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Pre-hurricane optimal placement model of repair teams to improve distribution network resilience

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ABSTRACT

Predictive planning for restoration and emergency reaction before occurrence of hurricane is an effective action in reducing time and cost of electricity interruption and improving resilience in overhead distribution networks. Traditionally, approaches in load and system recovery are constructed based on reliability studies, with the consideration of equipment failure. However, widespread outages due to the extreme natural events with low probability and high destruction intensity have different properties in comparing the interruptions due to the failures in equipment. Therefore, this paper proposes a new method for restoration and emergency reaction planning. The purpose of this method is resilience improvement of distribution network against hurricane. In the proposed pre-hurricane repair team placement model (PHRTPM), using Monte Carlo simulation method and fragility curves, different failure samples of poles and conductors of medium voltage distribution network are generated according to the predicted speed of hurricane. Furthermore, the forward dynamic programming algorithm is used to determine the path of the repair teams. In this method, using a square grid topology, the optimum locations of utility teams are achieved. The objective function of problem considers the importance of loads and the cost of outages. In the numerical studies, the proposed model is implemented on a modified and real distribution network in Iran which consisted of 81 buses. The results are discussed and the sensitivity analysis is performed for various parameters.

1. Introduction

Various natural hazards, such as hurricanes and wind storms, can threaten the resilience of power distribution networks. Natural catastrophes, which can occur in different geographical areas in different times, can create undesirable social, technical, economic and organizational consequential problems by causing outages and widespread blackouts. Due to global warming and climate change, natural disasters have occurred with much intensity during the past few decades. Furthermore, it is expected that the number, severity, and time period of these events will be increased in the future [1]. Nowadays, considering the mentioned issues, and given the extreme dependence of critical infrastructures on electrical energy (including transportation, economic activities, health system, purification and supply of drinking water, and emergency services), strengthening of energy infrastructure and increasing its resilience have become necessary as an important priority [2]. Although authentic standards exist for power system reliability, there is no comprehensive standard or guideline in the domain of power system resilience studies.

In Ref. [3], the UK Energy Research Centre (UKERC), stated a new definition of resilience: “Resilience is the capacity or the ability of a system to withstand disturbances and the capability of delivering continuous energy to consumers.” A resilient energy system can quickly recover from shock mode and can offer alternatives for energy requirements in the advent of incidents resulting from an external event. In the National Infrastructure Advisory Council (NIAC) definition, strength, resource adequacy, fast recovery, and adaptability are introduced as the main features of resilience [4]. In the mentioned definitions, quick restoration of curtailed loads is considered as one of the main features of resilience.

In the context of the system resiliency and emergency response, two study areas exist including: (i) Assessment and forecasting of outage rate and damage level and (ii) Recovery and resource allocation.

The first domain, the assessment and forecasting of outage rate and damage level caused by the occurrence of destructive events such as hurricanes, is considered in some literature. Ref. [5] analyzes the mutual effects between biophysical environment and power distribution networks from resilience viewpoint and offers prioritizing method for recovery activities of this environment. Moreover, Ref. [6] provides a statistical method based on data fitting using a large database of past

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storms that predicts the restoration time of power networks. The proposed model improves the notification process to consumers for required time to restore the damaged networks after the storm. In Ref. [7], a data mining approach is proposed to assess the impact of climate and geographical conditions on blackout predicting models related to the storm event. In Ref. [8], a probabilistic framework is studied for vulnerability analysis of distribution network poles with respect to climate change. From the results, the life of poles and climate changes affect the failure rates of distribution network poles. In Ref. [9], the concept of resilience trapezoid is developed to assess the different time phases of resilience which a power system can experience during a severe event. This approach provides an effective aid to understand the features related to performance degradation and system recovery process by using time dependent indicators. In addition, operational and structural resilience and the strategies to improve them are presented in this paper. In Ref. [10], a supporting tool is described, with the aim of improving the supervision on the situation, promotion of accessing to information for distribution companies, and recovery management of damaged equipment due to severe storms. In this reference, the site of switching and protection equipment and the location of the consumers are determined in order to allocate resources based on a cost/benefit pattern for blackouts caused by the storm.

The occurrence of a natural disaster can damage the infrastructure of power system consequently leading to power interruption. After this event, the most important task of the system operator is power system recovery in the shortest possible time, with the aim of restoring the sensitive loads and reducing economic damages imposed to the consumers [11].

In the second context, i.e. recovery and resource allocation, preventive planning for real time emergency response (for instance locating and determining the number of repair teams) is one of the most important fields in resilience studies of power systems which has been investigated by different researches. In line with this topic, Ref. [12] provides a non-deterministic and two-stage preventive model for retrieving and allocating resources before the occurrence of storm. Ref. [13] presents three mathematical models for allocating the locations of repair teams and restoration of distribution and transmission lines. Optimal tactical plan of repair teams in extreme weather conditions, short-term strategic plan for optimal placing of repair teams in normal weather conditions, and determining the optimal number of teams for long term planning are the proposed models of this paper. In Ref. [14], a decision making problem for load restoration in densely populated areas is proposed which maximizes the retrieved power in the post-disaster recovery process. The problem is modeled by a mixed-integer programming. In Ref. [15], the warehouses siting model with the objective of optimal restoration is developed to manage the resource and crew needs with economic considerations. The purposes of this paper include determining the appropriate number of warehouses, the optimum warehouse locations, and the optimum number of repair teams including repair vehicles, crews, and equipment. In Ref. [16], load restoration problem is studied to minimize the service interruption considering the constraints of transportation in the emergency conditions. In this problem the issue of restoration resources is considered in a systematic way to obtain the optimal time of service actions. Ref. [17] provides a non-deterministic integer programming method developed for planning, damage evaluation, and scheduling of repair for restoration of power systems after an earthquake. The optimization problem, which minimizes the service interruption time, is solved using the genetic algorithm. In Ref. [18], to assess the extent of the failure, destruction and restoration of power systems after natural disasters, an approach is presented. Ref. [19] provides an analytical statistical model that utilizes data of interruptions in power grids during storm. This model, with the utilizing of publicly available information and data, could predict the interruption in electricity along US coastline and provides an approach for decision makers to determine the appropriate location and geographical distribution of resources. Ref. [20] proposes a multi-objective optimization technique for system restoration during disaster recovery. This model permits tradeoffs between cost minimization and system power flow maximization. Furthermore, Ref. [21] studies the proactive recovery strategies to retrieve power system assets.

As demonstrated by the literature review, there are only few works in the scope of resiliency and emergency response against hurricane hazard in distribution network. Hence, in this paper, a pre-hurricane repair team placement model (PHRTPM) is proposed as a heuristic model that aims to find the best locations of the operational crews and vehicles to improve the resilience of the network prior to the storm occurrence. Using this model, the best locations and number of repair teams can be obtained according to the costs. This approach is a good basis for distribution companies to make decisions according to their resources before the storm. In order to take into account the uncertainty of network equipment damage against a predicted storm, probabilistic investigations of the storm destruction are conducted based on the Monte Carlo simulation (MCS). In the presented model, with the intention of deciding the path through which the restoration team moves toward the destructed regions, a heuristic technique based on a square grid topology and forward dynamic programming algorithm is used. The proposed model of this paper has been applied to a real modified distribution network in Iran. Considering the literature review, the main advantages of the proposed model are: (1) a heuristic technique based on a square grid topology is proposed which is applicable for large real systems, (2) the proposed objective function considers the lost profits and penalty factor cost of distribution company simultaneously, (3) the probabilistic nature of destructive events and the uncertainty of equipment failure are considered, (4) the proposed model do not need wide information and data base, (5) it presents a pre-storm proactive restoration planning. Therefore, it can help DSO for pre-disaster preparation, (6) the proposed approach can be generalized for other natural disasters like thunderstorms, ice storms and floods because it is not dependent to the procedure of obtaining fragility curves of components.

The second part of the paper presents the proposed model. In this section, the suggested algorithms of the heuristic method are described. The simulation results are described in Section 3, and the discussions are presented. Finally, the conclusions are provided in the last section.

2. Proposed PHRTPM

Occurrence of storm causes damage to the poles and network conductors. Under such circumstances, it is necessary that crews arrive to more important sites in the shortest possible time, with aim of commencing restoration operations. At the same time, decision-making on the basic recovery indicators is of high importance. The main goal of PHRTPM is to find the best places for units of restoration resources before the storm and to calculate the decision indicators. According to Fig. 1, this method fulfills these goals based on the weather forecasting information and the distribution system data using some computations.

2.1. Description of the proposed model

In the proposed model, by having prior knowledge of the number of crews and vehicles (cr) and the candidate positions (cp), a large number of failure samples of poles and network conductors are generated based on the Monte Carlo sampling method. For each failure sampling, with a consideration of different permutations of distinct repair teams in the selected candidate locations (the number of permutations is cp^{cr}), the routing is determined from the viewpoint of minimizing the objective function using the forward dynamic programming algorithm. In each iteration of MCS, three permutations with the lowest values of objective function are selected and weighted from 3 to 1. When the MCS is completed, all the allocated weights are gathered for each permutation. Finally, among all the permutations (having a permutation number as

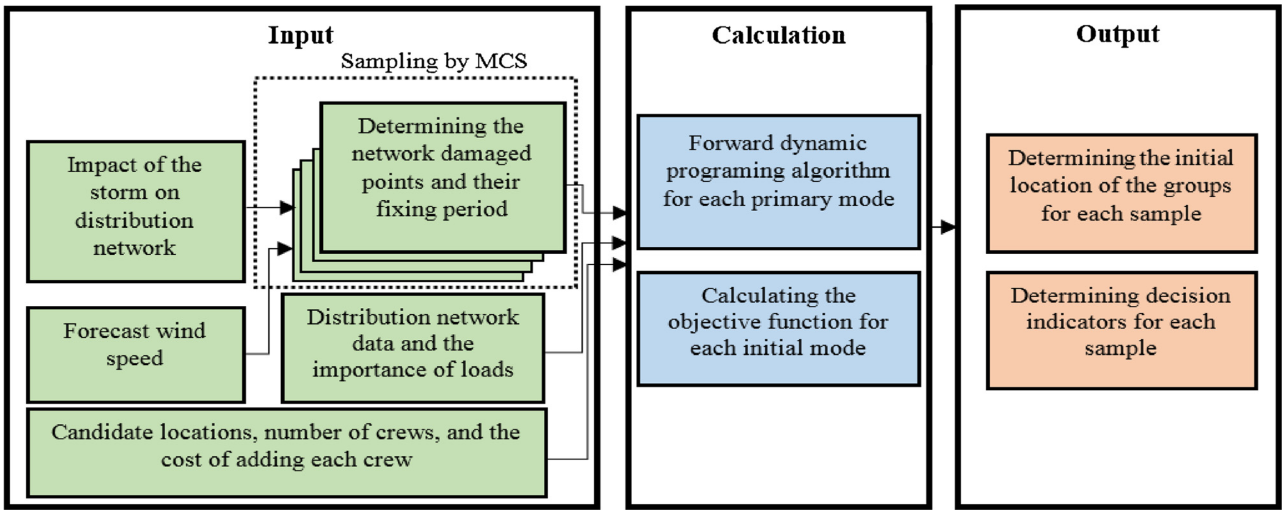

Fig. 1. The pre-hurricane repair team placement model.

$\binom{cp}{cr} + cp$), the permutation with the maximum weight will be considered as the best location of repair teams. It should be noted that the heuristic algorithms can obtain close-to-best solution among all possible ones. Therefore, the proposed heuristic algorithm can obtain the more suitable locations between the candidate ones to place the repair teams. However, these locations are considered as the optimal solution of model.

One of the modeling requirements presented in this paper is the introduction of a square grid-based approach for network topology. For obtaining square grid topology, it is assumed that each bus is located in one square of this grid, and no square contains two buses. Another assumption is that the dimensions of all squares are the same. In addition, the size of each square is larger than the minimum required size for establishment of repair teams and equipment. The failure of each component (pole or conductor) at upstream of bus c causes the outage at this bus and all its downstream buses. In Fig. 2, the square grid topology of a sample network is shown.

The considered objective function is cost-based which models the cost of the energy not supplied (*ENS*) and the electricity interruption penalty cost of the distribution company. Also, the importance of loads is modeled in the objective function. The importance of each bus is considered using a coefficient which not only includes the economic factors, but also considers various social and political factors according to the judgment of the experts [22]. After determining the importance factor (*IF*) of each bus, while approaching the beginning of the feeders, these factors cumulatively increase from bus to bus. Thus, a cumulative importance factor (*CIF*) is allocated to each bus. Considering the radial structure of network, *CIF* of bus *c* is calculated by summing the *IF* value of this bus with the *IF* values of buses downstream of this bus. Eq. (1)

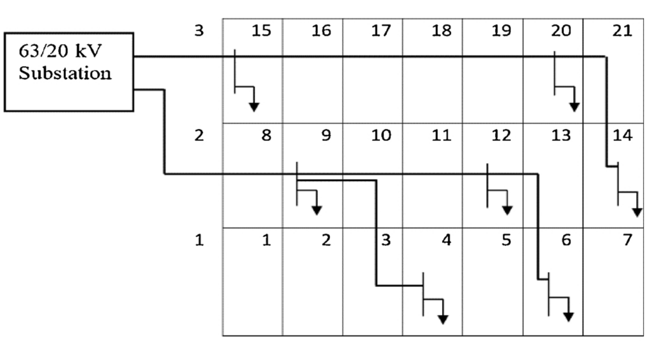

Fig. 2. Square grid topology of a sample network.

shows the paper objective function (*POF*) to fix the damages of bus *c*. It is assumed that when a crew comes to a bus, it eliminates all the failures of the lines connected to that bus, caused by damages of poles and/or conductors, and immediately after the operation of crew, the load is restored.

$$POF(c) = CIF(c) \times ENS(c) \times M_c + consumer(c) \times T(c) \times P_n(c) \quad (1)$$

where *consumer*(c) is the number of consumers supplied from bus c; M_c and $P_n(c)$ are energy price in dollars per kilowatt-hour and the amount of penalty in dollars per hours that the distribution company must pay for the duration of the power interruption at bus c, respectively; $T(c)$ and $ENS(c)$ are the outage duration in hours and the energy not supplied in kilowatt-hour related to the bus c, respectively, and they are calculated using Eqs. (2) and (3).

$$T(c) = T_b + \frac{f(b, c) \times d}{V_c} + TTR(c), \quad (2)$$

$$ENS(c) = T(c) \times P(c). \quad (3)$$

In Eqs. (2) and (3), the parameters T_b, $f(b, c)$, d, V_c, $TTR(c)$, and $P(c)$ are the time interval from the moment of starting the operation to the moment when crew b starts to fix the interruption of bus c in hours, the distance between the crew and the bus in kilometers, the distance between the centers of two adjacent locations in kilometer, average speed of utility vehicle in kilometer per hour, estimated operation time for eliminating the failure of bus c in hours, and the average value of the active power of substation c during the 24-h of network normal condition prior to the storm, respectively. In Eq. (1), the first term indicates the economic damage imposed to the distribution network because of ENS, while the second term presents the penalty cost which distribution company must pay because of electricity interruption. $P_n(c)$ can be calculated based on the value of lost load (VoLL). As an alternative, the penalty factor can be obtained using the *CIF* and demand of each consumer. The objective function is in terms of dollars and is calculated according to Eq. (4). In this equation, S represents the number of buses suffered from the interruption.

$$O.F. = \sum_{j=1}^{S} POF(j). \quad (4)$$

Wind velocity is constant as the prediction data, but in each Monte Carlo repeat, the failures of two components, i.e. the poles and conductors, are determined by the fragility curves according to Eq. (5) as a string consisting of binary numbers. More explanation of this method can be found in [2,23,24].

$$P_x = A_x \times e^{B_x \times V_W}, \quad x = c, p. \tag{5}$$

In Eq. (5), V_W represents the wind speed; A_x and B_x represent the conductor (c) or pole (p) coefficients that are usually obtained experimentally by examining the historical data.

Using the fragility curve of each component, the parameters A_x and B_x can be calculated. When wind speed is determined, it is mapped to the related fragility curve of each component to obtain the failure probability of component. At each trial of MCS, a random number between 0 and 1 is generated. This number is compared with the obtained failure probability. A number larger than the value of failure probability implies that the component does not fail. On the other hand, a number lower than the value of failure probability implies that the component fails. Therefore, in each iteration of MCS, using the generated random numbers and probabilistic functions with the pattern of Eq. (5), all the damaged poles and conductors of the network are determined. It should be noted that the failure of each one of these components leads to the failure of one or more buses of system.

In this step, the time of troubleshooting of each damaged pole and conductor is obtained by applying the random numbers generated from the normal distribution function in accordance with Eq. (6) [24,25].

$$y = f(x|\mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}. \tag{6}$$

In the equation, μ and σ represent the mean value and standard deviation, respectively, which are different for the pole and conductor failure elimination. These values are obtained from the corresponding distribution company. Other data of distribution companies such as energy costs, average load of substations before the storm, and number of crews, will be inquired and considered.

For each sample of the failure created by the MCS and any initial position of the repair teams, the routing of the repair teams to eliminate the failures is characterized by forward dynamic programming. The principles of this method are expressed in the Ref. [26]. At the beginning of each step of the algorithm, the non-busy team is selected. In the first step of the algorithm, since all teams are free, they are dispatched according to their priority number.

In the next steps, each team that has completed its previous work is selected. For example, in step k of the algorithm, after selecting the vehicle, for each of the paths that has passed until that moment for fixing the defects of the buses (P path of step $k-1$), primary defective buses of feeders that can be selected (for instance, for one of paths as $B_K = \{B_{1K}, B_{2K}, ..., B_{rK}\}$) are considered. Due to the *CIF* value of the considered buses (from a set with r member), m paths are selected. For each one of these m new paths, the objective function of the path that is traversed from the beginning to the present (*SPF*) is calculated using Eq. (7). In this step, the chosen team moves towards P buses having the smallest amount of *SPF* and the objective function and needed indicators will be updated for these P paths. After updating, step $k+1$ commences where its process is repeated as the previous step (step k). The algorithm continues as long as there is a defective bus. At the end of the algorithm, based on the initial location of the service teams, routing will be determined for the purpose of minimizing the objective function. This method has a heavy computational burden, but it is close to reality, because in practice, the moves done by management of repair team are implemented by considering the importance of loads and economic issues. This method is a kind of artificial intelligence to fix the defects of the buses.

$$SPF(k) = \sum_{j=S_1}^{S_k} POF(j). \tag{7}$$

In Eq. (7), S_k represents the number of the fixed bus in step k.

It should be noted that in this paper to evaluate different samples from the resiliency point of view, restored consumers index (*RCI*) is used according to Eq. (8). *RCI* is the ratio of number of all restored consumers (*NRC*) to the duration of operation (*DO*).

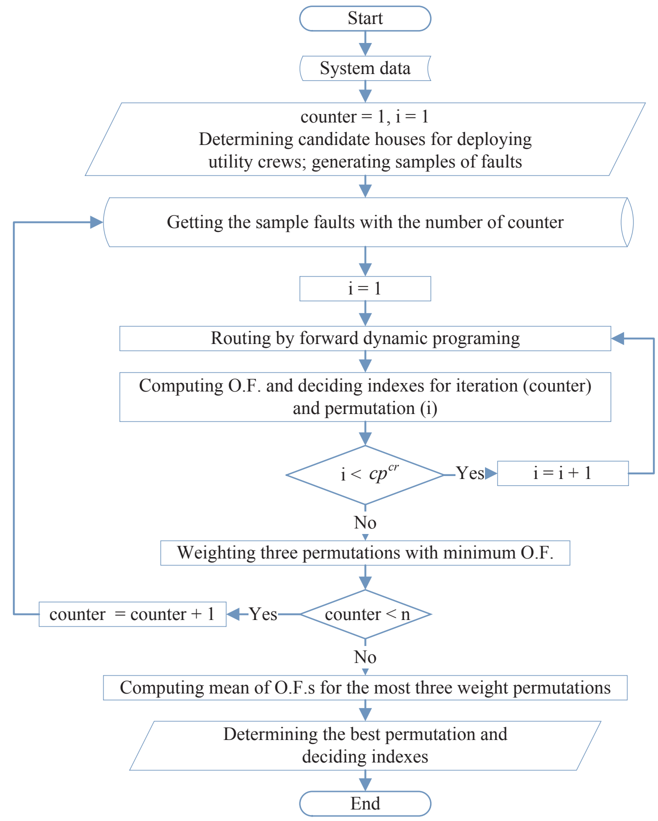

Fig. 3. Flowchart of PHRTPM.

$$RCI = \frac{NRC}{DO}. \tag{8}$$

Distributed company decision-making indicators including the real-cost index (*Cost*), the resiliency index (*RCI*), and the objective function are calculated for all Monte Carlo samples. These variables are a part of the PHRTPM outputs.

The cost is calculated without considering the importance of the loads and the cost of adding each service unit (P_c), according to Eq. (9). This cost does not include the value of replaced commodities which are not related to the utility teams. In Eq. (9), P_c represents the cost of adding a team to the operation.

$$Cost = cr \times P_c + \sum_j (ENS(j) \times M_c + consumer(j) \times T(j) \times P_n(j)). \tag{9}$$

Fig. 3 presents the PHRTPM flowchart. According to this flowchart, the MCS produces n samples of the pole and conductor failures. For each sample, cp^{cr} permutations of distinct repair team positions are considered. For each one of the permutations, routing is performed by the proposed manner and the objective function for each routing is calculated. For each iteration, the three permutations which have the lowest value of the objective function are weighted and stored as the optimal permutations of that trial. The optimal placement calculations of service units are repeated for n samples, so that the permutation with the maximum total weight is selected by the model as the best location will be introduced as the final output of PHRTPM and the relevant indices will be obtained.

At each step of problem, to obtain the best routes based on the proposed forward dynamic programming algorithm, firstly, m unrecovered buses with the highest *CIF* are selected. Then, the objective function for the possible paths is calculated, and the best routes are selected. The procedure continues until all the buses are recovered.

Table 1
The required data.

Pole destruction	σ (h)	0.4
	μ (h)	2
	A_P	0.0012
	B_P	0.045
Conductor destruction	σ (h)	0.4
	μ (h)	0.5
	A_C	0.0057
	B_c	0.047
V (m/s)		75
d (m)		100
Pc (dollars/crew)		4285.714
Pn (dollars/h)		0
Mc (dollars/kWh)		0.02286

Table 2
Candidate locations for placing the repair teams.

Candidate's number	1	2	3	4	5
x	160	70	94	77	85
y	35	80	95	97	110

3. Numerical results and discussion

Table 1 presents the required data for simulation of PHRTPM. These data are provided based on the data of one of Iran's power distribution networks. The simulation is implemented on an electric power distribution network with a voltage of 20 kV. In Fig. 4, the topology of the distribution system is presented. To avoid the negative values related to the normal distribution for repair time, the distributions of the datasets are skewed to the right. To achieve this goal, the normal distributions with known parameters are estimated by similar log-normal distributions.

Considering the square grid-based method described in Section 2, the network of Fig. 4 is converted to a square grid. Considering the size of distribution network and equipment and vehicle of operational teams, the size of $100 \times 100\ m^2$ is selected for each square. In such condition, the number of squares is 170×170. Therefore, each one of the buses has a coordinate (length and width) which is used to calculate the distances between the buses. The candidate locations for placing the

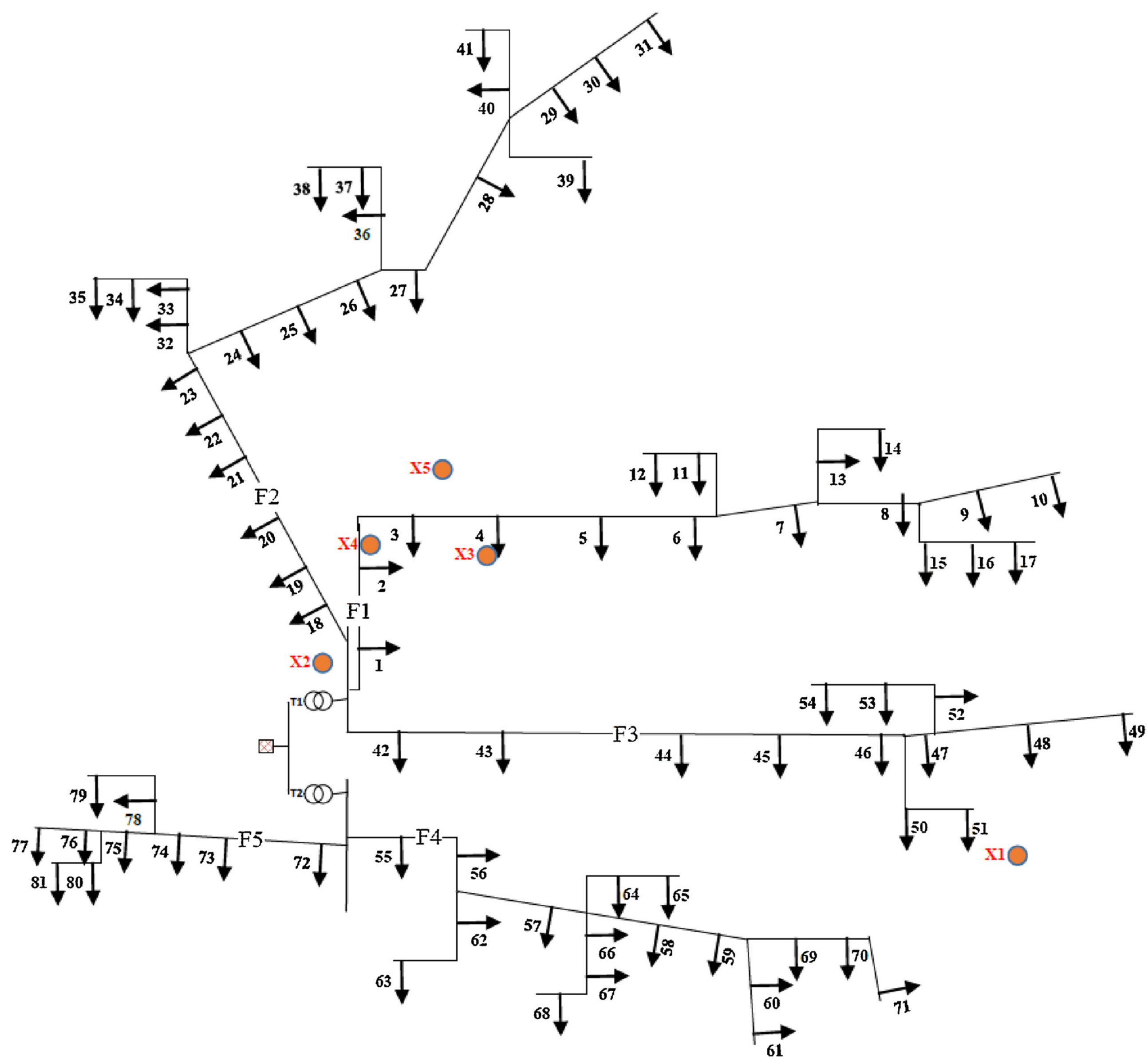

Fig. 4. Sample network with candidate locations for placing the repair teams.

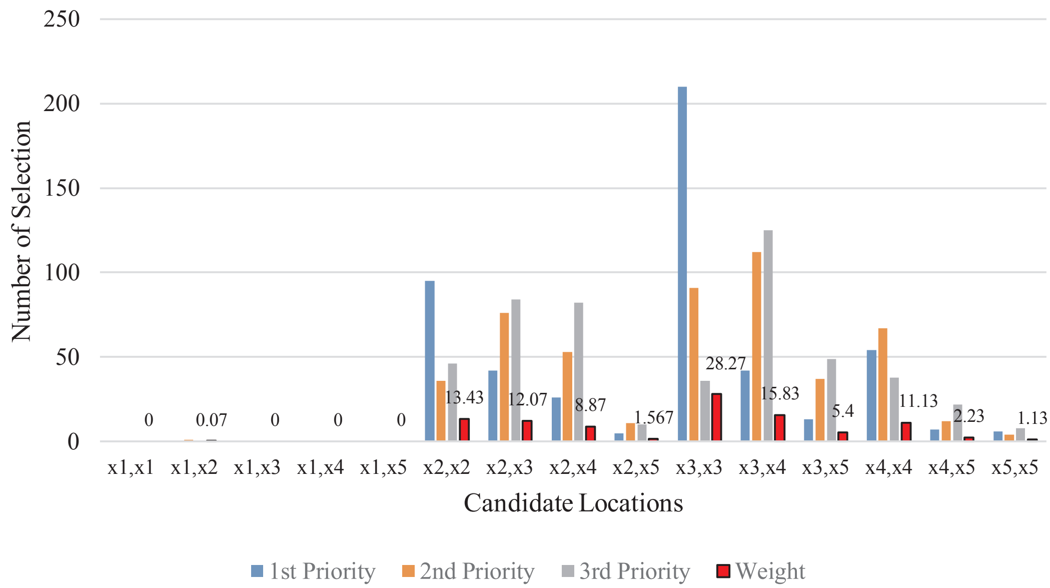

Fig. 5. Number of optimal candidates, selected by the proposed algorithm.

repair teams on this large grid are shown in Fig. 4 (see Table 2).

The simulation results based on the PHRTPM for two repair teams and for 500 Monte Carlo iteration are as follows:

Fig. 5 illustrates that how many times each permutation is selected in MCS iterations as the first, second, or third priority. According to this figure, weight percentage of each permutation is computed by dividing the corresponding weight of that permutation by summation of all weights of MCS iterations. The permutations (X3,X3), (X3,X4), and (X2,X2) with weight percentages of 28.27%, 15.83%, and 13.43%, respectively, are obtained as the best candidates. Among these permutations, the first one, with the mean value of 772,380 $ for objective function is selected by the PHRTPM as the best location for establishment of service units before the storm occurrence.

The mean values for selected candidate locations are listed in Table 3. Table 4 presents the simulation results for one and three repair teams per 500 Monte Carlo iterations. In order to ensure about the accuracy of the random sampling by MCS method, a confidence interval evaluation is used [27]. Thereby, for one repair team, the 95% confidence intervals for the mean of objective function are [1,444,445, 1,456,955] $ and [1,448,140, 1,453,259] $ for 500 and 2000 trials of MCS, respectively. Although the results are close, the latter iteration number need four times computational burden.

Using the results, a comparison of the indicators is made for different number of teams (see Fig. 6). The comparison of the resilience index of different teams is also presented in Fig. 7. As the number of utility units increases up to four teams, the values of the objective function and the resiliency index will be improved. According to Fig. 6, from the cost point of view, selection of three numbers of teams is optimal. However, the distribution system management should compromise between the cost and the resilience indicator and must determine how much it is willing to cost for the resilience improvement according to the available financial resources of the distribution company. In this manner, the best number of repair teams can be determined. As a result, this paper proposes that the distribution network company can find the final solution of the problem as follows:

1. The resilience improvement rate is obtained by dividing cost by *RCI*. The case with the minimum rate is selected. For the system test of this paper, the minimum rate of this index is 32.89, related to the four repair teams.

Table 3
Mean values of selected candidate locations.

The mean value of required time from start to end of operation (h)	36.7
The mean value of *RCI*	365
The mean value of *ENS* (MWh)	660
The mean value of objective function ($)	772,380
The mean value of cost ($)	23,661

Table 4
The results for different numbers of teams.

1 Team	Best permutation	*X*3 with 38.1% weight
	The mean value of required time from start to end of operation (h)	72.3
	The mean value of *RCI*	185
	The mean value of *ENS* (MWh)	1289
	The mean value of objective function ($)	1,450,700
	The mean value of cost ($)	33,755
3 Teams	Best permutation	*X*3, *X*3, *X*3 with 17.4% weight
	The mean value of required time from start to end of operation (h)	24.57
	The mean value of *RCI*	549
	The mean value of *ENS* (MWh)	457
	The mean value of objective function ($)	580,140
	The mean value of cost ($)	23,319

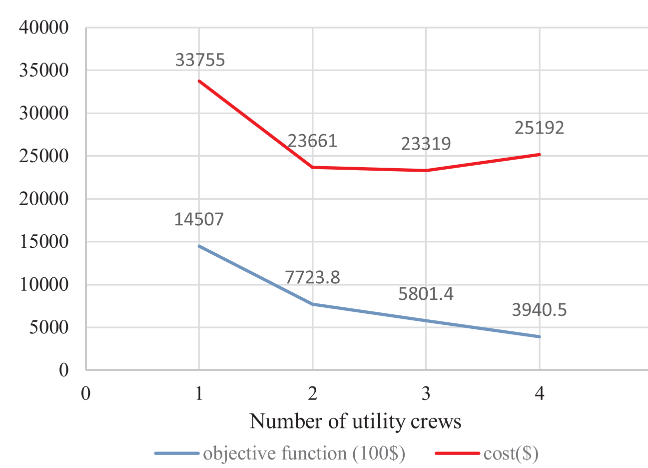

Fig. 6. Comparison of costs and objective functions.

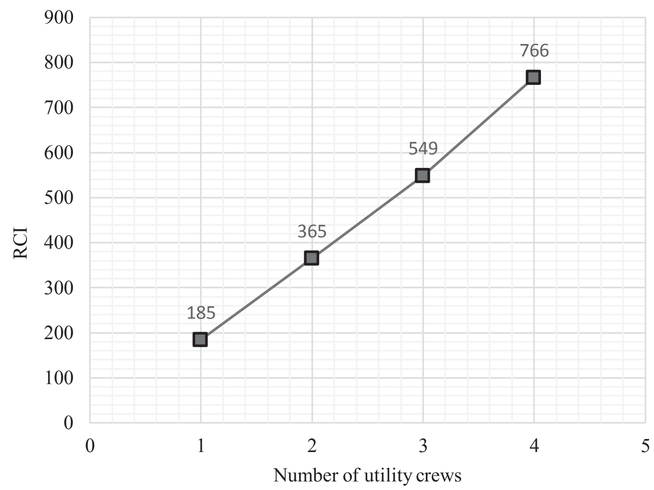

Fig. 7. Comparison of resilience indexes.

2. Distribution company or system regulator determines a desirable level for *RCI*. The result with the minimum cost which satisfies the predetermined *RCI* level is the final solution. This level can be determined considering network circumstance and geographical condition of the area.

In order to carry out the sensitivity analysis, one of the effective system parameters has been changed in each step, and the results for 500 Monte Carlo iterations and two repair teams are presented in Table 5.

According to sensitivity analysis, the following results can be deduced:

- The duration of the failure elimination of buses (*TTR*) by repair teams has a huge impact on the objective function, cost, and the resiliency index. According to Table 5, with a 20% increase in *TTR*, the resiliency index is reduced by 15% and the final cost is increased by 10.9%. In the same way, when the *TTR* increases by 50%, the resiliency index decreases by 33.4% and the final cost increases by 33.6%. Therefore, it can be concluded that costs increase with a steeper slope with respect to the resiliency index. According to these results, it is necessary to reduce the *TTR* before the storm occurs. This will be attained by conducting maneuvers and other actions to coordinate related service units.
- The speed of the operational vehicle has no significant effect on the optimal initial location of vehicle, the objective function, and the resiliency.
- At high wind speed, the objective function increases significantly, and the resiliency index decreases meaningfully. For instance, for wind speed of 95 $\left(\frac{\mathrm{m}}{\mathrm{s}}\right)$ with two repair teams, the objective function is more than doubled and the resiliency index is less compared to the results for one team and wind speed of 75 $\left(\frac{\mathrm{m}}{\mathrm{s}}\right)$. Furthermore, an increase in wind speed will result an increase in total cost and ENS of system. Consequently, it is clear that in this wind speed, two operational units are inadequate.

4. Conclusion

In this paper, the optimal placement problem of repair teams preceding the storm is considered to improve the network resilience and retrieving consumers in the fastest possible time. For routing the teams, a heuristic algorithm is proposed to optimize the location of units prior to the storm and failure elimination routing based on the forward dynamic programming algorithm. The proposed algorithm minimizes the objective function of the paper which simultaneously considers the cost and importance of loads.

The main advantages of the proposed methodology can be summed up as follows:

- The previous works in this scope, mainly concentrated on the reliability and risk assessment and social impacts of destructions and restorations. The consideration of resilience as an important topic is generally neglected in the literature, whereas this paper has focused on this concept.
- The studied problem is conducted from distribution network perspective while previous studies investigated the problem in the view point of power system, emergency and rescue services, or similar topics.
- The heuristic-based method of paper is computationally efficient and can be developed to handle distribution network resilience encountering other natural disasters.

Simulations are implemented on a real distribution network with 81 buses which belongs to Iran's power distribution networks. The most important simulation results are:

- By using the proposed algorithm, the most appropriate locations of the service units before the storm can be determined for each distribution network. The management of the distribution system can determine the suitable number of repair teams for operation by considering the financial resources and determining an appropriate level of resilience index.
- Wind speed plays a very important role in finding the best location and number of teams and the resilience assessment of the poles and conductors of each distribution network.
- Due to the high impact of repair times on resiliency indicators, it is necessary that prior to the occurrence of storm, by performing maneuvers and training personnel and etc., reduction of repair time should be in the priority of distribution networks.
- Due to the fact that there are no considerable effects of vehicle speed of the operational units on indicators (if the events do not cause destructive obstacles such as the bridge collapse, etc.), the precise

Table 5
The results of sensitivity analysis.

Parameters of PHRTPM	TTR × 1.2	TTR × 1.5	$V_c = 25\left(\frac{\mathrm{km}}{\mathrm{h}}\right)$	$V_c = 60\left(\frac{\mathrm{km}}{\mathrm{h}}\right)$	$V_w = 55\left(\frac{\mathrm{m}}{\mathrm{s}}\right)$	$V_w = 95\left(\frac{\mathrm{m}}{\mathrm{s}}\right)$
Best permutation	*X*3, *X*3 with 30.1% weight	*X*3, *X*3 with 28.4% weight	*X*3, *X*3 with 28.6% weight	*X*3, *X*3 with 26.1% weight	*X*3, *X*3 with 22.2% weight	*X*3, *X*3 with 38.9% weight
The mean value of required time from start to end of operation (h)	43.2	54.2	37.4	36	15.1	89.8
The mean value of *RCI*	310	243	358	376	610	171
The mean value of *ENS* (MWh)	772	988	674	647	180	2141
The mean value of objective function ($)	932,760	1,190,600	805,700	782,510	340,010	1,021,000
The mean value of cost ($)	26,231	31,157	23,971	23,372	12,690	57,523

modeling of the move route of the units seems unnecessary in computations.

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