Holistic Approach to Resilient Electrical Energy Distribution Network Planning

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Abstract- This paper proposes a two-objective linearized resilient architecture (LRA) model for distribution networks to achieve a strictly resilient network during natural disasters like earthquakes and floods. To obtain this goal, the proposed LRA framework is based on the planning of the energy storage system (ESS), hardening and tie lines, and backup distributed generation (DG). Therefore, the proposed model minimizes the sum of planning and expected operation costs in the first objective function, and the total load shedding and repair costs originates from earthquakes and floods in the second objective function. Also, it constraints to the network planning model, linearized equations of the system operation, and system reconfiguration formulation. Moreover, stochastic programming models the uncertain availability of the network equipment during the natural disaster condition, the load and electricity price. In the next step, the ε-constraint-based Pareto optimization is used to achieve an equivalent single-objective LRA model and obtain the best compromise solution. Finally, the proposed strategy is applied to a standard test distribution network. Numerical simulation confirms the capability of the proposed method in obtaining a resilient distribution network during natural disasters.

Keywords: Natural disasters; Optimal power flow; Resilient architecture; Network equipment planning.

Nomenclature

1) *Sets & Indices*

j	Index of bus
k, K	Index and set of linear part for circular plane limit
l, L	Index and set of linear part in the voltage term
n, N	Index and set of bus
n_l	Total number of linear parts for the linearized voltage term
n_k	Total number of linear parts for the circular plane limit
t, ST	Index and set of operation hour
w, S	Index and set of scenario sample obtained by scenario reduction method

2) *Parameters*

A	Incidence matrix for bus and distribution line
B, G	Susceptance and conductance for a distribution line in per-unit (pu)
c^{dg}, c^{rg}	Construction and repair cost for DG in \$
c^{es}, c^{re}	Construction and repair cost for ESS in \$
c^{hl}, c^{tl}	Construction cost for hardening and tie lines in \$
c^{rl}	Repair cost for the distribution line in \$
DR, CR	Discharge and charge rate of ESS in per unit [pu].
E^{min}, E^{I}, E^{max}	Minimum, initial and maximum stored energy in ESS [pu].
du, Y	Total day including earthquakes or floods, planning horizon in year
M	A fixed parameter including high value such as 10^6
N_{bus}	Total buses of the distribution network
P^D, Q^D	Active and reactive power a load (pu)
S^{DGmax}	Capacity of DG (pu)
m	Line slop in linearization segments for voltage magnitude.
S^{Lmax}	Capacity of distribution line (pu)
S^{Smax}	Capacity of station (pu)

$VOLL$	Penalty price called "value of lost load" in \$/MWh.
$\underline{V}, \overline{V}$	Lower and upper allowed voltage in pu
$\Delta\alpha$	Deviation of angle in linearization method of circular plane limit .
π	Probability of a scenario sample
κ, ρ^{dg}	Price of energy, and price of DG fuel in \$/MWh
η^{ch}, η^{dis}	Efficiency of ESS in charging and discharging mode

3) *Variables* [pu]

P^{DG}, Q^{DG}	Active and reactive power of the backup DG.
P^{ESch}, P^{ESdch}, Q^{ES}	Active power charge and discharge as well as the reactive power of ESS.
P^{L}, Q^{L}	Power flow of a line in active and reactive terms
P^{NS}, Q^{NS}	Power not supplied of a load in active and reactive terms
P^{S}, Q^{S}	Power flow of a station in active and reactive terms
V, ΔV, δ	Magnitude, deviation and angle of the voltage [rad], respectively.
x^{dg}, x^{es}, x^{hl}, x^{tl}, x^{0}	Construction state of the backup DG, ESS, tie, hardening and existing lines.
x^{ch}, x^{dch}	Binary variables related to charging and discharging operation model for ESS.
y, y^{hl}, y^{tl}, y^{0}	Binary variables associated with the state of the line, tie, hardening and existing lines.
λ_{sub}, μ_{sub}	Dual variables associated with the primal subproblem's equality and inequality constraints.

1. Introduction

1.1. Motivation

Resilience is one of the most important indices in the operation of the smart distribution networks, where it refers to network resistance versus negative effects such as disconnection of several distribution lines due to natural disaster condition [1-2]. Hence, the smart grid concept presents a resilient architecture (RA) strategy on the distribution network to protect this system under the condition of extreme weather [3-4]. This strategy uses the planning and operation model of the energy storage system (ESS), hardening and tie lines, backup distributed generation (DG) and other equipment based on improving the network resilience [5]. Therefore, the mentioned strategy defines an optimization problem that is obtained optimal location and schedule for the referred strong equipment against natural disaster events based on lower planning and operation cost and higher system resiliency.

1.2. Literature review

There is a variety of types of research presented in the area of power system's resilience. Reference [6] that is improved resiliency in the distribution system employing back-up DGs, hardening and tie-line, where it uses a linearized distribution flow in the stochastic resilience-oriented design framework. The authors of [7] are combined time-to-event methods to assess the distribution network resilience as a probabilistic model along with different natural disasters condition. In [8], a risk assessment method is reported to study the probability of possible disturbances to the distribution systems and find accurate advice for trading renewable energy customers based on the capability of resilient network. In addition, the impacts of variability and inadequacy of DGs to enhance the distribution system resiliency is considered [9]. Furthermore, the network reconfiguration technique in conditions of extreme climate is taken into account in [10] to enhance the distribution network resiliency. Resilience enhancement strategy was modeled in [11] for a coupled distribution network and urban transportation system for allocation of hardening lines and DGs while there are outages in distribution lines and traffic lights. In [12], it is modeled a tri-level resilience enhancement framework to minimize the cost of hardening investment and load shedding in different natural disasters. Moreover, the impacts of different power equipment (e.g., power electronics and energy storage) and distribution system topology on the resiliency during extreme events are presented in [13]. In [14], the planning of hardening lines and renewable DG is reported to enhance the resiliency. Ref. [15] models the robust planning of DGs to achieve high resiliency. In [16], a method based on decision support after an earthquake is expressed to enable the operators to restore the critical loads of a distribution grid.

In [17], the planning of MGs to strengthen the network against severe faults has been studied. To do so, three methodologies are proposed aiming to determine the optimal nodes for connecting MGs, and the capacity of the dispatchable generation units deployed within MGs. Also, [18] explains an applied methodology for the resilient planning and routing of distribution systems taking real scenarios generated from georeferenced data into account. Consumers' demand and their location are the base for distribution transformer allocation in view of the minimal construction costs and decrease of utility's budget. Minimum Spanning Tree techniques are employed to allocate distribution transformers and medium voltage network routing. Furthermore, tie points allocation is carried out to minimize the total load shedding when extreme events occur, while improving reliability and resilience reducing downtime. Authors of [19] explain the implementation of an intelligent decision tool that allows the design of network distribution system planning considering the current electrical company standards, in order to have a clear and quick initial overview of the configuration that an electricity network should have in response to an increasing demand, considering not only the coverage and capacity of the transformers but also voltage drop along the conductors, which must not exceed 3% of the nominal value. In [20], a three-layer model has been proposed to find the optimal routing of an underground electrical distribution system, utilizing a graph search heuristic. In the model, the first layer considers transformer allocation and medium voltage network routing, the second layer uses the low voltage network routing and transformer sizing, and the third presents a method to allocate distributed energy resources in the distribution system.

1.3. Contributions

According to the literature, there are various approaches to enhance the network resilience such as utilizing strong equipment against natural disasters and the network reconfiguration. However, previous studies have only considered one of the aforementioned aspects and there is limited number of research in the area such as [6] that proposes a hybrid approach to increase the resilience of the distribution systems under extreme weathers and the natural disasters. While, in [6], the capability of ESS is not investigated on the network resiliency improvement. Also, almost all the available literature has formulated the resilient architecture as a mixed-integer non-linear programming (MINLP). But, the solvers of this model cannot obtain the global optimal solution, generally.

To cope with mentioned subjects, this paper as Fig. 1 models a two-objective linearized RA (LRA) strategy in the distribution grid, where it uses the backup DG, ESS and hardening and tie lines in this system to enhance the system resiliency under the earthquake and flood conditions. Hence, the proposed strategy minimizes the sum of the investment and operation costs in the first objective function, and it considers minimizing the resiliency cost equaling to the total cost of repair and load shedding in the second objective function. Also, the constraints of the optimization model includes: the linearized optimal power flow (LOPF) equations, planning model of strong equipment against natural disaster events, and reconfiguration constraints. Moreover, to consider the uncertainty of the parameters of load, energy price and network equipment availability, the scenario-based stochastic programming (SBSP) model are implemented. In other words, the Monte-Carlo Simulation (MCS) generates a high number of scenarios based on the standard probability distribution function (PDF) for the mentioned parameters, and thus, the simultaneous backward method (SBM) obtains a low number of scenarios with high occurrence probability. Also, the Pareto optimization approach based on ε-constraint method is used in this paper to obtain a single-objective LRA model with the best compromised optimal solution.

Hence, the main contributions of this paper are summarized as follows:

– Obtaining a resilient distribution network using optimal planning and operation of backup DG, ESS and hardening and tie lines, and reconfiguration strategy;

– Presenting a two-objective linearized resilient architecture strategy in the distribution network to achieve high system resiliency based on the optimal planning and operation cost.

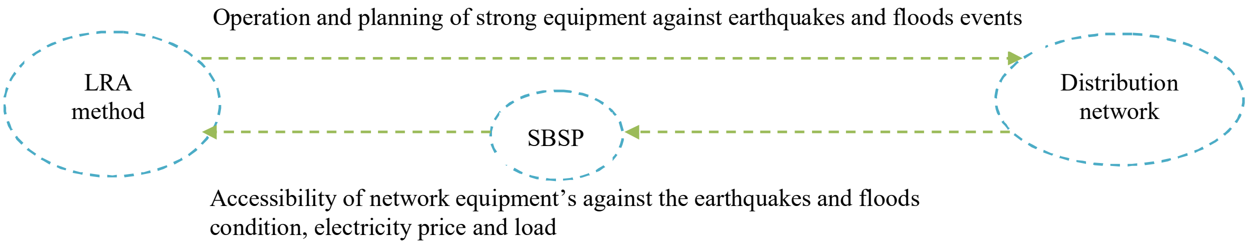


Fig. 1. The proposed LRA scheme in the distribution system

1.4. Paper organization

In the following, Section 2 expresses the stochastic LRA formulation as a two-objective problem. Then, Section 3 obtains the single-objective model of LRA according to Pareto optimization approach. In the end, numerical results and conclusions is addressed in Sections 4 and 5, respectively.

2. Problem model

In this section, the two-objective linearized resilient architecture (LRA) model for the distribution network is expressed. This optimization problem minimizes the summation of the daily investment and operation cost and daily repair and load shedding cost in the first and second terms, respectively. Also, this problem is subjected to some constraints the planning model of network, grid reconfiguration strategy and the linearized optimal power flow (LOPF) equations. Therefore, the proposed problem is written as follows:

$$\min \quad F_1 = \overbrace{\frac{1}{365\times Y}\left\{\sum_{n\in N} c_n^{dg} x_n^{dg} + \sum_{n\in N} c_n^{es} x_n^{es} + \sum_{(n,j)\in N} c_{n,j}^{hl} x_{n,j}^{hl} + \sum_{(n,j)\in N} c_{n,j}^{tl} x_{n,j}^{tl}\right\}}^{\text{Daily investment cost}} + \overbrace{\sum_{w\in S} \pi_w \sum_{t\in ST} \sum_{n\in N} \kappa_t P_{n,t,w}^{S} + \rho_n^{dg} P_{n,t,w}^{DG}}^{\text{Operational cost}} \tag{1a}$$

$$\min \qquad F_2 = \overbrace{\frac{1}{du \times Y}.\left\{\sum_{n\in N} c_n^{rg} x_n^{dg} + \sum_{n\in N} c_n^{re} x_n^{es} + \sum_{(n,j)\in N} c_{n,j}^{rl}\left(x_{n,j}^0 + x_{n,j}^{hl} + x_{n,j}^{tl}\right)\right\}}^{\text{Daily repair cost}} + \overbrace{\sum_{w\in S}\pi_w \sum_{t\in ST}\sum_{n\in N} VOLL.P_{n,t,w}^{NS}}^{\text{Load sheding cost}} \tag{1b}$$

Subject to:

$$P_{n,t,w}^{S} + P_{n,t,w}^{DG} + \left(P_{n,t,w}^{ESdch} - P_{n,t,w}^{ESch}\right) - \sum_{j\in N} A_{n,j} P_{n,j,t,w}^{L} = P_{n,t,w}^{D} - P_{n,t,w}^{NS} \quad \forall\, n,t,w \tag{1c}$$

$$Q_{n,t,w}^{S} + Q_{n,t,w}^{DG} + Q_{n,t,w}^{ES} - \sum_{j\in N} A_{n,j} Q_{n,j,t,w}^{L} = Q_{n,t,w}^{D} - Q_{n,t,w}^{NS} \quad \forall\, n,t,w \tag{1d}$$

$$\begin{aligned} -M.\left(1-y_{n,j,t}\right) \le P_{n,j,t,w}^{L} - \left\{G_{n,j}\left(\sum_{l\in L}\left(m_l - \underline{V}\right)\Delta V_{n,t,l,w} - \underline{V}.\Delta V_{j,t,l,w}\right) - \left(\underline{V}\right)^2 B_{n,j}\left(\delta_{n,t,w} - \delta_{j,t,w}\right)\right\} \\ \le M.\left(1-y_{n,j,t}\right) \quad \forall n,j,t,w \end{aligned} \tag{1e}$$

$$\begin{aligned} -M.\left(1-y_{n,j,t}\right) \le Q_{n,j,t,w}^{L} - \left\{-B_{n,j}\left(\sum_{l\in L}\left(m_l - \underline{V}\right)\Delta V_{n,t,l,w} - \underline{V}.\Delta V_{j,t,l,w}\right) - \left(\underline{V}\right)^2 G_{n,j}\left(\delta_{n,t,w} - \delta_{j,t,w}\right)\right\} \\ \le M.\left(1-y_{n,j,t}\right) \quad \forall n,j,t,w \end{aligned} \tag{1f}$$

$$\delta_{n,t,w} = 0 \quad \forall\, n = \text{Slack bus}, t, w \tag{1g}$$

$$P_{n,j,t,w}^{L}\cos\left(k.\Delta\alpha\right) + Q_{n,j,t,w}^{L}\sin\left(k.\Delta\alpha\right) \le S_{n,j}^{L\max}.y_{n,j,t} \quad \forall\, n,j,t,k,w \tag{1h}$$

$$P_{n,t,w}^{S}\cos\left(k.\Delta\alpha\right) + Q_{n,t,w}^{S}\sin\left(k.\Delta\alpha\right) \le S_{n}^{S\max} \quad \forall\, n = \text{Slack bus}, t,k,w \tag{1i}$$

$$0 \le \Delta V_{n,t,l,w} \le \left(\overline{V} - \underline{V}\right)/n_l \quad \forall\, n,t,l,w \tag{1j}$$

$$y_{n,j,t} = y_{n,j,t}^{0} + y_{n,j,t}^{hl} + y_{n,j,t}^{tl} \quad \forall n,j,t \tag{1k}$$

$$y_{n,j,t}^{0} \le x_{n,j}^{0} \quad \forall n,j,t \tag{1l}$$

$$y_{n,j,t}^{hl} \le x_{n,j}^{hl} \quad \forall n,j,t \tag{1m}$$

$$y_{n,j,t}^{tl} \le x_{n,j}^{tl} \quad \forall n,j,t \tag{1n}$$

$$x_{n,j}^{0} + x_{n,j}^{hl} + x_{n,j}^{tl} \le 1 \quad \forall n,j \tag{1o}$$

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

$$P_{n,t,w}^{DG}\cos\left(k.\Delta\alpha\right) + Q_{n,t,w}^{DG}\sin\left(k.\Delta\alpha\right) \le x_n^{dg} S_n^{DG\max} \quad \forall\, n,t,k,w \tag{1q}$$

$$\left(P_{n,t,w}^{ESdch}-P_{n,t,w}^{ESch}\right)\cos\left(k.\Delta\alpha\right)+Q_{n,t,w}^{ES}\sin\left(k.\Delta\alpha\right)\le x_n^{es}S_n^{ES\max}\quad \forall\ n,t,k,w \tag{1r}$$

$$0\le P_{n,t,w}^{ESch}\le x_{n,t}^{ch}CR_n\quad \forall\ n,t,w \tag{1s}$$

$$0\le P_{n,t,w}^{ESdch}\le x_{n,t}^{dch}DR_n\quad \forall\ n,t,w \tag{1t}$$

$$x_n^{es}E_n^{\min}\le E_n^I+\sum_{\tau=1}^{t}\left(\eta^{ch}P_{n,\tau,w}^{ESch}-\frac{1}{\eta^{dch}}P_{n,\tau,w}^{ESdch}\right)\le x_n^{es}E_n^{\max}\quad \forall\ n,t,w \tag{1u}$$

$$x_{n,t}^{dch}+x_{n,t}^{ch}\le x_n^{es}\quad \forall\ n,t \tag{1v}$$

The proposed objective functions are formulated in equation (1a) and (1b), where first and second functions in these equations minimize the daily network and resiliency cost, respectively [6]. So that the network cost includes investment cost of network equipment such as backup DG, ESS, distribution and tie lines, expected energy cost obtained from the upstream network, and expected DGs fuel cost based on (1a). Also, resiliency cost contains repair and expected load shedding costs according to (1b). Noted that according to the “wear and tear” strategy for the assets during its operations under extreme weather conditions, the repair cost for different elements such as DG, ESS, existing, hardening and tie lines, is considered in the first part of objective function (1b). In equations (1c)-(1j), the LOPF constraints including nodal active and reactive power balance, (1c) and (1d), active and reactive power flowing from the distribution line, (1e) and (1f), voltage angle of the slack bus, (1g), system operation limits such as distribution line and station capacity limit as well as voltage deviation limit, (1h), (1i) and (1j) [21, 22]. This model is based on the voltage deviation and angle to achieve the linear formulation in the AC OPF problem related to the distribution network [22]. Hence, according to [22], voltage magnitude (V) /V^2 is equal to $\underline{V}+\sum_{l\in L}\Delta V_l$ / $\left(\underline{V}\right)^2+\sum_{l\in L}m_l\Delta V_l$ based on the conventional piecewise linearization method [22], where m is line slop. Moreover, the distribution line or station capacity limit is a circular plane, i.e. $P^2+Q^2\le S^2$, generally. The circular plane is able to approximate to a polygon plane containing high number edges [23], where more details are presented in [23]. Also, network reconfiguration and distribution line planning model are expressed in (1k)-(1p) [24], so that switch state on the distribution line, i.e. close or open mode, determinates by (1k), while it between buses n and j depends on construction state of the existing, hardening or tie lines, x^0, x^{hl} and x^{tl}, according to (1l)-(1n), where only one of those lines can be built between these busses based on the constraint (1o). Also, the radial structure of the distribution network will be obtained using constraint (1p) [24], where based on this equation; the total line number should be equal to difference f total number buses and 1 in the radial network. Finally, the backup DG and ESS planning models are demonstrated in constraints (1q)-(1v) that are referred respectively to DG capacity limit, ESS charger capacity limit, charge and discharge rate of ESS, stored energy limit of ESS, and a logical limit that prevents the simultaneous operation of charging and discharging modes in ESS [25]. Noted that in these equations, backup DG or ESS is built if x^{dg} / x^{es} = 1, otherwise, x^{dg} / x^{es} = 0.

In the proposed LRA model, active and reactive loads, P^D and Q^D, energy price, κ, and repair cost, c^{rg} and c^{rl}, are uncertain parameters, where repair cost of different devices is depended on their availability in earthquake or flood condition. In other words, there is this cost for device if it locates in a zone consisting of an earthquake or flood. Then, scenario-based stochastic programming (SBSP) is utilized to model these parameters. In this technique, the MCS generates many scenario samples for the mentioned uncertain parameters by using normal probability distribution function (PDF) [24]. In the next step, the simultaneous backward method (SBM) as scenario reduction approach obtains a low number of scenarios that are included high occurrence probability [24].

3. Solution method

The Pareto optimization is applied here to find the best compromise solution of the proposed two-objective LRA model. The Pareto optimization approaches assist the decision-makers to find, compare and select their choice among a set of acceptable solutions. The ε-constraint-based Pareto optimization of this work is a straightforward approach that re-organizes the two-objective model and solves it the in form of a single-objective model [26]. Based on this approach, F_1 in (1a) is the objective function of the single-objective problem, and F_2 in (1b) will be constrained to ε as shown in the following formulation:

$$\min \quad F_1 = \overbrace{\frac{1}{365\times Y}\left\{\sum_{n\in N} c_n^{dg} x_n^{dg} + \sum_{n\in N} c_n^{es} x_n^{es} + \sum_{(n,j)\in N} c_{n,j}^{hl} x_{n,j}^{hl} + \sum_{(n,j)\in N} c_{n,j}^{tl} x_{n,j}^{tl}\right\}}^{\text{Daily investment cost}} + \overbrace{\sum_{w\in S}\pi_w \sum_{t\in ST}\sum_{n\in N}\kappa_t P_{n,t,w}^{S} + \rho_n^{dg} P_{n,t,w}^{DG}}^{\text{Operational cost}} \tag{2a}$$

Subject to:

$$F_2 = \overbrace{\frac{1}{du\times Y}\cdot\left\{\sum_{n\in N} c_n^{rg} x_n^{dg} + \sum_{n\in N} c_n^{re} x_n^{es} + \sum_{(n,j)\in N} c_{n,j}^{rl}\left(x_{n,j}^{0} + x_{n,j}^{hl} + x_{n,j}^{tl}\right)\right\}}^{\text{Daily repair cost}} + \overbrace{\sum_{w\in S}\pi_w \sum_{t\in ST}\sum_{n\in N} VOLL.P_{n,t,w}^{NS}}^{\text{Load sheding cost}} \le \varepsilon \tag{2b}$$

$$\text{Constraints (1c)-(1v)} \tag{2c}$$

where ε is constrained by the lower and upper values of the F_2 (here, F_2^{min} and F_2^{max}). Considering these minimum and maximum values for F_2 and by dividing this range into some equidistant intervals, a series of a single-objective optimization problem that each one of them constrained with a special ε value will be achieved that by solving them, a range of semi-optimal values will be obtained for the constrained optimization of F_1 subject to an additional constraint for F_2. When these results are shown with the values of the constrained objective function, (here, F_2), the Pareto front of the problem is achieved [26]. To help the decision-makers for selecting the best compromise solution, here we proposed a fuzzy decision support system (FDSS) to achieve the best compromise solution [27]. The pseudocode of the FDSS approach is presented in Algorithm 1.

Algorithm 1 Algorithm of the FDSS

The best compromise solution of a Pareto front;
Pareto optimal solution along with the preferences of the decision-maker;

Step 1: Computation of the Fuzzy membership function

Calculation the values of the linear fuzzy membership function ($\hat{F}_i$) for each member of the Pareto optimal front:

```
for i = 1:2
    if F_i ≤ F_i^min
       The fuzzy membership function will be equal to 1;
    elseif F_i^min ≤ F_i ≤ F_i^max
       The fuzzy membership function will be equal to (F_i − F_i^max)/(F_i^min − F_i^max);
    elseif F_i ≥ F_i^max
       The fuzzy membership function will be equal to 0;
    end
end
```

Step 2: Obtain value of α_m

$$\alpha_m = \min\left(\hat{F}_1^m, \hat{F}_2^m\right) \quad \forall m \in \{1, 2, ..., n_m\}$$

Step 3: The best compromise solution

Find The best compromise solution by computing $\max_m \ \alpha_m$

Algorithm 1. Pseudocode of the fuzzy decision support system

4. Numerical Simulation and Discussion

4.1. Data

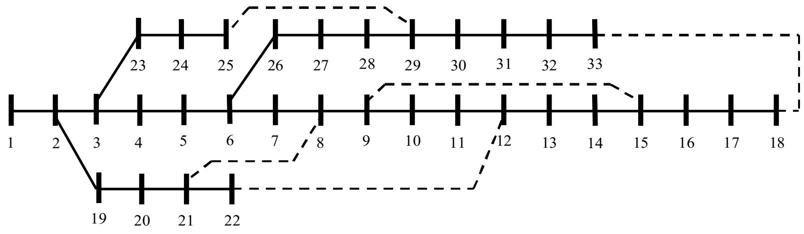
In this paper, the mentioned LRA method is applied on the radial distribution grid in form of 33-bus and 119-bus, where their single-line circuits are plotted in Fig. 2 [28]. The characterizes of distribution lines in these networks are presented in [28], and also, their peak load data is reported in [28]. Daily curves of load factor and energy price are demonstrated in [29-31] so that hours 1:00-7:00 is low load period including energy price of 16$/MWh, hours of 8:00-16:00 and 23:00-24:00 are related to medium load period containing energy price of 24 $/MWh, and peak load hours are 17:00-22:00 with considering electricity price of 30 $/MWh [29-31]. To achieve high resiliency for the mentioned networks, VOLL is considered to 100 $/MWh. Also, characterizes of backup DG, tie and hardening line including candidate location, investment and operation cost, and capacity are expressed in [6], but these data for ESS is presented in Table 1.

Also, it is considered that the ESS charge and discharge rates (*CR*, *DR*) is equal to 40% of ESS capacity (E^{max}), its charger capacity is 50% of E^{max}, E^{min} is 10% of E^{max}, and its charging/discharging efficiency is 0.95/0.95. One of the important applications of ESS is providing energy in critical condition, where this purpose is based on the high value of ESS initial energy (EI). Hence, it is equal to Emax in this paper. Moreover, this paper assumes that the tie and hardening lines, backup DG and ESS are very robust against the earthquakes and floods. Hence, it is expected that the repair cost of these elements can be considered close to zero, but, it is 3211 $/pole for the existing distribution line [6].

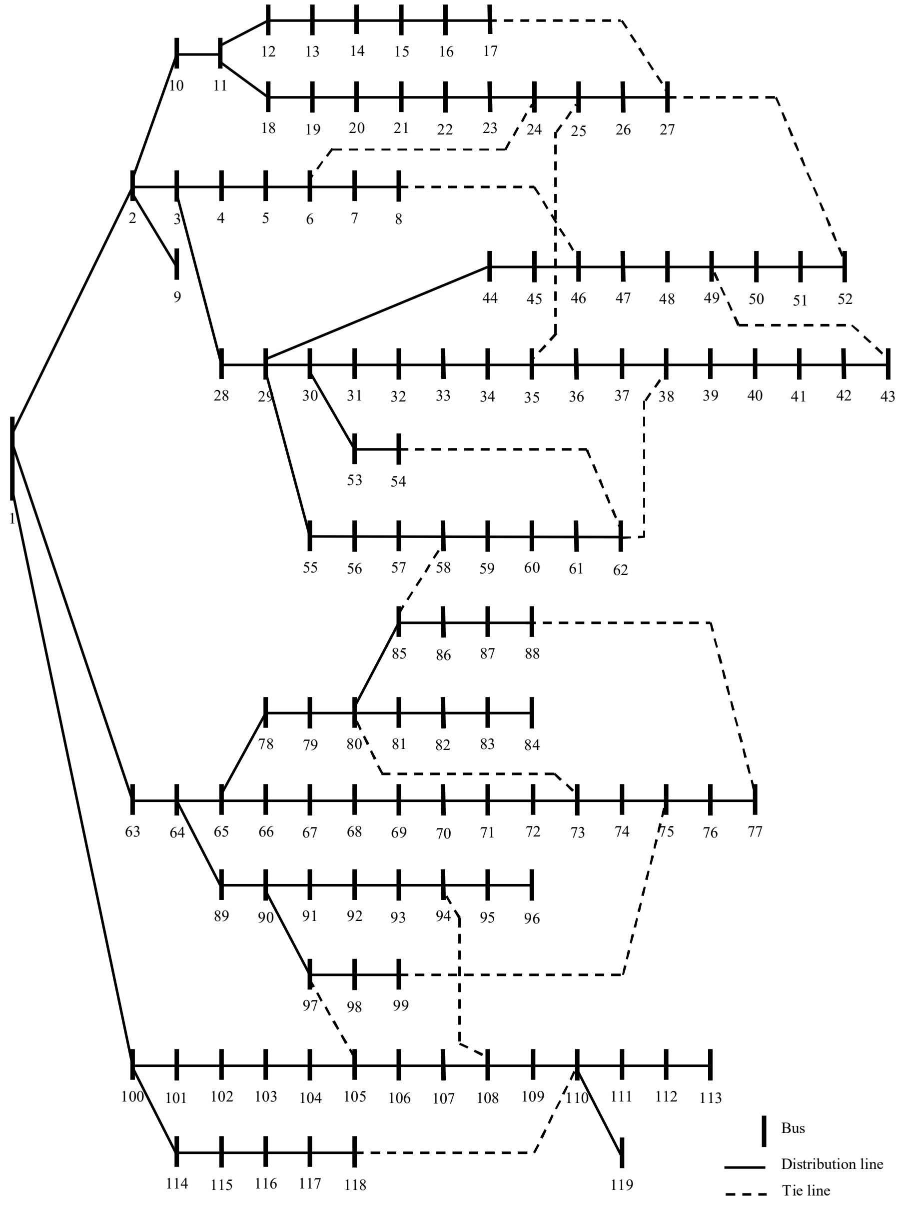
This paper considers that earthquake (flood) happen in buses 11-16 and 23-24 (20-22 and 29-31) in the 33-bus network. Also, there are earthquake, earthquake, flood, flood, and flood in buses (21-25), (28-30, 53, 53), (39-43), (70-73) for the 119-bus system. Finally, in the proposed SBSP method, the MCS generates 1000 scenarios according to normal PDF with considering a standard deviation of 10% for the mentioned uncertain parameters in section 2. Then, the SBM obtains 20 scenarios that are included high occurrence probability.

Table 1: Characterizes of the ESS [22]

Proposed (candidate) location	Size	Construction cost
All buses	4 MWh	150 $/kWh



(a)



(b)

Fig. 2. Single line diagram of, a) 33-bus [28], b) 119-bus [28] distribution networks

4.2. Results

All the numerical results of this work were performed based on the mathematical models developed using (1) and (2) in the GAMS environment using the well-known CPLEX solver [26].

A) *The best compromised solution*: The Pareto front of the proposed LRA strategy in the 33-bus and 119-bus distribution networks are plotted in Fig. 3. Accordingly, the resilience index, F_2, and the resilience cost (repair + load shedding costs) of zero achieved for the mentioned networks for the condition that the total planning and operation cost (F_1) has the maximum value. In other words, increasing F_1 will result in low resilience cost or high system resilience. Because, increasing resiliency leads to decreasing the expected energy not supplied (EENS) and that is, it will utilize strong equipment against earthquake and flood in the distribution network. Also, low EENS is reached for a system with a high number of local sources or storages. Finally, the best compromised solution for the mentioned networks based on the fuzzy decision-maker method in section 3 and different scenario number applied to the proposed problem is addressed in Table 2. According to this table for 1000 scenarios generated by MCS and 20 scenarios applied to the proposed problem by SBM, the proposed LRA strategy is achieved with the resilience costs of 263.1$ and 396.3$, for 33-bus and 119-bus distribution networks, respectively, while the planning and operation costs of these networks are equal to 1238.2$ and 2720.4$, respectively. Comparing the results in Fig. 3 and Table 2 shows that the LRA method is able to obtain F_1 and F_2 such that they are close to their minimum values. In addition, based on Table 2, the objective functions and problem calculation time with 20 and 25 scenarios obtained by SBM in 1000 and 2000 generated scenarios by MCS are almost same, but this condition is not true for comparison between 15 and 20 scenarios achieved by SBM. Therefore, this paper uses 1000 generated scenarios by MCS and 20 obtained scenarios by SBM due to its rational calculation time for the stochastic process and the low calculation error with respect to high scenario numbers that are applied to problem by SBM based on the reported results in Table 2.

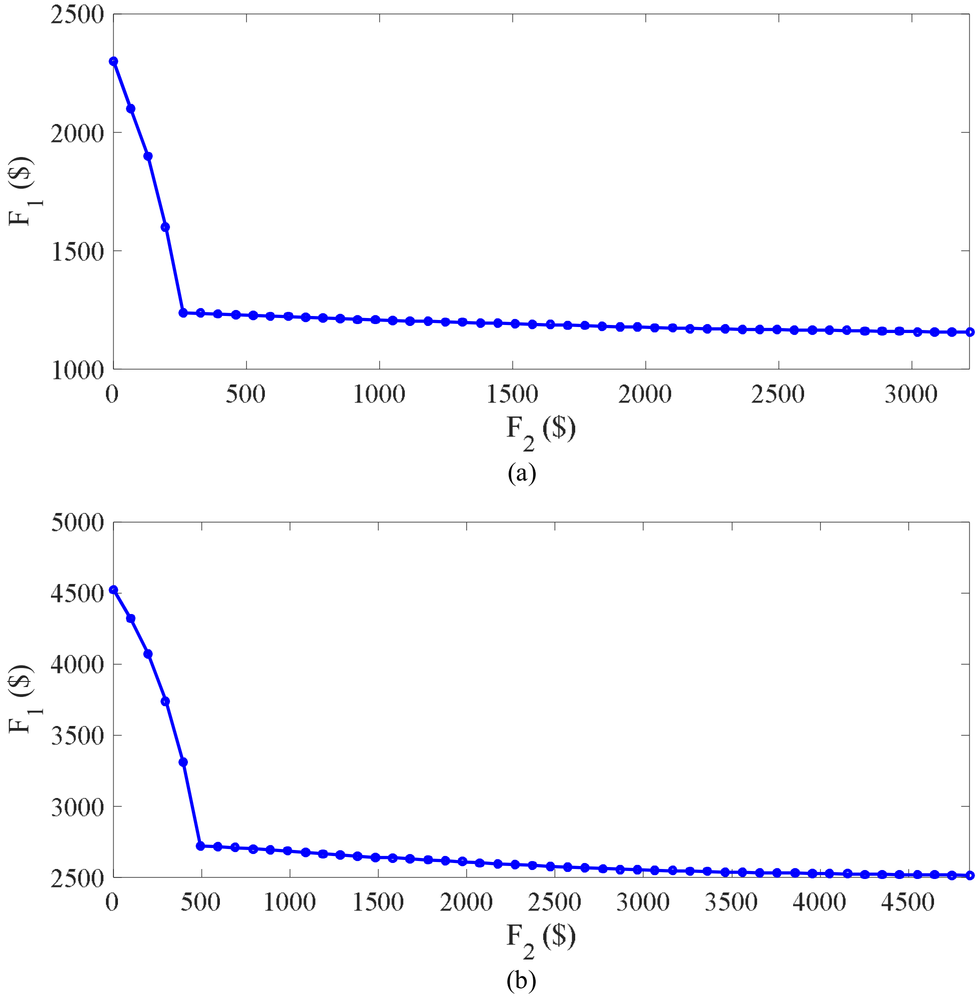


Fig. 3. Pareto front for the proposed LRA strategy, a) 33-bus network, b) 119-bus network

Table 2: The best compromised solution results in different networks

Number of generated scenarios by MCS	1000					
Number of applied scenarios by SBM	15		20		25	
Objective function ($)	F_1	F_2	F_1	F_2	F_1	F_2
Objective functions in 33-bus network	1231.1	260.3	1238.2	263.1	1239.5	263.7
Objective functions in 119-bus network	2709.2	390.5	2720.4	396.3	2721.9	397.1
Calculation time (s) of stochastic process (MCS+SBM)	71		82		90	
Calculation time (s) of problem solving	352		375		398	
Number of generated scenarios by MCS	2000					
Number of applied scenarios by SBM	15		20		25	
Objective function ($)	F_1	F_2	F_1	F_2	F_1	F_2
Objective functions in 33-bus network	1232.2	260.8	1238.4	263.2	1239.8	263.8
Objective functions in 119-bus network	2710.4	391.1	2720.7	396.4	2722.3	397.3
Calculation time (s) of stochastic process (MCS+SBM)	93		101		109	
Calculation time (s) of problem solving	351		375		397	

B) *Planning results of the distribution networks in the LRA framework*: Results of the proposed LRA strategy on 33-bus and 119-bus distribution test systems are presented in Table 3. Based on this table and the provided data in section 4.1, since the hardening strategy is to use a strong line with a lower outage probability under the extreme weather events with respect to the conventional lines, it is utilized in the zones that earthquake and flood are happening. Thus, the network would not experience a blackout and it would have a high resilience in such conditions. On the other hand, the backup DG and ESS are generally used in the zones that are far from the distribution substation at the slack bus.

As it is demonstrated in Table 3, there are 4 and 12 tie lines that installed in the 33-bus and 119-bus, respectively, to minimize the investment and operation costs and maximize the system resilience, i.e., minimum repair and load shedding costs. Also, the resilient 33-bus distribution network includes daily investment and operation costs of $664.1 and $574.1, respectively. However, the repair and load shedding costs are low, i.e., $22.3 and $238.2, because of selecting the high value for VOLL, which results in high resiliency of this network under earthquake and flood conditions. It should be noted that the condition happens to 119-bus distribution system, while it needs to daily investment cost $1481.1 and daily operation cost $1239.3 to have a repair cost of $41.8 and load shedding cost of $355.5.

Table 3: Planning results in different distribution networks

Network	Optimal location of strong equipment in earthquake and flood conditions			
	Backup DG (bus)	ESS (bus)	Hardening line	Tie line
33-bus	13	30 and 17	Between buses (11 to 16), (1 to 3), (28 to 31), feeders between busses (3, 25) and (2, 22)	Between buses 12-22, 25-29, 9-15, 18-33
119-bus	25 and 29	41, 73, 110	Buses 1-2, 1-63, 1-100, 21-26, 41-43, 70-74, feeders 3-30, 30-54, 100-118	Between buses 6-24, 8-46, 25-35, 54-62, 43-49, 38-62, 58-85, 73-80, 75-99, 94-108, 97-105, 110-118
Network	Daily costs ($) calculated in the proposed LRA strategy			
	Investment	Operation	Repair	Load shedding
33-bus	664.1	574.1	22.3	238.2
119-bus	1481.1	1239.3	41.8	355.5

C) *Investigating the operation and resilience indices*: The results related to the operation indices such as energy loss (EL) and maximum voltage deviation (MVD) are shown in Fig. 4 for following two cases:

- Case I: Network power flow analysis (Network without considering DG, ESS, hardening and tie lines).
- Case II: Proposed scheme by formulation (1).

Noted that the EL is equal to the sum of the network active power loss at whole study time. Also, MDV is equal to the maximum value of the absolute term of voltage deviation in all buses over whole study period. According to Fig. 4(a), the EL for the case I in 33-bus and 119-bus distribution networks is 3.077 MWh and 5.262 MWh, respectively. But, in the case II, it is reduced to 1.899 MWh and 3.371 MWh, respectively. In other words, this strategy is able to reduce or improve EL about to 38.3% ((3.077 – 1.899)/3.077) and 35.9% ((5.262 – 3.371)/5.262) for the mentioned networks, respectively. This condition is met to network MVD so that the LRA can improve this index in case II compared to the case I about 41.4% and 32.6% for the 33-bus and 119-bus distribution systems, respectively, according to Fig. 4(b).

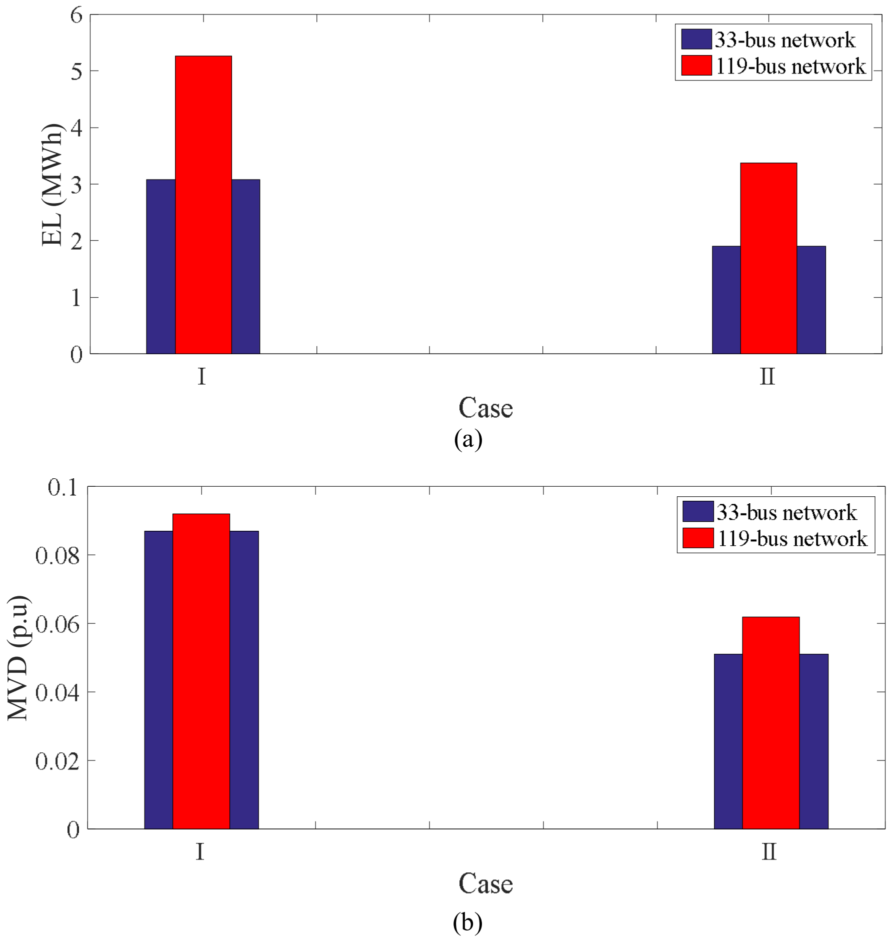


Fig. 4. Operation indices: (a) energy loss, (b) maximum voltage deviation

Finally, the results of resilience index such as EENS is illustrated in Fig. 5, where EENS is equal to the division of load shedding cost by VOLL, or it is equal to the sum of total network load not supplied (P^{NS}) at all simulation hours. Based on this figure, EENS values in case I are 28.9 MWh and 43.9 MWh for 33-bus and 119-bus networks, but, the EENS can be reduced to 2.83 MWh and 3.55 MWh for these systems in case II. Indeed, the proposed LRA method is able to achieve the low EENS that is close to zero to achieve the higher system resilience. In addition, the EENS changes versus VOLL are plotted in Fig. 6 for 33-bus and 119-bus networks. It is seen that the EENS can be reduced by increasing VOLL to 70 (90) \$/MWh for 33-bus (119-bus) network, also, it is fixed for VOLL ≥ 70 (90) \$/MWh in the 33-bus (119-bus) distribution grid. Noted that VOLL is a penalty price to avoid unnecessary power outage according to N – k contingency, hence, increasing this term causes that the EENS to be reduced. Accordingly, in VOLL = 100 \$/MWh, the high resilience (minimum EENS) can be obtained.

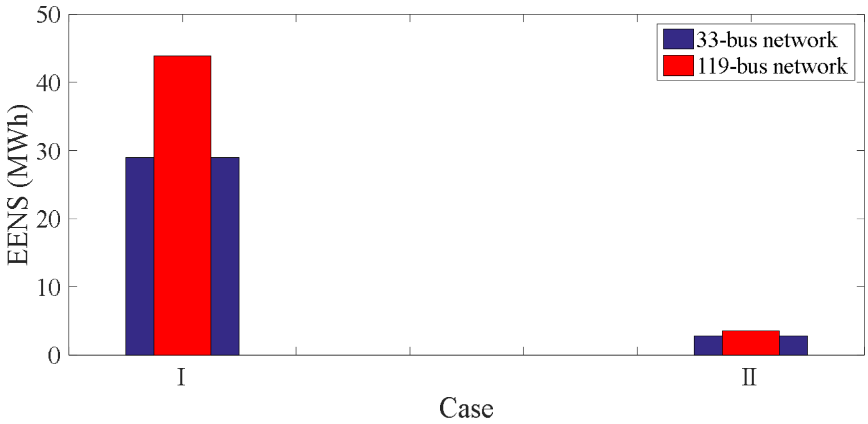


Fig. 5. EENS in different cases and networks

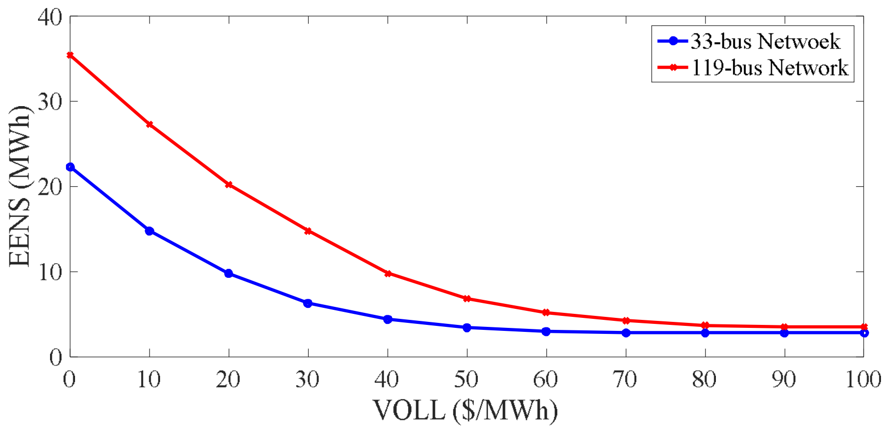


Fig. 6. EENS changes vs. VOLL

5. Conclusion

In this paper, a two-objective LRA strategy was applied to a distribution network to obtain high resiliency in the condition of earthquakes and floods. Hence, the problem aimed to minimize the sum of planning the cost of backup DG, ESS and hardening and tie lines, and operation cost of network and backup DG in the first objective function. Also, the second objective function minimized the resiliency cost including repair and load shedding costs. These objectives were subjected to LOPF model, planning and reconfiguration constraints. Moreover, the SBSP approach based on a hybrid method of MCS and SBM was used to model the uncertainty of load, energy price, and network equipment in the proposed natural disaster conditions. In the following, the proposed two-objective problem is converted to a single-objective formulation using the ε-constraint-based Pareto optimization.

According to the numerical results, the proposed LAR strategy is able to obtain a network with high resiliency, that is the low values for resiliency cost, i.e., summation of repair and load shedding cost, can be achieved. This condition happened while a sufficient number of local sources and strong equipment against earthquake and flood occurred. Also, this strategy could improve energy losses and voltage deviations in about 37% and 40%, respectively. The proposed formulation is presented for the balanced MV distribution networks. As a future research work, the proposed scheme will be implemented in the unbalanced 3-phase distribution networks as well. Also, the network resiliency can be improved by different power electronic interfaced systems such as electric vehicles' charging stations, where this case is not considered in this paper, but it will have investigated in the future studies.

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References

[1] A. Shahbazi, J. Aghaei, S. Pirouzi, M. Shafie-khah, J.P.S. Catalão. "Hybrid stochastic/robust optimization model for resilient architecture of distribution networks against extreme weather conditions", *International Journal of Electrical Power & Energy Systems*, 2021.

[2] A. Shahbazi, J. Aghaei, S. Pirouzi, T. Niknam, M. Shafie-khah, J.P.S. Catalão. "Effects of resilience-oriented design on distribution networks operation planning", *Electric Power Systems Research*, 2021.

[3] D. Kakadia, J.E. Ramirez-Marquez, "Machine learning approaches for network resiliency optimization for service provider networks," *Computers & Industrial Engineering*, vol. 146, pp. 106519, 2020.

[4] J. Zhu, Y. Yuan, W. Wang, "An exact microgrid formation model for load restoration in resilient distribution system," *International Journal of Electrical Power & Energy Systems*, vol. 116, pp. 105568, 2020.

[5] A. Barnes, H. Nagarajan, E. Yamangil, R. Bent, and S. Backhaus, "Resilient design of large-scale distribution feeders with networked microgrids," *Electric Power Systems Research*, vol. 171, pp. 150-157, 2019.

[6] S. Ma, L. Su, Z. Wang, F. Qiu, and G. Guo, "Resilience enhancement of distribution grids against extreme weather events," *IEEE Transactions on Power Systems*, vol. 33, no. 5, pp. 4842-4853, 2018.

[7] M. Bessani, and *et al.*, “Probabilistic assessment of power distribution systems resilience under extreme weather,” *IEEE Systems Journal*, vol. 13, no. 2, pp. 1747-1756, 2019.

[8] X. Chen, J. Qiu, L. Reedman, and Z.Y. Dong, “A statistical risk assessment framework for distribution network resilience,” *IEEE Transactions on Power Systems*, vol. 34, no. 6, pp. 4773-4783, 2019.

[9] L. Yang, Y. Zhao, C. Wang, P. Gao, and J. Hao, “Resilience-oriented hierarchical service restoration in distribution system considering microgrids,” *IEEE Access*, vol. 7, pp. 152729-152743, 2019.

[10] M.S. Khomami, K. Jalilpoor, M.T. Kenari, and M.S. Sepasian, “Bi-level network reconfiguration model to improve the resilience of distribution systems against extreme weather events,” *IET Generation, Transmission & Distribution*, vol. 13, no. 16, pp. 3302-3310, 2019.

[11] X. Wang, M. Shahidehpour, C. Jiang, and Z. Li, “Resilience enhancement strategies for power distribution network coupled with urban transportation system,” *IEEE Transactions on Smart Grid*, vol. 10, no. 4, pp. 4068-4079, 2019.

[12] S. Ma, B. Chen, and Z. Wang, “Resilience enhancement strategy for distribution systems under extreme weather events,” *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 1442-1451, 2018.

[13] V. Krishnamurthy, and A. Kwasinski, “Effects of power electronics, energy storage, power distribution architecture, and lifeline dependencies on microgrid resiliency during extreme events,” *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 4, no. 4, pp. 1310-1323, 2016.

[14] X. Wang, Z. Li, M. Shahidehpour, and C. Jiang, “Robust line hardening strategies for improving the resilience of distribution systems with variable renewable resources,” *IEEE Transactions on Sustainable Energy*, vol. 12, no. 1, pp. 1-9, 2017.

[15] W. Yuan, J. Wang, F. Qiu, C. Chen, C. Kang, and B. Zeng, “Robust optimization-based resilient distribution network planning against natural disasters,” *IEEE Transactions on Smart Grid*, vol. 7, no. 6, pp. 2817-2826, 2016.

[16] E.A. Gol, B.G. Erkal, and M. Göl, “A novel MDP based decision support framework to restore earthquake damaged distribution systems,” *IEEE PES Innovative Smart Grid Technologies Europe (ISGT-Europe), Bucharest, Romania*, pp. 1-5, 2019.

[17] M. Borghei, M. Ghassemi, “Optimal planning of microgrids for resilient distribution networks,” *International Journal of Electrical Power & Energy Systems*, vol. 128, pp. 106682, 2021.

[18] A. Valenzuela, E. Inga, S. Simani, “Planning of a resilient underground distribution network using geroeferenced data,” *Energies*, vol. 12, no. 4, pp. 1-13, 2019.

[19] A. Valenzuela, I. Montalvo, E. Inga, “A decision-making tool for electric distribution network planning based on heuristics and georeferenced data,” *Energies*, vol. 12, no. 21, pp. 20-29, 2019.

[20] W. Pavon, E. Inga, S. Simani, “Optimal routing an ungrounded e;ectrical distribution system based on heuristic method with micro-grids integration,” *Sustainability*, vol. 11, no. 6, pp. 11-20, 2019.

[21] M.A. Norouzi, J. Aghaei, S. Pirouzi, T. Niknam, and M. Lehtonen, “Flexible operation of grid-connected microgrid using ES,” *IET Generation, Transmission & Distribution*, vol. 14, no. 2, pp. 254-264, 2020.

[22] S. A. Bozorgavari, J. Aghaei, S. Pirouzi, A. Nikoobakht, H. Farahmand, M. Korpås, “Robust planning of distributed battery energy storage systems in flexible smart distribution networks: A comprehensive study,” *Renewable and Sustainable Energy Reviews*, vol. 123, pp. 109739, 2020.

[23] S. Pirouzi, M.A. Latify, G.R. Yousefi, “Conjugate active and reactive power management in a smart distribution network through electric vehicles: A mixed integer-linear programming model,” *Sustainable Energy, Grids and Networks*, 2020.

[24] A. Kavousi-Fard, A. Khodaei, “Efficient integration of plug-in electric vehicles via reconfigurable microgrids,” *Energy*, vol. 111, pp. 653-663, 2016.

[25] H.R. Hamidpour, J. Aghaei, S. Pirouzi, S. Dehghan, T. Niknam, “Flexible, reliable, and renewable power system resource expansion planning considering energy storage systems and demand response programs,” *IET Renewable Power Generation*, vol. 13, no. 11, pp. 1862-1872, 2019.

[26] V. Vahidinasab, “Optimal distributed energy resources planning in a competitive electricity market: Multiobjective optimization and probabilistic design,” *Renewable Energy,* vol. 66, pp. 354-363, 2014.

[27] A. Bagheri, V. Vahidinasab, K. Mehran. “A novel multiobjective generation and transmission investment framework for implementing 100% renewable energy sources,” *IET Generation, Transmission & Distribution*, vol. 12, no. 2, pp. 455-465, 2018.

[28] S. Ghasemi, and J. Moshtagh, “Radial distribution systems reconfiguration considering power losses cost and damage cost due to power supply interruption of consumers,” *International Journal on Electrical Engineering and Informatics*, vol.5, pp. 297-315, 2013.

[29] S. Pirouzi, J. Aghaei, M.A. Latify, G.R. Yousefi, G. Mokryani, "A robust optimization approach for active and reactive power management in smart distribution networks using electric vehicles," *IEEE Systems Journal*, vol. 12, no. 3, pp. 2699-1710, 2017.

[30] S. Pirouzi, J. Aghaei, "Mathematical Modeling of Electric Vehicles Contributions in Voltage Security of Smart Distribution Networks," *SIMULATION: Transactions of the Society for Modeling and Simulation International*, vol. 95, pp. 429-439, 2018.

[31] S. Pirouzi, J. Aghaei, M. Shafie-khah, G.J. Osório, J.P.S. Catalão, "Evaluating the security of electrical energy distribution networks in the presence of electric vehicles," *Proc. PowerTech Conf, IEEE Manchester*, pp. 1-6, 2017.

[32] Generalized Algebraic Modeling Systems (GAMS). [Online]. Available: http://www.gams.com.

[33] S.A. Bozorgavari, J. Aghaei, S. Pirouzi, V. Vahidinasab, H. Farahmand, M. Korpås, "Two-stage hybrid stochastic/robust optimal coordination of distributed battery storage planning and flexible energy management in smart distribution network," *Journal of Energy Storage*, vol. 26, pp. 100970, 2019.

[34] J. Aghaei, S.A. Bozorgavari, S. Pirouzi, H. Farahmand, M. Korpås, "Flexibility Planning of Distributed Battery Energy Storage Systems in Smart Distribution Networks," *Iranian Journal of Science and Technology, Transactions of Electrical Engineering*, vol. PP, pp. 1-17, 2019.

[35] S. Pirouzi, J. Aghaei, T. Niknam, H. Farahmand, and M. Korpås, "Proactive Operation of Electric Vehicles in Harmonic Polluted Smart Distribution Networks," *IET Generation, Transmission and distribution*, vol. 12, pp. 967-975, 2018.