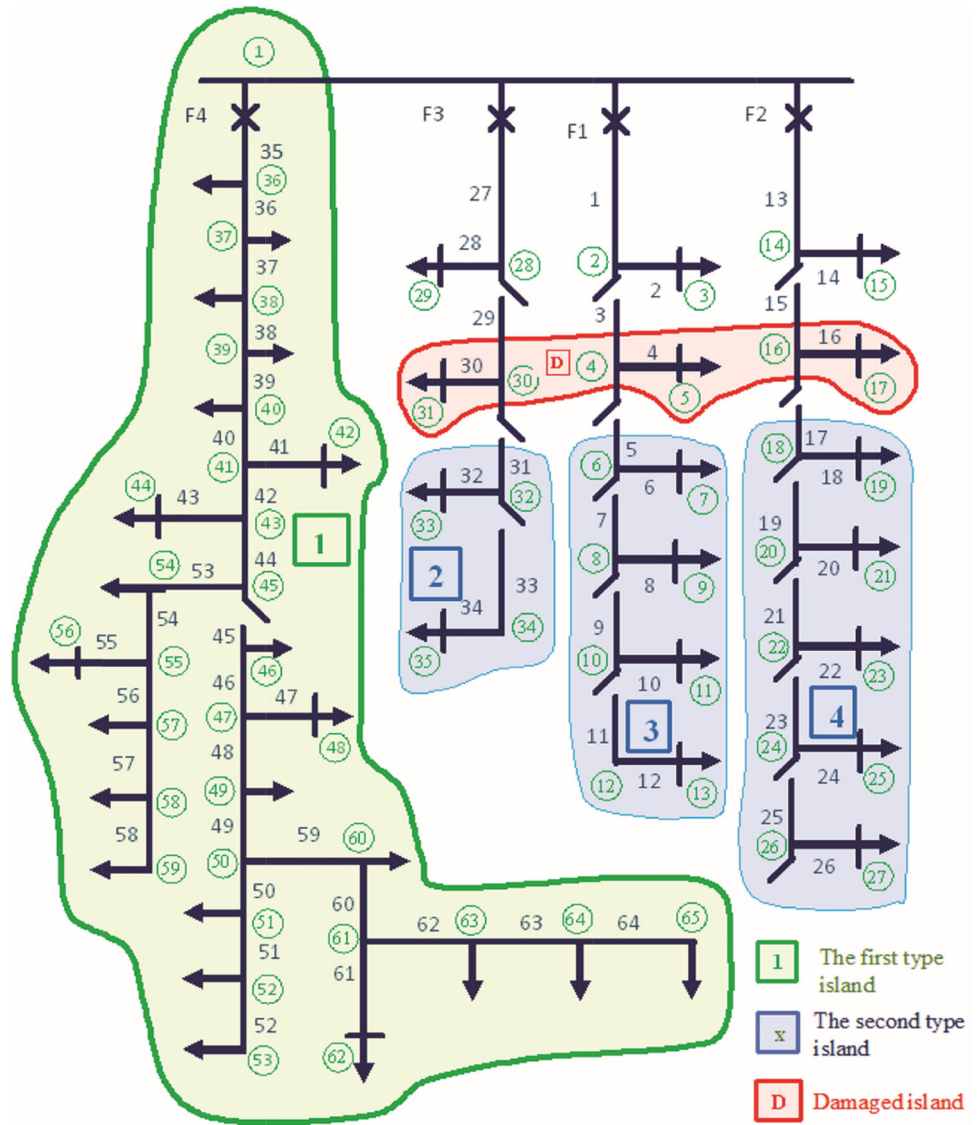
$$X_{ai} = \{0, 1\} \tag{12}$$

if $X_{ai} = 0$ Do not take any action.

if $X_{ai} = 1$ Take any action

The cost of PM varies according to the different activities in each work scenario. In each work scenario, the cost of PM varies according to the activities appropriate to that scenario.

Fig. 3 The RBTS bus 6 diagram



2.2 Constraints of the problem

The constraints of the optimization problem in this study are as follows:

- *Load flow equations*

The constraints of load flow equations are calculated from Eqs. (13)-(14):

$$P_j = \sum_{i=1}^{N_{Bus}} V_i V_j Y_{ij} \cos(\theta_{ij} - \delta_i + \delta_j) \tag{13}$$

$$Q_j = \sum_{i=1}^{N_{Bus}} V_i V_j Y_{ij} \sin(\theta_{ij} - \delta_i + \delta_j) \tag{14}$$

where P_j and Q_j are the active and reactive power injected by the network in the i th bus, respectively [23–25]. Y_{ij} and θ_{ij} are the amplitude and angle of the voltage at the i th bus, respectively. Y_{ij} and θ_{ij} are the magnitude and angle of branch admittance between buses i and j , respectively.

- *Bus voltage range*

$$V_{min} \leq V_i \leq V_{max} \tag{15}$$

where V_{min} and V_{max} are the minimum and maximum allowable voltage value of i th bus, respectively [23, 24].

- *Feeder current*

$$|I_{f,i}| \leq I_{f,i}^{Max} \quad i = 1, 2, \dots, N_{feeder} \tag{16}$$

Table 2 Test system's data [26]

Number feeder	Line length (km)
2, 3, 8, 9, 12, 13, 17, 19, 20, 24, 25, 28, 31, 34, 41, 47	0.6
1, 5, 6, 7, 10, 15, 22, 23, 26, 27, 30, 33, 43, 61	0.75
4, 11, 16, 18, 21, 29, 32, 35, 55	0.8
44, 38	0.9
39, 42, 49, 54, 62, 37	1.6
36, 40, 52, 57, 60	2.5
64, 59, 56, 50, 46, 35	2.8
45, 51, 53, 58, 63	3.2
48	3.5

where $I_{f,i}$ and $I_{f,i}^{\text{Max}}$ are the amplitude of the current and the maximum current of i th feeder, respectively [23, 24].

- *Radial structure of the network*

The necessary condition for the network to work radially is as follows:

$$N_{\text{branch}} = N_{\text{bus}} - 1 \quad (17)$$

where N_{branch} and N_{bus} are the number of branches and buses, respectively [23, 25].

3 Case study simulation

The purpose of this section is to perform PM in different scenarios to improve the level of resilience of the distribution network on the standard Roy Billinton Test System (RBTS) and to compare the results of different scenarios in terms of reduction of EUSE and reconstruction time.

3.1 Bus 6 data from RBTS

Figure 3 shows bus 6 of the RBTS [22]. This bus has 40 load points with an average load of 10.7155 MW, also, the number of users on this bus is equal to 2938. Table 2 shows the Bus 6 feeder information.

Assuming that this network is located in a mountainous point, due to rain and flooding, feeders No. 1, 2, and 3 are damaged. In this case, the total loads connected to these three feeders are 5.9002 MW, which will be taken out of service due to the incident. Figure 2 shows the incident-prone area. In case of flood in this area, lines 2 and 3 related to feeder 1 with a length of 0.6 km each, lines 15 and 16 related to feeder 2 with a length of 0.6 and 0.8 each, and line number 29 with

a length of 0.6 km are generally destroyed. This incident causes a total outage in these three feeders. Feeder number 1 can maneuver with feeder number 4. This is not possible for feeders 2 and 3. With the help of switching and maneuvering operations, the range of outage can be minimized in the event of an incident. The following is a set of actions after the incident:

Feeder No. 1 In feeder number 1, by opening the switch at the beginning of line number 3, LP1 load point and by closing the end switch of the same feeder and feeding on feeder number 4 and simultaneously opening the switch at the beginning of line number 5, LP3 to LP6 loads are supplied, 0.9684 MW is supplied with electricity in the first hour with switching maneuvering operation. The LP2 load point remains unchanged until lines 3 and 4 are reconstructed. The reconstruction time of each kilometer of medium voltage network is one week. Therefore, with the total length of lines 3 and 4 with a length of 1.4 km, the outage time of the LP2 load point is approximately equal to 9.8 days, equivalent to 235.2 h.

Feeder No. 2 In feeder No. 2, by opening the switch at the beginning of line No. 15, the LP7 load point is supplied with electricity, thus supplying 0.1659 MW in the first hour, and the LP8 to LP13 load points remain without electricity until lines 15 and 16 are reconstructed, which a total amount of unsupplied load is 3.9534 MW. The outage time of these load points until the reconstruction of lines 15 and 16 with a length of 1.55 km is 10.85 days, equivalent to 260.4 h.

Feeder No. 3 In feeder No. 3, by opening the switch at the beginning of line No. 29, the LP14 load point is supplied. Thus, 0.4697 MW of power is supplied in the first hour, and the load points of LP15 to LP17 remain without electricity until the reconstruction of Line 29, which a total amount of unsupplied load is 1.4757 MW. The outage time of these load points until the reconstruction of Line 29, 0.8 km in length, is 5.6 days, equivalent to 134.4 h.

To simulate this incident, some coefficients such as the probability of occurrence and the severity of the incident are needed so that the probability of occurrence $p = 0.01\%$ and the severity of the incident $K = 100\%$ are considered. Also, the time of reconstruction of the medium voltage network (T_i) per kilometer is 7 days.

3.2 Simulation results

To perform the study and calculations, four scenarios are considered. Considering these scenarios and comparing them with each other, the resilience index is measured according to Eq. (7). In reviewing the scenarios at each stage, the network reconstruction time is also improved by performing PM, and overall network resilience is improved.

Base scenario

Fig. 4 Resilience curve in the base scenario

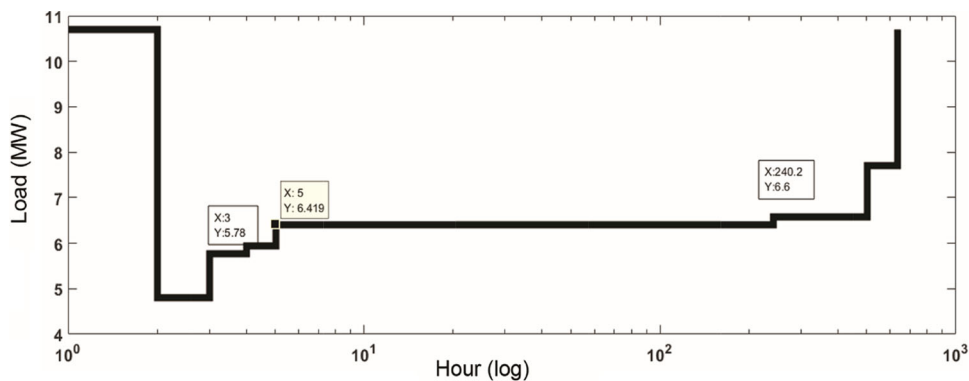


Table 3 Activities with their costs

Type of maintenance activity	Cost (\$ per 3 km)
A1: Move the poles in the direction from the floods	7708.33
A2: Correction of the installation depth of the pole along with the replacement of worn poles	4309.52
A3: Stoning around the poles	476.19
A4: Installation of the additional poles on long span length	1928.57
A5: Installation of the low voltage boards on the pole	1109.47

Table 4 The rate of incident reduction

Type of maintenance activity	The rate of reduction of network degradation in critical situations (%)
Repair and molding of poles A3 and A5	10
Replacement of some worn and shallow poles A2 and A4	30
Network replacement and replacement of A1 fittings	50

PM activities are not performed on the three required network feeders in this scenario. According to Fig. 4, the most outage time and unsupplied load are observed. The EUSE value is 24.9274 MWh, and the network reconstruction time is 240.2 h. Before implementing the scenarios, a set of PM activities to improve the system’s resilience before the possible incident are presented in Table 3.

Table 4 shows the rate of incident reduction of each type of repair in each scenario. A decrease of 10% is related to the first scenario, a decrease of 30% is related to the second scenario, and a decrease of 50% is related to the third scenario.

• Scenario 1

In this scenario, minor PM activities such as repair and molding of poles and minor excavations are performed in the affected area. As a result of doing this scenario, the severity of the incident is reduced by ten percent. According to Fig. 5, the effect of PM on the network is specified. Comparing Figs. 5 and 4 in a load of 6.6 MW, the network reconstruction time for the base scenario is 240.2 h, while in scenario 1 it is equal to 216 h.

• Scenario 2

In this scenario, PM activities, including replacing worn poles with the relevant fittings, are performed, and the effect of reducing this scenario on the severity of the incident is considered 30%. Figure 6 shows the EUSE value in Scenario 2, equal to 17.4668 MWh, which is reduced compared to Scenario 1. Reconstruction time in this scenario is 47 h less than the previous scenario at 6.6 MW and is equal to 169 h.

• Scenario 3

As a result of doing this scenario, the severity of the incident is reduced by 50% and the network reconstruction time after the incident is significantly reduced. In this scenario, the entire network, including the poles and replacement fittings, and the installation location of the foundations are moved out of the flood path to significantly reduce the flood effect.

Figure 7 shows the EUSE value in Scenario 3. Comparing this scenario with the previous three scenarios, it can be seen that the EUSE value in this scenario is much lower than the previous scenarios. The EUSE value in this case is 12.4932 MWh. At 6.6 MW, the reconstruction time compared to the base scenario, one and two, decreased by 117.4, 93.4, and 46.4 h, respectively, and is equal to 122.6 h. For a complete comparison of the unsupplied load value in the four scenarios, all four diagrams are plotted together in Fig. 8. As can be seen, with the implementation of each scenario, the EUSE value which is related to the area below the graph decreases.

Fig. 5 Resilience curve in the first scenario

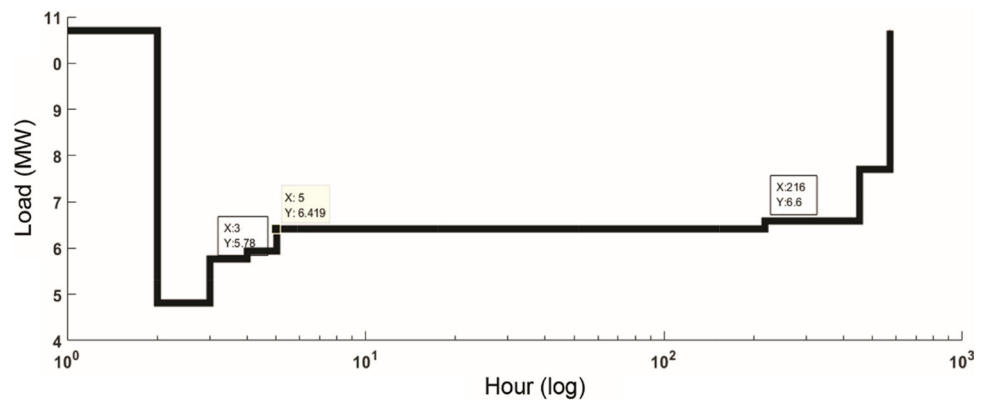


Fig. 6 Resilience curve in the second scenario

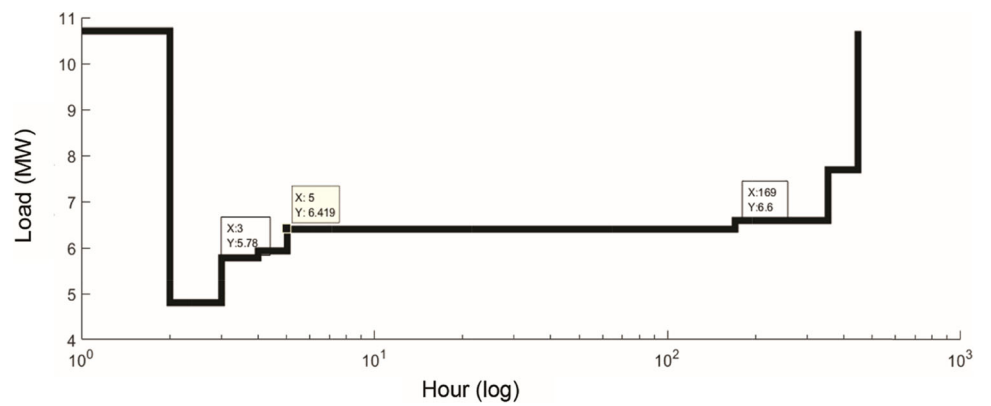


Fig. 7 Resilience curve in the third scenario

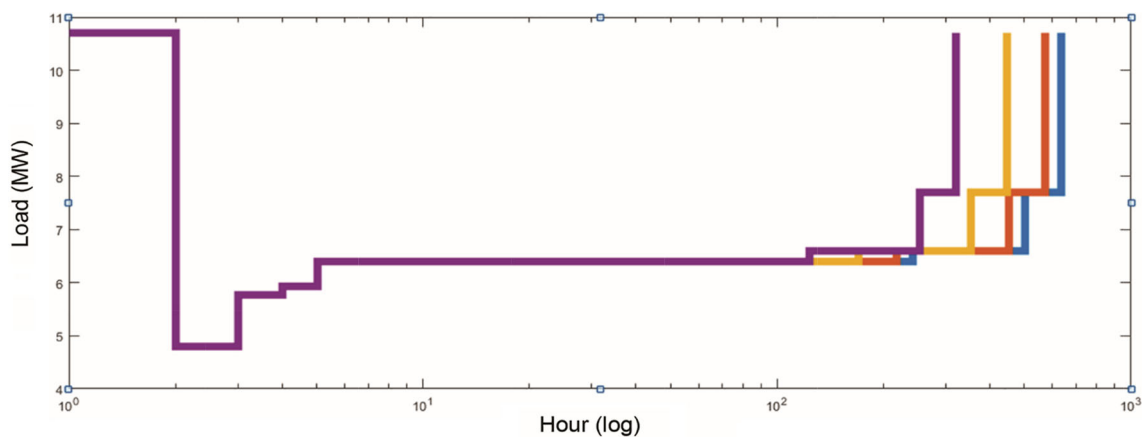
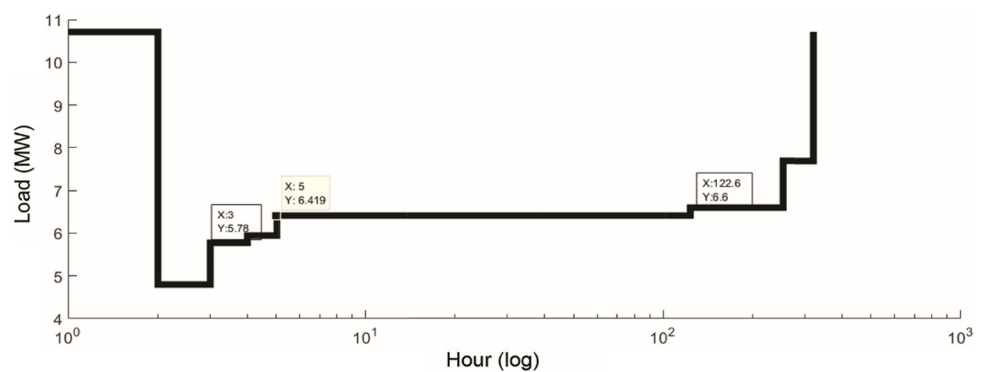


Fig. 8 Resilience curve in all scenarios

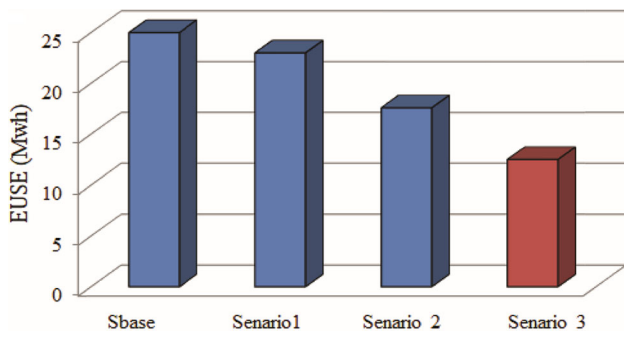


Fig. 9 Comparison of the EUSE value between scenarios

Also, the amount of reconstruction time is decreased, which indicates an improvement in the network resilience index.

The EUSE value in each scenario is shown in Fig. 9. As shown in Fig. 9, the EUSE value in the base scenario is greater than all scenarios, and the third scenario has the lowest EUSE value compared to the other scenarios. In fact, at each stage of the implementation of the scenarios, the EUSE is reduced.

In Table 5, a comparison is made between the objective resilience function in all four scenarios. According to Table 5, it is clear that in each scenario, the cost of PM increases, and in return for the increase in costs, the amount of EUSE decreases significantly, so that the cost of PM is reduced compared to the cost of EUSE. It should be noted that in calculating the costs of this table, the probability of occurrence $p = 0.01$, and the severity of the incident is considered 100%.

According to Table 4, considering that no PM is done in the incident-prone network before the incident, the highest cost of resilience and the highest cost of network reconstruction is observed in the base scenario. Performing PM to improve resilience at each stage reduces the costs of resilience, reliability, and network reconstruction, so it is clear that the more targeted PM activities before the incident to improve resilience reduce overall costs and ultimately improve network resilience.

In the following, the effects of the probability of events and the severity of different incidents are examined and explained with a diagram. Figures 10 and 11 show the probability of doing scenarios 1 and 2. In these figures, the vertical axis is the severity of the incident in terms of percentage, and the

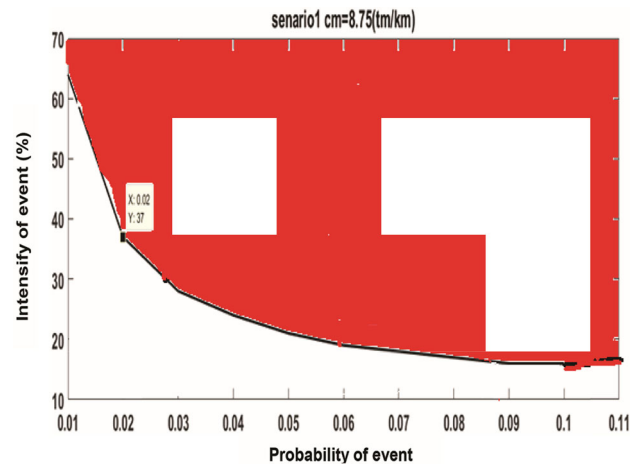


Fig. 10 The probability of doing the first scenario

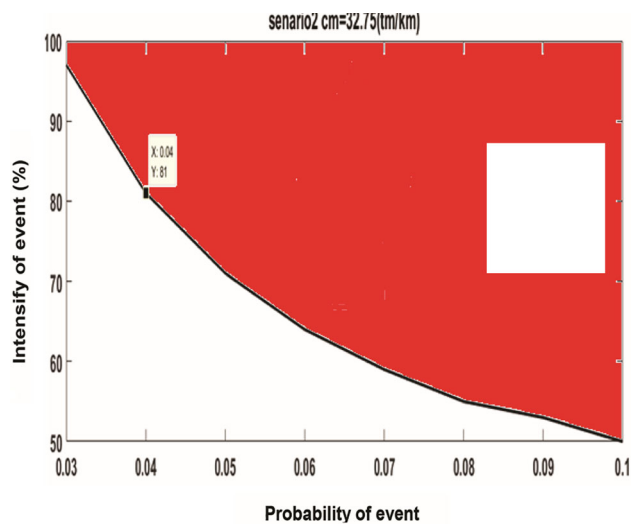


Fig. 11 The probability of doing the second scenario

horizontal axis is the probability of the accident. Based on Fig. 10, for example, at the point $x = 0.02$ and $y = 37$, we can say that 0.02, if the severity of the incident is more than 37%, it would be economical to do a scenario. In general, the area above the chart is a convenient and economically viable area to perform PM activities to improve the distribution network efficiency per scenario one, shown in red.

Table 5 Comparison of costs (\$)

Scenarios	Cost of reliability	Cost of EUSE	Cost of network reconstruction	Cost of PM	Cost of resilience
Base	9706.89	296,750	91,071.45	0	387,821.45
Scenario 1	9706.89	267,154.76	81,964.28	2083.33	349,119.04
Scenario 2	9706.89	207,940.45	63,750	7797.61	271,690.45
Scenario 3	9706.89	148,726.16	45,535.7	9635.42	194,261.86

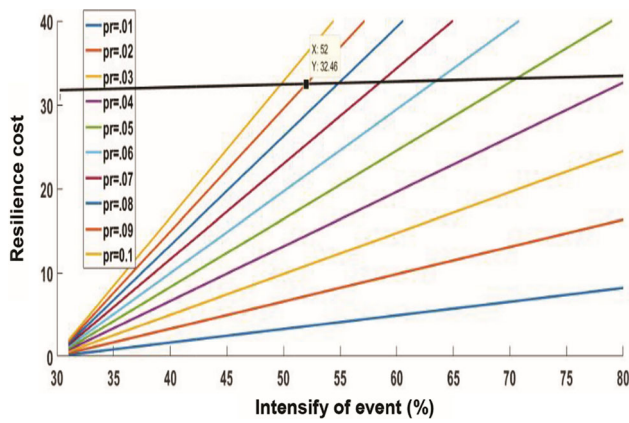


Fig. 12 The rate of being economical of scenario 1

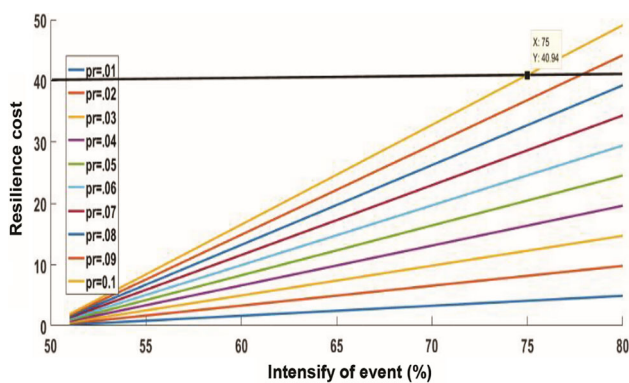


Fig. 13 The rate of being economical of scenario 2

Figures 12 and 13 are related to scenarios one and two. The horizontal axis of the severity of the incident, and the vertical axis is the cost of resilience. The horizontal line is black in the number of repair costs in scenarios one and two. In these diagrams, the conditions for performing repairs to improve the distribution network’s efficiency are investigated in terms of the probability of events and the severity of various incidents. These figures show that the area above the horizontal line is part of the economic area. Based on Fig. 12, for example, at the point $x = 23$ and $y = 8.57$ and the probability of an incident occurring is 0.04, which is marked in purple, that is, in the severity of the incident less than 23 with a probability of 0.04, it is not economical to perform PM activities to improve the distribution network efficiency in the scenario.

In the following, we review and compare the three scenarios to see how likely it is that the incident will occur and its severity. As shown in Fig. 14, in the diagram of scenario 1 (including all three colors) for incidents with a probability of occurrence of 0.01 and also the severity of the incident of 60%

and above with a preventive maintenance cost of \$ 2083.33 is cost-effective. Scenario 2 (red and blue) is economical for incidents with a probability of occurrence of 0.03 and above with a preventive maintenance cost of \$ 7797.6. Scenario 3 (red color) for incidents with a probability of occurrence of 0.05 and above and the severity of the incidents 80% and above with a preventive maintenance cost of \$ 9635.52 is cost-effective. It is also specified that the space above Scenario 3 (red) should be used for all three scenarios. That is, it is suitable for all three scenarios. The space above Scenario 2 (red and blue) is economically suitable for Scenarios 1 and 2. The space at the top of Scenario 1 to Scenario 2 is suitable for doing Scenario 1.

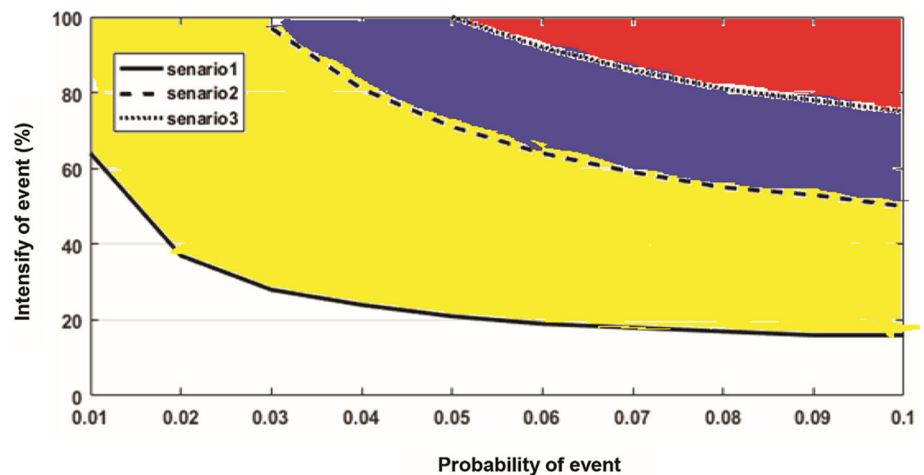
4 Conclusion

Sudden natural disasters cause high costs and damage power distribution networks, and many household and industrial users are without electricity for several days. Therefore, there is urgent to make repairs with a resilient approach. In such cases, important distribution network areas exposed to natural damage should be identified, and natural and geographical conditions should be repaired. Also, examining the probability of occurrence and severity of incidents in this regard helps a lot to improve resilience indicators. So that in any case of occurrence and severity of various initial incidents, it should be checked whether the repairs are economically viable to improve the resilience of the distribution network or not, then that maintenance should be done.

To evaluate the resilience of the distribution network against natural disasters, in this study, a set of preventive maintenance activities to improve resilience and reliability has been applied in an area of the network with a high probability of an incident occurring. In this regard, four PM scenarios in a test network based on Cost–benefit analysis are implemented, and each scenario’s results are compared. The proposed objective function minimizes the sum of the cost of resilience, reliability and PM costs in this study.

The simulation results in different scenarios show that the PM strategy has good results in reducing the cost of resuscitation. PM activities improve resilience indices in each scenario compared to the base scenario and provide network restoration conditions after the incident. In this way, performing PM activities with a cost-cutting approach provides the conditions that sudden incidents have the least impact on the network and, to a large extent, cause the network to be stable.

Fig. 14 Investigation of the probability of occurrence of three scenarios together



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Declarations

Conflict of 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.

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