Effects of Resilience-Oriented Design on Distribution Networks Operation Planning

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Abstract- This paper presents an optimal framework for the resilience-oriented design (ROD) in distribution networks to protect these grids against extreme weather events such as earthquakes and floods. This strategy minimizes the summation of daily investment and repair costs of back up distributed generation (DG), hardening and tie lines, operation cost of network and DGs, and load shedding cost. Also, it considers AC power flow equations, system operation limits and planning and reconfiguration constraints. This problem is generally a mixed integer non-linear programming (MINLP) problem, but it is converted to a mixed integer linear programming (MILP) problem to achieve a globally optimal solution with a low computation time. Moreover, the Benders decomposition (BD) approach is used for the proposed problem to obtain higher computation speed in large scale networks. In addition, this problem includes uncertain parameters such as load, energy price, and availability of network equipment in the case of extreme weather conditions. Hence, a scenario-based stochastic programming (SBSP) approach is used to model these uncertain parameters in the proposed ROD method, based on a hybrid approach, including roulette wheel mechanism (RWM) and the simultaneous backward method. The proposed problem is simulated on 33-bus and large-scale 119-bus distribution networks to prove its capabilities in different case studies.

Keywords: Distributed generation; Natural disasters; Mixed integer linear programming; Resilience; Stochastic programming.

Nomenclature

1) *Indices and Sets*

k, K	Index and set of linearization segments of circular constraint, respectively
l, L	Index and set of linearization segments of voltage magnitude term, respectively
m, TN_F	Index and total number of iterations of the primal sub-problem to be feasible, respectively
n, j, N	Indices of bus and bus, set of bus, respectively
r, TN_{IF}	Index and total number of iterations of the primal sub-problem to be infeasible, respectively
t, ST	Index and set of simulation time, respectively
TN_K	Total number of linearization segments for circular constraint
TN_L	Total number of linearization segments for voltage magnitude term
w, S	Index and set of scenario, respectively

2) *Parameters*

A	Bus incidence matrix (if line existed between buses b and j, $A_{b,j}$ is equal to 1, and 0 otherwise)
c^{dg}, c^{hl}, c^{tl}	Investment cost (in \$) for backup DG, hardening and tie lines corresponding to whole planning years
c^{rg}, c^{rl}	Repair cost (in \$) for backup DG and distribution line
DN, Y	Number of natural disasters during planning years, planning year, respectively
G, B	Line conductance and susceptance in per unit (pu), respectively
M	Large constant, 10^6
N_{bus}	Total number of network buses
P^D, Q^D	Active and reactive load in p.u., respectively
S^{DGmax}	Maximum loading of backup DG in p.u.
$slop$	Line slop in linearization segments for voltage magnitude
S^{Smax}, S^{Lmax}	Maximum loading of distribution station and line in p.u., respectively
u^L, u^S, u^{DG}	Availability of distribution line, distribution station and DG in the case of extreme weather condition
$VOLL$	Value of lost load in \$/MWh

$\underline{V}, \overline{V}$	Minimum and maximum voltage magnitude in p.u., respectively
$\Delta\alpha$	Angle deviation
π	Occurrence probability
κ, ρ^{dg}	Energy price, operation price of DG in $/MWh

3) *Variables*: All variables are in per unit (pu)

P^{DG}, Q^{DG}	Active and reactive power of backup DG, respectively
P^{L}, Q^{L}	Active and reactive power flow of distribution line, respectively
P^{NS}, Q^{NS}	Active and reactive power not supplied, respectively
P^{S}, Q^{S}	Active and reactive power of distribution station, respectively
V, ΔV, δ	Magnitude, deviation and angle of voltage (in rad), respectively
x^{dg}, x^{hl}, x^{tl}, x^{0}	Binary variables related to investment state of backup DG, hardening, tie and existing lines, respectively
y, y^{hl}, y^{tl}, y^{0}	Binary variables related to switching state of line, hardening, tie and existing lines, respectively
λ_{sub}, μ_{sub}	Dual variables of equality and inequality constraints in the primal sub-problem, respectively

1. Introduction

Generally, most of the distribution networks are designed based on normal weather conditions [1]. Hence, they incur high costs if extreme weather events such as earthquakes, floods, storms, etc. happen in different zones of these networks [2-3]. Therefore, the resilience-oriented design (ROD) strategy is necessary for the distribution network to protect them against these natural disasters [4-5]. The ROD approach uses the hardening network equipment such as back up distributed generations (DGs), hardening lines, tie switches or lines in the distribution systems to strengthen this system against extreme weather conditions [6]. Thus, this method needs an optimization framework to determine optimal location of the hardening network equipment based on minimum investment, repair, operation and reliability costs.

There are different researches about the power system resiliency in the area. In [7], a nonlinear binary programming model is used for the distribution network reliability. Noted that reliability indices can be used as resiliency indices, with the difference that N – k contingency is considered for resilience problem. The authors of [8] present a probabilistic model to resilience of the distribution networks based on different weather conditions where it combines time-to-event models to estimate resilience in the system.

In [9], a risk assessment method is expressed to investigate the probability of potential disturbances in the distribution networks and obtain an accurate decision for trading renewable energy customers according to resilient network capabilities. In [10], it investigates the impact of critical loads against natural disasters to evaluate the distribution network resilience.

In [11], to obtain the high resilience in the distribution grids at major disaster conditions, a three-level optimization problem is used to investigate the variability and scarcity of DGs in micro-grids based on the service restoration method. Also, the bi-level distribution system reconfiguration approach is modelled in [12] to improve the resilience of this system against extreme weather conditions. In [13], the resilience enhancement strategy is modelled in the coupled distribution network and urban transportation system to determine the optimal placement of hardening lines and DGs when outages occur in distribution lines and traffic lights. Also, in [14], the Great Britain distribution network operators present different approaches to improve network resilience under flood conditions. The authors of [15] have modelled a tri-level resilience enhancement strategy to minimize grid hardening investment and load shedding costs under different natural disasters. In [16], it proposes a novel distribution system operational approach by forming multiple micro-grids energized by DGs in the real-time operations of radial distribution system restore critical loads from the power outage due to different natural disasters.

It is noted that in the available literature according to Table 1, there are different approaches to improve the network resilience against extreme weather events, such as planning of back up DGs, expansion planning of distribution grid based on hardening lines, reconfiguration, etc. But the hybridization of these approaches can obtain higher network resilience. Moreover, more researches use the MINLP model for the proposed problem, however, this method reveals locally optimal solutions at high calculation time. Hence, it cannot be implemented on a large scale distribution network. Therefore, this paper models the resilience-oriented design (ROD) in the distribution system to obtain the optimal location for back up DGs, hardening and tie lines according to extreme weather events such as earthquake and flood. This problem includes an objective function to minimize the planning, operation and resilience costs subject to AC power flow equations, system operation limits, and planning and reconfiguration constraints. In the next step, the original MINLP model of the proposed problem is converted to MILP formulation based on the conventional linearization approaches to achieve the globally optimal solution at high calculation speed. Then, the Benders decomposition (BD) approach is used in this paper to improve the calculation speed in a large scale network.

Moreover, the scenario-based stochastic programming (SBSP) is used in this paper to model the uncertainty of load, energy price, and availability of network equipment under the earthquake and flood conditions. In this strategy, the roulette wheel mechanism (RWM) and the simultaneous backward method are used as the scenario generation and reduction methods, respectively.

Table 1: Taxonomy of recent works in the area

Ref. No.	Resilience sources				Problem model
	Tie line	Hardening line	Backup DG	Reconfiguration	
[6]	Yes	Yes	Yes	Yes	MINLP
[7]	No	No	No	Yes	MINLP
[8]	Yes	No	No	Yes	MINLP
[9]	No	No	Yes	No	NLP
[10]	No	No	No	No	NLP
[11]	Yes	No	Yes	Yes	MINLP
[12]	Yes	No	No	Yes	LPMINLP
[13]	No	Yes	Yes	No	MINLP
[14]	Yes	No	No	Yes	MINLP
[15]	No	Yes	No	No	MINLP
[16]	No	No	Yes	No	NLP
Proposed method	**Yes**	**Yes**	**Yes**	**Yes**	**LP based on BD approach**

The main contributions of this paper with respect to the previous works in the area are summarized as follows:

– Modelling the ROD strategy in the distribution network to improve its resilience against earthquake and flood conditions by selecting the optimal location of back up DGs, hardening and tie lines.
– Using MILP ROD model based on BD approach to improve the calculation speed in large scale distribution networks.
– Evaluating the uncertainty of load, energy price, and availability of network equipment under the earthquake and flood conditions using SBSP that combines the RWM and simultaneous backward method.

The rest of the paper is organized as follows: Section 2 describes the ROD formulation, and Section 3 presents the proposed solution method. Sections 4 and 5 address numerical simulations and the main conclusions of the paper, respectively.

2. ROD formulation

2.1. Original non-linear model

In this section, the non-linear model of the proposed ROD strategy, shown in Fig. 1, is presented based on the distribution network formulation. This approach minimizes the summation of the planning, operation and resilience costs, where planning/operation cost refers to daily investment/energy and DGs fuel cost.

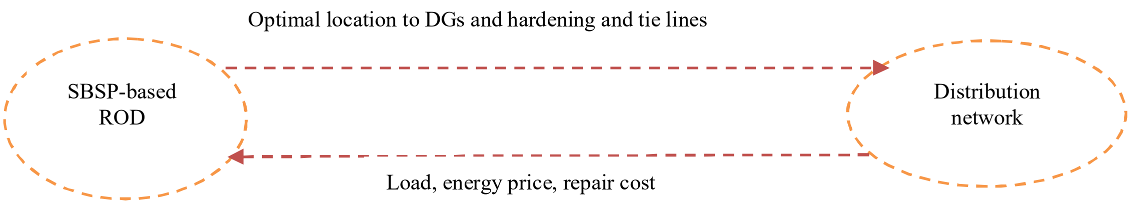


Fig. 1. The proposed ROD framework in the distribution network

Also, the daily repair and load shedding cost resulting from extreme weather events such as earthquake and flood are considered as resilience costs. Moreover, the proposed ROD method are subjected to the AC power flow equations, system operation limits, reconfiguration constraints and DGs limitations.

Therefore, this problem is modelled as follows:

$$\min \quad \overbrace{\frac{1}{365\times Y}\left\{\sum_{n\in N} c_n^{dg} x_n^{dg} + \sum_{(n,j)\in N} c_{n,j}^{hl} x_{n,j}^{hl} + \sum_{(n,j)\in N} c_{n,j}^{tl} x_{n,j}^{tl}\right\}}^{\text{Daily investment cost}} + \tag{1}$$

$$\overbrace{\frac{DN}{365\times Y}.\sum_{w\in S}\pi_w\left\{\sum_{n\in N} c_{n,w}^{rg}\left(1-u_{n,w}^{DG}\right)x_n^{dg} + \sum_{(n,j)\in N} c_{n,j,w}^{rl}\left(1-u_{n,j,w}^{L}\right)\left(x_{n,j}^{0}+x_{n,j}^{hl}+x_{n,j}^{tl}\right)\right\}}^{\text{Daily repair cost}} +$$

$$\overbrace{\sum_{w\in S}\pi_w\sum_{t\in ST}\sum_{n\in N}\kappa_{t,w}P_{n,t,w}^{S}+\rho_n^{dg}P_{n,t,w}^{DG}}^{\text{Operational cost}} + \overbrace{\sum_{w\in S}\pi_w\sum_{t\in ST}\sum_{n\in N}VOLL.P_{n,t,w}^{NS}}^{\text{Load sheding cost}}$$

S.to:

(a) $$P_{n,t,w}^{S}+P_{n,t,w}^{DG}-\sum_{j\in N}A_{n,j}P_{n,j,t,w}^{L}=P_{n,t,w}^{D}-P_{n,t,w}^{NS}:\lambda_{n,t,w}^{p} \quad \forall\, n,t,w$$

(b) $$Q_{n,t,w}^{S}+Q_{n,t,w}^{DG}-\sum_{j\in N}A_{n,j}Q_{n,j,t,w}^{L}=Q_{n,t,w}^{D}-Q_{n,t,w}^{NS}:\lambda_{n,t,w}^{q} \quad \forall\, n,t,w$$

(c) $$P_{n,j,t,w}^{L}=\left\{G_{n,j}\left(V_{n,t,w}\right)^{2}-V_{n,t,w}V_{j,t,w}\left(G_{n,j}\cos\left(\delta_{n,t,w}-\delta_{j,t,w}\right)+B_{n,j}\sin\left(\delta_{n,t,w}-\delta_{j,t,w}\right)\right)\right\}y_{n,j,t}u_{n,j,w}^{L} \quad \forall n,j,t,w$$

(d) $Q^{L}_{n,j,t,w} = \left\{ -B_{n,j}(V_{n,t,w})^2 + V_{n,t,w}V_{j,t,w}\left(B_{n,j}\cos\left(\delta_{n,t,w}-\delta_{j,t,w}\right) - G_{n,j}\sin\left(\delta_{n,t,w}-\delta_{j,t,w}\right)\right)\right\} y_{n,j,t}u^{L}_{n,j,w} \quad \forall n,j,t,w$

(e) $\delta_{n,t,w} = 0 : \lambda^{\delta}_{n,t,w} \quad \forall\, n = \text{Slack bus}, t, w$

(f) $\left(P^{L}_{n,j,t,w}\right)^2 + \left(Q^{L}_{n,j,t,w}\right)^2 \le \left(S^{L\max}_{n,j}\right)^2 \quad \forall\, n,j,t,w$

(g) $\left(P^{S}_{n,t,w}\right)^2 + \left(Q^{S}_{n,t,w}\right)^2 \le \left(S^{S\max}_{n}\right)^2 u^{S}_{n,w} \quad \forall\, n = \text{Slack bus}, t, w$

(h) $\underline{V} \le V_{n,t,w} \le \overline{V} \quad \forall\, n,t,w$

(i) $y_{n,j,t} = y^{0}_{n,j,t} + y^{hl}_{n,j,t} + y^{tl}_{n,j,t} \quad \forall n,j,t$

(j) $y^{0}_{n,j,t} \le x^{0}_{n,j} \quad \forall n,j,t$

(k) $y^{hl}_{n,j,t} \le x^{hl}_{n,j} \quad \forall n,j,t$

(l) $y^{tl}_{n,j,t} \le x^{tl}_{n,j} \quad \forall n,j,t$

(m) $x^{0}_{n,j} + x^{hl}_{n,j} + x^{tl}_{n,j} \le 1 \quad \forall n,j$

(n) $\sum_{(n,j)\in N} y_{n,j,t} = N_{bus} - 1 \quad \forall t$

(o) $\left(P^{DG}_{n,t,w}\right)^2 + \left(Q^{DG}_{n,t,w}\right)^2 \le x^{dg}_{n}\left(S^{DG\max}_{n}\right)^2 u^{DG}_{n,w} \quad \forall\, n,t,w$

A) *Objective function*: Equation (1) expresses the proposed ROD objective function that respectively includes the daily investment and repair costs of backup DG, hardening and tie lines [6], the operation cost of network and DGs [17], and load shedding cost [18]. In this problem, to calculate the costs the day wherein the earthquake or flood is happened is considered. Hence, the investment and repair costs are divided into 365×*Y*. *DN* in this equation refers to number of the earthquake or flood happened in total planning year, *Y*. Also, the operation and load shedding costs are formulated for a day, i.e., 24 hours, where it is obtained by summation of the cost over set of *ST*.

B) *AC optimal power flow (network operation) constraints*: The network operation constraints are formulated in (1a) to (1h), where, equations (1a) to (1e) refer to the AC power flow model in the distribution network [19-21]. This model consists of active and reactive power balance of buses, active and reactive power flow of lines, and voltage angle value in the slack bus, respectively. Also, system operation limits are expressed in (1f) to (1h) as line capacity limits, distribution substation capacity limit, and buses voltage limit, respectively [22]. In these equations, P^S and Q^S

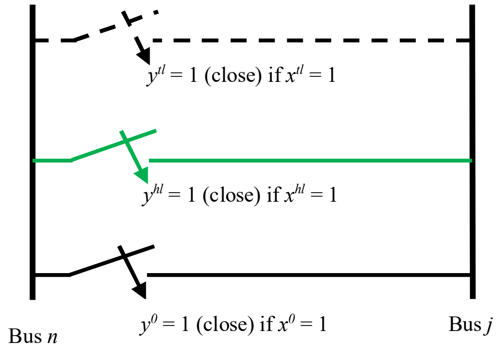
present the active and reactive power of the distribution substation connected to the slack bus. Hence, the values of these variables are zero on all buses except the slack bus.

C) *Network planning and reconfiguration constraints*: The hybrid planning and reconfiguration constraints are presented in equations (1i) to (1o). Planning model of distribution line is based on Fig. 2. Accordingly, in (1i), the switch state (open or closed) of line is determined, where it depends on the line construction state according to (1j) to (1l). It is noted that the total number of lines between buses n and j is considered to be 1, hence, it can be said that:

- Existing line is suitable, thus, $x^0 = 1$, and $x^{hl} = x^{tl} = 0$.
- Hardening line should be installed between buses n and j to obtain a resilience network, hence, $x^{hl} = 1$, and $x^0 = x^{tl} = 0$.
- A new line between buses n and j should be constructed, therefore, $x^{tl} = \{0, 1\}$, and $x^0 = x^{hl} = 0$.

Where, n and j are neighboured buses for the first and second assumptions, but n and j is non-neighboured buses for the third assumption. This condition is formulated in the constraint (1m). In (1n), the constraint corresponding to the redial topology for the distribution network is modelled, and the backup DG capacity limit is presented in (1o). In this paper, it is considered that the distribution network includes one slack bus and several PQ buses. The slack bus is the distribution substation bus, and loads and DGs are located in PQ buses. Hence, a constraint based on radial topology of distribution network implies that the total number of distribution lines is equal to the total number of PQ buses (total number of network busses – 1). Noted that the constraints (1i)-(1n) are coordinated with the operation model of the distribution network by equations (1c) and (1d) to determine binary variable of y.

Noted that the parameters of u^L, u^S and u^{DG} refer respectively to availability of distribution line, distribution station and DG in the case of extreme weather condition. Hence, u^L, u^S or u^{DG} in different zones is equal to zero if there is the condition of extreme weather in this zone. Thus, distribution line, distribution station or DG is not available in this case, and equations (1c), (1d), (1g) and (1o) are discarded for the mentioned zone. In this case, the objective function (1) can include repair and load shedding costs. In addition, λ is dual variable. Finally, the decision variables of the model (1) are binary variables of x^{dg}, x^{hl} and x^{tl}, and continuous variables of P^{DG}, Q^{DG}, P^{NS} and Q^{NS}. Also, other variables are considered as output variables that are calculated based on the mentioned decision variables values.



Note: There is only one line between busses *n* and *j*

Fig. 2. Planning model of distribution line and network reconfiguration framework

2.2. Proposed linear model

It is noted that the proposed ROD model, (1), is a non-convex MINLP formulation due to non-linear constraints (1c), (1d), (1f), (1g) and (1o), non-convex equations (1c) and (1d) [19-22], and different binary variables. Hence, this method achieves locally optimal solutions due to non-convex constraints at a low calculation speed because the MINLP solvers are generally based on the numerical analysis such as Newton Raphson [23-25]. Therefore, to obtain global optimal solution at the low calculation time, in this paper, an equivalent MILP model is developed as follows:

- For linearization of AC power flow equations, i.e., (1c) and (1d), while the voltage angle difference across a line (between buses *n* and *j*) is generally less than 6 degree or 0.105 radiant in the distribution networks [26], hence, the terms of $\cos\left(\delta_{n,t,w}-\delta_{j,t,w}\right)$ and $\sin\left(\delta_{n,t,w}-\delta_{j,t,w}\right)$ can be approximated by 1 and $\left(\delta_{n,t,w}-\delta_{j,t,w}\right)$, respectively. Moreover, the voltage magnitude can be expressed as $\underline{V}+\sum_{l\in L}\Delta V_l$ based on the piecewise linearization method [27], where ΔV refers to voltage deviation, and $\Delta V << 1$. Therefore, the terms V^2 and V_nV_j are approximately expanded as $\left(\underline{V}\right)^2+\sum_{l\in L} slop_l \Delta V_l$ and $\left(\underline{V}\right)^2+\underline{V}.\sum_{l\in L}\left(\Delta V_{n,l}+\Delta V_{j,l}\right)$ according to the piecewise linearization method. In addition, these equations include the multiplication of binary and continuous variables as $a = b\times c$, where b and c are continuous and binary variables, respectively. In this term, $a = b$ if $c = 1$, and $a = 0$ if $c = 0$. Thus, this term can be linearized by Big M approach [17] as $-M\times(1-c) \le a-b \le M\times(1-c)$ and $b_{min}\times c \le a \le b_{max}\times c$, where b_{min} and b_{max} are the minimum and maximum values of b, respectively, and M is a large constant.

- Noted that inequalities (lf), (lg), and (lo) are circular plane limits, hence, these constraints can be approximated by the polygon plane limit based on Fig. 2. Accordingly, each edge of the polygon is a straight line and its equation can be obtained from tangent to the circle at a specific point as depicted in Fig. 2 [18]. More details of this method can be found in [28].

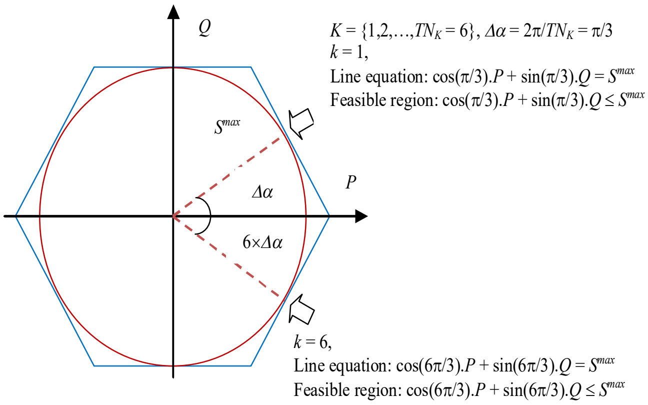


Fig. 2. The linearization method of circular inequality [28]

Therefore, the MILP model of the proposed ROD method can be written as follows considering the above assumptions:

$$\min \quad \overbrace{\frac{1}{365\times Y}\left\{\sum_{n\in N} c_n^{dg} x_n^{dg} + \sum_{(n,j)\in N} c_{n,j}^{hl} x_{n,j}^{hl} + \sum_{(n,j)\in N} c_{n,j}^{tl} x_{n,j}^{tl}\right\}}^{\text{Daily investment cost}} + \tag{2}$$

$$\overbrace{\frac{DN}{365\times Y}.\sum_{w\in S}\pi_w\left\{\sum_{n\in N} c_{n,w}^{rg}\left(1-u_{n,w}^{DG}\right)x_n^{dg} + \sum_{(n,j)\in N} c_{n,j,w}^{rl}\left(1-u_{n,j,w}^{L}\right)\left(x_{n,j}^{0}+x_{n,j}^{hl}+x_{n,j}^{tl}\right)\right\}}^{\text{Daily repair cost}} +$$

$$\overbrace{\sum_{w\in S}\pi_w\sum_{t\in ST}\sum_{n\in N}\kappa_{t,w}P_{n,t,w}^{S} + \rho_n^{dg}P_{n,t,w}^{DG}}^{\text{Operational cost}} + \overbrace{\sum_{w\in S}\pi_w\sum_{t\in ST}\sum_{n\in N}VOLL.P_{n,t,w}^{NS}}^{\text{Load sheding cost}}$$

S.to:

(a)

$$-M.\left(1-y_{n,j,t}\right)u_{n,j,t,w}^{L} \le P_{n,j,t,w}^{L} - \left\{G_{n,j}\left(\sum_{l\in L}\left(slop_l-\underline{V}\right)\Delta V_{n,t,w,l} - \underline{V}.\Delta V_{j,t,w,l}\right) - \left(\underline{V}\right)^2 B_{n,j}\left(\delta_{n,t,w}-\delta_{j,t,w}\right)\right\}$$
$$\le M.\left(1-y_{n,j,t}\right)u_{n,j,t,w}^{L} : \underline{\mu}_{n,j,t,w}^{pl}, \overline{\mu}_{n,j,t,w}^{pl} \quad \forall n,j,t,w$$

(b)

$$-M.\left(1-y_{n,j,t}\right)u_{n,j,t,w}^{L} \le Q_{n,j,t,w}^{L} - \left\{-B_{n,j}\left(\sum_{l\in L}\left(slop_l-\underline{V}\right)\Delta V_{n,t,w,l} - \underline{V}.\Delta V_{j,t,w,l}\right) - \left(\underline{V}\right)^2 G_{n,j}\left(\delta_{n,t,w}-\delta_{j,t,w}\right)\right\}$$
$$\le M.\left(1-y_{n,j,t}\right)u_{n,j,t,w}^{L} : \underline{\mu}_{n,j,t,w}^{ql}, \overline{\mu}_{n,j,t,w}^{ql} \quad \forall n,j,t,w$$

(c)

$$P_{n,j,t,w}^{L}\cos\left(k.\Delta\alpha\right) + Q_{n,j,t,w}^{L}\sin\left(k.\Delta\alpha\right) \le S_{n,j}^{L\max}.y_{n,j,t}u_{n,j,t,w}^{L} : \overline{\mu}_{n,j,t,w,k}^{sl} \quad \forall\ n,j,t,w,k \in K \triangleq \{1,2,\ldots,TN_K\}, \Delta\alpha = \frac{2\pi}{TN_K}$$

(d) $P^{S}_{n,t,w}\cos\left(k.\Delta\alpha\right)+Q^{S}_{n,t,w}\sin\left(k.\Delta\alpha\right)\le S^{S\max}_{n}u^{L}_{n,j,t,w} : \bar{\mu}^{s}_{n,t,w,k} \quad \forall\ n=\text{Slack bus},\ t,w,k$

(e) $P^{DG}_{n,t,w}\cos\left(k.\Delta\alpha\right)+Q^{DG}_{n,t,w}\sin\left(k.\Delta\alpha\right)\le x^{dg}_{n}S^{DG\max}_{n}u^{L}_{n,j,t,w} : \bar{\mu}^{dg}_{n,t,w,k} \quad \forall\ n,t,w,k$

(f) $0\le \Delta V_{n,t,w,l}\le\left(\bar{V}-\underline{V}\right)/TN_{l} : \bar{\mu}^{v}_{n,t,w,l} \quad \forall\ n,t,w,l\in L \square \{1,2,\ldots,TN_{L}\}$

(g) Constraints (1a), (1b), (1e), (1i) to (1n)

The objective function in (2) is the same as the original ROD model, i.e., (1). Constraints (2a) to (2c) are linear forms of the active and reactive power flow equations of line and line capacity limit according to the above-mentioned two linearization methods. Note, the term of y appears in line capacity limit due to Big M approach in the proposed MILP model. Also, the linear form of the distribution station and backup DG capacity limit are as (2d) and (2e), respectively, based on the presented second linearization method in Fig. 2. In the new ROD model, the voltage deviation variable is used instead of the voltage magnitude variable, where its limit is presented in (1f). In this constraint, n_l is the total number of linearization segments based on the piecewise linearization method. Finally, constraints (2g) refer to linear equations of the proposed MILP ROD model, where they are the same as linear constraints in the original ROD formulations, (1). In addition, λ and μ are dual variables.

2.3. SBSP model

In the proposed ROD problem, the parameters of active and reactive load, P^D and Q^D, energy price, κ, and availability of network equipment in the earthquake and flood conditions, u^{DG}, u^S and u^L, are uncertain parameters. Hence, the SBSP is used to model these parameters in the ROD strategy. In the first step, the roulette wheel mechanism (RWM) generates a large number of scenario samples for these parameters based on Normal (Bernoulli) probability distribution function (PDF) related to the first and second (third) uncertain parameters. Then, the simultaneous backward approach is used in this paper as a scenario reduction method, because it includes low computational effort and high accuracy [29]. Noted that this strategy achieves the distance between different scenarios to select the most dissimilar and probable scenarios. More details of this method are expressed in [29]. Finally, availability of network equipment such as distribution line, u^L, distribution station, u^S, and backup DG, u^{DG}, in the earthquake and flood conditions depends on the forced outage rate (FOR) of each element against the mentioned extreme weather events [30]. Also, the probability of this uncertainty parameter is based on Bernoulli PDF, where for example for DG in bus

n, it can be expressed as $\pi_n^{DG} = \left(1-u_n^{DG}\right) FOR_n^{DG} \left(1-FOR_n^{DG}\right)\pi^0$ [29]. $u^{DG} = 0$ if there is earthquake or flood condition in this bus. FOR^{DG} refers to FOR of backup DG against the mentioned extreme weather events. Also, π^0 is the probability of the case without earthquake and flood events, and it is formulated as $\pi^0 = \prod_{n\in N}\left(1-FOR_n^{DG}\right)\prod_{n\in N}\left(1-FOR_n^{S}\right)\prod_{(n,j)\in N}\left(1-FOR_{n,j}^{L}\right)$, where FOR^S and FOR^L are FOR of distribution station and line, respectively [29]. Finally, in the stochastic programming, the RWM generates different scenarios to specify different values for P^D, Q^D, κ, u^{DG}, u^S and u^L. Then, it calculates occurrence probability of P^D, Q^D or κ by normal PDF, and u^{DG}, u^S and u^L by Bernoulli PDF. In the following, probability of each scenario is equal to the product probability of all uncertain parameters. In the next step, the simultaneous backward approach is used as the scenario reduction method to obtain scenarios with the higher probabilities.

3. Solution methodology

The problem (2) is in the form of MILP, hence, to accelerate the optimization solution procedure, the proposed MILP ROD model is decomposed by means of BD approach [31]. The BD algorithm includes a master problem (MP) and sub-problem (SP) [31]. The planning and reconfiguration model of the proposed ROD is used in MP, and SP consists of the operation model of ROD. The details of this method are expressed in follows:

Master problem (MP): This section includes the planning and reconfiguration model of the proposed MILP ROD approach as follows:

$$\min \quad z_{lower} \tag{3}$$

S.to:

(a)

$$z_{lower} \geq \frac{1}{365\times Y}\left\{\sum_{n\in N} c_n^{dg} x_n^{dg} + \sum_{(n,j)\in N} c_{n,j}^{hl} x_{n,j}^{hl} + \sum_{(n,j)\in N} c_{n,j}^{tl} x_{n,j}^{tl}\right\} + \frac{DN}{du\times Y}.\sum_{w\in S}\pi_w\left\{\sum_{n\in N} c_{n,w}^{rg}\left(1-u_{n,w}^{DG}\right)x_n^{dg} + \sum_{(n,j)\in N} c_{n,j,w}^{rl}\left(1-u_{n,j,w}^{L}\right)\left(x_{n,j}^0 + x_{n,j}^{hl} + x_{n,j}^{tl}\right)\right\}$$

(b) Constraints (1i)-(1n)

(c) $$z_{lower} \geq \frac{1}{365 \times Y}\left\{\sum_{n \in N} c_n^{dg} x_n^{dg} + \sum_{(n,j) \in N} c_{n,j}^{hl} x_{n,j}^{hl} + \sum_{(n,j) \in N} c_{n,j}^{tl} x_{n,j}^{tl}\right\} + \frac{DN}{365 \times Y} . \sum_{w \in S} \pi_w \left\{\sum_{n \in N} c_{n,w}^{rg}\left(1-u_{n,w}^{DG}\right) x_n^{dg} + \sum_{(n,j) \in N} c_{n,j,w}^{rl}\left(1-u_{n,j,w}^{L}\right)\left(x_{n,j}^{0}+x_{n,j}^{hl}+x_{n,j}^{tl}\right)\right\} + J_{sub}^{(m)}(\lambda_{sub}^{(m)}, \mu_{sub}^{(m)}) \quad \forall m = 1,2,...,TN_F$$

(d) $$J_{sub}^{(r)}(\lambda_{sub}^{(r)}, \mu_{sub}^{(r)}) \leq 0 \qquad \forall r = 1,2,...,TN_{IF}$$

Equation (3) refers to MP objective function that is equal to the first and second parts of equation (2) according to (3a). Also, Equation (3b) includes the constraints consisting of the binary variables, i.e., planning and reconfiguration limits (1i)-(1n). This model, (3)-(3b), is named initial MP (MP1). Moreover, constraints (3c) and (3d) are feasibility and infeasibility cuts, respectively. Accordingly, the feasibility/infeasibility cut has been added to MP1 if the sub-problem include bounded/unbounded feasible solution. Finally, the output variables of MP are x^{dg}, x^{0}, x^{hl}, x^{tl}, y, y^{0}, y^{hl} and y^{tl}, and thus, they are as inputs for the sub-problem with a constant value [31].

Sub-problem (SP): The SP for the ROD problem (2) is written as follows:

$$\min \quad \sum_{w \in S} \pi_w \sum_{t \in ST} \sum_{n \in N} \kappa_{t,w} P_{n,t,w}^{S} + \rho_n^{dg} P_{n,t,w}^{DG} + \sum_{w \in S} \pi_w \sum_{t \in ST} \sum_{n \in N} VOLL.P_{n,t,w}^{NS} \tag{4}$$

S.to:

(a) Constraints (1a), (1b), (1e), (2a)-(2f)

The objective function of SP in (4) is the same the third and last parts of equation (2). In constraints (4a), the operation or AC optimal power flow model of distribution network in the presence of the backup DGs, (1a), (1b), (1e), (2a)-(2f), is used, where values of x^{dg}, x^{0}, x^{hl}, x^{tl}, y, y^{0}, y^{hl} and y^{tl} are constant based on the results of MP. This model, (4), is named primal sub-problem (SP1), where variables of λ, $\underline{\mu}$ and $\overline{\mu}$ refer to the dual variables of SP1's constraints. Noted that the feasibility region of SP1 is depended on the value of mentioned output variables of MP, hence, it changes in a different iteration of BD approach. Therefore, the dual formulation of sub-problem is used in the next step to obtain an independent feasibility region from these variables [31]. The new model is named dual sub-problem (SP2) that is written as follows:

$$\max \quad J_{sub} = \sum_{n,t,w} \left\{ P^{D}_{n,t,w}\lambda^{p}_{n,t,w} + Q^{D}_{n,t,w}\lambda^{q}_{n,t,w} + \sum_{k} \left\{ S^{S\max}_{n} u^{L}_{n,j,t,w}\overline{\mu}^{s}_{n,t,w,k} + x^{dg}_{n} S^{DG\max}_{n} u^{L}_{n,j,t,w,k}\overline{\mu}^{dg}_{n,t,w} \right\} \right\} +$$
$$\sum_{n,j,t,w} \left\{ M.\left(1-y_{n,j,t}\right) u^{L}_{n,j,t,w} \left(\overline{\mu}^{pl}_{n,j,t,w} - \underline{\mu}^{pl}_{n,j,t,w} + \overline{\mu}^{ql}_{n,j,t,w} - \underline{\mu}^{ql}_{n,j,t,w} \right) + \sum_{k} S^{L\max}_{n,j} . y_{n,j,t} u^{L}_{n,j,t,w} \overline{\mu}^{sl}_{n,j,t,w,k} \right\} +$$
$$\sum_{n,t,w,l} \overline{\mu}^{v}_{n,t,w,l} \left(\overline{V} - \underline{V} \right) / TN_{l} \tag{5}$$

S.to:

(a) $$\lambda^{p}_{n,t,w} + \sum_{k\in K} \cos\left(k.\Delta\alpha\right) \overline{\mu}^{s}_{n,t,w,k} \leq \pi_{w}\kappa_{t,w} : P^{S}_{n,t,w} \qquad \forall n,t,w$$

(b) $$\lambda^{q}_{n,t,w} + \sum_{k\in K} \sin\left(k.\Delta\alpha\right) \overline{\mu}^{s}_{n,t,w,k} = 0 : Q^{S}_{n,t,w} \qquad \forall n,t,w$$

(c) $$\underline{\mu}^{pl}_{n,j,t,w} + \overline{\mu}^{pl}_{n,j,t,w} - \sum_{j\in N} A_{n,j}\lambda^{p}_{n,t,w} + \sum_{k\in K} \cos\left(k.\Delta\alpha\right) \overline{\mu}^{sl}_{n,j,t,w,k} = 0 : P^{L}_{n,j,t,w} \qquad \forall n,j,t,w$$

(d) $$\underline{\mu}^{ql}_{n,j,t,w} + \overline{\mu}^{ql}_{n,j,t,w} - \sum_{j\in N} A_{n,j}\lambda^{q}_{n,t,w} + \sum_{k\in K} \sin\left(k.\Delta\alpha\right) \overline{\mu}^{sl}_{n,j,t,w,k} = 0 : Q^{L}_{n,j,t,w} \qquad \forall n,j,t,w$$

(e) $$\lambda^{p}_{n,t,w} + \sum_{k\in K} \cos\left(k.\Delta\alpha\right) \overline{\mu}^{dg}_{n,t,w,k} \leq \pi_{w}\rho^{dg}_{n} : P^{DG}_{n,t,w} \qquad \forall n,t,w$$

(f) $$\lambda^{q}_{n,t,w} + \sum_{k\in K} \sin\left(k.\Delta\alpha\right) \overline{\mu}^{dg}_{n,t,w,k} \leq 0 : Q^{DG}_{n,t,w} \qquad \forall n,t,w$$

(g) $$\lambda^{p}_{n,t,w} \leq \pi_{w} VOLL : P^{NS}_{n,t,w} \qquad \forall n,t,w$$

(h) $$\lambda^{q}_{n,t,w} \leq 0 : Q^{NS}_{n,t,w} \qquad \forall n,t,w$$

(i) $$\left(\underline{V}\right)^{2} B_{n,j} \left(\underline{\mu}^{pl}_{n,j,t,w} - \underline{\mu}^{pl}_{j,n,t,w} + \overline{\mu}^{pl}_{n,j,t,w} - \overline{\mu}^{pl}_{j,n,t,w} \right) + \left(\underline{V}\right)^{2} G_{n,j} \left(\underline{\mu}^{ql}_{n,j,t,w} - \underline{\mu}^{ql}_{j,n,t,w} + \overline{\mu}^{ql}_{n,j,t,w} - \overline{\mu}^{ql}_{j,n,t,w} \right)$$
$$+ \vartheta_{n}\lambda^{\delta}_{n,t,w} = 0 : \delta_{n,t,w} \qquad \forall n,t,w, \vartheta_{n} = 1 \big| n = \text{Slack bus}$$

(j) $$\overline{\mu}^{v}_{n,t,w,l} - G_{n,j} \left(\left(slop_{l} - \underline{V}\right) \underline{\mu}^{pl}_{n,j,t,w} - \underline{V}\underline{\mu}^{pl}_{j,n,t,w} + \left(slop_{l} - \underline{V}\right) \overline{\mu}^{pl}_{n,j,t,w} - \underline{V}\overline{\mu}^{pl}_{j,n,t,w} \right) +$$
$$B_{n,j} \left(\left(slop_{l} - \underline{V}\right) \underline{\mu}^{ql}_{n,j,t,w} - \underline{V}\underline{\mu}^{ql}_{j,n,t,w} + \left(slop_{l} - \underline{V}\right) \overline{\mu}^{ql}_{n,j,t,w} - \underline{V}\overline{\mu}^{ql}_{j,n,t,w} \right) \leq 0 : \Delta V_{n,t,w,l} \qquad \forall n,t,w,l$$

The method of dual formulation is expressed in [31]. In this model, equation (5) is the objective function of SP2, and (5a)-(5j) are its constraint that is referred to the dual equations related to different variable in SP1. Finally, there are three states to SP2 according to the duality theory [31]:

1- *SP2 is feasible and its objective function is bounded*: In this condition, the feasibility cut as (6) is added to MP, (3).

$$
\begin{aligned}
z_{lower} \geq & \frac{1}{365\times Y}\left\{\sum_{n\in N} c_n^{dg} x_n^{dg} + \sum_{(n,j)\in N} c_{n,j}^{hl} x_{n,j}^{hl} + \sum_{(n,j)\in N} c_{n,j}^{tl} x_{n,j}^{tl}\right\} + \\
& \frac{DN}{365\times Y} \cdot \sum_{w\in S} \pi_w \left\{\sum_{n\in N} c_{n,w}^{rg}\left(1-u_{n,w}^{DG}\right) x_n^{dg} + \sum_{(n,j)\in N} c_{n,j,w}^{rl}\left(1-u_{n,j,w}^{L}\right)\left(x_{n,j}^{0}+x_{n,j}^{hl}+x_{n,j}^{tl}\right)\right\} + \\
& J_{sub}^{(m)}(\hat{\lambda}_{sub},\hat{\mu}_{sub}) \qquad \forall J_{sub}^{(m)}(\hat{\lambda}_{sub},\hat{\mu}_{sub}) = Eq.(5)\Big|_{\hat{\lambda}_{sub},\hat{\mu}_{sub}}
\end{aligned} \tag{6}
$$

where $\hat{\lambda}_{sub}$ and $\hat{\mu}_{sub}$ are the optimal values of λ, $\underline{\mu}$ and $\overline{\mu}$ in SP2, (5), respectively.

2- *SP2 is feasible and its objective function is unbounded*: In this condition, the infeasibility cut as (7) is added to MP, so that $\hat{\lambda}_{sub}$ and $\hat{\mu}_{sub}$ are obtained from problem of SP3 as (8).

$$
J_{sub}^{(r)}(\hat{\lambda}_{sub},\hat{\mu}_{sub}) \leq 0 \qquad \forall J_{sub}^{(r)}(\hat{\lambda}_{sub},\hat{\mu}_{sub}) = Eq.(8)\Big|_{\hat{\lambda}_{sub},\hat{\mu}_{sub}} \tag{7}
$$

$$
J_{sub} = Eq.(5)\big|_{\Omega};\Omega \square \left\{\lambda,\mu \,\middle|\, Eqs.(5a)-(5j), \lambda=[-1,1], \overline{\mu}=[0,1], \underline{\mu}=[-1,0]\right\} \tag{8}
$$

3- *SP2 is infeasible*: In this condition, the main problem, (2), is infeasible.

Finally, the convergence criteria for the BD algorithm is to satisfy $\left|z_{upper}-z_{lower}\right| \leq \varepsilon$, where ε is the BD's convergence tolerance, and z_{upper} is the value of the objective function that is obtained by (9). Note, the second part of (9) is the objective function of SP2 or (5), and z_{lower} determinates by (3).

$$
\begin{aligned}
z_{upper} = & \frac{1}{365\times Y}\left\{\sum_{n\in N} c_n^{dg} x_n^{dg} + \sum_{(n,j)\in N} c_{n,j}^{hl} x_{n,j}^{hl} + \sum_{(n,j)\in N} c_{n,j}^{tl} x_{n,j}^{tl}\right\} + \\
& \frac{DN}{365\times Y} \cdot \sum_{w\in S} \pi_w \left\{\sum_{n\in N} c_{n,w}^{rg}\left(1-u_{n,w}^{DG}\right) x_n^{dg} + \sum_{(n,j)\in N} c_{n,j,w}^{rl}\left(1-u_{n,j,w}^{L}\right)\left(x_{n,j}^{0}+x_{n,j}^{hl}+x_{n,j}^{tl}\right)\right\} + \\
& J_{sub}(\hat{\lambda}_{sub},\hat{\mu}_{sub}) \qquad \forall J_{sub}(\hat{\lambda}_{sub},\hat{\mu}_{sub}) = Eq.(5)
\end{aligned} \tag{9}
$$

4. Numerical results and discussion

4.1. Data

In this section, the proposed ROD-based expansion planning is implemented on 33-bus and 119-bus distribution network that are shown in Fig. 3 [32]. The network characteristics and peak load data of these networks are expressed in [32], but the hourly load data is equal to multiplication of peak load data and hourly load factor curve that is presented in [22]. Also, it is assumed that the backup DG with the capacity 500 kVA and the investment cost of 1500$/kVA [6] can be placed in all buses of the networks, and hardening line can be installed in all line sections in Fig. 3 for different networks. The characteristics of hardening lines such as reactance, resistance, length, and capacity are the same as existing line data that are presented in [6], while its investment cost is 5924$/pole, where it is assumed the span of two consecutive poles is 150 ft [6]. Moreover, the location of tie line with the investment cost of 15000 $ in 33-bus and 119-bus networks are shown in Figs. (3a) and (3b), respectively. Also, *DN* and planning year (*Y*) are considered respectively to be 2 and 10 years.

It should be noted that in this paper, it is assumed that backup DG, hardening and tie line design are very resistant to natural disasters. Therefore, it is possible that their repair cost is very low, which is omitted in the article. Hence, it is considered that the repair cost of backup DG, hardening and tie lines are zero, but, it is equal to 3211$/pole for an existing line. It is assumed that in the 33-bus network, buses (11-16), (20-22), (23-24), (29-31) are respectively located in zones that include earthquake, flood, earthquake and flood. In the 119-bus test network, buses (21-25), (29-31, 37, 38), (52-56), (73-76), and (119-123) are located in zones with the condition of earthquake, earthquake, flood, flood, and flood, respectively. The hourly energy price is presented in [22], and the operation price of DG and VOLL is considered to be 20 and 100 $/MWh, respectively. Also, the RWM generates 1000 scenario samples for the considered uncertainty parameters based on normal PDF considering 10% standard deviation, and then, the simultaneous backward approach reduces the number of scenarios to 20 scenarios with the higher occurrence probability.

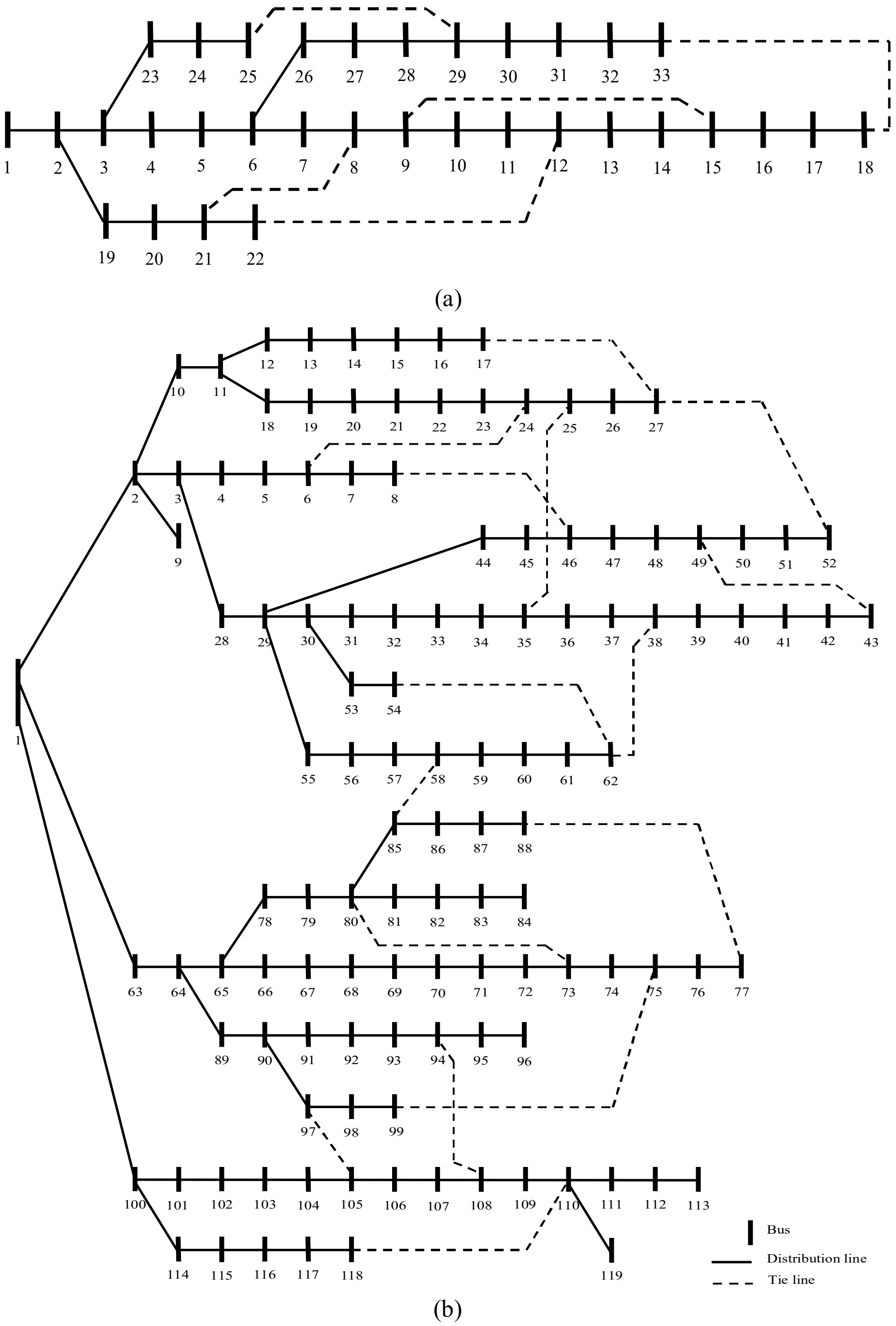


Fig. 3 The radial distribution test networks, a) 33-bus, b) 119-bus [32]

4.2. Results

The proposed ROD problem is simulated on the GAMS software and solved by CPLEX solver to obtain the capabilities of this strategy [33].

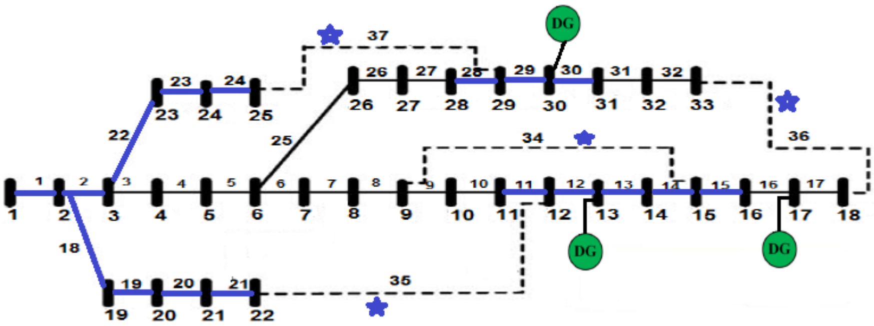
1) *Comparison of different solvers results*: Table 2 presents the results of different solvers in the various models of ROD. In this section, the solvers of BARON, BONMIN, DISOPT and KNITRO are used to investigate the capability of the proposed MINLP ROD method. Based on this table, the total number of variables and equations are the same for these solvers. But, the solver of BONMIN can obtain local optimal solution with the objective function value of 2963.5 $ for this problem at 48823 seconds, while the other solvers of the proposed MINLP model are not able to achieve a feasible solution.

In the proposed MILP ROD method that includes high number of variables and equations in comparison with MINLP method, solvers BONMIN, CPLEX and GLPK obtain a global optimal solution with the convergence point of 2437.9 $ at 1045, 951 and 112 seconds, respectively. Therefore, the proposed MILP solvers can reduce the objective function value about 17.73 % with respect to MINLP solvers, accordingly the solver of CPLEX obtains this point at low calculation time compared to other solvers. Finally, the results of the proposed MILP model based on BD approach are addressed in the last row of this table. Accordingly, it achieves the same results with MILP model, but, the calculation time in this method is less than the calculation time in the MILP solvers about 847 seconds (951 – 104). Therefore, it can be said that the proposed MILP ROD model based on BD approach is more suitable with respect to other models. Finally, the proposed ROD model according to the BD-based MILP formulation is better than the ROD model presented in [6-15] with MINLP formulation, generally, based on Table 1. Thus, this statement confirms the benefits of the proposed ROD strategy based on the second contribution in Section 1.

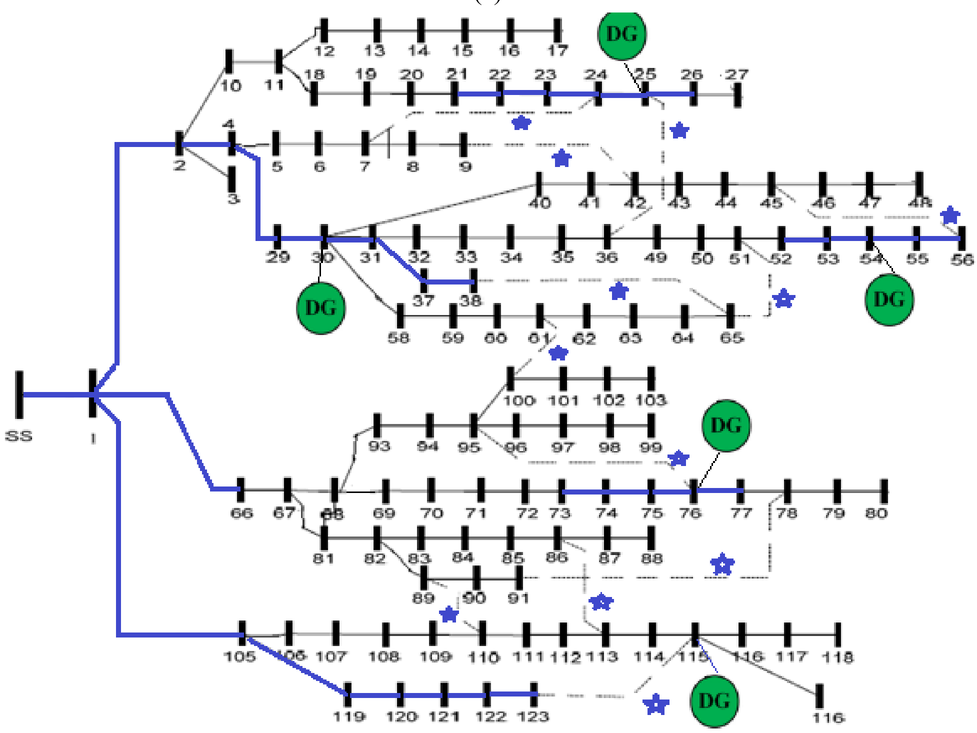
Table 2: Comparison of the proposed MINLP, MILP and BD-based MILP models for ROD strategy in the 33-bus distribution test network

Model	Solver	Total number of variables	Total number of equations	Calculation time (s)	Objective function ($)	Model status
MINLP	BARON	9103	82184	-	-	Infeasible
	BONMIN	9103	82184	4823	2963.5	Locally optimal
	DISOPT	9103	82184	-	-	Infeasible
	KNITRO	9103	82184	-	-	Infeasible
MILP	BONMIN	9823	84945	1045	2437.9	Globally optimal
	CPLEX	9823	84945	951	2437.9	Globally optimal
	GLPK	9823	84945	1112	2437.9	Globally optimal
BD with $\varepsilon =$ 0.1	CPLEX	3168* / 6685**	3238* / 81191**	104	2437.9	Globally optimal

2) *Expansion planning results based on ROD strategy*: The planning results for the 33-bus and 119-bus distribution networks are shown in Fig. 4. According to Fig. 4, the hardening line is used in the mentioned zones in the case of happening earthquake and flood, because, this line is strong and the probability of its outage is low under these extreme weather events in comparison with the conventional existing line. Hence, the network does not experience the blackout, and it has high resiliency in these conditions. As another point, the backup DG is generally used in the zones that are farther from the distribution station on the slack bus, and 4 and 12 tie lines are installed in the 33-bus and 119-bus as shown in Fig. 4 according to the minimum investment and operation costs and maximum resiliency, i.e., the minimum repair and load shedding costs.



(a)



(b)

Fig. 4 Expansion planning results in the distribution test networks, a) 33-bus, b) 119-bus

The economic and technical results of the proposed expansion planning are presented in Tables 3 and 4, respectively. Table 3 expresses the results for 5 cases as follows:

- Case I: Power flow analysis
- Case II: ROD strategy in distribution network including only backup DG
- Case III: ROD strategy in distribution network including only hardening line
- Case IV: ROD strategy in reconfigurable distribution network including only tie line
- Case V: ROD strategy in reconfigurable distribution network including backup DG, hardening and tie line

According to Table 3, Case I includes high operation, repair and load shedding cost, because, there are not the local sources and resilient devices in this case. But, in Case II, by including backup DG in the 33-bus network data, these costs have been reduced to 16%, 16.3%, and 81%, respectively, compared to Case I. These values are equal to 0, 51% and 65.3% in Case III, and 0.2%, 9%, 35% in Case IV. Noted that these results present the benefits of each resilient device, i.e., backup DG, hardening and tie line in the ROD strategy. Also, similar results are seen in the 119-bus test network. However, based on Table 3, the resilient 33-bus distribution network in Case V has daily investment and operation costs of 1046.3 $/day (616.4 + 413.5 + 16.4) and 1391.6 $/day, respectively. However, the repair and load shedding costs are zero due to considering the high value for VOLL which shows the high resiliency of this network under earthquake and flood conditions. Also, it is noted that this condition is happened in the 119-bus distribution network with the daily investment cost of 2008.2 $/day and daily operation cost of 2516.1 $/day.

In addition, two cases have been investigated in Table 4, where the cases I and V refer to power flow analysis and the proposed ROD method, respectively. According to this table, the maximum voltage deviation, i.e. max($|1 - V_{n,t,w}|$), in the 33-bus distribution network is reduced about 39% ((0.087 – 0.053)/0.087) based on ROD-based expansion planning with respect to the case I. Also, the energy loss of this network has been reduced about 31.4% ((3.077 – 2.111)/3.077) in the case V compared with the case I. These benefits of ROD-based expansion planning are similar to the 119-bus distribution test network, so that the maximum voltage deviation and energy loss are decreased about 29.3% and 34.9%, respectively, in comparison with the case I. Finally, the explanations in this section refer to the benefits of the proposed ROD strategy based on the first contribution in Section 1, where it can achieve high resilience network (repair and load shedding costs are zero) and optimal situation for operation indices, while it selects optimal location and operation for resilience sources based on economic indices.

Table 3: Economic results of expansion planning in the distribution test networks

Network	Daily cost		Value ($/day).0				
			Case I	Case II	Case III	Case IV	Case V
33-bus	Investment	DG	0.0	821.9	0.0	0.0	616.4
		Hardening line	0.0	0.0	478.6	0.0	413.5
		Tie line	0.0	0.0	0.0	20.5	16.4
	Repair		113.6	95.1	55.7	103.2	0.0
	Operation		1416.2	1393.6	1416.2	1413.4	1391.6
	Load shedding		2911.0	553.0	1012.0	1891.0	0.0
	Total		4440.8	2803.6	2962.5	3428.1	2437.9
119-bus	Investment	DG	0.0	1232.9	0.0	0.0	1027.4
		Hardening line	0.0	0.0	1002.4	0.0	931.5
		Tie line	0.0	0.0	0.0	61.5	49.3
	Repair		238.7	192.9	98.8	213.5	0.0
	Operation		2562.3	2519.5	2562.3	2555.8	2516.1
	Load shedding		4561.0	903.0	2011.0	3722.0	0.0
	Total		7362.0	4848.3	5674.5	6552.8	4524.3

Table 4: Technical results of expansion planning in the distribution test networks

Case	Network	Variable	Value
I	33-bus	Maximum voltage deviation (p.u)	0.087
		Energy loss (MWh)	3.077
	119-bus	Maximum voltage deviation (p.u)	0.092
		Energy loss (MWh)	5.262
V	33-bus	Maximum voltage deviation (p.u)	0.053
		Energy loss (MWh)	2.111
	119-bus	Maximum voltage deviation (p.u)	0.065
		Energy loss (MWh)	3.427

3) *Investigating resiliency capability*: In this section, the curve of resiliency indices such as expected energy not supplied (EENS), i.e., $\sum_{w \in S} \pi_w \sum_{t \in ST} \sum_{n \in N} P_{n,t,w}^{NS}$, repair and load shedding cost in VOLL are plotted in Fig. 5.

The 33-bus and 119-bus distribution networks have high ENNS and repair cost (low resiliency) and zero load shedding cost (due to zero VOLL) in VOLL = 0, because, there is no incentive to improve resiliency in this condition. But, EENS and repair costs are reduced by increasing VOLL, however, load shedding cost increases/reduces for

VOLL between 0 to 20 $/MWh / 20 to 100 $/MWh. Hence, they are equal to zero (high resiliency condition) in VOLL of 60 and 80 $/MWh for 33-bus and 119-bus networks, respectively. It is noted that according to Fig. 6, improvement of the network resiliency is related to the high planning cost, i.e., summation of daily investment and operation costs. Therefore, the VOLL should be increased to improve network resiliency, where in this case, the planning cost will be increased.

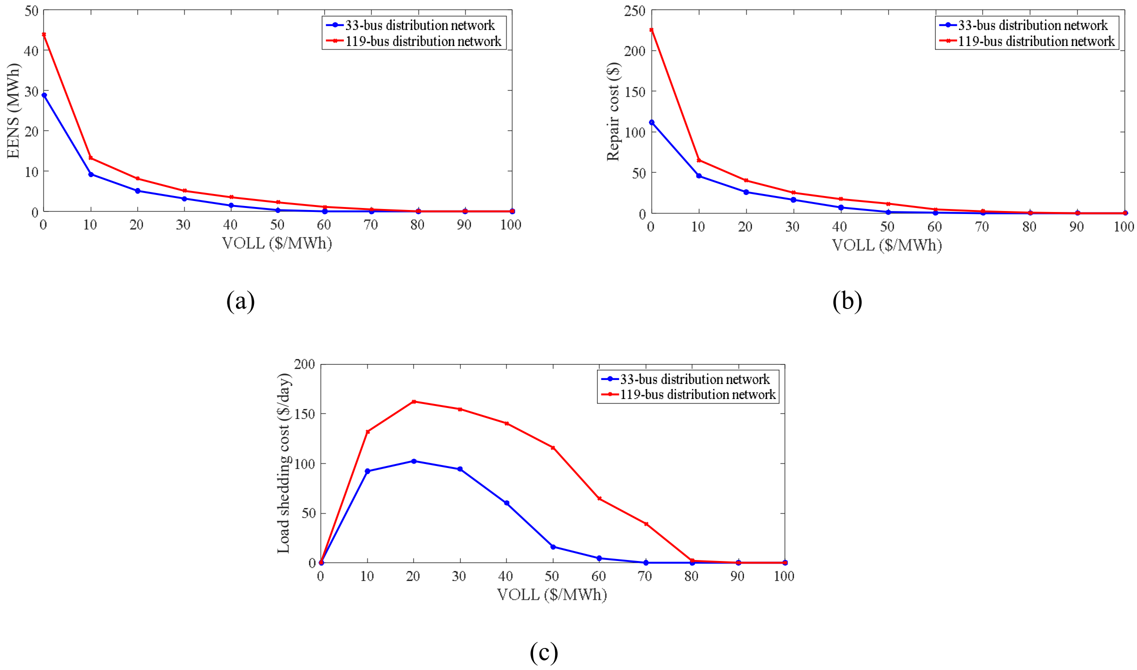


Fig. 5 Variations of resiliency indices versus VOLL, a) EENS, b) repair cost, c) load shedding cost

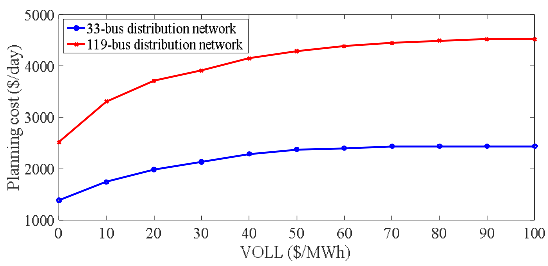


Fig. 6 Variations of daily planning cost versus VOLL

5. Conclusions

In this paper, a model of the ROD-based expansion planning in distribution networks has been presented to improve the network resiliency under extreme weather events such as earthquakes and floods. Hence, it aimed at minimizing the summation of daily investment, repair, operation and load shedding costs as the objective function, while it is subjected to AC power flow equations, system operation limits, and planning and reconfiguration constraints. Also, the original MINLP ROD model has been converted to a MILP method by the conventional linearization approach, and thus the BD approach is used to solve this problem at lower calculation time. Moreover, the hybrid RWM and the simultaneous backward method have been implemented to model the uncertainty of load, energy price, and repair cost. According to the results, the proposed MILP model based on BD approach can obtain a global optimal solution at the least calculation time with respect to other solvers. Also, it is able to improve the computational time by 98% with respect to solvers of the MINLP model. Moreover, the proposed ROD strategy can achieve the higher resiliency in different distribution networks that EENS and repair as well as load shedding costs are equal to zero. It is able to reduce energy loss and maximum voltage deviation about 30% in comparison with the load flow analysis. Note that the proposed problem in this paper is suitable for the balanced distribution networks; however, real distribution networks include unbalanced situations as well. Accordingly, the resilience model for the unbalanced distribution systems will be considered in the future works. Also, the network resiliency can be improved by different sources such as renewable energy sources and energy storage systems that are not investigated in this paper. But, this work is considered in future researches.

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