A two-stage approach to enhance distribution network resilience against natural disasters

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The natural disasters such as floods and storms have always led to widespread damages and serious disruptions in power distribution networks. After presenting a new index to quantitatively calculate the resilience of the power distribution network, this paper proposes a two-stage approach to enhance distribution network resilience against natural disasters in the presence of distributed generation (DG) units including solar cells and conventional gas-fired power sources. The first stage includes determining the boundaries of isolated zones and the optimal capacity of the DG units in each zone to improve the resilience by considering budget constraints. The second stage includes determining the optimal location of DG units in each zone to optimize the distribution network losses. A genetic algorithm (GA) based optimization method is developed to solve the proposed problem. The performance of the proposed approach is assessed and illustrated by numerical studies on a practical power distribution system from Iran.

keywords: *Flood, Storm, Resilience, Distributed Generation, Genetic Algorithm.*

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1. INTRODUCTION

Resilience in the power system means the ability to predict high-impact low-probability events, to quickly recover from these disruptive events, and to acquire knowledge to modify for planning and operation to inhibit or mitigate the impact of similar events in the future [1].

Evaluation of traditional distribution networks is performed using reliability criteria. By using the same criteria, the power system is capable of dealing with predefined threats and providing high-quality power to customers [2]. However, given the widespread blackouts that have been occurring over the recent decades, low probability/high impact events and an increase in the number and severity of unexpected events in the future due to climate change, the need for resilience enhancement of distribution network is becoming increasingly apparent; for example, the Sandy storm in 2012 caused infrastructural damage to the eastern United States, destruction of several distribution transformers and flooding of several distribution stations. In the summer of 2010 and 2011, floods and heavy rains in Australia caused damage to several power poles, transformers and overhead lines, and consequently, caused a power outage of about 150,000 customers [3].

When an unexpected event occurs, the access to the main distribution network and the power supply may become impossible; moreover, due to damage to the distribution network equipment, some isolated regions may be created in the distribution network. Therefore, traditional distribution network recovery methods cannot guarantee supplying consumers after an unexpected even [4].

When failure occurs in the main network, an alternative way of supplying loads is to isolate the fault location using switching equipment. In this way, some isolated zones are formed, and the customers are supplied with distributed generation (DG) units. DG units can prepare the network to respond quickly to natural disasters, and thus can improve the network resilience by supplying customers with an accessible and secure resource [5].

To enhance distribution network resilience, in one sense, the configuration of the distribution network needs to be modified by adding new switching equipment. Therefore, the problem of optimal planning of the installation location of switches should be considered as one of the resilience enhancement requirements. Additionally, planning of DG, which means determining the optimal type, location and size of these sources, should be taken into account. Ultimately, a resilient distribution network can be achieved even with a limited budget.

The problem of resilience enhancement of the distribution network has two stages. First stage: determining the number/location of switches for forming isolated zones in the distribution network as well as determining the capacity of the DG in each zone; these are done by considering the main aim of the problem that is to improve the resilience of the network and to limit the investment costs of the new equipment. Second stage: optimally locating DG in each zone to optimize losses.

Solar cells as a renewable energy source and conventional gas-fired sources as a non-renewable energy source are considered as DG units. In the mathematical formulation, the introduced model for solar cell can be used for any other type of source having variable power output. In other hand, the introduced model for conventional gas-fired sources is common for all sources having constant power output. Therefore, considering more DG types will not change the generality of the proposed model.

Actually, resilience is a new concept in the field of power systems studies. Most studies in this field have presented the concept of resilience [6], how it affects the distribution network operation [5], and presenting a formulation of resilience index [7], measuring and enabling of resiliency [8], quantifying resiliency with distributed energy resources [9].

In [10], a methodology to quantify resiliency using graph theoretic approach and maintain power supply to critical loads during extreme contingencies has been proposed. Resource adequacy is discussed as another important factor of network resilience in [11]. This reference introduces the index of availability of DG units in extreme events and optimizes the size and site of these resources. Moreover, a deterministic approach is used based on the adequacy of resources to investigate the improvement of network resilience against an extreme event.

In [12], the formation of a microgrid from an existing distribution network to improve system resilience parameters is discussed. In this reference, by modeling unexpected events and moving from an existing distribution network to a microgrid, it is shown that the resilience indexes are optimally improved. In [13], studies of resilience are focused on distribution networks with a variety of DG units. In this reference, first, the concept of resilience and its characteristics and how switching equipment affects each resilience characteristic is discussed, and then, the problem of switch placement in distribution networks with a variety of DG units is proposed to improve the resilience of the distribution network.

In [14], a resilience-enhancing strategy to make distribution systems more resilient against wind-induced climatic hazards is proposed. In this reference the proposed strategy consists of three resilience-oriented design, namely line hardening, installing backup distributed generators (DGs), and adding automatic switches. A probabilistic framework for planning resilient distribution system via distributed wind and solar integration is presented in [15].

Providing a comprehensive study on optimal resilient planning of distribution networks aiming to find an optimal solution for simultaneous optimal feeder routing problem and substation allocation, finding types of installed conductors and cost-effective hardening of the lines considering the deliberate attacks on urban critical infrastructures, is organized in [16].

The most important disadvantages of the mentioned references are as follows:

- When it comes to the indexes of network resilience improvement, the network resilience against supplying load demand and the DG sources resilience have not been assessed simultaneously as a unique index.
- In many of the mentioned studies, the investment cost limitation to improve network resilience has not been taken into account.
- Simultaneous designing of DG sources (solar cells as a renewable energy source and natural gas as a non-renewable energy source) and Switch Planning, which was intended to improve the resilience of the distribution network, has not been considered in previous studies, while it is a concern in the present study.

In the present paper, after describing the objectives of the resilience enhancement problem for a distribution network, the modeling of common natural events, such as floods and storms, is conducted, and the impact of these events on the resilience of the distribution network are evaluated. Following with introduction of resilience indexes for the load supply and DG sources (solar cells and conventional gas-fired sources), a new index is presented to quantitatively calculate the resilience of the distribution network in the presence of DG. Then, using the genetic algorithm as a tool for optimization, we attempt to enhance the resilience of the distribution network in two stages. The first stage involves determining the boundaries of isolated zones and optimal capacity of the DG units in each zone, to improve the resilience by considering budget constraints. The second stage involves determining the optimal location of DG units in the network to optimize the distribution network losses. Finally, the performance of the proposed approach is demonstrated by performing numerical studies on a practical distribution system from Iran.

2. RESILIENT DISTRIBUTION NETWORK

Having a resilient distribution network, it is attempted to identify the fundamental changes in the field of system planning studies by introducing some indexes and adding them to the planning equations.

In this paper, the problem of enhancing distribution network resilience is studied in two stages, and the solution is obtained for each of the following cases:

A. Distributed Generation Planning

DG units improve the resilience of the distribution network by supplying loads when the main network fails. In addition, considering the high cost of construction, optimal planning and finding the best combination of resources are important in a given weather condition.

In fact, determining the optimal type, location and size of DG have a major impact on the resiliency of the distribution network. As such, utilizing these resources in improper sites and sizes not only deteriorates the resilience of the distribution network, but also increases system losses and costs.

B. Switch Planning

Switches are not able to generate power or supply loads, but are employed as a tool in distribution networks so that the network can easily use alternative suppliers. Accordingly, a set of isolated zones are formed using switching equipment and customers are supplied by DG units. As a result, the resilience of the distribution network is improved [17].

However, the installation of this equipment requires relatively high costs. Therefore, the optimal placement of switches is one of the planning variables that has an effect on the resilience indexes of the system and determines the optimal network configuration.

C. Budget Constraints

The budget constraints and investment costs in the distribution networks have led to the selection of plans that are economically justified in addition to technical justification.

In the economic evaluation, on the one hand, the investment costs of new equipment (DG units and switching equipment), and on the other hand, the cost of system losses, which determines the optimality, efficiency and long-term maintenance costs of the system, are examined.

In this paper, by introducing a new index, the distribution network resilience is enhanced in two stages in the presence of DG units. In the first stage, the problem is formulated to improve the resilience of the network as the main objective function, take into account the investment costs of the new equipment as a constraint and using the genetic algorithm as the optimization method. The result of this stage is the determination of the number and location of the switches, and thus, the determination of the isolated zones in the distribution network. In addition, the capacities of the DG units in each zone are determined at this stage. In the second stage, the optimal locations of DG sources are obtained by considering the losses of the entire distribution network and including the results obtained from the first stage (that is, islanded zones and the capacity of sources in each zone).

3. MODELING NATURAL DISASTERS

Natural disasters are usually very uncertain events. Therefore, it is difficult to estimate, model and predict them. Many efforts to raise our awareness of natural disasters have been based on historical data and the tutorials we have learned. The prediction of a natural disaster is often based on statistical or simulated models [18]. For evaluating the impact of weather events on the distribution network, their impact on distribution network components should be estimated. A normal logarithmic distribution curve can be used to illustrate the failure probability of distribution network components. Using these curves, known as fragility curves [19], the failure probability of a component for a given event level (wind speed or flood) is obtained. The generic shape of the fragility curve is defined according to equation (1).

$$P(damage/x) = \int_{x}^{-\infty} \frac{1}{\sigma\sqrt{2\pi}} \times \exp(\frac{-(\ln x-\mu)^2}{2\sigma^2})dx \quad (1)$$

where $P(damage/x)$ is the failure probability of the component at the specified event level x, and parameters μ and σ represent the logarithmic mean and standard deviation of the fragility curve, which are calculated from statistical data over a given period.

The generic fragility curve shown in Fig. 1 corresponds to the failure probability of the components as a function of the weather intensity.

Fragility curves have been used in studies where the aim is to assess the impact of a weather event or a natural disaster on the resilience of transmission or distribution networks [19].

For some given weather characteristics of the study region, by having the weather profile (e.g., wind speed and flood velocity) as well as the dependence of the failure probability of network components on the severity of the weather event that can be extracted from statistical records, the fragility curves for the network components are obtained. These curves help us identify components of the network that are at high risk of climate events, and consider them in assessing resilience [19].

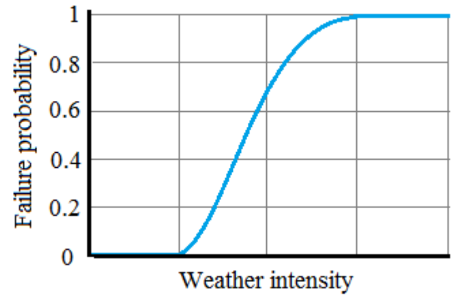

Fig. 1. Fragility curve [19].

In this paper, the most common natural disasters affecting distribution networks, namely storm and flood, are studied. In summary, the steps of modeling the impacts of storms and floods on distribution network components can be described as follows:

- Using statistical data to predict the path of storm and flood, as these events often follow the path that they consist of.
- Dividing the distribution network into several weather regions based on the path of the storm and flood and considering the specific wind speed and flood velocity in each region.
- Using fragility curves to calculate the failure probability of the components in different weather regions.

4. MATHEMATICAL FORMULATION

In the two-stage problem of enhancing the resilience of the distribution network, the decision variables at each stage are described as follows:

- Stage one: Determine the optimal number and location of switches (isolate zones) and determine the capacity of DG units in each zone.
- Stage two: Determine the optimal location for the installation of DG units in each zone.

In the following, the mathematical formulation of each stage is described.

A. First stage

At this stage, the main objective is to optimize the network resilience index. In this paper, the Distribution Risk Index (DRI) is used to evaluate the resilience of the distribution network.

The objective function of the problem at this stage, which aims to minimize DRI, is composed of two parts and is defined in equation (2). The lower the DRI the higher the resiliency of the network.

$$obj \Rightarrow .Min \Rightarrow DRI = DRI_{load} - GRI_{DG} \quad (2)$$

where DRI_{load} indicates the network's resilience for supplying the load. Actually, this index reflects the amount of load shedding in the distribution network when an unexpected event occurs.

Since DG units can act as alternatives to the main source for supplying loads in case of unexpected events, the accessibility of these units in the event of disasters is of particular importance [11]. The generation resiliency index, GRI_{DG}, indicates the amount of available production of DG units that is used as the resilience index of DG sources when unexpected events occur. In fact, the larger this index, the higher the resilience. Therefore, to evaluate the impact of DG units on the resilience of the distribution network, it is necessary to simultaneously calculate the network resilience for supplying the load and DG resilience. Finally, the resilience index of the whole network in the presence of DG is obtained. In other words, DRI_{load} is proportional to the amount of shed load, and GRI_{DG} is proportional to the amount of available generation in case of an unexpected event. Therefore, with a larger generation resiliency index and a lower distribution risk index, a more resilient distribution network is achieved. Actually, these two indexes act in opposite directions, and to calculate the network resilience, the two indexes must be subtracted from each other. In the following, the calculations of these indexes are discussed.

A.1. Load Supply Resiliency Index

Equations (3)-(9) are used to calculate DRI_{load}.

$$DRI_{load} = \sum_{\sec=1}^{k} LS_{\sec} \times P_{\sec}(W,F) \times S_{\sec} \tag{3}$$

$$LS_{\sec} = \frac{\sum_{t=1}^{T}\sum_{l=1}^{n} Load(t)_{l,\sec}}{T} \tag{4}$$

$$Load(t)_{l,\sec} = w(h) \times w(m) \times Load(p)_{l,\sec} \tag{5}$$

$$P_{\sec}(W,F) = P_{\sec}(W) + P_{\sec}(F) - P_{\sec}(W)P_{\sec}(F) \tag{6}$$

$$P_{\sec}(F) = 1 - (1 - P_{T.single}(F))^{NTF} \tag{7}$$

$$P_{\sec.T}(W) = 1 - (1 - P_{T.single}(W))^{NT} \tag{8}$$

$$P_{\sec}(W) = P_{\sec.c}(W) + P_{\sec.T}(W) - P_{\sec.c}(W)P_{\sec.T}(W) \tag{9}$$

In equation (3), $P_{\sec}(W,F)$ is the probability of a section failure (the points in the distribution network where the conductor is cut off) that is caused by a storm or flood, $LS_{\sec}$ is the amount of load shedding when a section fails, $S_{\sec}$ is the sensitivity coefficient based on the value or priority of the load for the respective section and K is the total number of studied distribution network sections.

The value of $LS_{\sec}$ is obtained from equation (4), where $Load(t)_{l,\sec}$ is the amount of load l in the section at time t; n is the number of loads that have been shed due to the section failure, and T is the period of study after the event.

Weather conditions and seasonal events affect the pattern of load consumption. Fortunately, many of these events occur repeatedly over one year, so the behavior of the power system loads is a recurring pattern. In this study, for building load models, the data are modeled as monthly and hourly weight factors. Equation (5) can be used to calculate the load at the desired time.

where $w(h)$ is the hourly weight factor, $w(m)$ is the monthly weight factor and $Load(p)_{l,\sec}$ is the peak load of l in the section. Figures 2 to 4 show, respectively, the hourly curve, the monthly curve and the peak load of the network buses.

In equation (6), $P_{\sec}(F)$ is the failure probability of the section due to the flood and $P_{\sec}(W)$ is the failure probability of the section due to the wind.

The major impact of the flood is on the utility poles of the distribution network. In fact, the impact of flooding on the utility poles of the distribution network can lead to the failure of the poles and consequently the failure of the relevant section. For utility poles in the distribution network adjacent to coastal

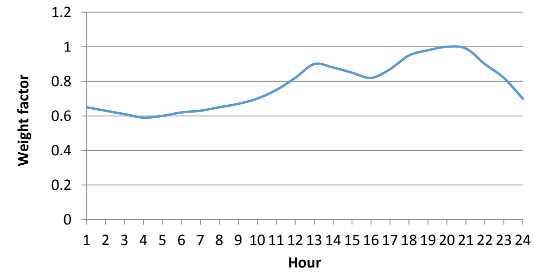

Fig. 2. Load hourly curve.

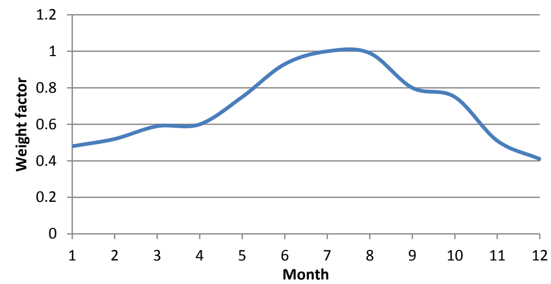

Fig. 3. Load monthly curve.

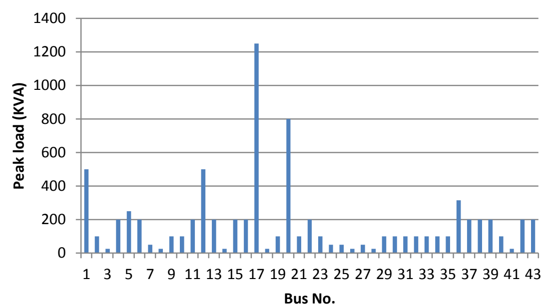

Fig. 4. Peak load of buses.

areas or along rivers, one of the most important factors in the failure of the section is the risk of flooding. Therefore, a suitable model should be used for utility poles located in these areas to assess resilience. To do this, we first use statistical data from past records to extract flood fragility curves, which is the failure probability of utility poles as a function of flood velocity for the studied area. Then, for the pole at risk of flooding, the failure probability is determined. Finally, using equation (7), it is possible to calculate the failure probability of the section as a function of flood velocity. In this equation, $P_{T.single}(F)$ is the failure probability of each pole due to flooding as a function of the flood velocity and NTF is the number of utility poles in the section that is at risk of flooding. If the studied network is not exposed to flooding, according to equation (7), the failure probability of the section will depend only on the events caused by winds and storms.

Based on [2], about 90% of the equipment outages in the network are related to severe wind and storm events. The effects of severe winds and storms are exerted for two major components, i.e., the conductors and the utility poles of the distribution network. Additionally, the failure of each section due to wind and storm events depends on the failure of both poles and conductors.

Since in each section of the distribution network there may be several utility poles that are connected in series, the failure of each pole alone leads to the failure of the respective section. Given that the utility poles failure is independent of each other and assuming the same failure probability for the utility poles in one section, equation (8) can be used to calculate the section failure probability due to pole failure. In this equation, $P_{\sec.T}(W)$ is the failure probability of the section due to the pole failure as a function of wind speed, $P_{T.single}(W)$ is the failure probability of each pole alone as a function of wind speed and NT is the number of utility poles in the section.

Since the pole failure or conductor failure lead to the loss of the section, so the failure probability of a section can be stated by equation (9).

where $P_{\sec.c}(W)$ is the failure probability of the section due to conductor failure as a function of wind speed. It should be noted that the values of $P_{T.single}(W)$ and $P_{\sec.c}(W)$ are obtained from the pole fragility curve and the conductor fragility curve, respectively.

Supplying critical loads are in priority in unexpected events [4], so losing the critical loads will extremely reduce network resiliency. For this purpose, the load sensitivity coefficient $S_{\sec}$ is used in the calculation of resilience; accordingly, higher sensitivity loads have a more pronounced effect on network resilience. Loads are divided into various categories with different sensitivity coefficients.

A.2. Distributed Generation Resiliency Index

Since DG units are an alternative to supply customers when the main network fails, these resources must be accessible and secure when a natural disaster occurs, so that the network can be prepared to respond quickly. Therefore, the resilience of DG units, which implies the availability of the generation of these resources, should be considered in the network resilience studies [11].

Since solar cells and conventional gas-fired sources are used as DG in this paper, equations (10)-(13) can be used to calculate the resilience of these sources.

$$GRI_{DG} = \frac{\sum_{t=1}^{T} \sum_{k \in bus} (P_{pv}^{k} A_{pv}^{k}(t) + P_{gen}^{k} A_{gen}^{k}(t)) \sum_{n \in bus} R_{k-n}}{T} \quad \textbf{(10)}$$

$$R_{k-n} = 1 - P_{k-n}(W, F) \quad \textbf{(11)}$$

$$P_{k-n}(W, F) = \sum_{\sec \in (k-n)} P_{\sec}(W, F) \quad \textbf{(12)}$$

$$A_{pv}^{k}(t) = \frac{G_{ING}(t)}{G_{STG}} \times (1 + k(T_c(t) - T_{ref})) \quad \textbf{(13)}$$

where P_{pv}^{k} and P_{gen}^{k} are the nominal powers of the solar cells and conventional gas-fired sources, respectively; $A_{pv}^{k}(t)$ and $A_{gen}^{k}(t)$ are, respectively, the power availability factors of the solar cells and conventional gas-fired sources installed at bus k at time t (these values vary under different environmental conditions); T is the period under study after the event and R_{k-n} is the network reachability between buses R_{k-n} and n; $P_{k-n}(W, F)$ is the failure probability of network between buses and , which denotes the sum of the failure probabilities of all sections between the two buses according to equation 12.

Solar radiation and ambient temperature make solar power generation unstable [20]. Equation (13) shows the solar cells power generation under different environmental conditions.

where G_{STG} is the amount of solar radiation in standard conditions (1000 W/m2) and $G_{ING}(t)$ is the amount of solar radiation in the studied environmental conditions at time t; k is thermal coefficient of power generation under nominal conditions; $T_c(t)$ and T_{ref} are the ambient temperature around the cells in the studied environmental conditions and standard conditions, respectively [21, 22].

Given the conditions of natural disasters (storms and floods), ambient temperature and solar radiation during an extreme event, equation (13) can be used to determine power availability factors of the solar cells at the time of the study. Conventional gas-fired sources are DG units with constant and predictable output power. Due to high reliability, low initial investment cost and fast start-up, the gas-fired sources are widely used in distribution networks. The output power of a gas-fired source is under the influence of some thermodynamic constraints resulted from weather information and demand curves. Height and ambient temperature are the most important factors affecting the performance of conventional gas-fired sources. Actually, every 1000 ft increase in height, reduces the efficiency of these sources by 3% and their maximum output power by 3.8%.Moreover, every 10 degrees increase in the ambient temperature reduces the efficiency of these sources by 1% [23]. Therefore, having information about the temperature and height of the installation location of these sources at the time of weather events, the power availability of the conventional gas-fired sources can be easily obtained.

A.3. First Stage Constraints

The constraint that must be considered in the first stage of the problem of enhancing distribution network resilience is the budget limitation. One of the most important issues in a resilient distribution network is the investment cost limitation. Accordingly, the total investment cost of new generation sources and switching equipment cannot exceed a monetary budget (B) for the network. The investment costs of the resilient distribution network are calculated by equations (15)-(18).

$$TotalCost \leq B \quad \textbf{(14)}$$

$$TotalCost = IC_{pv} + IC_{gen} + IC_{sw} \quad \textbf{(15)}$$

$$IC_{pv} = \sum_{n \in N_{pv}} C_{pv} \times P_{pv}^{n} \quad \textbf{(16)}$$

$$IC_{gen} = \sum_{k \in N_{gen}} C_{gen} \times P_{gen}^{k} \quad \textbf{(17)}$$

$$IC_{sw} = \sum_{s \in N_{sw}} C_{sw}^{s} \quad \textbf{(18)}$$

where, IC is the investment cost; the values of C_{pv}, C_{gen} and C_{sw} are, the costs of construction of solar power plants, conventional gas-fired sources and new switches, respectively; N_{pv}, N_{gen} and N_{sw} are, respectively, the number of solar power plants, gas-fired sources and new switches installed in the network.

B. Second Stage

At this stage, by determining the isolated zones and capacities of DG units from the previous stage, the optimal location of DG is determined in each zone with the aim of loss reduction. The objective function of the problem at this stage is the network losses, which is expressed by equations (19) and (20).

$$obj \Rightarrow Min \Rightarrow CL_{total}^{normal} \tag{19}$$

$$CL_{total}^{normal} = (\sum_{\text{sec}} 3R_{\text{sec}} \times I_{\text{sec}}^2) \times T \times CE_{loss} \tag{20}$$

where CL_{total}^{normal} is the cost of total energy losses under normal operating conditions; R_{sec} and I_{sec} are, respectively, the values of resistance and current of the section, and CE_{loss} is the cost of energy losses per kWh.

B.1. Second Stage Constraints

Constraints that must be considered in the second stage of the resilience enhancement problem of a distribution network are bus voltage, sections current and network short circuit level. Therefore, Therefore, the values of voltage and current should be within the permissible range both under normal operating conditions and when an unexpected event occurs, which are expressed by equations (21)-(24). Besides, The system short levels with DG units should be less than or equal the pre-values without DG units for all buses, which is expressed by equation (25).

$$V_{min}^{n} \leq V_{bus}^{n} \leq V_{max}^{n} \tag{21}$$

$$V_{min}^{cr} \leq V_{bus}^{cr} \leq Vmax^{cr} \tag{22}$$

$$I_{sec}^{n} \leq I_{max}^{n} \tag{23}$$

$$I_{sec}^{cr} \leq I_{max}^{cr} \tag{24}$$

$$ISC_{bus}^{with-DG} \leq ISC_{bus}^{without-DG} \tag{25}$$

where V_{bus}^{n} and V_{bus}^{cr} are the values of buses voltage under normal operating conditions and during an unexpected event, respectively; I_{sec}^{n} and I_{sec}^{cr} are the values of sections current under normal operating conditions and in case of an unexpected event, respectively; $ISC_{bus}^{with-DG}$ is short circuit level with DG units and $ISC_{bus}^{without-DG}$ is short circuit level without DG units.

5. OPTIMIZATION ALGORITHM

The proposed objective and its related constraints are expressed as a nonlinear optimization problem. A heuristic optimization technique based on genetic algorithm (GA) is implemented to optimize the proposed model. This algorithm can solve many optimization problems that can not be solved by standard optimization algorithms, especially when the objective function is discrete and nonlinear [24, 25].

In the problem of resilience enhancement of distribution network in two stages, discrete decision variables in each stage are generated and searched by the GA. The algorithm starts by generating a random initial population, and in each iteration, the GA uses the current population to create the children that make up the next generation using crossover and mutation operators. After some predetermined iterations, the best solution for each stage is determined.

6. CASE STUDY NETWORK

To illustrate the performance of the proposed methodology in the problem of resilience enhancement of distribution network, the proposed model is applied to a practical distribution system from Iran. This network, as shown in Fig. 5, is a 20 kV distribution network with 44 buses belonging to the South Khorasan distribution network. The network starts from the 132 kV substation and has 43 load points along the feeder and a total load of 7790 kVA. Point A0 is the reference bus and the starting point of the feeder located at the substation, and points A1 to A24 are starting points of branches from the main feeder.

Information on candidate sites for solar and conventional gas-fired power plants on the network under study is shown in Fig. 5. All buses and branches from the main feeder are also considered as candidate locations for switch installation. Load points and sections data are given in Table 1. Other technical and economical parameters of the problem are given in Table 2.

To model the effects of storm and flood, the studied distribution network is based on the storm path that can be extracted from wind profiles in the region of the study; according to the geographical locations of the distribution lines poles with the probability of flooding, the study region is divided into five regions (Fig. 6). Assuming the same weather conditions in a specific region, all components of the distribution network within the region are exposed to similar weather conditions; that is, the fragility of the components of the distribution network, including the utility poles and conductors, are the same in the region. According to this division, Region 1 includes the part of the distribution network located within the city, so due to the surrounding urban texture and constructions around the network, wind and storm generally have little effect on the conductors and utility poles. Region 2 is a part of the network that is enclosed on one side and the impact of wind and storm is greater than Region 1. Region 3 is not enclosed on any side, so the impact of wind and storms is serious in this region. In Region 4, the distribution network poles are located in the river and wind and storm have little effect, but the risk of flooding can have a serious impact on the utility poles of the network. In Region 5, the distribution network poles are located in the highlands, so distribution lines are seriously affected by the storm. Maximum wind speeds and floods information are given in Table 3.

The proposed model framework focuses on the effects of storms and floods on the utility poles and conductors of the distribution network. Figure 6 shows the fragility curves of the utility poles as a function of wind speed, of the conductors as a function of wind speed and of the utility poles as a function of flood velocity.

By having wind speed and flood velocity in different regions, these curves can be used to determine the failure probability of conductors and utility poles of the distribution network, and consequently, the failure probability of the section can be obtained.

It is assumed that the utility poles of the distribution network are of rectangular concrete type, and there is a pole at every 60 meters. The utility poles are connected in series along a section, so the failure of a pole alone will lead to the failure of the entire section. In this study, according to the sensitivity of loads, they are prioritized into four categories of sensitive (priority 1), industrial (priority 2), commercial (priority 3) and residential (priority 4), with different sensitivity coefficients. Figure 7 shows the prioritization of the distribution network loads for each bus separately.

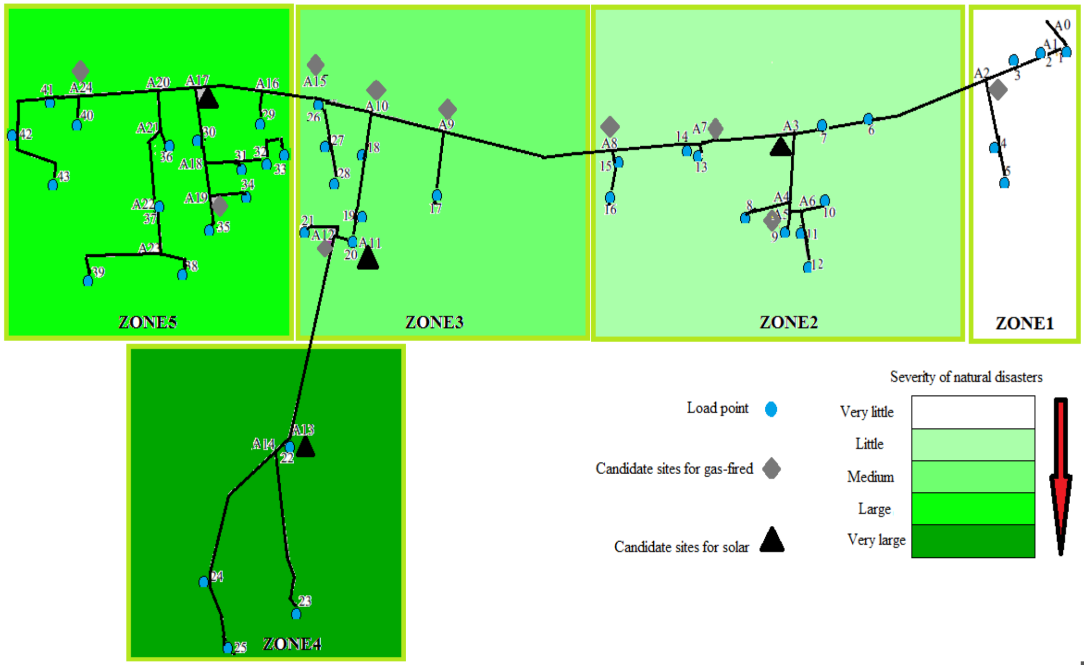

Fig. 5. Modeling effects of storm and flood on the test network.

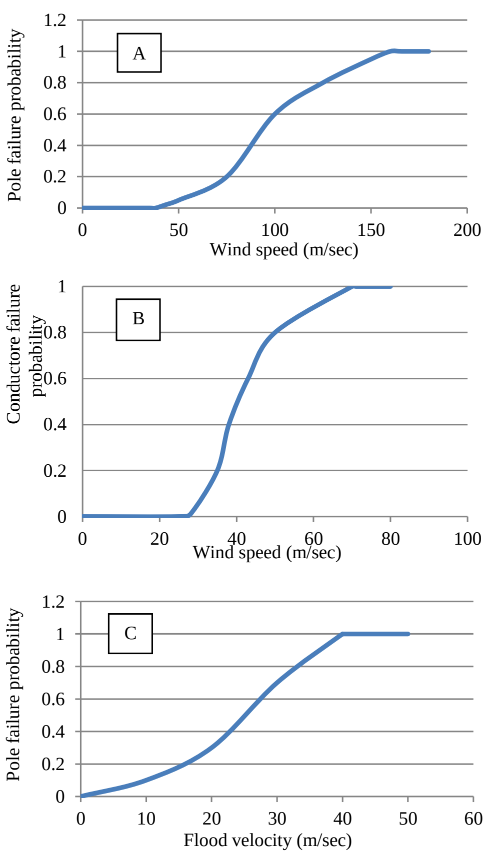

Fig. 6. Fragility curves
A-Pole as a function of wind speed
B-Conductor as a function of wind speed
C-Pole as a function of flood velocity.

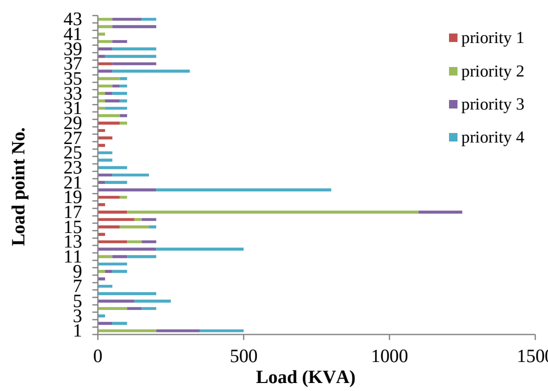

Fig. 7. Distribution network load prioritization.

7. NUMERICAL RESULT

In this section, the two-stage problem of enhancing the resilience of the distribution network is solved using genetic algorithm in MATLAB. The distribution network resilience over 24 hours after the event is studied using the proposed model. Optimal solutions are obtained after performing 50 iterations in the genetic algorithm with an initial population of 20 and a mutation rate of 0.3. It is assumed that some DG units with sizes of multiples of 100 kVA and a maximum of 1 MVA can be installed in candidate sites.

In the first stage, the capacity of DG units is simultaneously determined with the switch placement. Four budget levels, from B1 to B4 are studied. The second budget level (B2) is three times the first budget level (B1), the third budget level (B3) is six times B1 and the fourth budget level (B4) is fifteen times B1. Level B4 is assumed to supply all loads in the distribution network after the event. In this stage, to optimize the resilience index and not exceeding the budget level, the number of switches, the

Table 1. Load points and sections data

Sections data				Load points data	
Poles in section	(m)Length	Section	Section No.	(KVA) Load	Load point No.
3	155	A0-A1	1	500	1
1	29	A1-2	2	100	2
1	60	A1-3	3	25	3
10	564	3–4	4	200	4
5	268	4-A2	5	250	5
9	502	A2-5	6	200	6
4	202	5–6	7	50	7
16	961	A2-7	8	25	8
7	375	7–8	9	100	9
4	236	8-A3	10	100	10
5	504	A3-A4	11	200	11
6	333	A4-9	12	500	12
1	57	A4-A5	13	200	13
2	86	A5-10	14	25	14
2	87	A5-A6	15	200	15
4	194	A6-11	16	200	16
2	101	A6-12	17	1250	17
5	298	12–13	18	25	18
13	256	A3-A7	19	100	19
2	121	A7-14	20	800	20
2	78	A7-15	21	100	21
12	692	15-A8	22	200	22
2	67	A8-16	23	100	23
6	312	16–17	24	50	24
22	1375	A8-A9	25	50	25
9	500	A9-18	26	25	26
10	590	A9-A10	27	50	27
5	280	A10-19	28	25	28
9	499	19–20	29	100	29
3	153	20-A11	30	100	30
1	30	A11-21	31	100	31
3	141	A11-A12	32	100	32
7	390	A12-22	33	100	33
25	1446	A12-A13	34	100	34
2	68	A13-23	35	100	35
3	145	A13-A14	36	315	36
20	1140	A14-24	37	200	37
19	1106	A14-25	38	200	38
10	568	25–26	39	200	39
7	370	A10-27	40	200	40
1	20	27-A15	41	25	41
6	316	A15-28	42	200	42
4	239	28?29	43	200	43
9	496	A15-A16	44		
3	174	A16-30	45		
9	537	A16-A17	46		
7	372	A17-31	47		
2	81	31-A18	48		
5	255	A18-32	49		
5	247	32–33	50		
8	469	33–34	51		
4	240	A18-A19	52		
5	282	A19-35	53		
4	224	A19-36	54		
6	320	A17-A20	55		
5	302	A20-A21	56		
1	59	A21-37	57		
10	574	A21-A22	58		
1	31	A22-38	59		
7	374	A22-A23	60		
4	244	A23-39	61		
13	747	A23-40	62		
8	464	A20-A24	63		
3	158	A24-41	64		
5	260	A24-42	65		
8	462	42–43	66		
9	518	43–44	67		

Table 2. Technical and economical parameters

Parameter	Value
Solar investment cost ($/kw) 1000	1000
Gas-fired investment cost ($/kw)	200
Switch investment cost ($)	5000
Cost of energy losses ($/kwh)	0.05

Table 3. Regions characteristics

Region No.	Wind speed (m/sec)	Flood velocity (m/sec)
1	26	-
2	28	-
3	30	-
4	28	20
5	36	-

installation locations and the boundaries of the created isolated zones for each budget level are obtained. The capacity of DG for each zone at different budget levels is also determined at this stage. The results of the first stage are presented in Table 4. Figure 8 shows the trend of changes in DRI as the budget level changes.

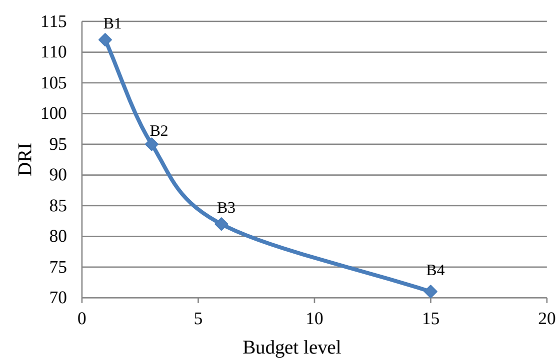

Fig. 8. DRI under different budget levels.

In the second stage, to minimize the network losses, optimal locations of the DG units in the isolated zones that are identified from the first stage are determined for the four budget levels. The results of this stage are presented in Table 5. Figures 9 to 12 illustrate the optimal plans obtained at the end of the second stage at different budget levels. By running the genetic algorithm several times for each state and obtaining the best results, the optimality of the obtained results is ensured.

The results show that at budget level B1, the resilient distribution network leads to the formation of 2 isolated zones with a total DG capacity of 1 MW. At this level, due to the highly limited spending, the zones are formed based on supplying loads that have high priority and the greatest impact on network resilience. For budget level B2, two zones are formed, and the total DG capacity is 2 MW. For budget level B3, three isolated zones are formed with a total DG capacity of 3 MW. Finally, for budget level B4 that is assumed to supply all loads, four isolated zones are formed with a total DG capacity of 8.6 MW. Therefore, by increasing budget levels in the early levels, the higher priority loads are supplied and network resilience increases at a high rate. However, by continuing to raise the budget level to a certain extent, the rate of increase in resilience is greatly re-

Table 4. First stage results of resilient distribution network

DRI	Distributed generation		Isolated zone		Budget level
	Capacity (KW)	Type	Switch placement	No.	
112	1000	DG	IZ1:A7-A8	2	B1
			IZ2:A10-A11-A16		
95	1800	DG	IZ1:6-A3-14	2	B2=3B1
	200	PV	IZ2:A9-A15-19		
82	2400	DG	IZ1:6-A8-A3	3	B3=6B1
	600	PV	IZ2:A9-19-A17		
			IZ3:A24		
71	7100	DG	IZ1:A8	4	B4=15B1
	1500	PV	IZ2:A10		
			IZ2:19		

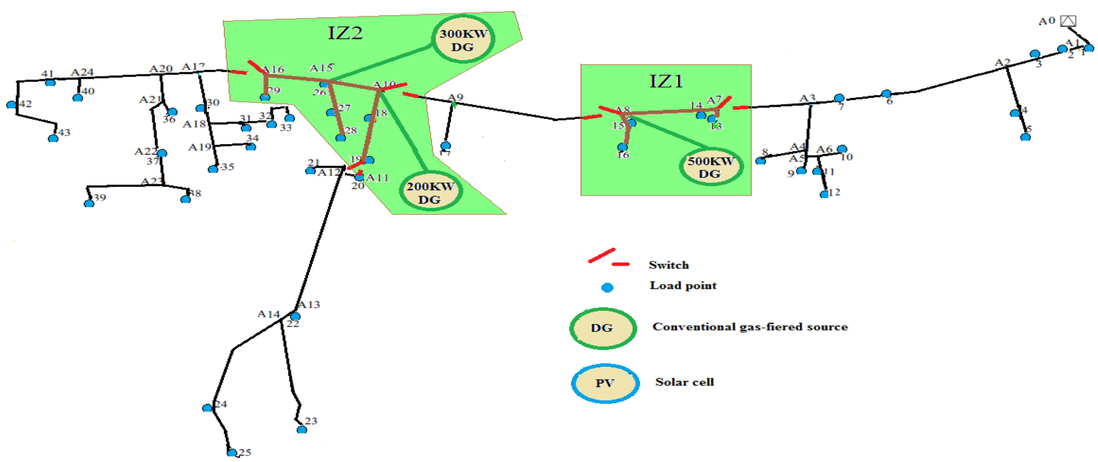

Fig. 9. Optimal plan of distribution network for budget level B1.

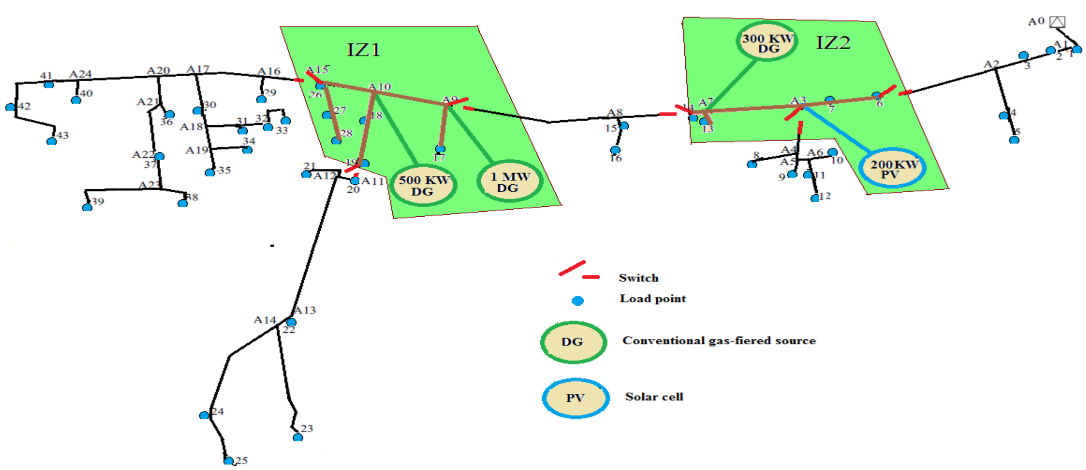

Fig. 10. Optimal plan of distribution network for budget level B2.

duced. Indeed, from budget level B3 to B4, despite a significant increase in the budget level as well as DG utilization, DRI does not change significantly (Fig. 8).

Comparing the results with reference [14], that the distributed generation planning problem and switch placement, is obtained based on the load supply resiliency index, there is no guarantee for supplying the loads with distributed generation when an unexpected event occurs, but in this paper with considering

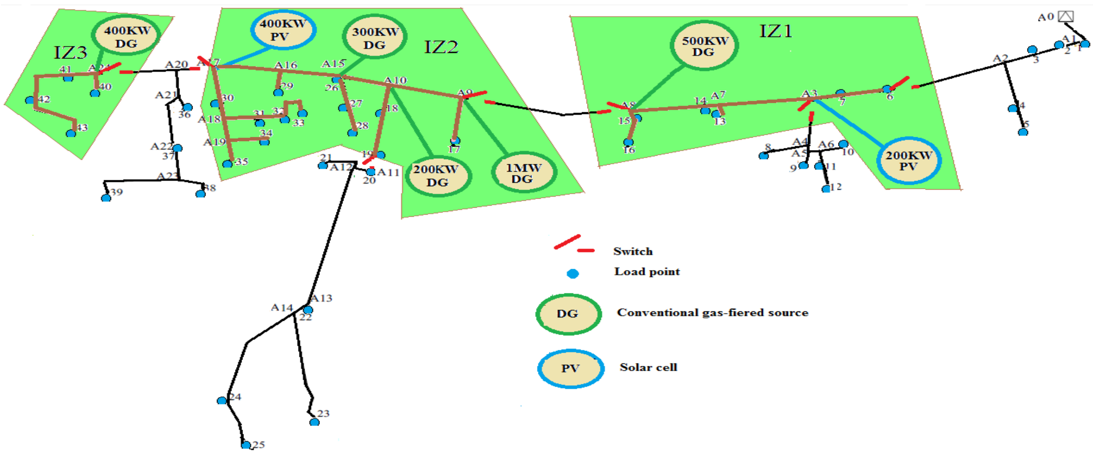

Fig. 11. Optimal plan of distribution network for budget level B3.

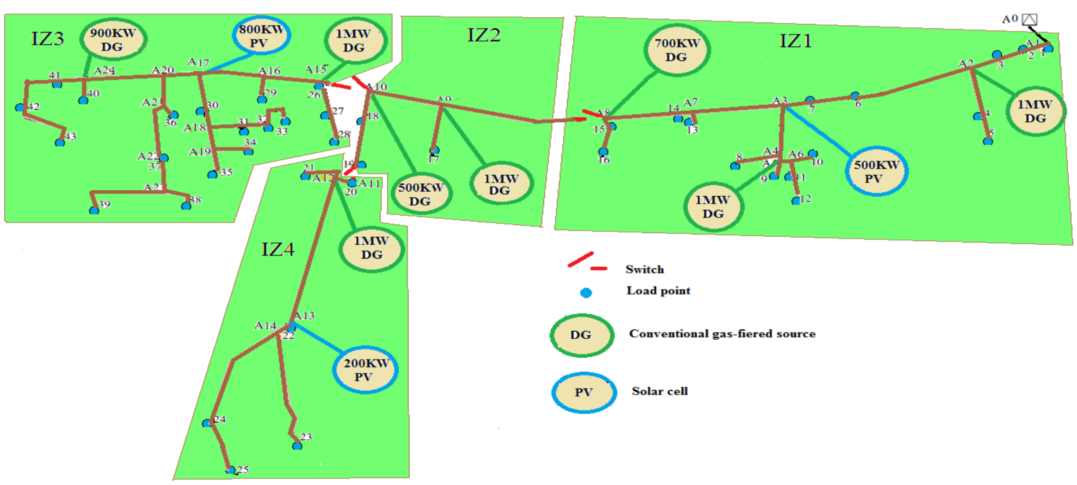

Fig. 12. Optimal plan of distribution network for budget level B4.

the distributed generation resiliency index with the load supply resiliency index, as the distribution risk index, load supply will be guaranteed against natural disasters. In addition, results comparison with reference [11], that the total load is concentrated and the location and capacity of distributed generation are obtained based on the distributed generation resiliency index, due to ignoring the network configuration, is not practical. However, in this paper with considering the configuration of the distribution network, a practical method has been developed to the distributed generation planning.

As can be seen, the presence of DG units in the distribution network improves the resilience of the network. Moreover, to have the highest level of resilience and to obtain the optimal structure with minimum losses, a two-stage DG planning and switch placement is necessary. As a concluding remark, we note that with a limited budget, moving toward a resilient distribution network is possible.

8. CONCLUSIONS

This paper presented a new index to quantitatively calculate the resilience of a distribution network in the presence of DG (including solar cells and conventional gas-fired sources) in case of natural events such as floods and storms. Moreover, a new approach for enhancing the resilience of the distribution network in two stages was proposed by using genetic algorithm as an optimization tool. The first stage determined the boundaries of isolated zones and optimal capacity of the DG units in each zone to improve the resilience and by considering a budget constraint, and the second stage determined the optimal locations of the DG units in the network to optimize the distribution network losses. The proposed model was tested on a real distribution network.

Numerical results showed that increasing the level of budget and thus the capacity of DG units, initially leads to the formation of zones based on supplying high priority loads, which significantly improves the resiliency level of the network. However, an excessive increase in budget will not have a significant impact on enhancing network resilience. In addition, to have the highest level of resiliency and the optimal distribution network structure at a specified budget level, the problem of DG optimal planning should be solved simultaneously with switch placement in two stages.

Table 5. Second stage results of resilient distribution network

Distributed generation			Budget level
Optimal location	Capacity (KW)	Type	
A8	500	DG	B1
A10	200		
A15	300		
A7	300	DG	B2
A9	1000		
A10	500		
A3	200	PV	
A8	500	DG	B3
A9	1000		
A10	200		
A15	300		
A24	400		
A3	200	PV	
A17	400		
A8	700	DG	B4
A10	500		
A24	900		
A2-A4-A9-A12-A15	1000		
A3	500	PV	
A13	200		
A17	800		

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