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# Two-Stage Seismic Resilience Enhancement of Electrical Distribution Systems

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A R T I C L E I N F O

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A B S T R A C T

Recent natural disasters have caused significant damage to electrical distribution systems, revealing the necessity to enhance distribution system resilience. This paper proposes a two-stage method which supports Distribution System Operator (DSO) decision-making to enhance the seismic resilience of distribution systems. In the first stage, the stochastic characteristics of seismic hazards are modeled to generate artificial earthquake events. In the second stage, the objective of resilience enhancement is to minimize Energy Not Supplied (ENS), which is formulated as a knapsack problem, and Particle Swarm Optimization (PSO) is applied to solve it. The resilience enhancement candidates are classified into distribution substation, distribution line, and Distributed Energy Resources (DERs) measures. The vulnerability of distribution system components is considered through fragility curves. The impact of tall buildings collapsing on the distribution system is also considered. Fault tree analysis is applied not only to evaluate the outage of end-user customers in the electrical distribution system but also to calculate the required repair time and ENS. A modified Fussell–Vesely (FV) is proposed to assess the resilience enhancement. The proposed method is applied to a real distribution system and the effectiveness of the proposed method is examined.

## 1. Introduction

### 1.1. Motivation

Modern civilizations rely heavily on electrical infrastructure because the dependency of backbone infrastructures on electric energy is increased (e.g., electrical transportation, new water treatment technologies, and communication), and new economic activities such as digital currencies require a reliable power supply. For example, it is announced that the failure of one of the critical components of the UK power grid could disrupt 25% of all trains nationally [1]. Among different natural disasters, earthquake is the most unpredictable and devastating, leading to widespread disruptions in all parts of electrical infrastructure [2]. Earthquakes have imposed physical damages to electrical infrastructure and have provided significant economic losses to the countries. The 2011 Tohoku earthquake damaged 42 transmission towers, 70 transformers, and 14 power plants in Japan [3]. The Christchurch earthquake destroyed 15% of cables at the distribution voltage level, 50% of cables at the transmission voltage level, and four substations in New Zealand [4]. It is estimated that the economic losses of the 2010 Chile earthquake and 2011 Japan earthquake are \$ 30 billion and \$ 14.5− 34.6 billion, respectively [5]. Furthermore, earthquake events imposed long-term outages on customers in the distribution systems. After the 2011 Japan main shook, 4.6 million customers experienced an outage for a long time [6].

Recently, extreme weather events have increased revealing the vulnerability of electrical infrastructures against natural disasters [7]. Power systems are exposed to natural disasters since they exist across extensive geographical areas. Natural disasters affect the electrical infrastructure in large regions with different intensities [8]. Aside from that, traditional power systems planning and operation standards have focused on reliability studies through $N-1$ and $N-2$ contingencies. However, recent natural disasters have indicated that classical reliability studies are insufficient to keep the lights on. For example, $N-72$ contingencies during Hurricane Sandy led to an extended outage [9]. Moreover, aging decreases the physical and electrical strength of components against extreme events which leads to more vulnerability [10] and [11]. The destructive impacts of natural disasters on electrical infrastructures and society, the increasing frequency of natural disasters, and the inherent defects of electrical infrastructures due to traditional

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design and extensive grids highlight the requirement for measures to mitigate the impacts of natural disasters. These actions are reflected in resilience studies.

### 1.2. Literature review

A resilient electrical infrastructure should withstand High Impact-Low Frequency (HILF) hazards and retain the continuity of supplying customers. Enhancement measures are classified into physical reinforcement, preventive and recovery actions [12]. Physical reinforcement measures such as substation retrofitting, transmission tower reinforcement, distribution pole replacement, and undergrounding overhead lines aim to reduce the vulnerability of critical components before events. Preventive measures are actions such as generation re-dispatching, preventive islanding, deployment of Distributed Energy Recourses (DERs), and mobile DERs aim to avoid uncontrolled propagation of cascading failures or supply critical loads before disasters. Therefore, physical reinforcement and preventive actions can be considered system planning. On the other hand, recovery measures such as network reconfiguration and repair crew scheduling after extreme events can be considered as operational measures.

In [5] and [13–18], two-stage frameworks to enhance resilience against earthquakes are presented. In [5], the optimization versus solution (OvS) framework is proposed to minimize Energy Not Supplied (ENS). In the first level, candidates for investment are selected, then in the second level, DC-Optimal Power Flow (OPF) is used to find the solutions. In [13–14], in the first state, Monte Carlo simulation (MCs) is applied to determine components' vulnerability. In [13], the scheduling and routing of mobile DERs and network reconfiguration are modeled as Mixed-Integer Linear Programming (MILP) to maximize the critical supplied loads. In [14], network corrective topology control is modeled through a DC-OPF to maximize the load outage recovery. In [15], the knapsack problem is applied to determine the proper candidates regarding the assigned budget for retrofitting. Then, an economic dispatch model is considered to compute the load shed. In [16], investments in grid-side measures (e.g., Battery Energy Storage Systems (BEES) and distribution lines retrofitting) and demand-side measures (e.g., home battery inverters and the related communications) are proposed. The network is clustered in vulnerable zones, and the problem is modeled as a Mixed-Integer Nonlinear Problem (MINP) to minimize load shedding. In [17], the impact of cascading outages is modeled as a MILP to mitigate the generation and load shed costs subject to power flow, budget, capacity, and demand constraints. In [18], Adaptive surrogate-based Network Reliability (ANR) analysis is developed to identify the most valuable components of electrical infrastructure. The machine learning predicts the damages to the power system, then AC-OPF is applied to assess resilience.

In [19], Physical reinforcement measures focus on improving the component's network robustness based on both network characteristics and network structures, which means that both electrical performances evaluated by a DC-Power Flow (DC-PF) and topological features should be analyzed completely. In [20], a risk assessment method is applied to rank the critical components of power systems. A DC-OPF is used to calculate ENS, and an importance measure is recommended for critically component ranking. In [21], retrofitting of critical components in a substation is modeled as a knapsack problem to minimize the costs of physical damage, DERs generation, and customer interruption. In [22], A Linear Programming (LP) optimization problem is proposed to determine the capacity and location of BESSs to maximize the critical loads supplied during emergency response time. In [23], the scheduling of repair crews in the post-earthquakes state is proposed to mitigate the average interruption time of each customer. In [24], a Performance-Based Earthquake Engineering (PBEE) method is proposed to quantify the failure probabilities of components. The components and their failure probabilities are modeled through an augmented bus-branch model to obtain the Cumulative Density Function (CDF) for interrupted demands. The author of [25] presents an upgrading solution to minimize the seismic costs incurred, including investment costs, the repair cost of damaged components, and customer interruption costs. Lagrange multipliers optimization is carried out to find the optimal upgrading components. In [26], substation failure is evaluated and Z-bus method power flow is carried out to assess the distribution system serviceability. The authors of [27] proposed topological measures to minimize ENS in the post-earthquake condition. A DC-OPF is used to model the power system recovery. In [28], mobile DERs allocation is modeled as a MILP to improve the critical load restoration using restoration paths. In [29], an optimal siting and sizing of DERs are proposed in both normal and post-earthquake is to minimize the costs of power loss and operation costs in normal operation and load curtailment after the earthquake event. The problem is presented as a Non-Linear Programming (NLP) optimization problem, and Non-Dominated Sorting Genetic Algorithm II (NSGAII) followed by fuzzy decision making is used to solve the problem. In [30], DER allocation and parallel distribution lines with sectionalizing switches are proposed as grid-side enhancement measures, and using the capability of electric vehicles in the post-earthquake condition is proposed as a demand-side measure. The problem is modeled MINP problem.

From the recovery viewpoint, In [31], a multi-objective optimization algorithm is suggested as a post-earthquake recovery planning to find the optimal repair schedule for damaged substations. A Bayesian network was applied to form a functional state model of the substation from a structural and electrical perspective. In [32], a mathematical model to classify the infrastructure interdependencies is proposed to develop infrastructures when the recovery of power systems after earthquake events are required.

The interactions of electrical and other infrastructure have recently been investigated in the literature. In [33], a multi-level strategy of recovery algorithm of water and electrical infrastructures is proposed, and a multi-objective optimization problem is solved to enhance systems resilience as well as to mitigate the costs of recovery. The mathematical model of the electric power infrastructure consists of a structural network and a power flow analysis. The electrical infrastructure is divided into several prioritized recovery zones where recovery activities are planned. In [10], Following [33], a multi-scale recovery plan for the water infrastructure is proposed to model the random duration of the recovery steps for each element. The water infrastructure is divided into several recovery zones to find recovery zone with high priority, and to schedule recovery activities for each zone. The impact of the aging of pipelines on water infrastructure resilience is investigated by means of a mathematical physics-based mode.

In [34], the interaction between electrical and water infrastructures is modeled by using interface functions, and their performance is evaluated in a post-earthquake condition. The model depicts supply, demands, capacities, and derived performance measures of the regional infrastructure. The results illustrate that quick recovery of electrical infrastructure increases the performance of water infrastructure. In [35], electrical power systems and distribution gas systems are considered Integrated Energy Systems (IES)s. A bi-level Distributional Robust Optimization (DRO) problem is proposed to enhance resilience. The vulnerable power transmission lines and gas pipelines are selected in the first stage. In the next stage, the operational costs of electricity and gas systems are minimized using DC-power flow and Weymouth gas flow models, respectively. In [36], the interdependence between natural gas and power systems is evaluated, while the integration of wind farms in power systems is also considered. The authors proposed a tri-level robust optimization method to retrofit IES, and Nested Column and Constraint Generation (C&CG) algorithm is implemented to solve it.

In [37], the authors suggest a framework to assess the impact of earthquakes on IES, mostly focusing on the lost connection of power systems and the leakage of pipelines, and load shedding is calculated regarding to generation and transmission line limitations. It is worth mentioning that only in [20] an important measure is proposed to assess the results. A taxonomy of the reviewed literature is presented in Table 1.

### 1.3. Research Contributions

Distribution systems are prone to damage due to the less reinforced structures, radial structures, widespread networks, and the impact of adjustment structures such as the collapse of tall buildings. As Table. I clarifies, currently, it is challenging for the distribution system operators (DSOs) to assign rational funds to improve the resilience of distribution systems due to the scarcity of resilience assessment studies consisting of comprehensive resilience enhancement measures [11]. In this paper, a wide range of resilience measures is proposed to cover the vulnerability of distribution systems. The resilience enhancement measures are classified into three measures, distribution substation measure (i.e., distribution substation retrofitting), distribution line measure (i.e., overhead lines retrofitting, undergrounding cables, and sectionalizing switches installation), and DER measures (i.e., adding DERs generation capacity and DERs retrofitting).

In this paper, a two-stage framework is proposed to enhance distribution system resilience against seismic hazards. In the first stage, the stochastic characteristics of seismic hazards i.e., the earthquake's intensity and the distance between the earthquake epicenter and the electrical components are considered, and MCs are used to generate earthquake scenarios. In the second stage, the logic behind the customer's interruption regarding the component's failure is modeled using fault tree analysis to calculate ENS. The objective function is to minimize the ENS incurred in earthquake events subject to budget restriction which is modeled as a knapsack problem, and Particle Swarm Optimization (PSO) is applied to solve it. In summary, the main contributions of the paper are as follows:

- Fault tree analysis is applied not only to evaluate the outage of end-user customers in the electrical distribution system but also to calculate the required repair time and ENS,
- Regarding the seismic characteristics of electrical components, a modified risk metric is proposed to assess the resilience enhancement measure,
- Resilience enhancement of the distribution system is modeled as a knapsack problem and is solved by PSO, while all possible enhancement measures are considered as particles in PSO,
- A sensitivity analysis of the retrofitting budget is carried out to present the relationship between retrofitting budget and resilience enhancement. The relationship gives insights to the decision-makers about the actual effects of resilience enhancement measures on the electrical distribution systems.

### 1.4. Paper structure

The remainder of this paper is organized as follows. Section II introduces the seismic hazard model and vulnerability evaluation, Section III describes the problem formulation and proposed solution, and Section IV presents the numerical results. Finally, Section V concludes the paper.

## 2. Seismic hazard model and vulnerability evaluation

### 2.1. Seismic hazard model

The impact of natural disasters on power system resilience is modeled using stress parameters. The stress parameters of different natural disasters are presented in Table 2 [38]. Peak Ground Acceleration ($PGA$) is the seismic stress parameter of the electrical components installed on the ground surface, such as the substations, overhead lines, DERs as well as the adjutant buildings. Peak Ground Velocity ($PGV$) is the stress parameter for underground components such as cable lines [39]. These seismic stress parameters are a function of the distance between site location and the center of the earthquake, the earthquake's magnitude, and the soil type [40]. The seismic stress parameters are presented through an attenuation relationship as follows [41]:

$$Ln\ (Y) = C_{Y,1} + C_{Y,2}\left(\frac{M_W + 0.38}{1.06}\right) + C_{Y,3}Ln(R) + C_{Y,4}R \tag{1}$$

$Y$ is the stress parameter, $M_W$ is the earthquake intensity in the moment magnitude scale, $R$ is the distance between the earthquake center to the site location in km. $\boldsymbol{C}_Y = [C_{Y,1},\ C_{Y,2},\ \ldots,\ C_{Y,4}]$ is a vector of constants that can be obtained through the historical seismic data of the case study. For example, the ground type at Lar, a city in the south of Iran is mostly of rock, and the constants are presented in Table 3.

### 2.2. Vulnerability evaluation of electrical components and buildings

The seismic response of electrical components is stochastic. Fragility curves determine the failure probability of components as a function of $PGA$ and $PGV$. Looking more closely, fragility curves are lognormal CDFs determined by the mean logarithmic value, $\lambda$, and the standard deviation of the logarithmic value, $\beta$. HAZUS proposes four damage states namely, minor, moderate, extensive, and complete damage [42]. Substations and power plants are classified regarding the voltage level, and generation capacity, respectively. The vulnerability model of distribution lines also exists in HAZUS. In this paper, the failure probability models proposed in HAZUS are applied. The Failure Probability ($FP_d$) is expressed as follows [42]:

$$FP_d(\text{PGA}) = K(P_{mi} - P_{mo})Q_{mi} + (P_{mo} - P_{ex})Q_{mo} + (P_{ex} - P_{co})Q_{ex} + P_{co}Q_{co} \tag{2}$$

$Q_{mi}$, $Q_{mo}$, $Q_{ex}$, and $Q_{co}$ are the percentage of damaged sections for minor, moderate, extensive, and complete states, respectively. $P_{mi}$, $P_{mo}$, $P_{ex}$, and $P_{co}$ are the minor, moderate, extensive, and complete failure cumulative probabilities, respectively. $K$ is one for substations and power plants and equals the length the distribution lines. Retrofitting measures mitigate the failure probability of components for a specific earthquake intensity. Tables IV and V show the fragility curves and the percentage of damaged components, respectively. The fragility curves of the damage states related to a distribution substation is presented in Fig. 1. In this paper, small gas turbines are the DERs installed in the distribution system.

For underground components (e.g., cables), the failure probability ($FP_{un}$) is a function of $PGV$ which can be obtained as follows [43]:

$$FP_{un} = \alpha(PGV)^d L \tag{3}$$

$d$, $\alpha$ and $L$ are a content, the failure rate of underground component, and the length of the cable, respectively.

Earthquakes have direct and indirect impacts on distribution systems. Collapsing the buildings next to the overhead lines is one important indirect impact leading to the distribution system failure. Interestingly, only the extensive and complete damage states contribute to the building collapse [42]. Furthermore, the distance between the electrical component and the adjacent building is another important issue. If the building height is more than the distance between the electrical component and the building, collapsing has a negative impact on the electrical component, otherwise, it is not. The probability of the building collapse ($FP_{bu}$) next to the electrical components can be presented as follows [22]:

$$FP_{bu}(\text{PGA}) = CDF_e(\text{PGA}).e^{-h.Dis} \tag{4}$$

$Dis$ and $h$ are the distance between the building and electrical component and the rate parameter of an exponential function, respectively. $CDF_e$ is the cumulative probability of the building's extensive damage state. The Failure Probability of distribution line ($FP_{ec}$) following an earthquake is shown as follows:

**Table 1**
Literature review of seismic studies on electrical infrastructure.

| Reference | Study Type | | Enhancement Measure | | | Voltage Level | | Vulnerable Components | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Assessment | Enhancement | Recovery | Preventive | Physical Reinforcement | Transmission | Distribution | Substations | Transmission lines | Distribution lines | Power Plant | DERs |
| [5] | × | ✓ | × | ✓ | ✓ | ✓ | × | ✓ | × | × | × | × |
| [13] | × | ✓ | × | ✓ | × | × | ✓ | × | × | ✓ | × | ✓ |
| [14] | × | ✓ | × | ✓ | × | ✓ | × | × | × | × | ✓ | × |
| [15] | × | ✓ | × | × | ✓ | ✓ | × | ✓ | ✓ | × | × | × |
| [35] | × | ✓ | × | × | ✓ | ✓ | × | × | ✓ | × | × | × |
| [16] | × | ✓ | × | ✓ | × | × | ✓ | ✓ | × | ✓ | × | × |
| [17] | × | ✓ | × | ✓ | × | ✓ | × | ✓ | ✓ | × | × | × |
| [18] | ✓ | × | × | × | × | ✓ | × | × | ✓ | × | × | × |
| [19] | × | ✓ | × | ✓ | ✓ | ✓ | × | ✓ | × | × | × | × |
| [20] | ✓ | × | × | × | × | ✓ | × | ✓ | × | × | ✓ | × |
| [21] | × | ✓ | × | × | ✓ | × | ✓ | ✓ | × | × | × | ✓ |
| [22] | × | ✓ | × | ✓ | × | × | ✓ | × | × | ✓ | × | × |
| [23] | × | ✓ | × | ✓ | × | ✓ | × | ✓ | × | × | × | × |
| [24] | ✓ | × | × | × | × | ✓ | × | ✓ | × | × | ✓ | × |
| [25] | × | ✓ | × | × | ✓ | ✓ | × | ✓ | × | × | × | × |
| [26] | ✓ | × | × | × | × | × | ✓ | ✓ | × | × | × | × |
| [27] | × | ✓ | × | ✓ | × | ✓ | × | ✓ | × | × | ✓ | × |
| [28] | × | ✓ | × | ✓ | × | × | ✓ | × | × | ✓ | × | ✓ |
| [29] | × | ✓ | × | ✓ | × | × | ✓ | ✓ | × | ✓ | × | ✓ |
| [30] | × | ✓ | × | ✓ | × | × | ✓ | ✓ | × | ✓ | × | × |
| [31] | × | ✓ | ✓ | × | × | ✓ | × | ✓ | × | × | × | × |
| [32] | × | ✓ | ✓ | × | × | ✓ | × | ✓ | × | × | × | × |
| [33] | × | ✓ | ✓ | × | × | ✓ | × | ✓ | × | × | × | × |
| [34] | ✓ | × | × | × | × | ✓ | ✓ | ✓ | × | × | × | × |
| [35] | × | ✓ | × | × | ✓ | ✓ | × | × | ✓ | × | × | × |
| [36] | × ✓ | | × | × | ✓ | ✓ | × | × | × | ✓ | × | ✓ |
| [37] | ✓ | × | × | × | × | ✓ | × | ✓ | ✓ | × | × | × |

**Table 2**
Stress parameters of different hazards [38].

| *Natural disaster* | *Stress Parameter* |
|---|---|
| Earthquake | PGA, PGV |
| Windstorm | Wind speed |
| Flood | Water level |
| Wildfire | Temperature, Carbone particles |
| Snow | Connectivity on insulators |
| Lightning | Flash to ground density |

**Table 3**
Constants of the attenuation relationship [41].

| Seismic Parameters | $C_1$ | $C_2$ | $C_3$ | $C_4$ |
|---|---|---|---|---|
| *PGA* | 5.67 | 0.318 | −0.77 | −0.016 |
| *PGV* | 0.74 | 0.67 | −0.93 | −0.003 |

$$FP_{ec} = FP_{bu} + FP_d - FP_{bu}.FP_d \tag{5}$$

$FP_d$ is the direct failure probability of distribution line due to earthquakes.

### 2.3. Monte Carlo simulation (MCs)

$M_W$ are $R$ are the stochastic seismic parameters leading to a wide range of *PGA* and *PGV*. MCs is applied to generate artificial earthquake events. $M_W$ and $R$ are sampled from historical earthquakes data available in the earthquake catalogs and a uniform Probability Density Function (PDF), respectively [44]. Aside from that, MC is used to determine the failure state of the components having a Bernoulli distribution [18]. A random number between [0-1] is generated through a uniform PDF for every earthquake scenario. The random number is compared with the failure probability obtained in Section II.B. If the generated random number is bigger than the obtained failure probability, the component state is not failed. Otherwise, the component state is failed. The component's failure states are the input to fault tree analysis and determine the distribution system failure and the downtime duration.

### 2.4. Vulnerability analysis of distribution system

Electrical distribution systems are complex systems consisting of many components such as distribution substations, distribution lines, DERs, and sectionalizing switches to change the configuration of the distribution network. A conventional measure to indicate system availability is a binary test. This technique is convenient to apply, however for complex systems such as distribution systems, the computational efforts rise dramatically [45]. A minimal cut set method is applied to decrease the computational time for resilience assessment. The unique combination of component failures that lead to a system failure is known as a Cut set. Those where if any component is eliminated from the cut set, the remaining components collectively are no longer a cut set are Minimal cut sets. The minimum cut set is usually shown as a fault tree analysis which is a top-down logical presentation [45]. Fault tree analysis uses Boolean algebra to combine a series of component failures to detect the distribution system failure and reduces computational time without losing the accuracy of analysis [45]. The set of components that leads to distribution system failure is a cut set. Minimal cut sets are those cut sets where if any component is removed from the set, the remaining components collectively are no longer a cut set. More details of fault tree analysis can be found in [45]. Fig. 2 and Fig. 3 present the distribution system diagram and the fault tree model of the customer's interruption of Line 1, and 2 respectively.

As depicted in Fig. 3, $minimalcut\ set\ 1 = \{DER, Substation\}$ and $minimal\ cut\ set\ 2 = \{DER, Line\ 1, Line\ 2\}$ are the minimal cut sets for the customs supplied through Line 1 or Line 2. Similarly, $minimalcut\ set\ 3 = \{Substation\}$ and $minimal\ cut\ set\ 4 = \{\ Line\ 3\}$ are the minimal cut sets for the customers fed through Line 3, and $minimalcut\ set\ 5 = \{DER, Substation\}$ and $minimal\ cut\ set\ 6 = \{DER, Line\ 4\}$ are the minimal cut sets for line 4.

## 3. Problem formulation and proposed solution

### 3.1. Problem formulation

The resilience enhancement of distribution systems is interpreted as the minimization of *ENS*. The optimization model is represented as a knapsack problem as follows:

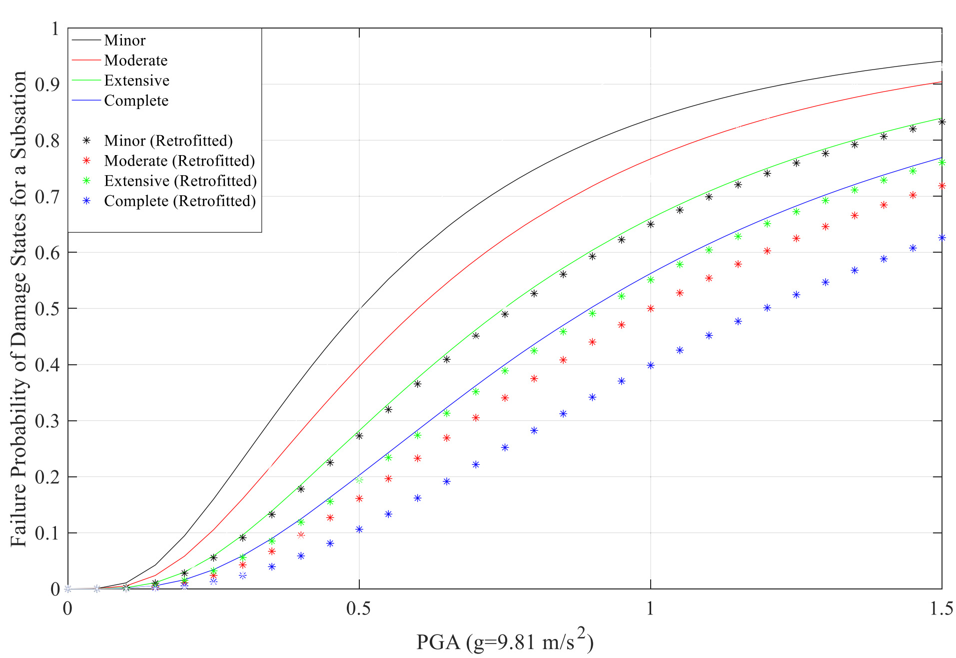


**Fig. 1.** Fragility curves of the damage states a distribution substation [42].

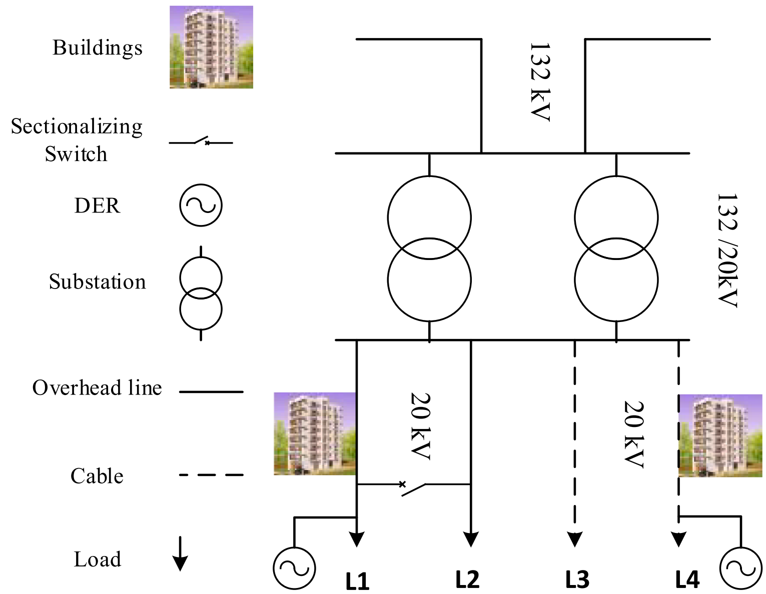


**Fig. 2.** Distribution system diagram.

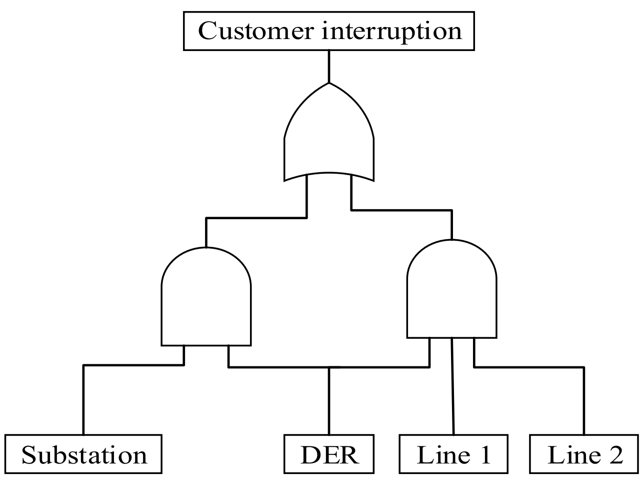


**Fig. 3.** Fault tree model for customer's interruption at Line 1 and Line 2.

$$\text{Min } ENS\ (\mathbf{X},\boldsymbol{\gamma}) \tag{6}$$

Subject to:

$$ENS\ (X,\boldsymbol{\gamma}) = \sum_{t=1}^{T_r\ (\mathbf{X},\boldsymbol{\gamma})} \left( \sum_{f\in F} P_{f,t} - \sum_{g\in G} P_{g,t}(\mathbf{X},\boldsymbol{\gamma}) - P_{u,t}\ (\mathbf{X},\boldsymbol{\gamma}) \right) \tag{7}$$

$$T_r\ (\mathbf{X},\boldsymbol{\gamma}) = \sum_{c\in C} T_c\ (\boldsymbol{\gamma}).z_c\ (\mathbf{X},\boldsymbol{\gamma}) \tag{8}$$

$$\sum_{i\in \mathbf{X}} a_i x_i \le b \tag{9}$$

$$x_i \in \{0,1\},\ \forall i \in \mathbf{X} \tag{10}$$

The objective function shown in (6) aims to minimize *ENS*. $\mathbf{X}$ and $\boldsymbol{\gamma}$ are the set of candidates and the set of random numbers used to determine the status of components as explained in Section II-B, respectively. Equation (7) defends *ENS* as the summation of the difference between demand and the supplied power through DERs and the transited power from the upstream substation. $P_{f,t}$, $P_{g,t}$, and $P_{u,t}$ are the active power load of feeder $f$, the active power generation of DER $g$, and the active power transferred from the upstream system at $t$, respectively. $\mathbf{F}$ and $\mathbf{G}$ are the sets of feeders and DERs, respectively. $T_r$ is the downtime duration of the distribution system that is equivalent to the total repair time of the damaged minimal cut set, as shown in (8). $T_c$ is the repair duration of minimal cut set $c$, and $\mathbf{C}$ is the set of minimal cut sets. The budget constraint of component retrofitting is presented in (9). $a_i$ is the resilience enhancement cost of candidate $i$ and $b$ is the resilience enhancement budget. If the candidate is selected $x_i = 1$, otherwise $x_i = 0$.

In complex systems such as distribution systems importance measure is fundamental because they bring insight into the relative importance of a particular solution regarding other solutions. Conventional Fussell–Vesely *(FV)* calculates importance as the relative reduction of losses of a system when the component under study ($x_i$) is assumed invulnerable [20]. The *FV* $(x_i,\boldsymbol{\gamma})$ for component $i$ states as a percentage, is calculated from a risk measure of the system under the default configuration $ENS_0(\boldsymbol{\gamma})$ and the same risk measure assuming component $I$ invulnerable $ENS(x_i,\boldsymbol{\gamma})$, as expressed in (11).

$$FV\ (x_i,\boldsymbol{\gamma}) = \frac{ENS_0(\boldsymbol{\gamma}) - ENS(x_i,\boldsymbol{\gamma})}{ENS_0(\boldsymbol{\gamma})} \tag{11}$$

For the conventional Fussell-Vesely, all components retrofitting brings about $FV = 1$, because all components are considered invulnerable to earthquakes. However, the retrofitted electrical components are still vulnerable to earthquakes due to practical limitations and the conventional Fussell-Vesely overestimates the positive effects of component retrofitting.

In this paper, a new modified importance metric, Fussell-Vesely, is proposed to evaluate the resilience enhancement of the distribution system against earthquakes. Due to the stochastic behavior of components during earthquakes, the Fussell-Vesely is modified to consider the uncertainty of the components. Therefore, the component under study ($x_i$) is assumed vulnerable having less failure probability. The modified Fussell-Vesely is defined as follows:

$$FV\ (x_i,\boldsymbol{\gamma}) = \frac{ENS_0(\boldsymbol{\gamma}) - ENS(x_i,\boldsymbol{\gamma})}{ENS_0(\boldsymbol{\gamma}) - ENS(x_t,\boldsymbol{\gamma})} \tag{12}$$

$ENS_0(\boldsymbol{\gamma})$, $ENS(x_i,\boldsymbol{\gamma})$, and $ENS(x_t,\boldsymbol{\gamma})$ refer to the *ENS* without any enhancement measure, *ENS* when enhancement measure $x_i$ is applied, and *ENS* when all enhancement measures are used, respectively. $\boldsymbol{\gamma}$ is the set of random numbers used to determine the status of components. *FV* is always a positive quantity and smaller or equal to one. The higher value of *FV*, the more effective enhancement measures. The rationale behind the proposed modified *FV* is to reduce avoidable damages and to support Distribution System Operator (DSO) decision-making to assign proper resilience enhancement budgets

### 3.2. PSO algorithm

PSO is a stochastic optimization method in that every possible solution is considered a particle. The particle consists of binary decision

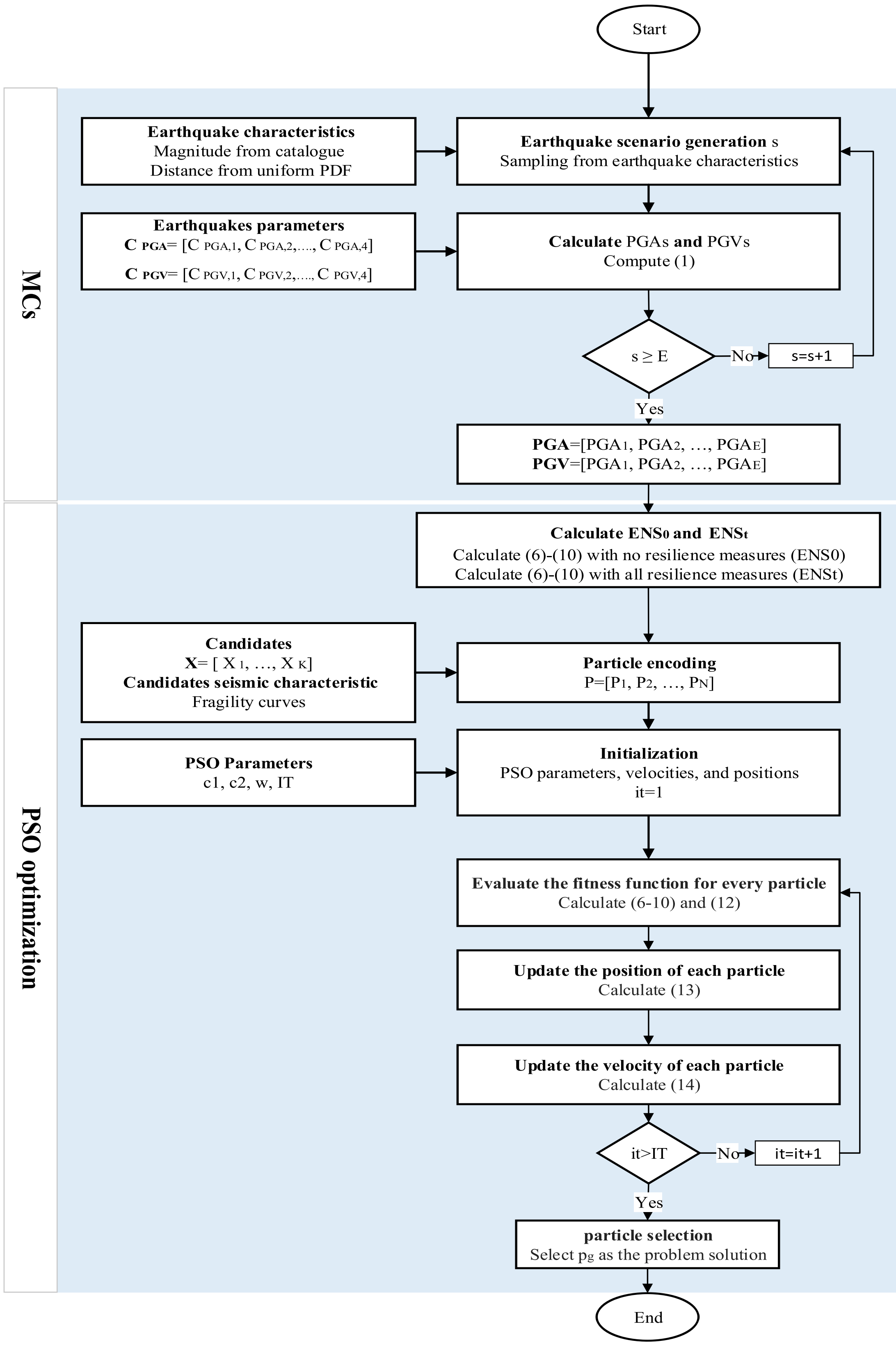


**Fig. 4.** framework of the proposed solution.

variables indicating the existence of the initial candidates in the particle. The particles move towards the best solution depending on their past experiences and neighbors. The fitness function determines the performance of each particle. PSO is governed by two rules indicating the position, $S$, and velocity, $V$, of every particle $i$ for each iteration $it$ as presented in (12) and (13). The position and velocity of a particle are updated at every iteration until a termination condition is reached.

$$S_i^{it+1} = S_i^{it} + V_i^{it+1} \tag{13}$$

$$V_i^{it+1} = w_n.V_i^{it} + c_1 r_1^{it}\left(p_i^{it} - S_i^{it}\right) + c_2 r_2^{it}\left(p_g^{it} - S_i^{it}\right) \tag{14}$$

$n$, $w$, $c_1$, and $c_2$ are counter of PSO iterations, inertia weigh, and acceleration constants, respectively. Moreover,$r_1$ and $r_2$ are random numbers in the range of [0-1]. $p_g$ and $p$ are the best global position and the best individual position for particle $i$, respectively. More details about PSO can be found in [46–47]. It is worth mentioning that other optimization solvers can be used to solve the problem without using the generality of the proposed method, while authors find PSO a fast solver [46–47].

### 3.3. Proposed solution

The proposed solution is a two-stage framework presented in Fig. 4. In the first stage, artificial earthquake events are adopted for seismic hazard modeling. The magnitude of an earthquake is sampled from historical data, and a random distance between the earthquake epicenter and electrical components is generated. $PGA$ and $PGV$ are calculated based on (1). $E$ is the total number of earthquake scenarios. In the next stage, every particle encodes which means the particle considers a decision variable vector of the resilience enhancement candidates. $N$ is the total number of particles. The PSO parameters, position, and velocities are initialized before starting the PSO algorithm. For every particle, the earthquake scenarios are used to evaluate the fitness function presented in (6)-(11). Looking more closely, for every earthquake scenario, the failure status of components is determined based on MCs described in Section II-C. In the next stage, the status of the distribution system and repair time are determined regarding fault tree analysis explained in Section II-D. The obtained outcomes are utilized to calculate $ENS$ as described in Section III-A. For every iteration $it$, the velocity and position of particles are updated as described in (12) and (13), respectively. Once the maximum number of iterations is achieved the algorithm is interrupted, and $p_g$ is the optimal solution. $IT$ is the number of PSO iterations.

## 4. Numerical results and discussion

### 4.1. Case study data

Iran is a high-risk seismic country located on the seismic belt. Lar is a city in the south of Iran that has been exposed to many destructive earthquakes. The greatest earthquake event in Lar was Mw 6.1 in 1960. The coefficients of attenuation relationship are shown in Table 3.

50,000 earthquakes scenarios are generated. The earthquake magnitudes are captured from the Iran earthquakes catalog [48]. A uniform PDF determines the distance of the earthquake epicenter to the electrical infrastructures within the range [0.05 km, 50 km]. Tall buildings are adjacent to overhead lines. The height of the buildings is 15 m, and the CDF of buildings' extensive damage state is based on available data in [42].

Lar city is supplied by a 132/20 kV distribution substation. The substation capacity is 100 MW, and 10 distribution lines (L1-L10) of 20 km in length transfer the electrical power from the distribution substation to the end-user customers. All distribution lines are overhead lines. The total load supplied by the distribution substation is 50 MW, and each contribution of each feeder is 5MW. Two small gas turbines exist to supply critical customers in emergencies. The generation capacity of every gas turbine is 5 MW. The single line diagram of the distribution system is presented in Fig. 5.

The resilience enhancement candidates are classified into three measures, distribution substation measures (i.e., distribution substation retrofitting), overhead lines measures (i.e., overhead lines retrofitting, undergrounding overhead lines, and sectionalizing switches installation), and DER measures (i.e., DER retrofitting and adding the generation capacity). IEEE Std. 693 recommendations are the physical retrofitting measures for the distribution substations and distribution lines [49]. Fragility curves and damage percentages are presented in Table 4 and 5, respectively. It is assumed that sectionalizing switches connect two lines (L1 and L2), (L3 and L4), (L5 and L6), (L7 and L8), and (L9 and L10) in post-earthquake states. Since the distribution system faces technical restrictions to the amount of power generation that can be injected into the system, the total DER generation is limited to 60% of the substation capacity which meets the Hydro One capacity requirement. [50]. The generation capacity is increased in 1 MW steps. The data of electrical components are shown in Table 6. Electrical components' repair time after earthquakes is double the repair time in the normal state [20], without entering into the details of the optimal repair process as solved in [31] and [32]. and the replacement cost of underground cable is 2500 $/km [45]. The investment cost of adding the DER generation and installation of sectionalizing switches are 100,000 $/MW and $4700, respectively [51] and [52]. PSO parameters are presented in Table 7.

### 4.2. Simulation results

#### 4.2.1. Sensitivity analysis on resilience enhancement budget

The proposed method is applied to the case study and the results are presented in Table 8. It is observed that the increment of budget leads to $ENS$ reduction; hence the resilience enhancement. For the budgets in the range of [$25,000 to $325,000] installing sectionalizing switches is a part of the optimal solution. Sectionalizing switches provide a parallel path to supply the customers when the main distribution line is damaged. For $325,000 budget, the distribution substation and sectionalizing switches are the optimal solutions. Based on the data presented in Tables 6, 7, and 8 the vulnerability and the repair time of the distribution substation are the highest of all. Moreover, the distribution substation is the main supplier of customers, and the downtime of this component leads to outages for customers who are not supplied through DERs. For the budgets in the range of [$325,000 to $625,000] underground cables are selected as a part of the optimal solution. The more budget, the more the underground cables are replaced with overhead lines.

The results indicate that underground cables are more effective measure than overhead lines retrofitting. Because the failure probability of cables is less than overhead lines for a similar earthquake event. Moreover, tall buildings have a negative impact on the availability of distribution lines. Adding DER generation capacity for budgets of more than $625,000 is an effective measure to enhance distribution system resilience. The results indicate that for the budgets in the range of [$625,000 to $2,025,000] $ENS$ is from 0.253 GWh to 0.129 GWh. However, adding DER generation capacity is an expensive measure. $ENS$ has a small variation for the budgets more than $3,025,000; hence, the $ENS$ reduction is negligible. As described in section II, the retrofitting measures are restricted due to the civil and structure limitations, and the interruption is unavoidable after extreme earthquakes. The results indicate that DERs and overhead lines retrofitting are not suitable measures.

The results indicate $ENS_0(\boldsymbol{\gamma})$ and $ENS(x_t, \boldsymbol{\gamma})$ are 1.584 GWh and 127 MWh, respectively. The modified $FV$ is calculated for different budgets and is illustrated in Fig. 6. Matlab curve fitting toolbox is used, and a two-term exponential curve fitting with the 0.04 Root Mean Square Error (RMSE) is considered to present modified $FV$ as a function of Budget ($B$) as follows:

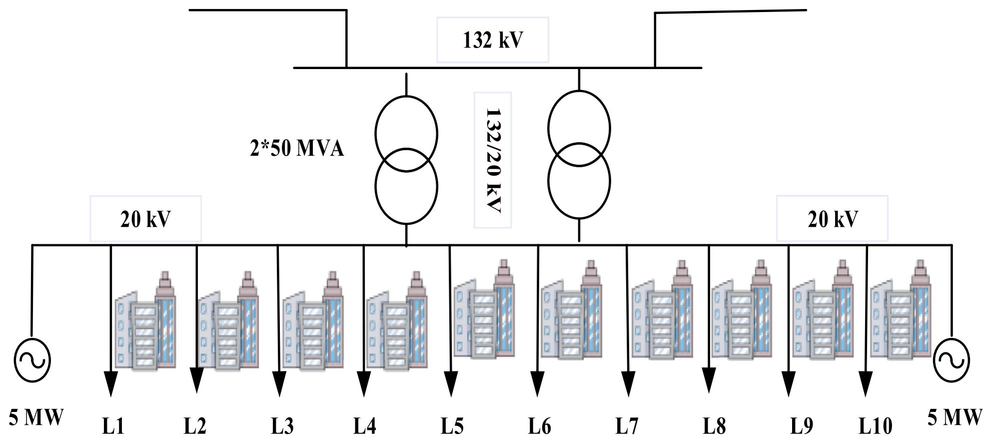


**Fig. 5.** Single diagram of the distribution system.

**Table 4**
Characteristics of fragility curves of electrical components [42] .

| Component | State | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | ***Non-retrofitted components*** | | | | | | | |
| | **Minor** | | **Moderate** | | **Extensive** | | **Complete** | |
| | $\beta$ | $\sigma$ | $\beta$ | $\sigma$ | $\beta$ | $\sigma$ | $\beta$ | $\sigma$ |
| **Distribution Substation** | 0.13 | 0.65 | 0.26 | 0.50 | 0.35 | 0.40 | 0.70 | 0.40 |
| **Distribution Line** | 0.24 | 0.25 | 0.33 | 0.20 | 0.58 | 0.15 | 0.89 | 0.15 |
| **DER** | 0.10 | 0.50 | 0.42 | 0.50 | 0.42 | 0.50 | 0.58 | 0.50 |
| ***Retrofitted components*** | | | | | | | | |
| **Distribution Substation** | 0.15 | 0.70 | 0.29 | 0.55 | 0.45 | 0.45 | 0.90 | 0.45 |
| **Distribution line** | 0.28 | 0.30 | 0.40 | 0.20 | 0.72 | 0.15 | 0.89 | 0.15 |
| **DER** | 0.10 | 0.55 | 0.21 | 0.50 | 0.48 | 0.50 | 0.78 | 0.50 |

**Table 5**
Values of damage precentage [42].

| Component | Damage percentage (%) | | | |
|---|---|---|---|---|
| | $Q_{mi}$ | $Q_{mo}$ | $Q_{ex}$ | $Q_{co}$ |
| Distribution Substation | 5 | 40 | 70 | 100 |
| Distribution Line | 4 | 12 | 50 | 80 |
| DER | 0 | 50 | 100 | 100 |

**Table 6**
Data of electical components [21,42], and [53].

| Components | Repair time (hours) | Repair cost ($\$;\ \times 10^3$) | Hardening cost ($\$;\ \times 10^3$) |
|---|---|---|---|
| Substation | 48 | 450 | 300 |
| Overhead line | 36 | 1.5 (per km) | 1 (per km) |
| DER | 24 | 50 ((per MW) | 20 (per MW) |

**Table 7**
Pso parameters.

| **Parameter** | $N$ | $w$ | $C_1$ | , $C_2$ | $IT$ |
|---|---|---|---|---|---|
| **Quantity** | 200 | 1.2 | 1.2 | 0.9 | 2000 |

$$FV(B) = 0.9\exp(-0.03B) - 0.88\exp(-2.3B \tag{15}$$

Fig. 6 depicts that the increase in *EB* reduces the *FV* rate. The resilience budget is classified into three categories: low, medium, and high. For the low range of *EB* [$0-$225,000], the optimal enhancement measure is distribution line measures. For the medium range of *EB* [$225,000-$625,000], distribution substation retrofitting and distribution lines enhancement measures are the optimal solutions. Finally, for the high range of *EB* [$625,000-$3,025,000], adding DER generation capacity is added to the optimal solution. For the budgets more than $3,025,000, *FV* is almost zero.

**Table 8**
Results of sensitivity analysis on budget.

| **Budget** ($\times\ \$;10^3$) | **Resilience Enhancement Measure** | | | | | *ENS* **(GWh)** |
|---|---|---|---|---|---|---|
| | **S** | **U** | **R** | **O** | **DER (MW)** | |
| 0 | 0 | 0 | 0 | 0 | 0 | 1.584 |
| 25 | 5 | 0 | 0 | 0 | 0 | 1.267 |
| 125 | 5 | 2 | 0 | 0 | 0 | 1.117 |
| 225 | 5 | 4 | 0 | 0 | 0 | 0.989 |
| 325 | 0 | 0 | 1 | 0 | 0 | 0.840 |
| 425 | 5 | 2 | 1 | 0 | 0 | 0.393 |
| 525 | 5 | 4 | 1 | 0 | 0 | 0.265 |
| 625 | 5 | 5 | 1 | 1 | 0 | 0.253 |
| 825 | 5 | 5 | 1 | 1 | 2 | 0.246 |
| 1,025 | 5 | 5 | 1 | 1 | 4 | 0.225 |
| 2,025 | 5 | 5 | 1 | 1 | 14 | 0.129 |
| 3,025 | 5 | 5 | 1 | 1 | 24 | 0.127 |

**S** stands for the number of installed sectionalizing switches
**U** stands for the number of underground cables
**R** stands for the substation retrofitting
**O** stands for overhead line retrofitting
**DER** stands for the adding DER generation capacity

*4.2.2. Resilience enhancement measures for underground distribution systems*

It is assumed that all distribution lines are underground cables; hence the enhancement measures for distribution line measures are only

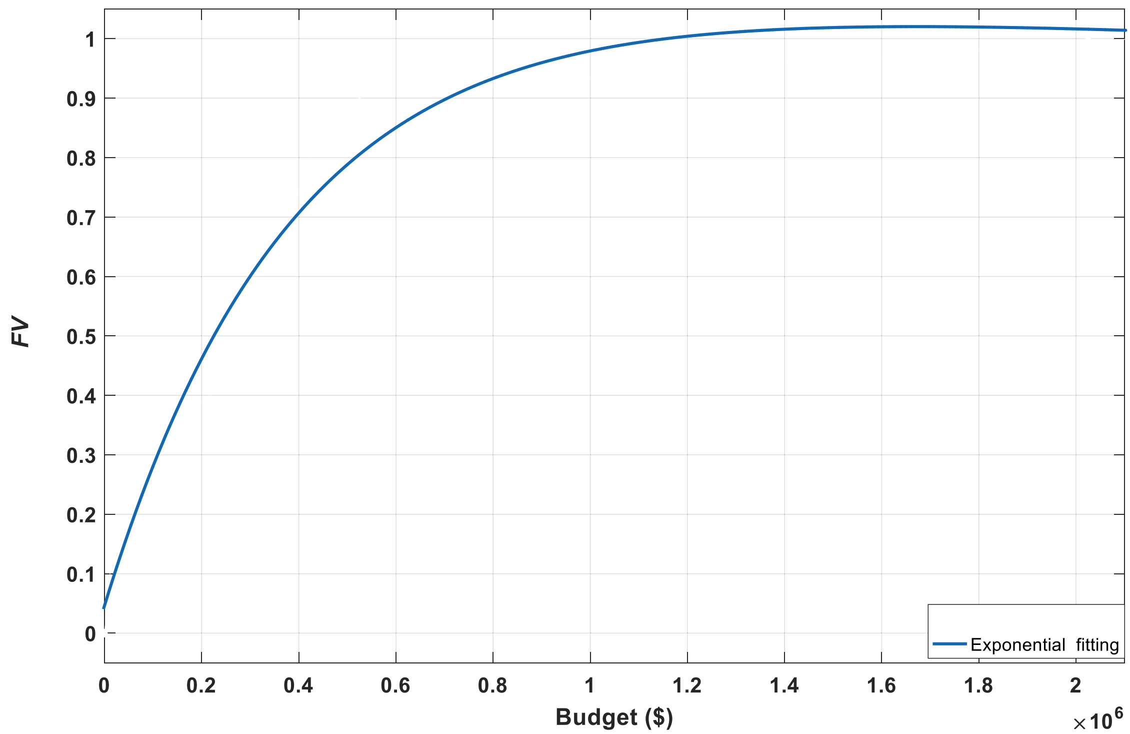


**Fig. 6.** *FV* variation in the range of [0$-$2,025,000].

replacing the old cables with new cables and installing sectionalizing switches. The cable age is 25 years, and the failure rates of the old cables and the new cables are $10.6 \times 10^{-2} year/km$ and $0.1 \times 10^{-2} year/km$, respectively [49]. The proposed method is applied to the modified case study, and the results are presented in Table 9. The calculated *ENS* without resilience enhancement measures, $ENS_0(\boldsymbol{\gamma})$, is 1.350 GWh. By Comparing with $ENS_0(\boldsymbol{\gamma})$ for the base case, it is clear that underground cables are more resilient against earthquakes. For the $25,000 budget, installing sectionalizing switches is the optimal solution and reduces *ENS* to 1.037 GWh. For the budgets in the range of [$25,000-$225,000], renewing old cables and installing sectionalizing switches are the solutions, and they reduce *ENS* from 1.037 GWh to 0.857 GWh. For the $325,000 budget, the distribution substation retrofitting is the most effective measure and reduces *ENS* to 0.655 GWH. More cables are renewed for the budgets in the range of [$425,000 to $625,000]. For the budgets in the range of [$625,000 to $3,025,000], adding DER generation is the most effective measure presented in Table 9.

Modified *FV* is illustrated in Fig. 7 by fitting a two-term exponential curve with 0.04 RMSE. The modified *FV* as a function of Budget ($B$) is as follows:

$$VF(B) = 1.1\exp\left(-2.3 \times 10^{-8}B\right) - 1.07\exp\left(-2.6 \times 10^{-6}B\right) \tag{16}$$

The resilience enhancement budget is classified into three categories explained in the previous part. For low, medium, and high budgets, the enhancement measures are distribution line measures, substation retrofitting measure, and adding DER generation capacity, respectively. It is interesting to mention that DERs retrofitting is not a feasible resilience enhancement measure against earthquakes for the base and the modified base cases.

**Table 9**
Results of sensitivity analysis on budget for modiffied study.

| Budget ($\times$ $;$10^3$) | Resilience Enhancement Measure S | U | R | O | DER (MW) | *ENS* (GWh) |
|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 1.350 |
| 25 | 5 | 0 | 0 | 0 | 0 | 1.037 |
| 125 | 5 | 2 | 0 | 0 | 0 | 0.967 |
| 225 | 5 | 4 | 0 | 0 | 0 | 0.857 |
| 325 | 0 | 0 | 1 | 0 | 0 | 0.655 |
| 425 | 5 | 2 | 1 | 0 | 0 | 0.396 |
| 525 | 5 | 4 | 1 | 0 | 0 | 0.267 |
| 625 | 5 | 5 | 1 | 1 | 0 | 0.255 |
| 825 | 5 | 5 | 1 | 1 | 2 | 0.247 |
| 1,025 | 5 | 5 | 1 | 1 | 4 | 0.228 |
| 2,025 | 5 | 5 | 1 | 1 | 14 | 0.128 |
| 3,025 | 5 | 5 | 1 | 1 | 24 | 0.127 |

**S** stands for the number of installed sectionalizing switches
**U** stands for the number of new underground cables
**R** stands for the substation retrofitting
**DER** stands for the adding DER generation capacity

### *4.3. Limitations and Future Works*

In this paper, the distribution system customers are considered a load point at the end of the lines. For future studies, the customers will be considered in different locations, and OPF will be applied to evaluate the operational constraints such as voltage limitations and line capacity. In this study, only gas turbines are the controllable DERs, and renewable DERs are ignored. The impact of earthquakes on renewable DERs is also the interest to the authors, and it will be investigated in future works. Finally, transportation infrastructure support the movement of repair crew and essential equipment. Damage to transportation systems after a natural disaster leads to a lack of accessibility and disrupts the regular flow of services and goods [54]. The role of transportation infrastructure in the recovery of electrical distribution systems is the research interest of the authors.

## 5. Conclusion

This paper proposes a two-stage decision-making framework to enhance distribution system resilience against earthquakes. The sto-

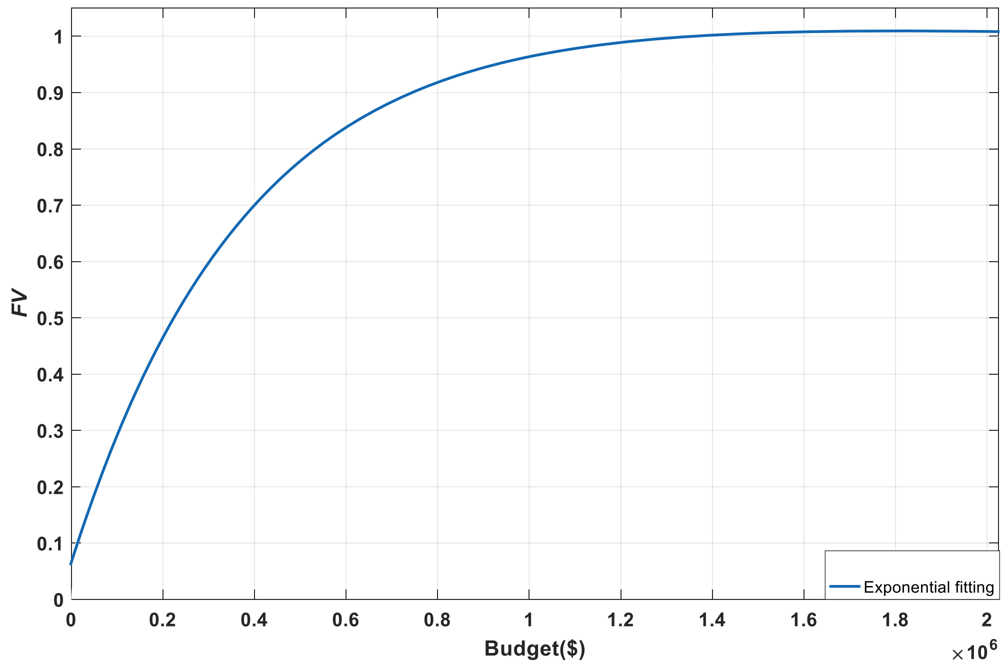


**Fig. 7.** *FV* variation in the range of [0$-$2,025,000] for the modified case study.

chastic characteristics of seismic hazard and component behavior are considered. The selection of enhancement measures to mitigate the seismic risk is formulated as an optimization problem, and PSO is applied to solve it. A modified *FV* importance measure is proposed to determine the relevant effects of the solutions. For example, if the resilience enhancement budget is $325,000, *FV* equals 0.51. The findings obtained from this research are summarized as follows:

- Providing parallel distribution lines through sectionalizing switches to supply customers in emergencies is an effective and economic resilience enhancement measure.
- Distribution substation retrofitting is one the most effective seismic enhancement measure requiring more investment than sectionalizing switches.
- Using the capacity of DERs to supply critical loads in emergencies is an effective but expensive resilience enhancement measure; hence multi-objective planning including emergencies and normal operation (e.g., minimizing power loss) conditions is desirable.

The DSOs can use the obtained results to find an insight to mitigate the seismic risk.

## CRediT authorship contribution statement

**Mohammad Hossein Oboudi:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Visualization. **Mohammad Mohammadi:** Validation, Resources, Writing – review & editing, Supervision, Project administration.

## Declaration of Competing Interest

All authors have participated in (a) conception and design, or analysis and interpretation of the data; (b) drafting the article or revising it critically for important intellectual content; and (c) approval of the final version.

This manuscript has not been submitted to, nor is under review at, another journal or other publishing venue.

The authors have no affiliation with any organization with a direct or indirect financial interest in the subject matter discussed in the manuscript

The following authors have affiliations with organizations with direct or indirect financial interest in the subject matter discussed in the manuscript:

## Data availability

No data was used for the research described in the article.

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