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Using a New Method to Incorporate the Load Uncertainty into the SEP Problem

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Abstract: In this paper, a new method is conducted for incorporating the forecasted load uncertainty into the Substation Expansion Planning (SEP) problem. This method is based on the fuzzy clustering, where the location and value of each forecasted load center is modeled by employing the probability density function according to the percentage of uncertainty. After discretization of these functions, the location and value of each of the new load centers are determined based on the presented fuzzy clustering based algorithm. A Genetic Algorithm (GA) is used to solve the presented optimization problem in which the allocations and capacities of new substations as well as the expansion requirements for the existing ones are determined. With the innovative presented method, the impact of uncertainty of the power and location of the predicted loads on the results of SEP is measured, and finally, it is possible to make a proper decision for the SEP. The significant features of this method can be outlined as its applicability to large-scale networks, robustness to load changes, the comprehensiveness and also, the simplicity of applying this method to various problems. The effectiveness of proposed method is demonstrated by application on a real sub-transmission system.

Keywords: Genetic Algorithm, Fuzzy Clustering, Load Uncertainty, Probability Density Function, Substation Expansion Planning.

Nomenclature

nlp	Number of load points.
nss	Number of sub-transmission substations.
$ness$	Number of existing sub-transmission substations.
$ncss$	Number of candidate sub-transmission substations.
α_{ij}^{f}	Binary variable for replacement of existing feeder ij.
α_{i}^{ss}	Binary variable for upgrading the capacity of existing sub-transmission substation i.
β_{ij}^{f}	Binary variable for installation of new feeder ij.
β_{i}^{ss}	Binary variable for installation of new sub-transmission substation i.
ξ_{ij}^{f}	Binary variable for feeder path.
L_{ij}^{f}	Length of feeder between buses i and j.
R_{ij}^{f}	Resistance of feeder ij.
X_{ij}^{f}	Reactance of feeder ij.
I_{ij}^{f}	Current of feeder ij.
$I_{ij,max}^{f}$	Thermal capacity of feeder ij.
θ_{ij}	Power factor of load flowing through the feeder ij.
ΔV^{max}	Maximum permitted voltage drop.
rf_i	Reserve factor of sub-transmission substation i.
S_{j}^{L}	Load of i-th sub-transmission substation.
$S_{i}^{ss,max}$	Thermal capacity of i-th sub-transmission substation.
c	Number of clusters.
n	Number of the data (or load centers).
C_i	Vector of cluster centers.

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R	Right-side percentage of uncertainty.
L	Left-side percentage of uncertainty.
u_{ij}	Stands for assigning j-th data to the i-th cluster, if X_j assigns to C_i then u_{ij}=1 and otherwise u_{ij}=0.
X	Data set.
d_{ij}	Distance between data X_j and cluster center C_i.
U_k	A binary matrix of $c\times n$ that is known as Partition Matrix.
N_p	Number of points of discrete PDF.
p_{ij}	Calculated probability for j-th load center of i-th cluster.
P_i	Forecasted power of load center i.
n_i	Number of allocated centers to the cluster i.

1 Introduction

ALONG with the population growth and development of industry in today's world, the consumer's load demand is rapidly increasing as well. This situation is frequently seen, especially in developing countries. To meet this ongoing load growth in an adequate and safe manner, there will be a need to either expand the existing substations or install some new ones. The substation expansion planning (SEP) is one of the most important parts of the power system planning studies which aims is to determine the way of expanding the existing substations or installing new ones. As the way of reinforcing the existing substations or installing the new ones has a great effect on the investment and operational costs of the whole network, therefore, a careful study must be implemented to make useful and cost-effective decisions for the SEP. This important task in the power system is performed by the substation expansion planning studies.

So far, different models have been presented for the optimal design of HV/MV sub-transmission substations [1-9]. In [2], a constructive heuristic algorithm (CHA) has been used to solve the power distribution system expansion planning problem. By employing a local improvement phase and a branching technique in CHA, the algorithm tries to find the optimal location and capacity of MV feeders and HV/MV substations. The objective function to be minimized includes the system operation costs and the cost of constructing feeders and substations taking into account the power flow, voltage drop, and radial configuration constraints. Authors in [3] presented a method for the optimal site, size, and number of distribution transformers using a MINLP formulation which is solved by the GAMS software. In this work, the transformer loading above its nameplate rating is allowed without any influence on the relative thermal aging rate. This is accomplished during peak hours to benefit from low load currents during off-peak hours.

In [4], a model is proposed for solving the multistage planning problem of a distribution system. The objective function is the net present value of the investment cost to add, reinforce, or replace the feeders and substations, losses cost, and operation and maintenance cost. The model considers three levels for the loads. The nonlinear objective function is approximated by a piecewise linear function, resulting in a mixed integer linear model that is solved using standard mathematical programming. Moreover, the reliability indices and the related costs are computed for each solution based on the regulation model of Brazil.

Reference [5] has developed a new model for the simultaneous expansion planning of distribution, sub-transmission, and transmission networks. The distribution network is modeled as the MV/LV load points which must be optimally supplied from the sub-transmission substations through MV feeders. The HV/MV sub-transmission substations are linked to transmission substations via an appropriate connection of HV sub-transmission lines. The EHV/HV transmission substations, in turn, are fed through the EHV transmission lines. The proposed simultaneous planning along with its technical and operational constraints is formulated as an optimization problem where a genetic algorithm with an efficient codification is employed to optimize such a complicated problem. The developed planning framework is tested on a real network of Zanjan Regional Electrical Company to validate its effectiveness in different experiments.

Reference [6] has formulated the planning problem of primary distribution networks as a multi-objective mixed-integer non-linear programming (MINLP) model in order to minimize the expansion and operation costs of network as well as the system's reliability costs in the contingency events. The objective functions of this model consist of the expansion and operation costs of distribution network's equipment, including the transformers, lines, and sectionalizing switches, as well as the system's reliability costs in the contingency events. A Multi-objective Reactive Tabu Search (MORTS) algorithm is proposed to optimize the problem. In [7], the authors proposed a multistage framework for the expansion planning of sub-transmission substations, and MV feeders in the presence of distributed generation (DG). The presented framework takes into account the investment, operation, maintenance, and customers' interruption costs by considering the load flow, voltage drop, network radiality, and budget restrictions. A hybrid self-adaptive global-based harmony search algorithm (HSA) and optimal power flow (OPF) are employed to search for the optimal solution. Simulations reveal the positive effects of DG on decreasing the investment and operational costs and on improving the network reliability.

In [9], the sub-transmission substations and lines have been optimally determined concurrent with the MV Feeders' layout. While the configuration of sub-transmission and transmission networks are dependent on each other, this study has considered pre-determined locations for the transmission substations. A new substation expansion planning (SEP) procedure is proposed in [10] for transmission substations in which the mathematical clustering technique is used to find, initially, a list of feasible candidates by observing the limitations on substation capacities, feeder capacities, and voltage regulations. Then, the GA is used to solve an optimization problem in which the allocations and capacities of new substations as well as the expansion requirements for the existing ones are determined. This work has neglected the distribution network details in the SEP problem.

In most of the presented methods for the SEP, for the sake of simplifying the problem optimization process, the impact of uncertainty on the parameters of the problem has been ignored [11]. While in large-scale networks, implementing the SEP without considering these uncertainties will not come to a real result; because, as the network becomes larger, both the possibility of uncertainty occurrence and the degree of these uncertainties on the parameters increase. However, the literature review reveals some researches which have regarded the uncertainty.

In [12-14], the fuzzy method has been used to apply the load uncertainty in the substation expansion planning. In this method, each load center is modeled by a membership function, usually triangular, and is included in the optimization process. At the end of the process, the obtained solution by the fuzzy method is de-fuzzied and the final result is obtained.

An uncertainty model for system's variables can be represented by discrete states, called scenarios. These scenarios are used for the optimization of SEP under uncertainty as it is difficult to consider all continuous states due to the computational burden [15]. The approach presented in [16] relies on scenario representation of uncertainty. The stochastic characteristics of load demand evolution is represented as a set of weighted scenarios. Each of the scenarios is a sequence of possibilities for the multistage horizon. In multistage models the actions must respond in time to increasing degrees of information that becomes available about a particular scenario being followed. So, in the multiple-scenario approach, regarding the nature of the problem and its objectives, different scenarios are established and by applying them to the problem, substation expansion planning would be implemented considering the load uncertainty. In [17-20] the load uncertainty based on the scenario based modeling has been considered.

In [21] Information-Gap Decision Theory (IGDT) has been used to apply the load uncertainty into SEP. Indeed IGDT method provides different solutions of an uncertain problem for decision maker. In robustness model IGDT method maximizes the horizon of uncertainty and finds a solution that guarantees a certain expectation of the objective function. In opportunistic model, the IGDT method minimizes the horizon of uncertainty and finds a solution that increase profit or decrease cost for minimum uncertainty.

Monte Carlo Simulation method [22-25] is another approach that has been proposed for uncertainty modeling. In a Monte Carlo simulation, a random value is selected for each of load points, based on the range of estimates. The model is calculated based on this random value. The result of the model is recorded, and the process is repeated. A typical Monte Carlo simulation calculates the model hundreds or thousands of times, each time using different randomly-selected values. When the simulation is complete, there is large number of results from the model, each based on random input values.

In this paper, a new method based on discrete probability density function (PDF) is employed to incorporate the load uncertainty into the SEP problem. This method is based on the fuzzy clustering in which the position and value of each predicted load is modeled using a discrete PDF proportional to the uncertainty percentage. Then, the location and the power of the new load centers considering the uncertainty are determined by using the fuzzy clustering method. This approach differs from the other presented approaches due to its new ideas such as using a discrete probability density function based on fuzzy clustering method for modeling of the load centers. The significant features of this method can be outlined as its applicability to large-scale networks, robustness to load changes, the comprehensiveness and also, the simplicity of applying this method to various problems.

This paper has been organized as the following sections. In Section 2, SEP problem is described. Section 3 presents the proposed solution method. Section 4 describes the numerical results. Inferring the robustness of the proposed method is presented in Section 5. Finally, the last section concludes the paper.

2 Substation Expansion Planning

The aim of sub-transmission network expansion planning is to appropriately supply the medium-voltage distribution loads through sub-transmission system with the minimum cost subject to the technical and operational constraints.

2.1 Objective Function

The objective function of the problem to be minimized is the total cost of the network expansion according to (1):

$$OF = MVFRC + MVFIC + SSEC + SSIC + MVFLC \tag{1}$$

The cost components included in (1) are detailed in the following.

MVFRC is the MV feeders' replacement cost as (2):

$$MVFRC = \sum_{i=1}^{nss}\sum_{j=1}^{nlp}\alpha_{ij}^{f} \times L_{ij}^{f} \times FRC_{ij}\left(S_{f,ij}^{old}, S_{f,ij}^{new}\right) \tag{2}$$

where, α_{ij}^{f} is a binary variable being 1 if the feeder between load point *i* and sub-transmission substation *j* is replaced, and is 0 otherwise; L_{ij}^{f} is the length of feeder between the load point *i* and sub-transmission substation *j*; $FRC_{ij}\left(S_{f,ij}^{old}, S_{f,ij}^{new}\right)$ is the per-km cost of replacing the feeder having the existing capacity of $S_{f,ij}^{old}$ with a new one having the capacity of $S_{f,ij}^{new}$.

MVFIC is the new MV feeders' installation cost as (3):

$$MVFIC = \sum_{i=1}^{nss}\sum_{j=1}^{nlp}\beta_{ij}^{f} \times L_{ij}^{f} \times FIC_{ij}\left(S_{f,ij}^{new}\right) \tag{3}$$

where, β_{ij}^{f} is a binary variable being 1 if the new feeder *ij* is installed, and is 0 otherwise; $FIC_{ij}\left(S_{f,ij}^{new}\right)$ is the installation cost of the new feeder *ij* with the capacity of $S_{f,ij}^{new}$.

SSEC is the sub-transmission substations expansion cost as (4):

$$SSEC = \sum_{i=1}^{ness}\alpha_{i}^{ss} \times EC_{ss,i}\left(S_{ss,i}^{old}, S_{ss,i}^{new}\right) \tag{4}$$

where, α_{i}^{ss} is a binary variable being 1 if the existing sub-transmission substation *i* is upgraded and is 0 otherwise; $EC_{ss,i}\left(S_{ss,i}^{old}, S_{ss,i}^{new}\right)$ is the cost of upgrading the capacity of sub-transmission substation *i* from $S_{ss,i}^{old}$ to $S_{ss,i}^{new}$.

SSIC is the sub-transmission substations installation cost as (5):

$$SSIC = \sum_{i=1}^{ncss}\beta_{i}^{ss} \times IC_{ss,i}\left(S_{ss,i}^{new}\right) \tag{5}$$

where, β_{i}^{ss} is a binary variable being 1 if the new substation *i* is installed and is 0 otherwise; $IC_{ss,i}\left(S_{ss,i}^{new}\right)$ is the cost of installing new sub-transmission substation *i* with the capacity of $S_{ss,i}^{new}$. This cost includes the required land and equipment cost.

MVFLC is the MV feeders loss cost as (6):

$$MVFLC = LC \times \sum_{i=1}^{nss}\sum_{j=1}^{nlp}\xi_{ij}^{f} \times L_{ij}^{f} \times R_{ij}^{f} \times \left|I_{ij}^{f}\right|^{2} \tag{6}$$

where, ξ_{ij}^{f} is a binary variable being 1 if the path *ij* exists between the load point *i* and sub-transmission substation *j*, and is 0 otherwise; I_{ij}^{f} is the current passing through the feeder *ij*, and R_{ij}^{f} is the resistance of the feeder *ij*. Also, *LC* is the loss cost in \$/MW.

2.2 Problem Constraints

The problem of substation expansion planning is subjected to some technical and operational constraints which are described subsequently.

2.2.1 Voltage Drop Constraint

The voltage drop at the MV load points must be lower than the permitted voltage drop value as (7):

$$L_{ij}^{f} \times \left(R_{ij}^{f}\left|I_{ij}^{f}\right|\cos\theta_{ij} + X_{ij}^{f}\left|I_{ij}^{f}\right|\sin\theta_{ij}\right) \le \Delta V^{\max}$$
$$\forall i \in \{1, 2, \ldots, nss\},\ \forall j \in \{1, 2, \ldots, nlp\} \tag{7}$$

where X_{ij}^{f} is the reactance of the feeder *ij*, and θ_{ij} is the power factor of load flowing through the *ij* path.

2.2.2 Feeders Thermal Capacity

The loading of MV feeders must be lower than their thermal capacity as (8):

$$\left|L_{ij}^{f}\right| \le \left|L_{ij,\max}^{f}\right| \quad \forall i \in \{1, 2, \ldots, nss\},\ \forall j \in \{1, 2, \ldots, nlp\} \tag{8}$$

2.2.3 Sub-Transmission Substations Thermal Capacity

The loading of sub-transmission substations must be lower than their thermal capacity as (9):

$$\sum_{j=1}^{nlp}\xi_{ij}^{sl} S_{j}^{L} \le \left(1 - rf_{i}\right) \times S_{i}^{ss,\max} \quad \forall i \in \{1, 2, \ldots, nss\} \tag{9}$$

where, ξ_{ij} is a binary variable being 1 if the load point *j* is supplied from the *i*th sub-transmission substation, and is 0 otherwise. S_{j}^{L} is the load of *j*-th substation. Also, rf_i is the reserve factor of *i*-th sub-transmission substation.

3 Proposed Solution Method

3.1 Solution Method of GA

To solve the SEP problem formulated in part 2, a genetic algorithm (GA) is employed as follows.

3.1.1 Genetic Algorithm

Genetic algorithm as a meta-heuristic optimization method has been inspired from the process of natural evolution. This algorithm is usually used to produce useful solutions to nonlinear and complex optimization problems using techniques such as reproduction, crossover and mutation [26, 27].As a strong and reliable optimization algorithm, the GA has been used for solving many of power system planning problems [28-29].

3.1.2 Chromosome Structure

To solve the proposed planning problem, the unknown variables of the problem are encoded within the genes of chromosomes. For this aim, an efficient codification has been proposed in this paper. The structure of the employed chromosome is depicted in Fig. 1. According to this figure, the chromosome is composed of two parts. In the first part, the value of *i*-th gene shows the supplying substation of *i*-th load point. The number of genes of this part is equal to the number of load points. The type of *i*-th MV feeder is determined using the value of *i*-th gene in the second part of the chromosome.

3.2 The Proposed Method to Incorporate the Load Uncertainty into the SEP Problem

The method proposed in this paper is based on the concepts of fuzzy clustering. Hence, in this section, at first, the definition of clustering, and then, the basic methods founded on the fuzzy clustering are introduced. Afterward, a brief description of the clustering method to incorporate the load uncertainty into the SEP problem is provided.

3.2.1 Clustering

Partitioning the data set into multiple subsets or clusters in such a way that the data contained in a cluster have the most similar features and the data in different clusters have the most non- similarity is called clustering [30]. The clustering methods are mainly used to reduce the data to a lower number. This method can be employed instead of dealing with a wide range of scattered data arranged in groups of related data. In the other words, a management with a bunch of different data exists.

3.2.2 Clustering Algorithms

Major clustering algorithms are Possibilistic C-Means (PCM) and Fuzzy C-Means (FCM) that are derived from Hard C-Means (HCM). The latter is also known as K-Means. Further description of these methods can be found in [30]. In this part, among the K-means relations, only the equations for updating the cluster centers and the objective function are mentioned because then, they also would be talked about. The relation for updating of the cluster centers is based on (10) [30].

$$C_i = \frac{\sum_{j=1}^{n} u_{ij} X_j}{\sum_{j=1}^{n} u_{ij}} \tag{10}$$

Equation (11) presents the objective function of the cluster centers in which $C = \{C_1, \ldots, C_c\}$ shows the initial clusters set.

$$J_k\left(X, U_k, C\right) = \sum_{i=1}^{c}\sum_{j=1}^{n} u_{ij} d_{ij}^2 \tag{11}$$

3.2.3 The Proposed Algorithm

The proposed approach for incorporating the load uncertainty into the SEP problem is based on the K-Means method introduced in the previous section. To better understand the proposed method, a simple example is described, and then, the flowchart of the proposed method is introduced.

Suppose a number of load centers with the specified powers according to Fig. 2. The probabilistic method to implement the uncertainty for each dimension uses a PDF. Here, similar to the probabilistic method, functions like PDFs are used. In the utilized functions, the vertical axis is based on the probability where the total probability for a given function must equal to one. Therefore, it is supposed that the *x*-coordinates of each load center are modeled as Fig. 3.

Fig. 3 shows x-coordinates of the load centers in which *R* and *L* are the amount of right and left uncertainties, respectively. The amount of *L* and *R* can be equal or unequal. x_{Mi} is the current x-position of the load centers. The y-coordinates of the load centers are also modeled similar to Fig. 3.

Instead of a point, the above method can use the composition of the probability functions of *x* and *y* as the coordinates of each load center. To obtain the total number of possible modes of combining the two functions, each of them can be considered as a set of points according to Fig. 4.

However, with the obtained probability functions, each *x* from a function can be used with *y* from another function as a new center. Obtaining all modes, each load center is transformed to a set of load centers with the specified locations. The new centers' places are (x,y)

Part 1	Part 2

Part 1: Supplying Substation of Load Points (LP)

Supplying Substation of LP #1	Supplying Substation of LP #2	…..	Supplying Substation of LP #n_{lp}

Part 2: Conductor Type of MV Feeders

Conductor Type of Feeder #1	Conductor Type of Feeder #2	…..	Conductor Type of Feeder # n_{lp}

Fig. 1 Structure of the proposed chromosome.

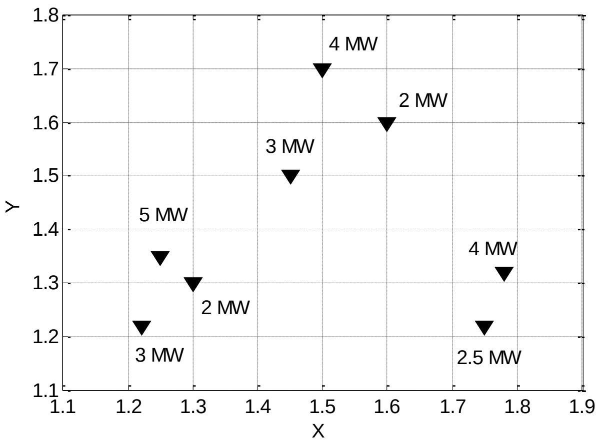

Fig. 2 The existing load centers of hypothetical network.

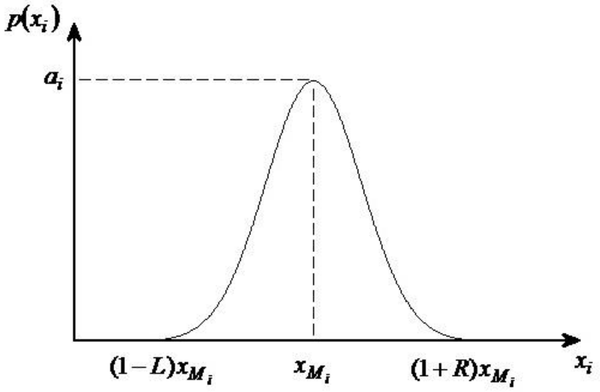

Fig. 3 PDF of the x_i-coordinate.

obtained from the discrete probability functions. In addition, each new load center has a probability calculated from (12).

$$p_{ij} = p\left(x_{ij}\right) p\left(y_{ij}\right),\ \left(i=1,\ldots,N_P^2\right),\left(j=1,\ldots,n\right) \qquad (12)$$

According to the above equation, the amount of the probability of the data nearer to x_{Mi} and y_{Mi} get the greater value and the farther data get the smaller value.

So far, each load center becomes $N_p \times N_p$ number of new centers. With a further clustering of the created data, the load centers are obtained after applying the uncertainty.

However, what exists in fact and has not been mentioned in the above steps is the effect of the power of each load center on its uncertainty. Thus, to get closer to reality, the power of each load center must be involved in the above steps.

To include the effect of power of load centers, the probability functions according to Fig. 5 are used.

In the mentioned figure, P_{Mi} is the forecasted power of the *i*-th load center. The impact of the power of load centers would be in such a way that P-probability function has N_p number of points with different $p(P)$ probabilities. Each point of *P*-probability function, which is multiplied with its related $p(P)$ in the existing

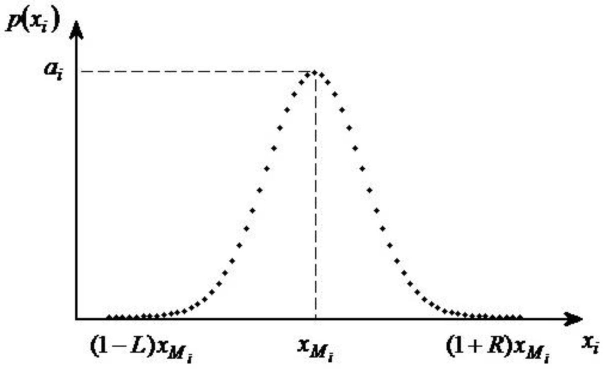

Fig. 4 Discrete PDF of the x_i-coordinate.

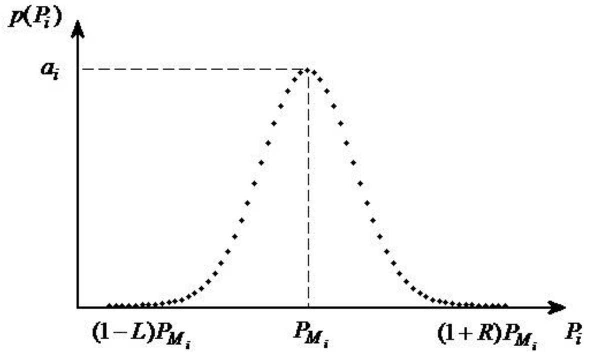

Fig. 5 Discrete PDF for the power of the *i*-th load center.

data, makes a series of data with different weights. In the other words, with the effect of *P*, the result would be N_p layers of multiplied data. Here, the number of points of *P*-probability function is equal to previous N_p; however, it is not necessary for them to be equal, in general.

After this step, according to K-Means method mentioned in the previous section, for each layer of the created layers, the clustering will be re-done, the optimal clustering for a layer from the existing layers is selected, and the new load centers are obtained. In the stage of updating the cluster centers, the degree of probability of each load center (p_{ij}) must be considered as the weight of that load center. In the other words, updating of equations will be as (13) and (14).

$$x_i = \frac{\sum_{j=1}^{N_P^2} u_{ij} x_j p_{ij}}{\sum_{j=1}^{N_P^2} u_{ij} p_{ij}},\ \left(i=1,\ldots,n\right) \qquad (13)$$

$$y_i = \frac{\sum_{j=1}^{N_P^2} u_{ij} y_j p_{ij}}{\sum_{j=1}^{N_P^2} u_{ij} p_{ij}},\ \left(i=1,\ldots,n\right) \qquad (14)$$

In above relations, u_{ij} shows the *j*-th data allocated to *i*-th cluster. Therefore, by the way the new load centers allocated, each center contributes to the movement of the cluster center depending on its probability degree; this behavior is similar to the concept of the fuzzy membership degrees.

The objective function is also calculated from (15).

$$fitness = \sum_{j=1}^{n_i} p\left(x_j\right) p\left(y_j\right) p\left(P_j\right) \times P_i \times d_{ij}, \quad i = 1, \dots, c \qquad (15)$$

However, a problem is still unsolved, and it is the amount of the power in each load center affected by the uncertainty. According to (16), determining the power of each load center is decided after the incorporation of the uncertainty, with respect to the clusters allocated to that load center.

$$P_i^{new} = \sum_{j=1}^{n_i} p\left(x_j\right) p\left(y_j\right) p\left(P_j\right) \times P_i, \quad i = 1, \dots, c \qquad (16)$$

Fig. 6 shows the flowchart of the proposed algorithm for incorporating the load uncertainty. According to the above descriptions, the load uncertainty with 10 percent of *R* and *L* is applied to the example network of Fig. 2, and the final results are shown in Fig. 7. It can be seen from Fig. 7 that all the centers are affected by the uncertainty based on their previous load and position. The powers of load centers are also shown after clustering. In the other words, both the load centers' position and their powers are obtained under the influence of the uncertainty.

4 Numerical Results

To investigate the proposed algorithm for the substation expansion planning, a real network has been considered. The data of this network have been presented in Tables 1.1 to 1.5 in Appendix 1. The system considered for evaluating the effectiveness of the proposed planning problem is part of the real network of Zanjan Regional Electrical Company (ZREC), located in northwest of Iran [31]. At first, the network is introduced. Then, the SEP is implemented on the network without considering the load uncertainty. Finally, the substation expansion planning is fulfilled by incorporating the load uncertainty in the problem.

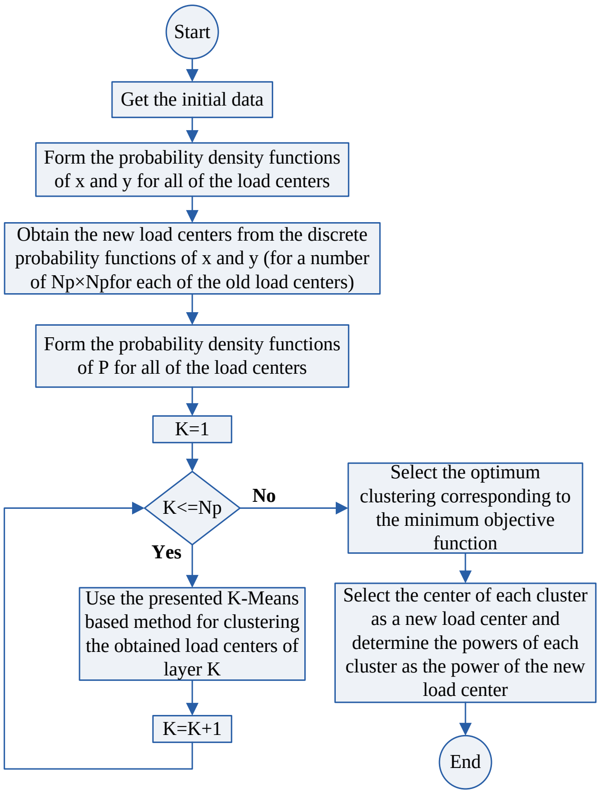

Fig. 6 Flowchart of the proposed algorithm.

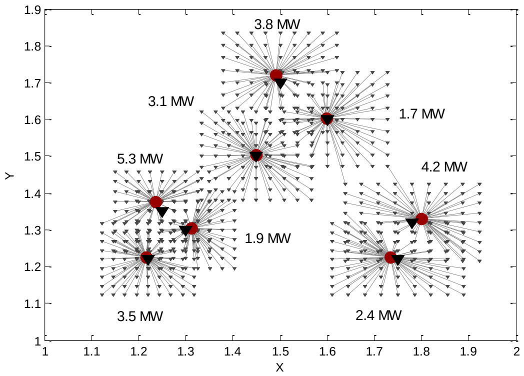

Fig. 7 Load centers before (▼) and after (●) applying load uncertainty.

In the proposed GA, number of chromosomes (individuals) has been set to be 40. The crossover rate has been adjusted to 0.75 and the mutation rate has been adjusted to 0.25.

The proposed planning model has been implemented in the programming environment of MATLAB software and executed on a laptop with Core i7, 2.0 GHz processor and 4 GB RAM.

4.1 Specifications of the Network Under Study

According to the data presented in Tables 1.1 to 1.5 in Appendix 1, the network under study is composed of 92 load centers and 19 substations in the horizon year. The base year is 2015, and the planning horizon year is 2020. The network parameters of the real network have been presented in Table 1.1 in the Appendix 1. Also, the expansion and installation costs of the substations are given in Table 2. The characteristics of feeders have been shown in Table 3. Moreover, the specifications of the existing substations of the network are exhibited in Table 4. Table 1.5 in Appendix 1 also represents the characteristics of the loads of the network in the planning horizon year. According to the Table 4, the Substation no. 13 will be out of service in the horizon year, hence, its capacity has been considered as zero.

4.2 Substation Expansion Planning Without Considering the Load Uncertainty

According to the data presented in Tables 1.1 to 1.3 in Appendix 1, which are dependent on the distribution network, the geographical location of the area under study, and the country's political and economic conditions, the substation expansion planning is implemented on the presented network.

The described genetic algorithm is used to solve the proposed problem without considering the load uncertainty. The algorithm receives the data of Tables 1 to 5 as the inputs, and delivers the expanded capacity of the existing substations, the number, location and capacity of new installed substations, the feeders' losses, the loads assigned to each substation, and finally, the total expansion cost as the outputs. The total cost includes the cost of expanding the existing substations, the cost of installing new substations, the feeders' losses cost, and the cost of connecting the substations to the loads or the downward substations.

The results of applying the method on the presented network have been shown in Fig. 8 and Table 1. It can be seen that by installation of new substations with a total capacity of 60 MVA at the shown places, and by expanding three existing substations, all the loads will be fed adequately in the horizon year. Table 1 provides more details.

To see the performance of the GA in the optimizing the objective function, its convergence has been illustrated in Fig. 9.

4.3 Substation Expansion Planning Considering Load Uncertainty

In this part, for the presented network, the load uncertainty is performed by use of the K-Means based algorithm, and the results are discussed. For incorporating the load uncertainty, at the first stage, equal *L* and *R* with 5 percent uncertainty are used. The results have been shown in Figs. 10 and 11, and Tables 2 and 3.

After performing 5 percent of load uncertainty for *L* and *R*, the locations of load centers are the same as Fig. 10, and their powers are according to Table 2. The SEP results after performing the load uncertainty are shown in Fig. 11. As it can be seen from Fig. 10, after incorporating the load uncertainty, some of the load centers are moved away from the load centers' aggregation points. Hence, it is expected that the network expansion cost be increased. This issue will be investigated later.

According to Table 3, which shows the outputs of software for the considered network, four new substations with a total capacity of 75 MVA have been installed, and the substations no. 1, 16 and 19 have been expanded. It can be seen in Fig. 11 that the substations no. 22 and 23 are installed just for feeding one load center. This is because these load centers are far from the other substations. Therefore, with respect to their load amount, the voltage drop constraint will not let them to be fed from the existing substations. The substations no. 20 and 21 have been installed due to the inability of the existing substations in the feeding of the

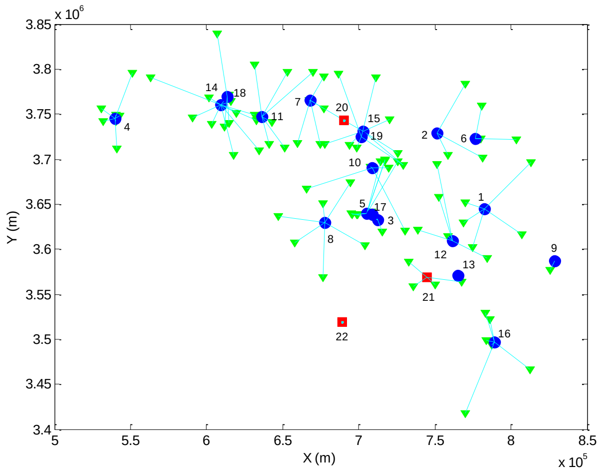

Fig. 8 SEP results for the real network, ▼: load centers, ●: existing substations, ■: new substations.

Table 1 Details of the SEP results for the real network.

New installed substations	20 (30 MVA), 21 (15 MVA), 22 (15 MVA)
Sum of the new substations capacity	60 [MVA]
Installation cost of the new substations	6,000,000 [$]
Expanded substations	1,16,19
Expansion cost of the existing substations	3,930,000 [$]
Expansion cost of the downward feeders	7,915,000 [$]
Total cost	17,845,000 [$]

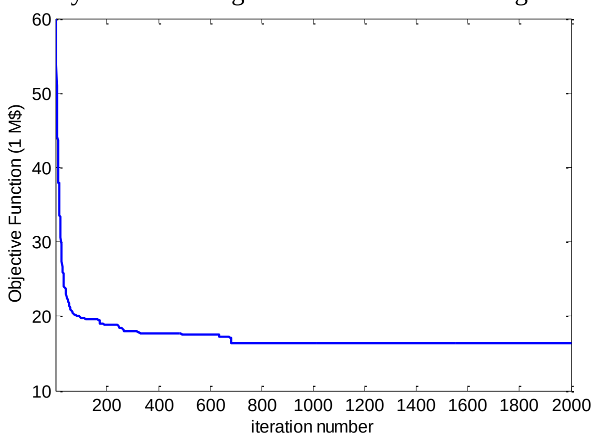

Fig. 9 Convergence trend of the GA.

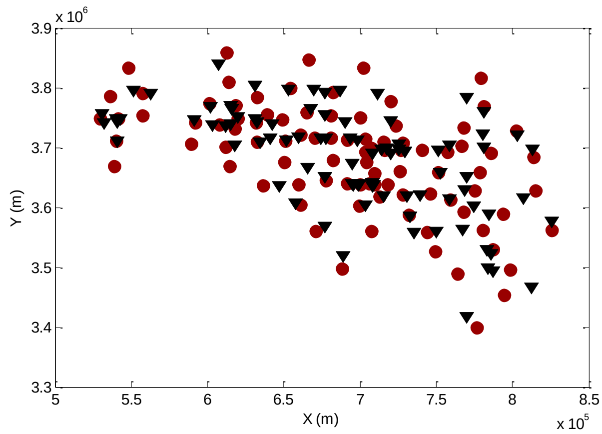

Fig. 10 Load centers of the real network before (▼) and after (●) performing 5 percent of load uncertainty.

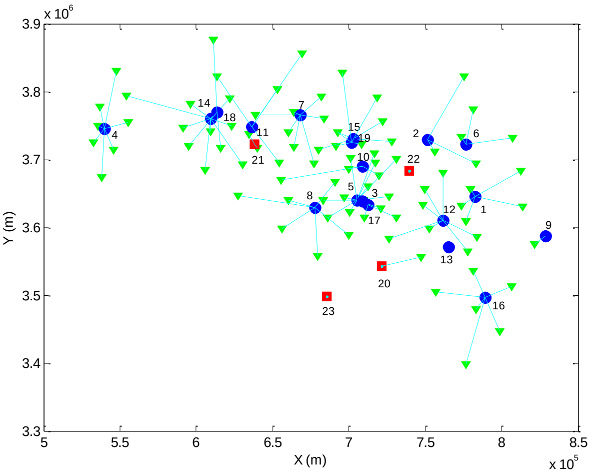

Fig. 11 SEP results for the real network with a 5 percent load uncertainly for *L* and *R*;▼: load center ● : existing substation ■ : new substation.

Table 2 The powers of load centers after performing 5 percent load uncertainty of L and R.

Load No.	Power [MW]	Load No.	Power [MW]	Load No.	Power [MW]	Load No.	Power [MW]
1	2.32	24	0.56	47	0.0	70	2.02
2	2.05	25	3.54	48	1.8	71	1.5
3	2.2	26	6.48	49	3.3	72	0.4
4	0.46	27	0.9	50	2.2	73	5.4
5	1.39	28	9.09	51	3.7	74	2.2
6	4.35	29	3.9	52	0.7	75	3.04
7	8.58	30	0.27	53	5.1	76	0.9
8	5.9	31	1.07	54	1.7	77	0.96
9	8.26	32	7.2	55	4.8	78	5.04
10	6.28	33	5.9	56	0.7	79	4.5
11	0.37	34	3.3	57	0.5	80	3.5
12	1.94	35	5.4	58	0.3	81	1.8
13	2.2	36	1.25	59	8.08	82	1.1
14	0.1	37	3.2	60	1.5	83	4.3
15	1.6	38	2.27	61	4.7	84	1.6
16	0.58	39	2.5	62	0.9	85	0.96
17	5.5	40	2.48	63	3.7	86	4.1
18	0.43	41	3.9	64	4.2	87	7.2
19	2.3	42	0.99	65	2.7	88	33.6
20	0.05	43	2.4	66	7.2	89	3.8
21	2.06	44	5.58	67	3.6	90	8.2
22	4.06	45	0.5	68	3.6	91	4.6
23	8.3	46	1.42	69	5.4	92	2.6

Table 3 Details of the SEP results considering 5 percent of load uncertainty.

New installed substations	20 (15 MVA), 21 (15 MVA), 22 (30 MVA), 23 (15 MVA)
Sum of the new substations capacity	75 [MVA]
Installation cost of the new substations	7,500,000 [$]
Expanded substations	1,16,19
Expansion cost of the existing substations	3,930,000 [$]
Expansion cost of the downward feeders	8,090,000 [$]
Total cost	19,520,000 [$]

load centers in their area.

As mentioned, after performing the load uncertainty, some of the load centers are moved away from the load centers' aggregation points. So, the expansion cost of the downward network and the number of new substations will be increased. The results shown in Table 3 verify this fact.

At the next stage, equal *L* and *R* with 10 percent of load uncertainty are used. The results have been shown in Figs. 12 and 13, and Tables 4 and 5.

The new locations of load centers after performing 10 percent of load uncertainty have been illustrated in Fig. 12, and their load amounts are presented in Table 4.

It can be seen that as the load uncertainty increases, the locations of the load centers in the horizon year, which actually are the gravity center of some load locations, moves more accordingly. Also, the percentage of their power changes is more. Therefore, it is expected that the network expansion results to be different from the previous network.

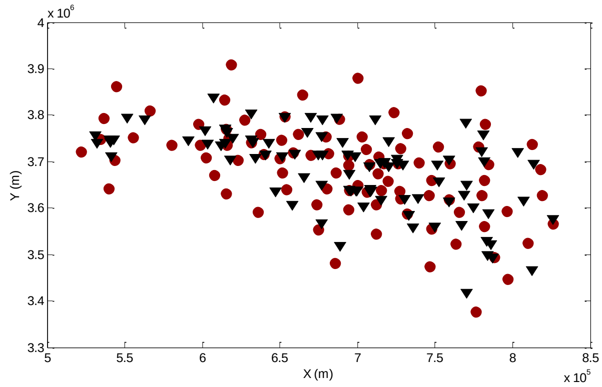

Fig. 12 Load centers of the real network before ▼ and after ● performing 10 percent of load uncertainty.

Table 4 The powers of load centers after performing 10 percent load uncertainty of L and R.

Load No.	Power [MW]	Load No.	Power [MW]	Load No.	Power [MW]	Load No.	Power [MW]
1	3.1	24	0.49	47	1.6	70	1.2
2	1.7	25	4.7	48	1.7	71	1
3	2.4	26	9.7	49	1.5	72	0.42
4	0.5	27	0.65	50	1.6	73	4.4
5	1.6	28	11.9	51	2.4	74	2.87
6	6.8	29	7.5	52	0.3	75	1.9
7	8.6	30	1.13	53	4.4	76	0.57
8	6.6	31	1.56	54	1.03	77	0.86
9	11.9	32	8.3	55	3.01	78	6.83
10	12.1	33	4.67	56	0.3	79	2.7
11	1.31	34	3.18	57	0.25	80	1.9
12	2.4	35	4.65	58	0.66	81	4.3
13	2.8	36	1.8	59	5.17	82	1.3
14	0.06	37	2.56	60	1.17	83	1.8
15	1.3	38	1.01	61	8.2	84	1.4
16	0.28	39	2.9	62	1.1	85	1.01
17	5.00	40	1.3	63	4.75	86	2.67
18	0.45	41	3.9	64	4.11	87	4.7
19	5.49	42	1.6	65	1.89	88	41.5
20	0.02	43	2.5	66	6.3	89	5.1
21	2.2	44	2.97	67	1.89	90	9.3
22	1.9	45	1.07	68	3.7	91	5.5
23	8.8	46	1.1	69	2.97	92	2.9

Fig. 13 shows the results of performing the algorithm on the presented network with 10 percent of load uncertainty. More details have been shown in Table 5.

In the above case, for 10 percent of load uncertainty of *L* and *R*, five new substations with a total capacity of 75 MVA have been installed, and the substations no. 1, 4, 6, 16, and 19 have been expanded. The main reason for the difference in the above two planning's, is the load centers' locations and powers after incorporating the load uncertainly; so that, for the load uncertainty of 10 percent, some of the load centers have been moved and located where there is not any substation nearby, and it is not possible for the load centers to be fed from the existing substations. Therefore, the need for the installation of new substations and consequently, the expansion cost are increased. On the other hand, since the number of the installed feeders becomes more, their expansion cost and losses are increased as well.

According to the simulation results, it can be seen that by performing 5 and 10 percent of load uncertainty for *L* and *R*, the location and capacity of new substations are different compared to the situation without the load uncertainty consideration. Likewise, the expanded substations are different from the case without the load uncertainty.

With regards to the outputs of the algorithm, it is clear that the SEP results without incorporating the load uncertainty will not be efficient for feeding of the future loads in the horizon year. Therefore, to design an adequate network for the horizon year, the load uncertainly should be taken into consideration. Also, the results show that the presented algorithm for incorporating the load uncertainty into the SEP problem is sufficiently applicable to the large-scale networks.

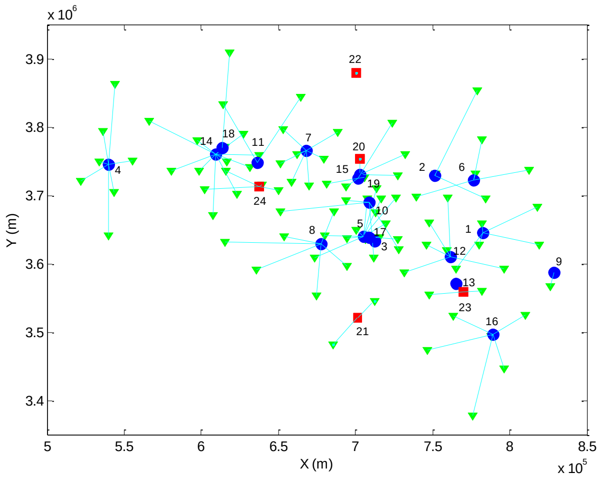

Fig. 13 The SEP results for the real presented network with a 10 percent load uncertainty for L and R; ▼: load center ●: existing substation ■ : new substation.

Table 5 Details of SEP response considering 10 percent load uncertainty.

New installed substations	20 (15 MVA), 21 (15 MVA), 22 (15 MVA), 23 (15 MVA), 24 (15 MVA)
Sum of the new substations capacity	75 [MVA]
Installation cost of the new substations	7,500,000 [$]
Expanded substations	1,4,6,16,19
Expansion cost of the existing substations	6,030,000 [$]
Expansion cost of the downward feeders	8,840,000 [$]
Total cost	22,370,000 [$]

5 Inferring the Robustness of the Proposed Method

To infer the robustness of the presented method, a random network is chosen and the SEP results for this network are obtained in two cases. In the first case, the justified substations (installed and expanded) for the network without considering the load uncertainty are also considered as the existing substations and the SEP results will be obtained for the random network. In the second case, the justified substations (installed and expanded) for the network by considering 10 percent of load uncertainty are also considered as the existing substations, and the SEP results will be obtained for the random network.

For obtaining a random network, a random number considering the permissible limitations is produced for *x*, *y*, and *P* (power) of each load center.

At first, for the mentioned random network, the SEP results in the first case are obtained and are shown in Fig. 14 and Table 6.

According to the presented results, it is clear that in the horizon year, there is a need to install two new substations with a total capacity of 30 MVA, and some feeders with the specified capacities. In the other words, the network which was expanded without considering the load uncertainty will not be an adequate network in

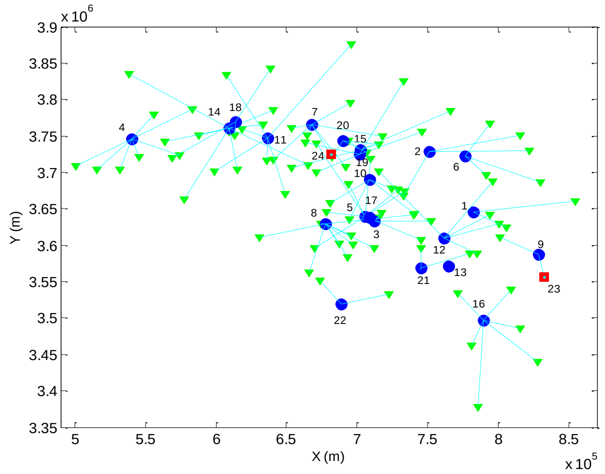

Fig. 14 Result of the SEP for the test network, in the first case.

Table 6 Details of SEP response on the test network.

New installed substations	23(15 MVA), 24(15 MVA)
Sum of the new substations capacity	30 [MVA]
Installation cost of the new substations	3,000,000 [$]
Expansion cost of the downward feeders	10,072,000 [$]

the horizon year.

In the following, the result of the SEP for the randomly selected network for the second case is obtained. Fig. 15 and Table 7 depict the results.

As it can be seen in Fig. 15, the existing substations in the second case are able to properly feed the selected network's loads in the horizon year. There is no need to install new substations, but some new feeders have been installed which is due to the movement of the load centers in the selected network. Hence, the network which was expanded by considering the load uncertainty will be an adequate network in the horizon year.

According to the obtained results, it is clear that the substation expansion planning which considers the load uncertainty by means of the presented K-Means based algorithm is capable of incorporating the load uncertainty in a suitable manner, and will be robust to load changes.

6 Conclusion

Substation expansion planning (SEP) is one of the important parts of the power system expansion planning studies. The diversity of decision variables in the SEP problem has made the solution process more difficult. Therefore, for the sake of simplification, in most of the presented methods for the SEP, the impact of the uncertainty in the parameters of the SEP has not been considered, whereas the expansion planning for the large-scale networks is not applicable without considering these factors.

In this study, a new method has been proposed to incorporate the uncertainty in the location and amount of the load centers in the SEP problem. The presented method is based on the K-Means which considers both the amount and location of load uncertainty simultaneously. By use of the proposed method, the load uncertainty for different amounts of *L* and *R* can be obtained. To demonstrate the ability of the conducted technique, it was first performed on a simple data, and then, on a real network. The simulation results verified the algorithm's ability in finding reasonable solutions for the real networks considering the existence of load uncertainty.

To find the SEP results with and without load uncertainty, a genetic algorithm has been applied. Also, to validate the appropriate performance of the presented K-Means based approach, a test case was suggested, and the presented method was examined based on the test case. The results verified the accuracy of the K-Means based conducted method.

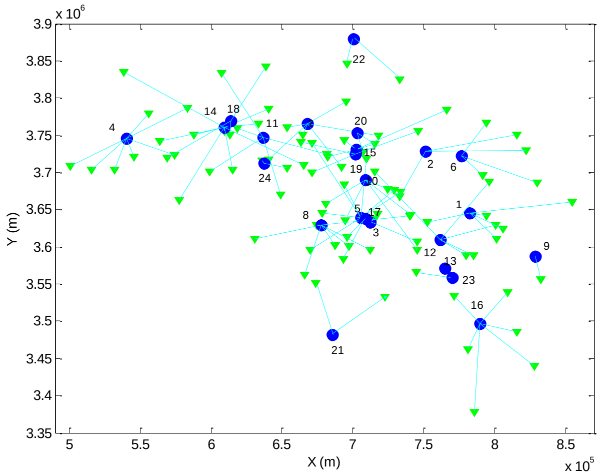

Fig. 15 Result of the SEP for the test network, in the second case.

Table 7 Details of SEP response on the test network.

New installed substations	–
Sum of the new substations capacity	0
Installation cost of the new substations	0
Expansion cost of the downward feeders	11,618,000 [$]

Appendix

Table 1.1 Parameters of the network.

Losses Cost [M$/MW]	Permitted Voltage Drop	Power Factor	Loss Factor	Reserve Factor
0.9	5%	0.85	0.36	0.3

Table 1.2 Expansion and installation cost of the substations.

Capacity of the substations [MVA]	45	30	15
Installation cost of the substations [M$]	4.5	3	1.5
Cost of expanding the existing substation to the higher capacity [M$]	–	0.7	0.430
No load losses [MW]	0.041	0.027	0.013

Table 1.3 Characteristics of the network's feeders.

Feeders' capacity [MVA]	5	10
Feeders' installation cost [$/Km]	8000	11000
Feeders' resistance [Ω/Km]	0.068	0.034
Feeders' reactance [Ω/Km]	0.04	0.08

Table 1.4 Specifications of the Existing substations.

Substations No.	Geographical Position		Reserve Factor	Existing Capacity [MVA]	Expandable Capacity [MVA]
	X [km]	Y [km]			
1	782.78	3644.97	0.3	15	30
2	751.23	3728.76	0.3	30	30
3	712.25	3632.59	0.25	60	60
4	540.115	3745.39	0.3	30	60
5	705.430	3639.61	0.25	60	60
6	776.31	3722.5	0.25	15	30
7	668.1	3765.45	0.3	30	60
8	677.93	3629.32	0.3	60	60
9	825.84	3576.61	0.3	30	30
10	709	3689.94	0.25	15	15
11	636.59	3747.46	0.3	30	30
12	761.62	3609.61	0.3	30	30
13	765.06	3570.94	0.3	0	0
14	609.16	3760.64	0.3	60	60
15	702.66	3730.53	0.3	60	60
16	789.41	3496.7	0.3	30	60
17	708.92	3638.46	0.3	7	0
18	613.79	3769.2	0.3	5	5
19	701.53	3724.41	0.3	16	30

Table 1.5 Specifications of the load centers .

Load Centers No.	Geographical Position		Load [MW]	Feeding Sub No.	Load Centers No	Geographical Position		Load [MW]	Feeding Sub No.
	X [km]	Y [km]				X [km]	Y [km]		
1	616.97	3839.29	1.45	18	47	750.04	3560.93	0.001	13
2	771.46	3701.35	2.33	2	48	531.1	3756.57	1.76	4
3	762.62	3658.31	2.03	12	49	708.04	3641.32	2.12	5
4	803.41	3696.85	0.82	1	50	768.51	3629.40	1.86	1
5	790.96	3759.38	0.99	6	51	703.59	3715.31	3.76	19
6	531.05	3711.72	3.11	4	52	615.75	3764.66	0.79	18
7	631.32	3804.81	3.83	11	53	685.76	3667.38	2.97	10
8	541.43	3795.6	3.28	4	54	632.71	3742.98	3	11
9	759.69	3783.94	6.88	2	55	601.86	3768.59	4.98	14
10	696.66	3795.18	5.61	19	56	531.91	3741.91	1.5	4
11	613.22	3738.70	0.92	18	57	699.37	3639.02	0.69	5
12	722.81	3585.92	1.67	12	58	687.01	3636.73	0.41	8
13	684.64	3674.55	1.25	8	59	703.79	3604.29	3.67	8
14	614.99	3740.40	0.16	18	60	543.14	3748.38	3.15	4
15	705.19	3619.16	1.55	10	61	783.95	3498.88	4.39	16
16	720.52	3620.20	0.55	10	62	562.95	3791.10	1.51	14
17	707.29	3699.59	9.21	5	63	784.39	3589.82	5.42	12
18	621.89	3736.17	0.99	18	64	695.73	3638.59	4.38	5
19	648.06	3607.20	2.66	8	65	642.69	3740.64	4	11
20	614.71	3751.60	0.1	14	66	720.13	3744.58	4.18	15
21	842.61	3466.57	1.36	16	67	719.94	3690.32	2.05	10
22	707.37	3698.72	10.14	5	68	676.81	3755.76	3.44	7
23	701.34	3790.80	3.92	19	69	699.41	3713.00	5	19
24	664.656	3716.48	1	7	70	677.66	3716.67	2.11	15
25	667.27	3791.98	2.21	7	71	540.34	3748.74	2.23	4
26	659.98	3796.83	3.86	11	72	698.77	3638.74	0.87	5
27	611	3746.12	2.48	14	73	770.11	3651.45	4	1
28	676.78	3568.45	5.83	8	74	758.76	3704.17	4	2
29	760.08	3417.60	3.91	16	75	540.73	3742.55	2	4
30	641.48	3712.68	0.38	11	76	708.75	3637.79	2	5
31	676.67	3650.90	1.28	8	77	708.78	3637.88	2	5
32	719.21	3693.89	12.02	17	78	694.85	3639.34	7	5
33	764.59	3601.82	4.91	1	79	780.28	3723.06	4	6
34	642.93	3797.19	2.55	11	80	667.51	3764.98	4	7
35	607.99	3704.20	3.49	14	81	688.92	3519.53	1.9	0
36	669.58	3717.56	2.24	7	82	707.91	3691.02	4	10
37	704.44	3697.42	11.52	5	83	640.85	3716.46	4	11
38	715.42	3696.98	3.15	5	84	631.35	3748.78	4	11
39	741.22	3694.93	4.17	12	85	758.75	3614.46	2	12
40	624.34	3709.33	1.94	14	86	739.11	3621.54	4	12
41	787.13	3493.81	4.06	16	87	614.91	3771.07	6	14
42	708.07	3637.01	4.15	17	88	701.39	3743.07	30	15
43	803.36	3721.71	3.32	6	89	783.47	3529.32	4	16
44	785.88	3522.17	3.87	16	90	825.84	3576.61	14.7	0
45	725.46	3706.14	1.55	15	91	735.62	3558.52	2.14	0
46	807.15	3616.75	1.32	1	92	767.35	3563.80	1.83	0

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