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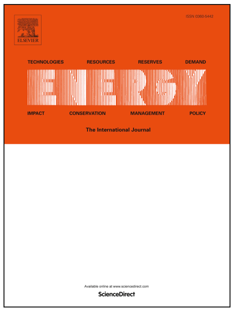

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Improved harmony search algorithm for electrical distribution network expansion planning in the presence of distributed generators

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Abstract

Distribution network expansion planning problem is carried out to supply the forecasted demand of distribution network in a certain time in which optimal size and location of distribution substations and feeders should be determined. In this paper, this problem in the presence of different types of distributed generators is addressed. For this purpose, a new approach is applied to model several practical aspects such as pollution, investment and operation costs of distributed generators, purchased power form the main grid, dynamic planning, and uncertainties of load demand and electricity prices. The uncertainties are modeled using the probability distribution function and Monte-Carlo simulation is applied to insert them into the planning problem. Because the problem involves many variables and constraints and is a non-convex and large-scale one, improved harmony search algorithm is used to solve it. To show the effectiveness of the proposed model and solving approach, it is applied to the 9-node and 69-node standard radial distribution networks and a real system of western part of Iranian national 20 kV distribution grid. The results show that the harmony search algorithm can solve the problem in a better manner in comparison with other methods such as genetic algorithm and particle swarm optimization.

Keywords: Distribution network expansion planning, Distributed generators, Improved harmony search algorithm, Sensitivity analysis, Monte Carlo simulation.

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Nomenclature

Indices and sets

t/Ω^t	Index/Set of time period
y/Ω^{CDS}	Index/Set of candidate distribution substations
λ/Ω^F	Index/Set of existing and candidate lines/feeders
$i,j/\Omega^N$	Index/Set of nodes
k/Ω^{DG}	Index/Set of DGs
h/Ω^{EDS}	Index/Set of existing distribution substation
m/Ω^{GE}	Index/Set of gaseous emission

Parameters

d	The discount rate (%)
C_{B}	Base MVA of system
C_λ	Investment cost of line/feeder ($)
C_y	Investment cost of distribution substation ($)
C_k^{INV}	Investment cost of *k*th DG technology ($/kW)
C_k^{OP}	Operation cost of *k*th DG technology ($/kWh)
pf	Penalty factor
$E_{k,m}^{\text{DG}}$	Emission factor of type m in *k*th DG technology (kg/kWh)
π_s	Electricity market Price ($/kWh)
TPH	Total planning horizon (year)
P_k^{CAP}	Capacity limit of kth DG technology (kW)
V_i^{Min}	Minimum voltage at node i
V_i^{Max}	Maximum voltage at node i
$P_h^{\text{SS-Max}}$	Distribution substation capacity limit (kW)
P_{ij}^{Max}	Thermal capacity of line/feeder connecting node i to node j (kW)
$\cos\varphi$	Power factor
Z_{ij}	Impedance of line/feeder connecting node i to node j
$\text{D}_{t,i}$	load demand at node i in time period t (kW)

Variables

$n_{t,\lambda}$	Number of lines/feeders must be installed in time period t
$\omega_{t,y}$	Number of substations must be installed in time period t

$P^{\mathrm{OP}}_{t.i.k}$	Operation generation of kth DG technology at node i in time period t (kW)
$Z_{t,i,k}$	On or off kth DG technology at node i in time period t
$P^{\mathrm{PS}}_{t,h}$	Purchased power from substation h in time period t (kW)
$P_{t,ij}$	Power flow in line/feeder connecting node i to node j in time period t (kW)
$V_{t,i}$	Voltage of node i in time period t
COF	Cost of lines/feeders ($)
CDS	Cost of distribution substation ($)
ICD	Cost of DGs ($)
OCD	Operation cost of DGs ($)
COL	Cost of losses ($)
CPP	Cost of purchased power from main grid ($)
PE	Pollution emission (kg/h)
TSC	Total social cost ($)

1 Introduction

1.1 Motivation and aim

Distribution network expansion planning (DNEP), as an important issue in power system studies, has been investigated by many researchers. The DNEP is an optimization problem to determine optimal location and size of distribution substations and feeders to meet the peak demand of radial distribution network (RDN) in the time horizon of planning in minimum costs considering technical constraints of the network. The growth of peak demand, low reliability, and high-power losses are major problems of distribution networks, which result in the high costs for DNEP. To mitigate these problems, distributed generators (DGs) are utilized in distribution networks to meet load locally and to reduce the peak demand of distribution network. DGs are small-scale power generation technologies that are connected to low/medium voltage distribution networks. DGs include fossils fuel-based generation units such as diesel engine (DE), gas turbine (GT), fuel cell (FC), and micro turbine (MT) and renewable energy-based DGs such as wind turbines (WTs) and photovoltaic arrays (PVs). Optimal planning of DGs is an optimization problem to determine the optimal location, type, and size of DGs to decrease peak demand and power losses and increase the reliability of the network. Therefore, in the presence of DGs, the DNEP problem is changed. The objective function of the DNEP in the presence of DGs includes total investment cost of DGs, total investment cost of substations and feeders, total operation cost of DGs, and total power purchased from the main grid [1]. The resulted model is a mixed integer, non-linear, and non-convex optimization. Therefore, the aim of this paper is to model the DNEP problem in the presence of DGs as a dynamic optimization problem and solved the proposed model using improved harmony search algorithm (IHSA) method as a meta-heuristic optimization approach which can solve the problem in a better manner compared with other methods such as genetic algorithm (GA) and particle swarm optimization (PSO).

1.2 Literature review and contributions

The DNEP problem can be investigated from several aspects as shown in Fig. 1. From viewpoint of planning horizon, the DNEP problem divided into two classes: static and dynamic planning horizons. In the static planning, only a single period of time is considered. On the other hand, in dynamic planning, the planner divides the period of planning into several stages. It is noteworthy that dynamic DNEP problem is a more complex optimization problem because it deals with more variables and constraints and consequently needs huge computational effort to get an optimal answer, especially in large-scale distribution systems. From viewpoint of uncertainty, uncertainties cause that the final plan always faced with technical and economic risks. Technical risk means that technical indices of the grid are not optimal due to unforeseen changes in input data. The uncertainties are classified into random and non-random approaches. In random approaches, the probability distribution function (PDF) of an occurrence such as electrical load growth is specified by observing its past behavior. In comparison, in non-random approaches, the PDF of an occurrence such as lightning struck in an area cannot be estimated by its behavior. Therefore, the proper method for modeling the uncertainties in DNEP problem should be taken carefully. From viewpoint of distribution network structure, the DNEP problem can be investigated in regulated and deregulated structures. In regulated structure, the main objective of the planner is to meet the demand while maintaining service quality and reliability of the network. In deregulated structure, distribution company (Disco) can participate in wholesale electricity market to purchase the required energy at minimum cost. Therefore, the DNEP is changed in deregulated structures. In the approaches studied for the DNEP problem, various methods are applied to optimize objective functions that can be divided into three major categories including mathematical, heuristic, and meta-heuristic methods. The mathematical optimization models find an optimum expansion plan using a calculation procedure that solves a mathematical formulation of the problem. Due to the impossibility of considering all aspects of the DNEP problem, the obtained plan is optimum only under some simplifications. Mathematical methods like linear programming (LP), dynamic programming (DP), and benders decomposition have been used for solving DNEP problem. The meta-heuristic algorithms like shuffled frog leaping algorithm (SFLA), GA, PSO, artificial immune system (AIS), artificial bee colony (ABC), ant colony system (ACS), bacterial foraging (BF), global search optimization (GSO), learning automat (LA), simulated annealing (SA), grey wolf optimizer (GWO), and tabu search (TS) have been used for solving the DNEP problem. In [2], a new static method for the DNEP problem is reported by optimal feeder routing in the radial distribution system. In [3], a direct static solution methodology is presented for solving DNEP problem by optimal feeder routing problem of radial distribution networks. A dynamic DNEP model considering DGs, sizing, locating of feeder and distribution substations, and electricity market impact via a load-dependent electricity price is employed in [4]. In [5], a static model for DNEP problem considering siting and sizing of distribution substations is presented. In [6], a dynamic multi-objective model for DNEP problem by locating the DGs and distribution substations considering the uncertainty of load is presented. In [7], a dynamic method for DNEP problem with DGs is implemented and the effectiveness of the proposed approach is investigated using practical case studies. In [8], the impact of energy carrier systems on DNEP problem and the adequacy of the system under contingencies is studied. In [9], the DNEP problem is investigated by GA. In [10], PSO algorithm is applied to solve the DNEP problem. In [11], ABC algorithm is applied to solve the DNEP. In [12], a risk-based optimization method is proposed to model a multistage DNEP problem that takes DG into account as a flexible option to temporarily defer large network investments. In [13], AIS algorithm is applied to solve the DNEP problem. In [14], a methodology for active distribution networks dynamic expansion planning based on GA, where DG integration is considered together with conventional alternatives for expansion. In [15], a long-term planning method to maximize the benefits of network reconfiguration and DG allocation in distribution networks is presented. In [16], a DNEP model that investigates the reinforcement of substations and feeders, and the integration of DGs are presented. The results illustrate that it is better to plan DGs and network reinforcement in combination rather than planning them distinctly. In [17, 18], a static DNEP model with considering locating and sizing of feeders is presented and solved by SA and TS. In [19, 20], a static DNEP model considering locating and sizing of feeders and uncertainty of load is presented and solved by PSO and GA. In [21], a competent optimization approach based on the GWO for multiple DG allocation (i.e., siting and sizing) in distribution networks is proposed. In [22], an interactive fuzzy satisfying method, which is based on SFLA is presented that minimizing total energy losses, total energy cost and total pollutant emissions produced are the objective functions. In [23], a new method to solve the network reconfiguration problem in the presence of DG with an objective of minimizing real power loss and improving voltage profile in distribution system. In [24], without considering uncertainties, a new approach using harmony search algorithm (HSA) is presented for placing DGs in radial distribution networks. In [25], the optimal sizing of the photovoltaic sources in the unbalanced distribution network by reinforcement learning, which is an efficient approach for handling the stochastic data in distribution networks. In [26], a new approach-based GA is presented for optimal siting of DG units in power systems from a probabilistic multi-objective optimization perspective. In [27], a new approach to determine the sizes and locations of DGs for voltage profile enhancement and loss reduction in distribution networks. In [28], a novel strategy is proposed that optimizes the placement and sizing of DGs on electrical distribution feeders based on both economic and technical constraints. In [29], a multi-objective performance index-based location and size determination of DGs in distribution networks with different load models is presented. In [30], the optimal location of DGs is considered as a stochastic optimization approach considering the uncertainty of DG outputs and load consumptions. In [31], a graph theoretic (GTH) based feeder routing in power distribution network including DGs is presented for the DNEP problem. In [32], an optimization approach has been presented to determine the appropriate size and proper allocation of DG in a distribution network. In [33], two generalized methods are presented for allocating and sizing of DGs. To determine the size and location of a single DG unit, a heuristic method based on sensitivity analysis and quadratic curve fitting technique has been proposed. In [34], a method for placement of DGs in distribution networks has been presented. This approach is based on the analysis of power flow continuation and determination of most sensitive buses to voltage collapse. The objective function of [35] is to optimally allocate locations and capacities of DGs in order to control the reactive power. In [36], a simple approach for considering the problem of choosing best size and location of DGs in three-phase unbalanced radial distribution system for power loss minimization is presented. In [25–36], the test systems which are proposed in the IEEE Radial Test Feeders benchmarks developed by Prof. William Kersing are used to show the effectiveness of the proposed models in those studies. In [37], renewable energy resources are applied for DNEP problem using ant lion optimization algorithm (ALOA). In [38], the DNEP problem is considered by optimal placement of DGs to minimize power losses and maximize voltage stability index using a novel solution method called big bang-big crunch (BB-BC). In [39], a dynamic model for DNEP problem is presented, where a minimum load shedding-based analytical method suggested for energy shortage minimization by sizing and locating of DGs using binary chaotic shark smell optimization (BCSSO) algorithm. In [40], a dynamic model for DNEP problem in the presence of DGs using nonlinear formulations is suggested, with the objective functions of the planning problem being the minimization of costs, maximization of reliability, minimization of losses and voltage stability index based on short circuit capacity. In [41], a static model for DNEP problem is presented considering investment costs and reliability using teaching learning optimization (TLO). For clarity, a review of previous studies for DNEP problem and their solving methods is presented in Table 1. Also, the proposed model in this paper is compared with other studies from different aspects in this table. The proposed model is solved by improved harmony search algorithm (IHSA). HSA has been successfully applied to various optimization problems, such as transportation problem [42], transmission expansion planning [43, 44], emergency inspection scheduling [45], and superstructure optimization of the olefin separation system [46]. Considering the works analyzed in the literature review and summarized in Table 1, the contributions of this paper are as follows:

- Modeling the DNEP problem in the presence of DGs considering the uncertainty of load, energy price and pollution of DGs as a mixed-integer non-linear and non-convex dynamic optimization problem.

- Using IHSA optimization approach to solve the proposed model.

1.3 Paper organization

The remainder of this paper is organized as follows. In section 2, the mathematical formulation of the proposed model is presented. Overview of IHSA, procedure and methodology for the problem are discussed in Section 3. Numerical results are reported and discussed in section 4 and finally, conclusion is presented in section 5.

2 Mathematical modeling

2.1 objective function

The proposed model as a total social cost (TSC) for DNEP problem in the presence of DGs is formulated as the following optimization problem:

$$\text{Min TSC} = \text{COF} + \text{CDS} + \text{ICD} + (365 \times 24 \times \text{OCD}) + (365 \times 24 \times \text{COL}) + (365 \times 24 \times \text{CPP}) + pf \times \text{PE} \quad (1)$$

$$\text{COF} = \sum_{t \in \Omega^t} \sum_{\lambda \in \Omega^F} (1+\text{d})^{-t} \times (C_\lambda \times n_{t,\lambda}) \quad (2)$$

$$\text{CDS} = \sum_{t \in \Omega^t} \sum_{y \in \Omega^{CDS}} (1+\text{d})^{-t} \times (C_y \times \omega_{t,y}) \quad (3)$$

$$\text{ICD} = \sum_{t \in \Omega^t} \sum_{i \in \Omega^N} \sum_{k \in \Omega^{\text{DG}}} (1+\text{d})^{-t} \times (C_k^{\text{INV}} \times C_B \times P_{t,i,k}^{\text{OP}} \times Z_{t,i,k}) \quad (4)$$

$$\text{OCD} = \sum_{t \in \Omega^t} \sum_{i \in \Omega^N} \sum_{k \in \Omega^{\text{DG}}} (1+\text{d})^{-t} \times (C_k^{\text{OP}} \times C_B \times P_{t,i,k}^{\text{OP}} \times Z_{t,i,k}) \quad (5)$$

$$\text{COL} = \sum_{t \in \Omega^t} (1+\text{d})^{-t} (\text{Losses} \times C_B \times \pi_s) \;,\; \text{Losses} = \sum_{\substack{i \in \Omega^N \\ i \neq j}} \sum_{\substack{j \in \Omega^N \\ i \neq j}} \left(\frac{(|V_{t,i}| - |V_{t,j}|)^2}{|Z_{ij}|} \right) \times \cos\varphi \quad (6)$$

$$\text{CPP} = \sum_{t \in \Omega^t} (1+d)^{-t} \times \sum_{h \in \Omega^{\text{EDS}}} P_{t,h}^{\text{PS}} \times C_B \times \pi_s \quad (7)$$

$$\text{PE} = \sum_{t\in\Omega^t}\sum_{i\in\Omega^N}\sum_{k\in\Omega^{\text{DG}}}(P^{\text{OP}}_{t,i,k}\times C_B\times Z_{t,i,k}\times \sum_{m\in\Omega^{\text{GE}}} E^{\text{DG}}_{k,m}) \tag{8}$$

where Eq. 2 describes the capital cost of lines/feeders in the network, Eq. 3 is used to model the capital cost of distribution substations, Eq. 4 and Eq. 5 describe investment and operation cost of applied DGs, respectively, Eq. 6 describes the cost of losses in the network, Eq. 7 is used for considering the cost of purchased power from main grid, and Eq. 8 is used to model the amount of DGs' pollution emission.

2.2 Constraints

The objective function described in Eq. 1 to model DNEP problem in the presence of DGs is optimized subjected to different constraints to get optimal feasible planning result. The following constraints should be satisfied.

a. DGs operational capacity

Constraint (9) shows the limitation of the operational capacity of DGs [19, 47].

$$P^{\text{OP}}_{t,i,k}\times C_B \le P^{\text{CAP}}_{k} \qquad \forall t\in\Omega^t,\ \forall i\in\Omega^N,\ \forall k\in\Omega^{\text{DG}} \tag{9}$$

b. Limitation in voltage of nodes

Constraint (10) represents a limitation of voltage. In this paper, the minimum and maximum voltages of nodes are assumed to be 0.95 p.u and 1.05 p.u, respectively [24, 47].

$$V^{\text{Min}}_{i} \le V_{t,i} \le V^{\text{Max}}_{i} \qquad \forall t\in\Omega^t,\ \forall i\in\Omega^N \tag{10}$$

c. Distribution substation capacity

Constraint (11) represents the limitation in distribution substation capacity [47].

$$P^{\text{PS}}_{t,h} \le P^{\text{PS-Max}}_{h} \qquad \forall h\in\Omega^{\text{EDS}},\ \ \forall t\in\Omega^t \tag{11}$$

d. Thermal capacity of distribution feeder

Constraint (12) denotes the limitation in thermal capacity of distribution feeder [19, 47].

$$P_{t,ij}\times C_B \le P^{\text{Max}}_{ij} \qquad \forall t\in\Omega^t,\ \ \forall_{i\neq j}\ i,j\in\Omega^N \tag{12}$$

e. Power balance limits

Constraint (13) represents the power balance constraint in which the term I' is the total loss power in feeder connecting node i to node j [47].

$$\{\sum_{j}\{P_{t,ij} - \underbrace{\sum_{\substack{i\\ i\neq j}}\sum_{\substack{j\\ i\neq j}}\frac{(|V_{t,i}|-|V_{t,j}|)^2}{|Z_{ij}|}\times\cos\varphi}_{I'}\} - \sum_{j} p_{t,ij} + \sum_{k} P^{\mathrm{OP}}_{t,i,k}\times Z_{t,j,k}\}\times C_B = D_{t,i} \tag{13}$$

$$\forall t\in\Omega^{t},\ \underset{i\neq j}{\forall}\ i,j\in\Omega^{N},\ \forall k\in\Omega^{\mathrm{DG}}$$

f. Radial structure limit

Constraint (14) is applied to keep the radial structure of distribution network.

$$\text{Radial structure of distribution network} = 1 \tag{14}$$

In this study, according to [48], a vertex (node) encoding based on Prufer number in GA is used to get a radial structure for the network. Thus, to evaluate the network radially, the following constraints must be satisfied simultaneously:

$$\det(A) = 0 \tag{15}$$

$$q = N_B - 1 \tag{16}$$

where A is a node-branch matrix with size $N_B \times N_B$ (N_B is the number of nodes) with its elements being either 1 or 0. If the node i is connected to the node j via a branch then $A(i,j)$=1 and otherwise, $A(i,j)$=0. Moreover, the operator det(.) denotes determinant of the matrix. The described constraint in Eq. (16) is a condition of the establishment of a tree in graphs theory, where q is the number of branches and N_B is the number of nodes. For example, in the structure shown in Fig. 2, without considering branch ℓ', the matrix A is shown in Eq. (17), which in this condition det(A)=0 and Eq. (16) can be satisfied. With considering branch ℓ', the constraint described in Eq. (16) cannot be satisfied and in this state, the network is not radial.

$$A = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \end{bmatrix} \quad (17)$$

3 Solution Methodology

3.1 Modeling of uncertainties

In the power system planning, the forecasted electrical load and electricity prices are usually associated with uncertainty due to different issues such as imprecise estimation and unanticipated load changing. Analyzing these uncertainties in planning studies leads to a more robust and flexible plan, which can successfully satisfy the network requirements under uncertainties [19]. In this regard, the uncertainties of the electricity prices and electrical load are modeled as the normal PDF. Then, the Monte Carlo simulation (MCS) as one of the appropriate tools for considering the random uncertainties is applied to analyze the uncertainties of the electricity prices and the electrical load for the proposed DNEP problem. An example of the continuous distribution function of the network load forecast is shown in Fig. 3, which is discretized into 13 intervals and each interval has a wide equal to one load forecast error standard deviation. To determine the probability of different load levels, the continuous function must be estimated with a normal discontinuous function. In this regard, if there are more intervals, then the approximation error becomes much smaller. The normal discontinuous function can be described by Eq. (18), where the vector shows the probability of each load level. In other words, the variables $p_1, p_2, ..., p_n$ show the load levels

$I_1, I_2, ..., I_n$, respectively.

$$P = \begin{cases} p_1 & \text{Load level } 1 = I_1 \\ p_2 & \text{Load level } 2 = I_2 \\ \vdots & \vdots \\ p_n & \text{Load level n} = I_n \end{cases} \tag{18}$$

The next step is to produce load and electricity price scenarios according to different levels and corresponding probabilities obtained from the mentioned normal PDF. For this purpose, a random number for each uncertain variable is produced based on its PDF. After generating a random number, the probability of the uncertain variable is calculated. For example, the load level is calculated according to Eq. (18). The same process is also used for other network uncertainties. The flowchart of the proposed MCS is shown in Fig. 4. In the first step, all the uncertain variables according to Eq. (18) are defined and a random number is produced for each variable. Then, the value of the variable and its probability in each scenario is specified. Once the power flow analysis is done, the convergence of MCS is considered. The convergence of MCS can be the variance of output variables, which means if the variance of output variable is less than the specified limit, the algorithm is finished; otherwise, the algorithm is repeated and a new scenario is generated. Finally, with increasing scenarios, there are a number of scenarios that each of them contains the value of the variable and their probability. Therefore, the planner can plot the value of output variable in terms of its probability. With this approach, the effect of uncertainty in input data appears in output and PDF of output variable can be specified.

3.2 Power flow analysis

The power flow studies in the distribution networks in the presence of DGs are investigated from different viewpoints in the literature. The power flow is used for fault analysis in distribution networks in [49, 50]. In [51], the operation problem of distribution networks in the presence of microgrids is investigated using a novel power flow analysis. Backward-forward sweep approach is used in the literature to solve the power flow problem in distribution network planning and operation problems as described in [52, 53]. Since the problem which is investigated in this paper is DNEP one, the power flow problem is solved using the forward/backward sweep approach. The forward/backward sweep method is Kirchhoff's Voltage Law (KVL) and Kirchhoff's Current Law

(KCL). In this method, in step 1, the current injection at each node i is calculated using Eq. (19):

$$I_i^{(k)} = (S_i / V_i^{(k)})^* - y_i V_i^{(k-1)}, \quad i = 1, 2, ..., N_B \tag{19}$$

where S_i is the power injection at node i, $V_i^{(k)}$ is the voltage of node i calculated from iteration k, and y_i is the shunt element of node i that is ignored in this paper. In step 2, the backward sweep is applied, this means that starting from the last ordered branch, current flow J_ℓ in branch ℓ is calculated using Eq. (20):

$$J_\ell^{(k)} = -I_{\ell r} + \sum_{\ell=1}^{N_B} J_{\ell r} \tag{20}$$

where $I_{\ell r}$ is the current injection of node ℓ_r calculated from step 1 and $\sum J_{\ell r}$ is the currents in branches emanating from the node ℓ_r. In step 3, the forward sweep is considered that means starting from the root bus, the node voltages are updated using Eq. (21).

$$V_{\ell r}^{(k)} = V_{\ell s}^{(k)} - Z_\ell J_\ell^{(k)}, \quad \ell = 1, 2, .., N_B \tag{21}$$

where ℓ_s and ℓ_r denote the sending, and receiving the end of the branch ℓ and Z_ℓ is the series impedance of branch ℓ. A comprehensive review on sweep-based approaches in solving power flow in the distribution network is presented in [54]. According to [55], voltage differences are used for convergence criteria, which are explained in Eq. (22):

$$|V^{(k+1)} - V^{(k)}| < \varepsilon \tag{22}$$

DGs are commonly modeled as PQ or PV buses in power flow analysis. Also, DGs can be connected to the buses directly or indirectly. In this paper, six types of DGs including FC, PV, MT, WT, GT, and DE are used to connect nodes directly and indirectly. According to [56], the FC, PV, WT, and MT can be modeled as PV and PQ nodes. Since DE and GT are connected directly, these resources are modeled as PV nodes. in this work, FC, PV, WT, and MT are modeled as PQ nodes, which are considered as negative load. In the PV nodes, compensation techniques are applied according to [57]. For these nodes, it is necessary to calculate the injected reactive current produced by DGs. Therefore, in PV nodes, the active power and voltage are constant and the reactive power injected into the system is calculated.

3.3 Harmony search algorithm

Harmony search algorithm (HSA) was derived by adopting the idea that the existing meta-heuristic algorithms are found in the paradigm of natural phenomena. The algorithm was recently developed in an analogy with music improvisation process, where music players improvise the pitches of their instruments to obtain better harmony [58]. The pitch of each musical instrument determines the aesthetic quality, just as objective function value is determined by a set of values assigned to each decision variable [43]. In Fig. 5, the pseudo code of HSA is shown. The general steps of the procedure of this algorithm are as follows:

1. Initialize the optimization problem and algorithm parameters such as harmony memory size (HMS) and harmony memory consideration rate (HMCR).
2. Initialize the harmony memory (HM).
3. Improvise a new harmony from the HM.
4. Update the HM.
5. Repeat steps 3 and 4 until the termination criterion is satisfied.

3.4 Improved Harmony search algorithm

To improve the performance of HSA method and eliminate the drawbacks involved in the fixed values of pitch adjustment rate (*PAR*) and bandwidth (*bw*), the improved HSA method incorporating variables *PAR* and *bw* in improvisation step (Step 3) is used. *PAR* and *bw* change dynamically with a generation number as [60]:

$$PAR(\mathrm{gn}) = PAR_{\min} + \frac{PAR_{\max} - PAR_{\min}}{\mathrm{NI}}\mathrm{gn} \tag{23}$$

$$bw(\mathrm{gn}) = bw_{\max}\, e^{\left(\frac{\mathrm{Ln}\left(\frac{bw_{\min}}{bw_{\max}}\right)}{\mathrm{NI}}\mathrm{gn}\right)} \tag{24}$$

where $PAR_{\min}$ and $PAR_{\max}$ are minimum and maximum pitch adjusting rate, respectively. *NI* is the number of solution vector generations and *gn* is generation number. Also, $bw(\mathrm{gn})$ is bandwidth for each generation, $bw_{\min}$ is minimum bandwidth, and $bw_{\max}$ is maximum bandwidth. HSA uses from all the existing solutions in its harmony memory to solve the problem as described in the literature. Therefore, due to high potential of this approach to determine the solution spaces in a short time and obtains the near optimal solutions, it is used in many complex mixed-integer non-linear problems [61].

3.5 Handling the constraints

In this paper, to handle the constraints, Deb's method [62] is employed. The Deb's method is actually a parameter-less penalty strategy based on the following three rules.

1. Any feasible solution is preferred to any infeasible solution.
2. Between two feasible solutions, one having the better objective value is preferred.
3. Between two infeasible solutions, one having the smaller constraint violation is preferred.

3.6 Proposed expansion planning

The proposed algorithm for DNEP problem considering uncertainty in load demand and energy price is shown in Fig. 6. In this algorithm, first, an initial random harmony memory is produced. Fig. 7 presents the coding of the solutions. According to this figure, each solution is presented via a matrix with respect to t planning stages and six types of DGs in N_B nodes. The matrix elements (harmony memory) determine some of DGs added for connecting to the node. As shown in Fig. 7, at t = TPH three fuel cells must be installed in nodes 1 and 2. Thus, a member of the harmony memory is selected. Then, a scenario according to Fig. 6 is produced by the selected member and the constraint is checked. If a constraint not satisfied, the created scenario from MCS is removed and a new scenario is produced. So, the investment cost and polution for the scenario are saved and convergence of MCS is considered. If the MCS does not converge, the production of scenarios is continued for converging. Therefore, the expected value of TSC of all scenarios are calculated. This process is repeated for all members of the harmony memory. Finally, the member of the harmony memory with an optimal solution is obtained.

4 Numerical results

In this study, to show the effectiveness of the proposed dynamic model and its solution methodology, three case studies are considered. Two standard systems consist of 9- and 69-node primary distribution systems and another one is Farhangian-Kangavar distribution system, which is a part of Iranian distribution power system as a practical example. Due to the limited installed capacity, it is assumed that DGs are able to produce their maximum power. For a precise analysis, the DNEP problem of the case studies in both presence and absence of uncertainties are investigated and finally the effects of these resources are studied in the planning problem. In this study, the 9-node distribution system without considering uncertainties, the 9-node distribution system considering uncertainties, the 69-node distribution system without considering uncertainties, the 69-node distribution system considering uncertainties, the Farhangian-Kangavar distribution system without considering uncertainties, and the Farhangian-Kangavar distribution system considering uncertainties are specified with numbers (1), (2), (3), (4), (5), and (6), respectively.

4.1 9-node primary distribution system

Fig. 8 shows the 9-node primary distribution test system. This system has 9 nodes which node consists a 132/33 kV substation with a capacity of 40 MVA and other nodes serving as load points. This system has 6 existing lines. Besides, it has a candidate substation with 40 MVA capacity, candidate lines, and two candidate load nodes that must be served in expansion planning as shown in Fig. 8. The initial load demand in peak time for this system is shown in Table 2. The data of size, installed capacity limit, investment and operation cost of these resources can be found in Table 3 and emission of pollutant rates of these technologies are shown in Table 4. Moreover, in this case, the power factor, the base MVA of the system, penalty factor, and discount rate are considered to be equal to 0.95, 100, 10000, and 3%, respectively. It should be noted that all load nodes are a candidate for installing DGs and also, the rated voltage is 33 kV. The data of candidate lines for expansion are shown in Table 5. It is assumed that the system should be expanded for a year planning horizon with the load growth of 15%. The elctricity price is considered 85 $/MWh. A load of each node in system (2) is considered as a normal distribution function, with the mean and standard deviation of the load in each node being similar to those in Table 2 and 10%, respectively. Also, the energy price for system (2) is modeled as a normal distribution function with the mean and standard deviation 85 $/MWh and 10%, respectively. Fig. 9 presents a sample of the number of experiments performed in system (2). Also, Fig. 10 shows the converged load demand in node (3) in 2000 iterations of MCS for this system. It is noteworthy that, unlike the deterministic methods, implementation of MCS does not need any extra calculations; it simply requires updating equations of system according to Eq. (25) and Eq. (26):

$$\bar{P}_{i,k}^{\mathrm{OP}} = \frac{1}{NE}\sum_{j=1}^{NE} P_{i,k}^{\mathrm{OP}}(j) \tag{25}$$

$$\bar{P}_i = \frac{1}{NE}\sum_{j=1}^{NE} P_i(j) \tag{26}$$

where NE is the number of iterations in MCS and $P_i(j)$ is the active power injected at node i at jth experiment. In order to investigate the impact of important control parameters in finding the optimum solution of the problem, sensitivity analyses were done on HMCR, HMS, $PAR_{\min}$, and $bw_{\min}$. These parameters are varied within their permissible range by keeping the rest parameters constant to the aforementioned values. Other parameters of the algorithm like $bw_{\max}$ and $PAR_{\max}$ are considered as 0.9 and 0.99, respectively. The number of iterations for simulation is considered 100. To obtain optimal values for each parameter, the algorithm is implemented 10 times and the best values of the objective function with its mean are presented in Tables 6- 9. It can be seen from Table 6 and Table 7 that the large values of HMCR parameter improve the performance of the algorithm. The best values for HMS and HMCR parameters for systems (1) and (2) are 25 and 0.99, respectively. In Table 8, sensitivity analysis is done on $PAR_{\min}$ parameter with HMCR and HMS obtained from the previous tables. For systems (1) and (2), $PAR_{\min}$ parameter is 0.01. In Table 9, the sensitivity analysis is done on $bw_{\min}$ parameter for HMCR, HMS, and $PAR_{\min}$ parameters obtained from Tables 6- 8. According to Table 9, the best mode for the $bw_{\min}$ parameter for systems (1) and (2) is 0.01. The optimal expansion plans for systems (1) and (2) are presented in Table 10 and Table 11, respectively. The time of installation and number of the new distribution substations, lines/feeders, and DGs for systems (1) and (2) are shown in Table 12. Moreover, the voltages of nodes in this system before and after the expansion are shown in Table 13.

4.2 69-node distribution system

The 69 node-distribution system is a radial 11 kV distribution network with 69 nodes, 68 existing lines, and one distribution substation with a capacity of 12 MVA (Fig. 11). The existing lines are the candidate lines for new construction or reinforcement. Also, this system has 5 candidate substations with capacity of 4 MVA. The data of existing loads and lines of this system are shown in Table 14. In this case study, the power factor, the base MVA of the system, penalty factor, and discount rate are considered to be equal to 0.95, 100, 10000, and 3%, respectively. It should be noted that all load nodes are a candidate for installing DGs and, also, the rated voltage is 11 kV. In comparison with other approaches proposed in the literature, it is assumed that the system should be expanded for a one-year planning horizon with the load growth 3%. The energy price is considered 0.07 \$/kWh. In this case study, four types of DGs consisting of WT, PV, MT, and FC are considered. The data of size, installed capacity limit, investment, operation cost, and emission factor of these DGs are shown in Table 15. A load of each node in system (4) is considered as a normal distribution function, where the mean and standard deviation of the load in each node are same as those shown in Table 14 and 5%, respectively. Also, the energy price for system (4) is modeled as a normal distribution function with the mean and standard deviation 0.07 $/kWh and 20%, respectively. In a sensitivity analysis for this case study, according to Table 16 and Table 17, the best values for HMS and HMCR parameters for the systems (3) and (4) are 35 and 0.99, respectively. Table 18 presents the results of sensitivity analysis done on $PAR_{\min}$, with HMCR and HMS obtained from Table 17 and Table 18 (for these systems, $PAR_{\min}$ was obtained 0.01). In Table 19, sensitivity analysis is done on $bw_{\min}$ parameter for HMCR, HMS, and $PAR_{\min}$ parameters obtained from Tables 16-18. According to Table 19, the best mode for $bw_{\min}$ parameter is 0.01 for systems (3) and (4). The optimal expansion plan for systems (3) and (4) are shown in Table 20. Also, the voltage of nodes in this system before and after the expansion is shown in Table 21.

4.3 Farhangian-Kangavar distribution system

The proposed approach was also applied to a part of Iranian (Farhangian-Kangavar) distribution power system as a practical example to compare the historical expansion plan and the expansion plan developed by the proposed methodology. Fig. 12 shows the simplified part of Iranian (Farhangian-Kangavar) 20 kV distribution grid considered in this case study. This system has 1, 72, and 47 distribution substation, lines, and nodes, respectively. It is assumed that the system should be expanded for a 5-year planning horizon with the load growth 15%. There is one candidate distribution substation with capacity of 4 MVA and all existing lines are a candidate for new construction or reinforcement. In Fig. 12, the points that the DGs can be installed in this system are shown with symptoms “a”, “b”, “c”, and “d”. In this case study, the power factor, the base MVA of the system, penalty factor, discount rate, and energy price are considered to be equal to 0.992, 100, 10000, 10%, and 0.07 $/kWh, respectively. The thermal capacity of line/feeder ($P_{ij}^{\max}$) connecting the node “a” to “b”, the node “b” to “c”, and node “c” to “d” is considered 4 MW. Table 22 shows the initial load at peak time in this system. The data of size, installed capacity limit, investment and operation cost of DGs can be found in Table 3. Moreover, the emission of pollutant rates of these technologies is shown in Table 4. A load of each node in systems (6) is considered as a normal distribution function, with the mean and standard deviation of the load in each node being same as those shown in Table 22 and 20%, respectively. Also, the energy price for the system (6) is modeled as a normal distribution function with the mean and standard deviation 0.07 $/kWh and

10%, respectively. As shown in Fig. 12, there is one 4 MVA candidate distribution substation with a construction cost of 2 M$; also, there are three candidate feeders with a capacity 4 MW specified with L_1, L_2, and L_3 with the construction costs of 0.45 M$, 0.43 M$, and 0.4 M$, respectively. In this case study, after performing the sensitivity analysis (Table 23 and Table 24), the best values for HMS and parameters for systems (5) and (6) were calculated as 35 and 0.99, respectively. Also, a sensitivity analysis (Table 25) is done on $PAR_{\min}$ parameter with HMCR and HMS obtained from the Table 23 and Table 24. For systems (5) and (6), the $PAR_{\min}$ parameter is 0.001. As shown in Table 26 sensitivity analysis is done on $bw_{\min}$ parameter for the HMCR, HMS, and $PAR_{\min}$ parameters obtained from Tables 23- 25. According to Table 26, the best mode for $bw_{\min}$ parameter is 0.01 for this practical case study. The optimal expansion plan for systems (5) and (6) are shown in Table 27 and Table 28, respectively. The time of installation and number of the new distribution substations, lines/feeders, and DGs for this system are shown in Table 29. Also, the voltages of nodes in this system before and after the expansion are shown in Table 30.

4.4 Sensitivity analysis

In order to show the validity and reliability of the proposed model, sensitivity analysis is done on four parameters consisting of load, electricity prices, DGs and distribution substation costs. Regarding different load levels in Table 31, the sensitivity analysis illustrates that in the case of load growth, there is no need to install new distribution substation and that applying new DGs, the load will be satisfied. In Table 32, the sensitivity analysis is performed on different electricity prices with the results showing that having the electricity price growing up, the planner will decide to install DGs to avoid the risk of high electricity market prices. In Tables 33 and 34, the sensitivity analysis on the costs of DGs/distribution substation is done increasing/decreasing their initial values to 50%, respectively. The results show that in the presence of DGs with available capacities, the installation of the distribution substations is not justifiable.

4.5 Discussion and comparison

The results clearly show the favorable effect of DGs on the distribution system. For example, according to Tables 13, 21, and 30, the voltage profile of nodes is improved by considering DGs, so that in the presence of DGs, the standard deviation of voltages is reduced by 25%, 23.68%, 17.2%, 19.5%, 16.25%, and 20% in systems (1) to (6), respectively. According to Tables 10, 11, 27 and 28, the deployment of DGs decreases the ultimate planning cost by 27%, 22%, 28%, and 25% in systems (1), (2), (5), and (6), respectively. Also, the deployment of DGs decreases the losses by 22%, 20%, 15.31%, 16.68%, 3.6%, and 2.71% in systems (1) to (6), respectively. Thus, the benefits of DGs in the DNEP problem are obvious. According to obtained results, there is no need to build a new substation in all systems. There is need to build a new line between node 6 and node 7 and also between node 4 and node 5 in systems (1) and (2), and there is no need to build a new line in systems (3) to (6). A comparison between the proposed model and its solving methodology and Refs. [63, 64] for systems (1) and (2) is presented in Table 35 for the first year. As can be seen, the proposed algorithm outperforms the other methods from different aspects and views and leads to a lower-cost plan. Similarly, in [65] it is demonstrated that HSA outperforms GA considering several famous benchmark functions. Moreover, according to [66] in the PSO algorithm, population size is an important parameter which converges the algorithm; therefore, the large population should not be considered because it increases the computation cost. Also, a comparison between the proposed model and its solving methodology for systems (3) and (4) and those of other studies is seen in Table 36. In Table 37, a comparison of losses function for different algorithms for the test system (3) is presented. The results show that the losses function becomes less after allocation of DGs. A comparison of costs for systems (5) and (6) with PSO, GA, and historical expansion plan (Table 38) shows that the TSC of the proposed method is better. In Figs. 13- 16, the convergence characteristic of the proposed methodology versus GA and PSO algorithms as well-known meta-heuristic optimization methods are shown for systems (1), (2), (5), and (6). Also, the number of constraints, variables and the computational time of the proposed algorithm and other ones in the case studies are given in Table 39. As shown in Figs. 13- 16 and Table 39, the proposed algorithm has the better performance in comparison with other methods.

5 Conclusion

In this paper, the distribution network expansion planning problem is investigated in the presence of distributed generators. For this purpose, the objective function is proposed considering the cost of feeders and substations, the cost of purchased power form the main grid, the cost of power losses, investment and operation costs of distributed generators, and the cost of pollutant emission. Moreover, the uncertainties of load and electricity price are modeled using normal probability distribution functions and analyzed by applying the Monte-Carlo simulation. To investigate the effectiveness of the proposed model and its solution methodology, three test cases consisting of two typical distribution networks and a real one were evaluated. The results of the proposed improved harmony search algorithm is compared with genetic algorithm and particle swarm optimization algorithm as the well-known approaches in the field of the distribution network expansion planning problem. The remarkable conclusions from the results are as follows:

- The application of distributed generators improves the system performance, reduces pollutant emission, enhances the voltage profile, reduces the costs of planning, and reduces power losses as well.
- The network expansion planning problem has the realistic outputs considering the uncertainties of demand and energy prices.
- Applying the proposed improved harmony search algorithm to solve the problem has the better performance in comparison with other metaheuristic approaches.

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Table 1: A review of previous studies on DNEP problem and their solving methods

Ref	Static/ Dynamic	Uncertainty	Considering DGs	Pollution	Variable	Objective function	Test system	Solving method
[2]	Static	No	No	No	Feeders location	Feeders installation cost	25-node RDN	BF
[3]	Static	No	No	No	Substations and feeders location	Energy cost and interruption cost	24-node RDN	GA
[4]	Dynamic	No	Yes	No	Substations, DGs and feeders location & size	Cost of DGs and substations	9-node RDN	GA
[5]	Static	No	No	No	Sizing and siting of substations	Cost of substations	A real network in Iran	LA
[6]	Dynamic	Load	Yes	No	Capacity and location of MV substation and DGs	Cost of DGs and substations	A real network	GSO
[7]	Static	No	Yes	No	Substations, DGs and feeders location & size	Cost of DGs and substations	A rural RDN	LP
[8]	Dynamic	No	Yes	No	Substations, DGs and feeders location & size	Investment and operational costs	An urban RDN	GA
[9]	Static	No	Yes	No	DGs location or size, feeders location	Voltage deviation, losses, DGs cost	26-node RDN	GA
[10]	Dynamic	No	Yes	No	Substations, DGs and feeders location & size	Cost of DGs and reliability	18-node RDN	PSO
[11]	Dynamic	No	Yes	No	Substations, DGs and feeders location & size	Cost of losses and DGs	33-node RDN	ABC
[12]	Dynamic	Load	Yes	No	Substations, DGs and feeders location & size	Max a return-per-risk index	A real RDN	PSO
[13]	Static	Load	No	No	Feeders location & size	Losses and feeders cost	23-node RDN	AIS
[14]	Dynamic	Load	Yes	No	Feeders location, DGs location	Losses and reliability cost	33-node RDN, 177-node RDN	GA
[15]	Dynamic	Load	Yes	Yes	Feeders location, DGs location	Cost of DGs, feeders and losses	33-node RDN, 119-node RDN	GA
[16]	Dynamic	No	Yes	No	Substations, DGs, and feeders size	Min total costs minus total revenues	24-node RDN	ACS
[17]	Static	No	Yes	No	Feeders location & size	Cost of DGs, losses and feeders	41-node RDN	SA
[18]	Static	Load	Yes	No	Feeders location & size	Cost of DGs and feeders	23-node RDN	TS
[19]	Static	Load	Yes	No	Feeders & DGs location	Cost of DGs	9-node RDN	PSO
[20]	Static	Load	Yes	No	Feeders & DGs location	Cost of DGs and feeders	33-node RDN	GA
[21]	Static	No	Yes	No	DGs location & size	Min of losses & voltage deviation	69-node RDN	GWO
[22]	Static	No	Yes	Yes	DGs location & size	Cost of DGs and losses	26-node RDN	SFLA
[23]	Static	No	Yes	No	Feeders location, DGs location	Power loss	33-node RDN, 69-node RDN	HSA
[24]	Static	No	Yes	No	Size and location of DGs	Minimize power losses	69-node RDN	HSA
[25]	Static	PV sources	Yes	No	Size and location of DGs	Power losses	IEEE 37-bus , IEEE 13-bus	LA
[26]	Dynamic	Load	Yes	No	Size and location of DGs	Investment cost of DGs, power losses, maximization of reliability	IEEE 37-bus	GA
[27]	Static	No	Yes	No	Size and location of DGs	Power losses, voltage enhancement	IEEE 34-bus	GA
[28]	Static	No	Yes	No	Size and location of DGs	Annualized System Benefit	IEEE 34-bus	Suggested
[29]	Static	No	Yes	No	Size and location of DGs	power losses, voltage profile	IEEE 37-bus	GA
[30]	Static	DGs	Yes	No	Size and location of DGs	Minimize load consumption	IEEE 37-bus	GA
[31]	Static	No	Yes	No	Size and location of DGs	Feeder routing	IEEE 123-bus	GTH
[32]	Static	No	Yes	No	Size and location of DGs	Power losses, improve reliability	IEEE 34-bus , IEEE 123-bus	Suggested
[33]	Static	No	Yes	No	Size and location of DGs	Power losses	IEEE 34-bus, IEEE 123-bus	Suggested
[34]	Static	No	Yes	No	Size and location of DGs	Power losses, voltage profile	IEEE 34-bus	Suggested
[35]	Static	No	Yes	No	Size and location of DGs	Minimize voltage variations	IEEE 37-bus	GA
[36]	Static	No	Yes	No	Size and location of DGs	Minimize power losses	IEEE 37-bus	Suggested
[37]	Static	No	Yes	No	Size and location of DGs	Minimize power losses	69-node RDN, 33-node RDN	ALOA
[38]	Static	Load	Yes	Yes	Size and location of DGs	Minimize power losses, pollution emission	25-node RDN, 33-node RDN	BB-BC
[39]	Dynamic	No	Yes	No	Size and location of DGs	Investment and operation costs	12-node RDN, 33-node RDN	BCSSO
[40]	Dynamic	Load	Yes	No	Size and location of DGs	Power losses, voltage profile, reliability	33-node RDN	PSO
[41]	Static	No	Yes	No	Feeders location, Size and location of DGs	Costs and reliability	33-node RDN, 69-node RDN	TLO
This paper	Dynamic	Load, electricity price	Yes	Yes	Location of substation and feeders, location and size of DGs, voltage profile	New construction of substations and feeders, purchased power from main grid, losses, pollution, investment and operation cost of DGs	9-node RDN, 69-node RDN and a real RDN	IHSA

Table 2: The initial load demand in peak time for the 9-node distribution system

Node	2	3	4	5	6	7	8	9
Load demand (kW)	6.6508	6.7901	6.6508	3.4821	3.9870	5.7455	5.3190	4.4745

Table 3: Data of six DG technologies

DG technology	Unit size (kW)	Installed capacity Limit (kW)	Investment cost ($/kW)	Operation cost ($/kWh)
DE	1000	2000	500	0.045
FC	1500	3000	3500	0.050
GT	1000	4000	1000	0.040
MT	200	2000	1500	0.050
PV	100	2000	5000	0.005
WT	1000	4000	4500	0.010

Table 4: Emission of pollutant rates of six DG technologies

DG technology	NO_x (kg/kWh)	SO_2 (kg/kWh)	CO_2 (kg/kWh)	CO (kg/kWh)	PM_{10} (kg/kWh)
DE	0.00213	0.00125	0.625	0.0028	0.00036
FC	0.000015	0.000024	0.447	0	0
GT	0.00029	0.000032	0.625	0.00042	0.000041
MT	0.0002	0.000037	0.725	0.00047	0.000041
PV	0	0	0	0	0
WT	0	0	0	0	0

Table 5: Existing and candidate lines data of the 9-node distribution system

From node (i)	To node (j)	Z_{ij} (p.u)	C_λ (M$)	P_{ij}^{Max} (MW)
1	2	0.0354	0.31	6.8
1	4	0.0457	0.42	6.8
1	6	0.0416	0.31	4.5
1	8	0.0554	0.31	5.5
2	3	0.0831	0.82	1.5
8	9	0.0776	0.31	1.6
3	7	0.0405	0.31	1.2
6	7	0.0457	0.42	1.2
2	6	0.0457	0.42	1.2
6	8	0.0346	0.31	1.2
4	8	0.0831	0.82	1.2
4	5	0.0831	0.82	1.2
5	9	0.0443	0.31	1.2
10	2	0.0416	0.31	1
10	6	0.0776	0.63	1
10	4	0.0416	0.31	1
10	5	0.0831	0.82	1
10	8	0.0346	0.31	1
10	9	0.0831	0.82	1

Table 6: Sensitivity analysis for HMS and HMCR parameters for $PAR_{\min} = 0.4$ and $bw_{\min} = 0.1$ in system (1)

	HMS							
	10		25		35		50	
HMCR	Best	Average	Best	Average	Best	Average	Best	Average
0	4.5336×10^8	4.6872×10^8	4.1232×10^8	4.1542×10^8	4.2112×10^8	4.3562×10^8	4.2336×10^8	4.3125×10^8
0.3	4.1521×10^8	4.1883×10^8	3.8582×10^8	3.9732×10^8	3.8745×10^8	3.9563×10^8	3.8895×10^8	3.9452×10^8
0.6	3.8532×10^8	3.9962×10^8	3.6251×10^8	3.6532×10^8	3.5212×10^8	3.6312×10^8	3.5333×10^8	3.6325×10^8
0.9	2.9853×10^8	3.01336×10^8	2.9733×10^8	3.0123×10^8	3.0127×10^8	3.1895×10^8	3.0287×10^8	3.1896×10^8
0.99	2.8334×10^8	2.9521×10^8	**2.7588×10^8**	**2.8263×10^8**	2.8739×10^8	2.9126×10^8	2.9132×10^8	2.9785×10^8

Table 7: Sensitivity analysis for HMS and HMCR parameters for $PAR_{\min} = 0.4$ and $bw_{\min} = 0.1$ in system (2)

	HMS							
	10		25		35		50	
HMCR	Best	Average	Best	Average	Best	Average	Best	Average
0	4.7522×10^8	4.7832×10^8	4.4251×10^8	4.5632×10^8	4.7632×10^8	4.7993×10^8	4.7852×10^8	4.8115×10^8
0.3	4.2698×10^8	4.3125×10^8	4.0012×10^8	4.1314×10^8	4.2991×10^8	4.3115×10^8	4.3556×10^8	4.3778×10^8
0.6	3.9621×10^8	4.0023×10^8	3.7326×10^8	3.8732×10^8	3.9785×10^8	3.9963×10^8	3.9936×10^8	4.0021×10^8
0.9	3.2158×10^8	3.3225×10^8	3.1461×10^8	3.2145×10^8	3.2536×10^8	3.2732×10^8	3.3112×10^8	3.3332×10^8
0.99	3.0025×10^8	3.1222×10^8	**2.9321×10^8**	**2.9832×10^8**	3.1322×10^8	3.1632×10^8	3.2366×10^8	3.3262×10^8

Table 8: Sensitivity analysis for $PAR_{\min}$ parameter for various values of HMS and HMCR and $bw_{\min} = 0.1$ obtained from previous stages

	$PAR_{\min}$							
	0.001		0.01		0.1		0.5	
Sytem	Best	Average	Best	Average	Best	Average	Best	Average
(1)	2.7331×10^8	2.7489×10^8	**2.7145×10^8**	**2.7265×10^8**	2.7452×10^8	2.7493×10^8	2.7299×10^8	2.7341×10^8
(2)	2.9045×10^8	2.9141×10^8	**2.8932×10^8**	**2.9001×10^8**	2.9002×10^8	2.9012×10^8	2.9221×10^8	2.9323×10^8

Table 9: Sensitivity analysis for $bw_{\min}$ parameter for various values of HMS, HMCR, and $PAR_{\min}$ obtained from previous stages

	$bw_{\min}$							
	0.0001		0.01		0.1		0.5	
Sytem	Best	Average	Best	Average	Best	Average	Best	Average
(1)	2.6632×10^8	2.6892×10^8	**2.6288×10^8**	**2.6539×10^8**	2.6532×10^8	2.6931×10^8	2.6725×10^8	2.6992×10^8
(2)	2.8931×10^8	2.9013×10^8	**2.8714×10^8**	**2.8999×10^8**	2.8929×10^8	2.9017×10^8	2.8943×10^8	2.9006×10^8

Table 10: The optimal expansion planning for system (1)

Node		Type, size (kW) and location of planned DGs					
		WT	PV	FC	MT	GT	DE
2	OG*	2000	2000	-	-	4000	2000
	PC*	2×1000	20×100	-	-	4×1000	2×1000
3	OG	2000	1000	-	-	4000	2000
	PC	2×1000	10×100	-	-	4×1000	2×1000
4	OG	2000	360	-	-	4000	2000
	PC	2×1000	4×100	-	-	4×1000	2×1000
5	OG	1000	-	-	-	4000	2000
	PC	1×1000	-	-	-	4×1000	2×1000
6	OG	-	1000	-	1000	4000	2000
	PC	-	10×100	-	5×200	4×1000	2×1000
7	OG	2000	1000	-	2000	4000	2000
	PC	2×1000	10×100	-	10×200	4×1000	2×1000
8	OG	-	1000	-	-	4000	2000
	PC	-	10×100	-	-	4×1000	2×1000
9	OG	-	2000	-	-	4000	2000
	PC	-	20×100	-	-	4×1000	2×1000

Investment cost (M$): 130.81	Losses (p.u): 0.00269
Operation cost (M$): 127.04	Substation investment cost (M$): 0
Cost of purchased power (M$): 0	Feeder investment cost (M$): 1.8
Pollution (ton/h): 32.306	Losses without DGs: 0.003492
Cost of planning without DGs (M$): 360.606	TSC (M$): 262.8806
* OG: operating generation (kW)	* PC: planned capacity (kW)

Table 11: The optimal expansion planning for system (2)

Node		Type, size (kW) and location of planned DGs					
		WT	PV	FC	MT	GT	DE
2	OG	2000	2000	-	-	4000	2000
	PC	2×1000	20×100	-	-	4×1000	2×1000
3	OG	2000	1000	-	-	4000	2000
	PC	2×1000	10×100	-	-	4×1000	2×1000
4	OG	2000	360	-	-	4000	2000
	PC	2×1000	4×100	-	-	4×1000	2×1000
5	OG	1000	-	-	2000	4000	2000
	PC	1×1000	-	-	10×200	4×1000	2×1000
6	OG	-	1000	-	1000	4000	2000
	PC	-	10×100	-	5×200	4×1000	2×1000
7	OG	2000	1000	-	2000	4000	2000
	PC	2×1000	10×100	-	10×200	4×1000	2×1000
8	OG	-	1000	-	2000	4000	2000
	PC	-	10×100	-	10×200	4×1000	2×1000
9	OG	-	2000	-	2000	4000	2000
	PC	-	20×100	-	10×200	4×1000	2×1000

Investment cost (M$): 139.81	Losses (p.u):0.00268
Operation cost (M$): 145.5362	Substation investment cost (M$): 0
Cost of purchased power (M$): 0	Feeder investment cost (M$): 1.8
Pollution (ton/h): 36.66	Losses without DGs: : 0.003304
Cost of planning without DGs (M$): 368.136	TSC (M$): 287.1462

Table 12: Installation time of the new lines/feeders, distribution substation and DGs for systems (1) and (2)

System	Year	New line		New substation	Number of DGs					
		From node	To node		WT	PV	FC	MT	GT	DE
(1)	1	6	7	-	-	8	-	3	5	3
		4	5							
	2	-	-	-	1	15	-	3	8	3
	3	-	-	-	2	30	-	2	5	3
	4	-	-	-	3	15	-	4	7	3
	5	-	-	-	2	16	-	3	7	4
(2)	1	6	7	-	1	7	-	5	5	4
		4	5							
	2	-	-	-	1	20	-	12	8	3
	3	-	-	-	3	32	-	15	5	3
	4	-	-	-	3	15	-	10	7	3
	5	-	-	-	1	10	-	3	7	3

Table 13: Voltage of nodes (p.u) in the 9-node-distribution system

Item	Initial system	System (1)	System (2)
Voltage of node (1)	1.0000	1.0000	1.0000
Voltage of node (2)	0.9837	0.9841	0.9842
Voltage of node (3)	0.9551	0.9577	0.9571
Voltage of node (4)	0.9685	0.9863	0.9862
Voltage of node (5)	-	0.9881	0.9852
Voltage of node (6)	0.9852	0.9861	0.9875
Voltage of node (7)	-	0.9771	0.9768
Voltage of node (8)	0.9806	0.9861	0.9867
Voltage of node (9)	0.9642	0.9786	0.9782
Standard deviation of voltage	0.0152	0.0114	0.0116

Table 14: Existing and candidate lines data of the 69-node distribution system

From node (i)	To node (j)	$\lvert Z_{ij}\rvert$	D (kW) Receiving	P_{ij}^{Max}(kW)	C_λ(M$)	From node (i)	To node (j)	$\lvert Z_{ij}\rvert$	D (kW) Receiving	P_{ij}^{Max}(kW)	C_λ(M$)
1	2	0.0013	0	10761	0.35	3	36	0.0117	6	10761	0.35
2	3	0.0013	0	10761	0.35	36	37	0.1691	26	10761	0.35
3	4	0.0039	0	10761	0.35	37	38	0.1619	26	5823	0.32
4	5	0.0387	0	5823	0.14	38	39	0.0467	0	5823	0.32
5	6	0.4107	2.6	1899	0.23	39	40	0.0028	24	5823	0.32
6	7	0.4276	40.4	1899	0.23	40	41	1.1200	24	5823	0.32
7	8	0.1035	75	1899	0.23	41	42	0.4768	1.2	5823	0.32
8	9	0.0553	30	1899	0.23	42	43	0.0630	0	5823	0.32
9	10	0.8626	28	1455	0.16	43	44	0.0148	6	5823	0.32
10	11	0.1972	145	1455	0.16	44	45	0.1752	0	5823	0.32
11	12	0.7492	145	1455	0.16	45	46	0.0015	39.22	6709	0.35
12	13	1.0847	8	1455	0.16	4	47	0.0091	39.22	10761	0.35
13	14	1.0995	8	1455	0.16	47	48	0.2250	0	10761	0.35
14	15	1.1143	0	1455	0.16	48	49	0.7660	79	10761	0.35
15	16	0.2071	45.5	1455	0.16	49	50	0.2173	384.7	10761	0.35
16	17	0.3943	60	1455	0.16	8	51	0.1042	384.7	1899	0.23
17	18	0.0050	60	2200	0.28	51	52	0.3501	40.5	2200	0.28
18	19	0.3450	0	1455	0.16	9	53	0.1953	3.6	1899	0.23
19	20	0.2216	0	1455	0.16	53	54	0.2278	4.35	1899	0.23
20	21	0.3598	1	1455	0.16	54	55	0.3189	26.4	1899	0.23
21	22	0.0147	114	1455	0.16	55	56	0.3157	24	1899	0.23
22	23	0.1607	5	1455	0.16	56	57	1.6772	0	2200	0.28
23	24	0.3647	0	1455	0.16	57	58	0.8267	0	2200	0.28
24	25	0.7886	28	1455	0.16	58	59	0.3204	0	1455	0.16
25	26	0.3253	0	1455	0.16	59	60	0.4035	100	1455	0.16
26	27	0.1824	14	1455	0.16	60	61	0.5695	0	1899	0.23
3	28	0.0117	14	10761	0.35	61	62	0.1093	1244	1899	0.23
28	29	0.1691	26	10761	0.35	62	63	0.1627	32	1899	0.23
29	30	0.4190	26	1455	0.16	63	64	0.7974	0	1899	0.23
30	31	0.0739	0	1455	0.16	64	65	1.1682	227	1899	0.23
31	32	0.3697	0	1455	0.16	11	66	0.2103	59	1455	0.16
32	33	0.8850	0	2200	0.28	66	67	0.0049	18	1455	0.16
33	34	1.7995	14	1455	0.16	12	68	0.7787	18	1455	0.16
34	35	1.5525	19.5	1455	0.16	68	69	0.0050	28	1455	0.16

Table 15: Data of four DG technologies used in the 69-node distribution system

Technology	Unit size (kW)	Installed capacity limit (kW)	Investment cost ($/kW)	Operating cost ($/kWh)	Emission factor (lb/MWh)		
					NO_X	SO_2	CO_2
FC	200	800	10000	1	1.15	0.008	1108
MT	150	600	1100	1.6	0.44	0.008	1596
PV	100	200	6000	0.005	-	-	-
WT	100	200	3500	0.010	-	-	-

Table 16: Sensitivity analysis for HMS and HMCR parameters for $PAR_{min} = 0.4$ and $bw_{min} = 0.1$ in system (3)

	HMS							
	10		25		35		50	
HMCR	Best	Average	Best	Average	Best	Average	Best	Average
0	8.701×10^6	8.709×10^6	8.514×10^6	8.517×10^6	8.295×10^6	8.299×10^6	8.458×10^6	8.462×10^6
0.3	8.547×10^6	8.553×10^6	8.309×10^6	8.313×10^6	8.287×10^6	8.291×10^6	8.447×10^6	8.451×10^6
0.6	8.509×10^6	8.514×10^6	8.293×10^6	8.302×10^6	8.271×10^6	8.277×10^6	8.433×10^6	8.439×10^6
0.9	8.485×10^6	8.489×10^6	8.285×10^6	8.289×10^6	8.263×10^6	8.268×10^6	8.407×10^6	8.411×10^6
0.99	8.463×10^6	8.501×10^6	8.275×10^6	8.279×10^6	$\mathbf{8.252\times10^6}$	$\mathbf{8.257\times10^6}$	8.401×10^6	8.408×10^6

Table 17: Sensitivity analysis for HMS and HMCR parameters for $PAR_{min} = 0.4$ and $bw_{min} = 0.1$ in system (4)

	HMS							
	10		25		35		50	
HMCR	Best	Average	Best	Average	Best	Average	Best	Average
0	8.448×10^6	8.452×10^6	8.423×10^6	8.428×10^6	8.417×10^6	8.419×10^6	8.411×10^6	8.413×10^6
0.3	8.426×10^6	8.429×10^6	8.409×10^6	8.414×10^6	8.402×10^6	8.406×10^6	8.406×10^6	8.409×10^6
0.6	8.417×10^6	8.421×10^6	8.402×10^6	8.406×10^6	8.394×10^6	8.399×10^6	8.398×10^6	8.401×10^6
0.9	8.409×10^6	8.413×10^6	8.396×10^6	8.399×10^6	8.388×10^6	8.389×10^6	8.392×10^6	8.394×10^6
0.99	8.401×10^6	8.404×10^6	8.391×10^6	8.393×10^6	$\mathbf{8.382\times10^6}$	$\mathbf{8.384\times10^6}$	8.387×10^6	8.391×10^6

Table 18: Sensitivity analysis for PAR_{min} parameter for various values and $bw_{min} = 0.1$, HMS, and HMCR obtained from previous stages

	PAR_{min}							
	0.001		0.01		0.1		0.5	
Sytem	Best	Average	Best	Average	Best	Average	Best	Average
(3)	7.841×10^6	7.846×10^6	$\mathbf{7.826\times10^6}$	$\mathbf{7.829\times10^6}$	7.837×10^6	7.841×10^6	7.872×10^6	7.876×10^6
(4)	7.942×10^6	7.944×10^6	$\mathbf{7.921\times10^6}$	$\mathbf{7.923\times10^6}$	7.937×10^6	7.939×10^6	7.943×10^6	7.944×10^6

Table 19: Sensitivity analysis for bw_{min} parameter for various values HMS, HMCR and PAR_{min} obtained from previous stages

	bw_{min}							
	0.0001		0.01		0.1		0.5	
Sytem	Best	Average	Best	Average	Best	Average	Best	Average
(3)	7.679×10^6	7.685×10^6	$\mathbf{7.673\times10^6}$	$\mathbf{7.677\times10^6}$	7.682×10^6	7.687×10^6	7.692×106	7.697×10^6
(4)	7.855×10^6	7.857×10^6	$\mathbf{7.836\times10^6}$	$\mathbf{7.838\times10^6}$	7.842×10^6	7.843×10^6	7.848×106	7.849×10^6

Table 20: The optimal expansion planning for systems (3) and (4)

System (3)						System (4)					
Node		Type, size (kW) and location of planned DGs				Node		Type, size (kW) and location of planned DGs			
		WT	PV	FC	MT			WT	PV	FC	MT
35	OG	-	-	9	-	35	OG	-	-	15	-
	PC	-	-	1×50	-		PC	-	-	1×50	-
67	OG	-	-	91	-	67	OG	-	-	93	-
	PC	-	-	2×50	-		PC	-	-	2×50	-
44	OG	-	-	60	-	44	OG	-	-	60	-
	PC	-	-	2×50	-		PC	-	-	2×50	-
10	OG	-	-	54	-	10	OG	-	-	62	-
	PC	-	-	2×50	-		PC	-	-	2×50	-
34	OG	-	-	-	83	34	OG	-	-	-	117
	PC	-	-	-	1×150		PC	-	-	-	1×150
13	OG	-	-	-	147	13	OG	-	-	-	147
	PC	-	-	-	1×150		PC	-	-	-	1×150
28	OG	-	-	-	107	28	OG	-	-	-	115
	PC	-	-	-	1×150		PC	-	-	-	1×150
68	OG	-	-	-	131	68	OG	-	-	-	133
	PC	-	-	-	1×150		PC	-	-	-	1×150
9	OG	-	59	-	-	8	OG	-	72	-	-
	PC	-	1×100	-	-		PC	-	1×100	-	-
66	OG	-	70	-	-	66	OG	-	81	-	-
	PC	-	1×100	-	-		PC	-	1×100	-	-
43	OG	99	-	-	-	43	OG	100	-	-	-
	PC	1×100	-	-	-		PC	1×100	-	-	-
19	OG	92	-	-	-	19	OG	100	-	-	-
	PC	1×100	-	-	-		PC	1×100	-	-	-
Investment cost (M$): 1.9165						Investment cost (M$): 1.9294					
Operation cost (M$): 3.5591						Operation cost (M$): 3.5832					
Pollution function: 7611.4062						Pollution function: 7712.32					
Losses (kW): 102.7065						Losses (kW): 101.0362					
Substation investment cost (M$): 0						Substation investment cost (M$): 0					
Feeder investment cost (M$): 0						Feeder investment cost (M$): 0					
Losses without DGs (kW): 121.273						Losses without DGs (kW): 121.273					
TSC (M$) (with respect to COL, ICD, OCD): 5.4756						TSC (M$) (with respect to COL, ICD, OCD): 5.5126					

Table 21: Voltage of nodes (p.u) in the 69-node-distribution system

Node voltage	Initial system	System (3)	System (4)	Node voltage	Initial system	System (3)	System (4)
1	1.0000	1.0000	1.0000	35	0.9837	0.9768	0.9852
2	0.9542	0.9768	0.9893	36	0.9542	0.9846	0.9842
3	0.9852	0.9867	0.9877	37	0.9837	0.9574	0.9862
4	0.9675	0.9782	0.9874	38	0.9551	0.9863	0.9847
5	0.9806	0.9574	0.9675	39	0.9685	0.9846	0.9875
6	0.9542	0.9768	0.9806	40	0.9675	0.9574	0.9768
7	0.9837	0.9768	0.9642	41	0.9806	0.9863	0.9846
8	0.9551	0.9867	0.9837	42	0.9642	0.9883	0.9852
9	0.9685	0.9846	0.9542	43	0.9542	0.9878	0.9875
10	0.9542	0.9574	0.9837	44	0.9837	0.9846	0.9842
11	0.9852	0.9863	0.9551	45	0.9551	0.9574	0.9842
12	0.9675	0.9768	0.9675	46	0.9685	0.9863	0.9571
13	0.9806	0.9867	0.9842	47	0.9542	0.9883	0.9862
14	0.9642	0.9782	0.9803	48	0.9542	0.9878	0.9675
15	0.9837	0.9862	0.9852	49	0.9837	0.9846	0.9806
16	0.9542	0.9852	0.9863	50	0.9837	0.9574	0.9642
17	0.9837	0.9875	0.9881	51	0.9542	0.9863	0.9837
18	0.9551	0.9768	0.9868	52	0.9837	0.9862	0.9542
19	0.9685	0.9846	0.9852	53	0.9551	0.9852	0.9837
20	0.9542	0.9574	0.9732	54	0.9685	0.9875	0.9675
21	0.9837	0.9863	0.9877	55	0.9542	0.9883	0.9806
22	0.9542	0.9883	0.9862	56	0.9542	0.9867	0.9642
23	0.9837	0.9878	0.9862	57	0.9837	0.9862	0.9837
24	0.9551	0.9846	0.9867	58	0.9542	0.9852	0.9542
25	0.9685	0.9574	0.9851	59	0.9837	0.9883	0.9868
26	0.9542	0.9862	0.9675	60	0.9551	0.9574	0.9877
27	0.9542	0.9852	0.9806	61	0.9685	0.9883	0.9862
28	0.9642	0.9875	0.9642	62	0.9542	0.9846	0.9768
29	0.9837	0.9768	0.9837	63	0.9542	0.9574	0.9667
30	0.9542	0.9867	0.9571	64	0.9852	0.9863	0.9782
31	0.9852	0.9862	0.9862	65	0.9675	0.9883	0.9862
32	0.9675	0.9852	0.9848	66	0.9806	0.9878	0.9868
33	0.9806	0.9875	0.9862	67	0.9542	0.9846	0.9744
34	0.9542	0.9768	0.9842	68	0.9837	0.9574	0.9862

Standard deviation of voltage without DGs: 0.0133
Standard deviation of voltage in system (3): 0.0110
Standard deviation of voltage in system (4): 0.0107

Table 22: Load data of part of Farhangian-Kangavar distribution grid

Node	2	3	4	5	6	7	8	9	10
Load (kW)	90	115	120	120	115	112	110	100	130
Node	11	12	13	14	15	16	17	18	19
Load (kW)	100	100	110	85	75	85	65	120	125
Node	20	21	22	23	24	25	26	27	28
Load (kW)	125	130	130	130	120	140	9	5 100	135
Node	29	30	31	32	33	34	35	36	37
Load (kW)	80	90	110	115	120	120	115	115	130

Table 23: Sensitivity analysis for HMS and HMCR parameters for $PAR_{\min} = 0.4$ and $bw_{\min} = 0.1$ in system (5)

	HMS							
	10		25		35		50	
HMCR	Best	Average	Best	Average	Best	Average	Best	Average
0	0.2003×10^8	0.2009×10^8	0.1997×10^8	0.2003×10^8	0.1992×10^8	0.1998×10^8	0.1992×10^8	0.1997×10^8
0.3	0.1965×10^8	0.1971×10^8	0.1974×10^8	0.2003×10^8	0.1925×10^8	0.1947×10^8	0.1965×10^8	0.1668×10^8
0.6	0.1902×10^8	0.1908×10^8	0.1935×10^8	0.2003×10^8	0.1892×10^8	0.1902×10^8	0.1923×10^8	0.1929×10^8
0.9	0.1823×10^8	0.1831×10^8	0.1882×10^8	0.2003×10^8	0.1832×10^8	0.1893×10^8	0.1863×10^8	0.1870×10^8
0.99	0.1795×10^8	0.1798×10^8	0.1796×10^8	0.1799×10^8	$\mathbf{0.1761\times10^8}$	$\mathbf{0.1785\times10^8}$	0.1794×10^8	0.1797×10^8

Table 24: Sensitivity analysis for HMS and HMCR parameters for $PAR_{\min} = 0.4$ and $bw_{\min} = 0.1$ in system (6)

	HMS							
	10		25		35		50	
HMCR	Best	Average	Best	Average	Best	Average	Best	Average
0	0.2013×10^8	0.2015×10^8	0.2018×10^8	0.2020×10^8	0.2017×10^8	0.2019×10^8	0.2021×10^8	0.2023×10^8
0.3	0.2009×10^8	0.2011×10^8	0.2011×10^8	0.2014×10^8	0.2011×10^8	0.2014×10^8	0.2016×10^8	0.2019×10^8
0.6	0.2005×10^8	0.2007×10^8	0.2007×10^8	0.2009×10^8	0.2002×10^8	0.2005×10^8	0.2010×10^8	0.2014×10^8
0.9	0.2002×10^8	0.2003×10^8	0.2001×10^8	0.2003×10^8	0.1997×10^8	0.2001×10^8	0.2002×10^8	0.2004×10^8
0.99	0.1997×10^8	0.1999×10^8	0.1996×10^8	0.1998×10^8	$\mathbf{0.1995\times10^8}$	$\mathbf{0.1999\times10^8}$	0.1998×10^8	0.2002×10^8

Table 25: Sensitivity analysis for $PAR_{\min}$ parameter for various values and $bw_{\min}$, HMS, and HMCR obtained from previous stages

	$PAR_{\min}$							
	0.001		0.01		0.1		0.5	
Sytem	Best	Average	Best	Average	Best	Average	Best	Average
(5)	$\mathbf{0.1747\times10^8}$	$\mathbf{0.1751\times10^8}$	0.1749×10^8	0.1754×10^8	0.1753×10^8	0.1759×10^8	0.1759×10^8	0.1762×10^8
(6)	$\mathbf{0.1982\times10^8}$	$\mathbf{0.1983\times10^8}$	0.1984×10^8	0.1986×10^8	0.1987×108	0.1989×10^8	0.1989×10^8	0.1991×10^8

Table 26: Sensitivity analysis for $bw_{\min}$ parameter for various values HMS, HMCR, and $PAR_{\min}$ obtained from previous stages

	$bw_{\min}$							
	0.0001		0.01		0.1		0.5	
Sytem	Best	Average	Best	Average	Best	Average	Best	Average
(5)	$\mathbf{0.1731\times10^8}$	$\mathbf{0.1732\times10^8}$	0.1738×10^8	0.1740×10^8	0.1742×10^8	0.1744×10^8	0.1748×10^8	0.1751×10^8
(6)	$\mathbf{0.1979\times10^8}$	$\mathbf{0.1980\times10^8}$	0.1980×10^8	0.1982×10^8	0.1982×10^8	0.1983×10^8	0.1985×10^8	0.1987×10^8

Table 27: The optimal expansion planning for system (5)

Node		Type, size (kW) and location of planned DGs					
		WT	PV	FC	MT	GT	DE
a	OG	-	-	-	-	-	2000
	PC	-	-	-	-	-	2×1000
b	OG	1000	-	-	-	-	-
	PC	1×1000	-	-	-	-	-
c	OG	-	-	-	-	-	2000
	PC	-	-	-	-	-	2×1000
d	OG	-	-	-	-	-	1000
	PC	-	-	-	-	-	1×1000

Investment cost (M$): 7	Losses (p.u): 0.0011199
Operation cost (M$): 10.3062	Substation investment cost (M$): 0
Cost of purchased power (M$): 0.0025	Feeder investment cost (M$): 0
Pollution (ton/h): 3.1577	Losses without DGs (p.u): 0.001162
Cost of planning without DGs (M$): 24.329	TSC (M$): 17.3087

Table 28: The optimal expansion planning for system (6)

Node		Type, size (kW) and location of planned DGs					
		WT	PV	FC	MT	GT	DE
a	OG	2000	-	-	-	-	1000
	PC	2×1000	-	-	-	-	1×1000
b	OG	-	-	-	-	-	-
	PC	-	-	-	-	-	-
c	OG	-	-	-	-	-	2000
	PC	-	-	-	-	-	2×1000
d	OG	-	-	-	-	-	1000
	PC	-	-	-	-	-	1×1000
Investment cost (M$): 11				Losses (p.u): 0.0011227			
Operation cost (M$): 8.7864				Substation investment cost (M$): 0			
Cost of purchased power (M$):0.0025				Feeder investment cost (M$): 0			
Pollution (ton/h): 2.5262				Losses without DGs (p.u): 0.001154			
Cost of planning without DGs (M$): 26.731				TSC (M$): 19.7889			

Table 29: The installation time of the new lines/feeders, distribution substation, and DGs for systems (5) and (6)

System	Year	New line		New substation	Number of DGs					
		From node	To node		WT	PV	FC	MT	GT	DE
(5)	1	-	-	-	1	-	-	-	-	1
	2	-	-	-	-	-	-	-	-	1
	3	-	-	-	-	-	-	-	-	1
	4	-	-	-	-	-	-	-	-	1
	5	-	-	-	-	-	-	-	-	1
(6)	1	-	-	-	2	-	-	-	-	-
	2	-	-	-	-	-	-	-	-	1
	3	-	-	-	-	-	-	-	-	1
	4	-	-	-	-	-	-	-	-	1
	5	-	-	-	-	-	-	-	-	1

Table 30: Voltage of nodes (p.u) in the Farhangian-Kangavar distribution system

Item	Initial system	System (5)	System (6)
Voltage of node (a)	0.9858	0.9843	0.9842
Voltage of node (b)	0.9778	0.9743	0.9745
Voltage of node (c)	0.9712	0.9734	0.9734
Voltage of node (d)	0.9675	0.9683	0.9691
Standard deviation of voltage	0.0080	0.0067	0.0064

Table 31: Sensitivity analysis regarding different load levels

Load level		WT	PV	FC	MT	GT	DE	TSC (M$)
System (2)								
Load level		Type, size (MW) and location of planned DGs						TSC (M$)
		WT	PV	FC	MT	GT	DE	
50%	*TPC	–	–	–	–	3,4,2,3,3,3,3,3	2,2,2,2,2,2,2,2	213.3621
	Node	–	–	–	–	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
75%	TPC	–	–	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	252.127
	Node	–	–	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
100%	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	287.1462
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
125%	TPC	2,2,2,1,2	2,1,1,1,1,1,2	1,1,1,1	2,2,2,2,2,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	328.3847
	Node	2,3,4,5,7	2,3,4,6,7,8,9	3,4,5,7	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
150%	TPC	2,2,2,2,2,3	2,2,2,2,2,2,2,2	3,3,3,3,3,3,3,3	2,2,2,2,2,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	359.6207
	Node	2,3,4,5,6,7	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
System (4)								
Load level		Type, size (kW) and location of planned DGs						TSC (M$)
		WT	PV	FC	MT			
50%	TPC	51	37	8,56,23,18	74,93,89,91			2.7963
	Node	43	8	35,67,44,10	34,13,28,68			
75%	TPC	85	72	11,87,51,56	114,137,112,126			3.8856
	Node	43	8	35,67,44,10	34,13,28,68			
100%	TPC	100,100	72,81	15,93,60,62	117,147,115,133			5.5126
	Node	43,19	8,66	35,67,44,10	34,13,28,68			
125%	TPC	118,114	84,112	35,107,73,85	142,178,148,162			7.153
	Node	43,19	8,66	35,67,44,10	34,13,28,68			
150%	TPC	152,142	115,133	43,124,94,85	168,196,178,191			8.6374
	Node	43,19	8,66	35,67,44,10	34,13,28,68			
System (6)								
Load level		Type, size (MW) and location of planned DGs						TSC (M$)
		WT	PV	FC	MT	GT	DE	
50%	TPC	–	–	–	–	–	1,2,1	8.1125
	Node	–	–	–	–	–	“a”, “c”, “d”	
75%	TPC	–	–	–	–	–	1,2,1	14.3642
	Node	–	–	–	–	–	“a”, “c”, “d”	
100%	TPC	2	–	–	–	–	1,2,1	19.7889
	Node	“a”	–	–	–	–	“a”, “c”, “d”	
125%	TPC	2	–	–	–	1,1	1,2,1	24.2863
	Node	“a”	–	–	–	“a”, “b”	“a”, “c”, “d”	
150%	TPC	2	–	–	–	1,1,1,1	1,2,1	28.3155
	Node	“a”	–	–	–	“a”, “b”, “c”, “d”	“a”, “c”, “d”	

*TPC: Total planned capacity

Table 32: Sensitivity analysis regarding different electricity prices

System (2)								
Price ($/MWh)		Type, size (MW) and location of planned DGs WT	PV	FC	MT	GT	DE	Investment cost (M$)
10	TPC	–	–	–	–	–	2,1,2,2,2,2,2,2	7.5
	Node	–	–	–	–	–	2,3,4,5,6,7,8,9	
40	TPC	–	–	–	2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	41.2
	Node	–	–	–	5,7	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
85	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	87.7
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
100	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	87.7
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
System (4)								
Price ($/MWh)		Type, size (kW) and location of planned DGs WT	PV	FC	MT			TSC cost (M$)
10	TPC	–	–	–	47,85			0.5032
	Node	–	–	–	34,13			
30	TPC	–	–	12	114,136,128			1.7262
	Node	–	–	35	34,13,68			
70	TPC	100,100	72,81	15,93,60,62	117,147,115,133			5.5126
	Node	43,19	8,66	35,67,44,10	34,13,28,68			
100	TPC	108,106	79,96	28,102,71,68	119,158,119,141			6.5525
	Node	43,19	8,66	35,67,44,10	34,13,28,68			
System (6)								
Price ($/MWh)		Type, size (MW) and location of planned DGs WT	PV	FC	MT	GT	DE	Investment cost (M$)
10	TPC	–	–	–	–	–	1,1	1
	Node	–	–	–	–	–	"a", "d"	
35	TPC	–	–	–	–	–	1,1,1	1.5
	Node	–	–	–	–	–	"a", "c", "d"	
70	TPC	2	–	–	–	–	1,2,1	11
	Node	"a"	–	–	–	–	"a", "c", "d"	
100	TPC	2,1	–	–	–	–	2,2,2	16.5
	Node	"a", "c"	–	–	–	–	"a", "c", "d"	

Table 33: Sensitivity analysis regarding different DGs cost levels

DGs cost		WT	PV	FC	MT	GT	DE	TSC (M$)
System (2)								
		Type, size (MW) and location of planned DGs						
110%	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	301.1142
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
120%	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	315.3252
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
140%	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	346.2526
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
150%	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	359.1225
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
System (4)								
DGs cost		Type, size (kW) and location of planned DGs						TSC (M$)
		WT	PV	FC	MT			
110%	TPC	100,100	72,81	15,93,60,62	117,147,115,133			6.8184
	Node	43,19	8,66	35,67,44,10	34,13,28,68			
120%	TPC	100,100	72,81	15,93,60,62	117,147,115,133			8.1614
	Node	43,19	8,66	35,67,44,10	34,13,28,68			
140%	TPC	100,100	72,81	15,93,60,62	117,147,115,133			11.0126
	Node	43,19	8,66	35,67,44,10	34,13,28,68			
150%	TPC	100,100	72,81	15,93,60,62	117,147,115,133			12.6331
	Node	43,19	8,66	35,67,44,10	34,13,28,68			
System (6)								
DGs cost		Type, size (MW) and location of planned DGs						TSC (M$)
		WT	PV	FC	MT	GT	DE	
110%	TPC	2	–	–	–	–	1,2,1	21.4337
	Node	"a"	–	–	–	–	"a", "c", "d"	
120%	TPC	2	–	–	–	–	1,2,1	23.7421
	Node	"a"	–	–	–	–	"a", "c", "d"	
140%	TPC	2	–	–	–	–	1,2,1	26.5332
	Node	"a"	–	–	–	–	"a", "c", "d"	
150%	TPC	2	–	–	–	–	1,2,1	28.8774
	Node	"a"	–	–	–	–	"a", "c", "d"	

Table 34: Sensitivity analysis regarding different distribution substation cost levels

System (2)

Substation cost		Type, size (MW) and location of planned DGs						TSC (M$)
		WT	PV	FC	MT	GT	DE	
90%	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	287.1462
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
80%	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	287.1462
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
60%	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	287.1462
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	
50%	TPC	2,2,2,1,2	2,1,1,1,1,1,2	–	2,1,2,2,2	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	287.1462
	Node	2,3,4,5,7	2,3,4,6,7,8,9	–	5,6,7,8	2,3,4,5,6,7,8,9	2,3,4,5,6,7,8,9	

System (4)

Substation cost		Type, size (kW) and location of planned DGs				TSC (M$)
		WT	PV	FC	MT	
90%	TPC	100,100	72,81	15,93,60,62	117,147,115,133	5.5126
	Node	43,19	8,66	35,67,44,10	34,13,28,68	
80%	TPC	100,100	72,81	15,93,60,62	117,147,115,133	5.5126
	Node	43,19	8,66	35,67,44,10	34,13,28,68	
60%	TPC	100,100	72,81	15,93,60,62	117,147,115,133	5.5126
	Node	43,19	8,66	35,67,44,10	34,13,28,68	
50%	TPC	100,100	72,81	15,93,60,62	117,147,115,133	5.5126
	Node	43,19	8,66	35,67,44,10	34,13,28,68	

System (6)

Substation cost		Type, size (MW) and location of planned DGs						TSC (M$)
		WT	PV	FC	MT	GT	DE	
90%	TPC	2	–	–	–	–	1,2,1	19.7889
	Node	“a”	–	–	–	–	“a”, “c”, “d”	
80%	TPC	2	–	–	–	–	1,2,1	19.7889
	Node	“a”	–	–	–	–	“a”, “c”, “d”	
60%	TPC	2	–	–	–	–	1,2,1	19.7889
	Node	“a”	–	–	–	–	“a”, “c”, “d”	
50%	TPC	2	–	–	–	–	1,2,1	19.7889
	Node	“a”	–	–	–	–	“a”, “c”, “d”	

Table 35: Comparison of proposed method for systems (1) and (2) in the first year with other studies

Item	Expansion cost of DGs cost of DGs(M\$/year)	Losses (p.u)	Number of violations in bus voltage constraint (constraint Eq. (10))	Number of violations in line flow constraint (constraint Eq. (12))	Type of DGs	Pollution
System (1)	11.4	0.00269	0	0	specified	✓
System (2)	12.1	0.00268	0	0	specified	✓
Ref. [63]	13.51	0.00270	2	1	Non-specified	–
Ref. [64]	12.39	0.00427	1	2	Non-specified	–

Table 36: A comparison of proposed algorithm with other evolutionary algorithms in systems (3) and (4)

Item	TSC (\$)	Pollution function	Losses function (kW)
Proposed (IHSA) (System (3))	5.475672×10^6	7611.4062	102.7065
Proposed (IHSA) (System (4))	5.512662×10^6	7712.32	101.0362
SFLA-DE [22]	5.565571×10^6	7739.82	109.4382
MSFLA [22]	5.565579×10^6	7786.06	111.0418
SFLA [22]	5.565620×10^6	8011.92	119.8061
PSO [67]	5.565716×10^6	8082.01	120.44
GA [68]	5.565744×10^6	8110.22	121.08

Table 37: A comparison of losses function for different algorithms in system (3)

Item	Losses function	Type of DGs
Proposed (IHSA)	102.7065	WT-MT-FC-PV
MHBMO [69]	121.9012	FC with CHP
GA [68]	129.5982	-
PSO [67]	128.9817	-
HBMO [69]	127.5179	-
MHBMO [69]	125.4165	FC-WT-PV

Table 38: A comparison of proposed algorithm with other evolutionary algorithms and historical expansion plan in systems (5) and (6)

	TSC (M\$)	
	System (5)	System (6)
IHSA	17.3087	19.7889
PSO	17.3225	19.8092
GA	17.3201	19.8217
Historical expansion plan [70]	26.928	-

Table 39: Number of constraints, variables and computation time in the proposed algorithm and other ones

System	Number of constraints	Number of variables	Computational time (sec)		
			IHSA	PSO	GA
(1)	519	710	68.6	71.2	75.6
(2)	519	710	82.3	85.4	88.7
(3)	496	777	69.9	72.6	75.9
(4)	496	777	82.1	87.2	91.9
(5)	875	990	81.7	83.3	86.9
(6)	875	990	96.4	98.8	103.4

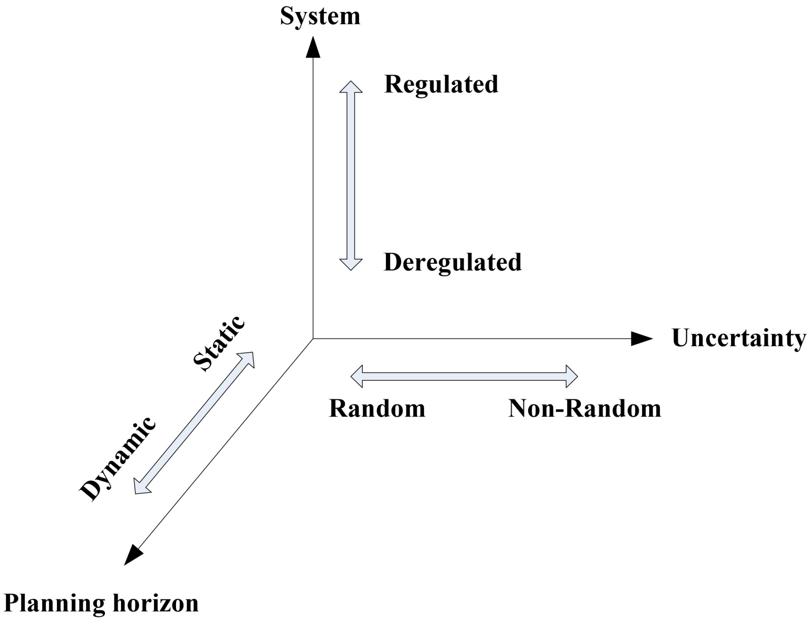

Figure 1: Aspects of the DNEP problem

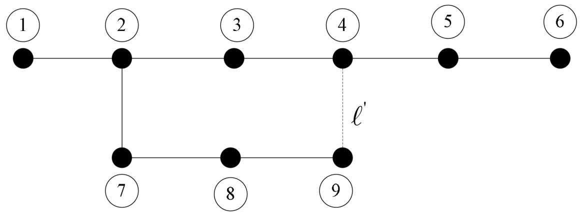

Figure 2: A sample of 9-node network

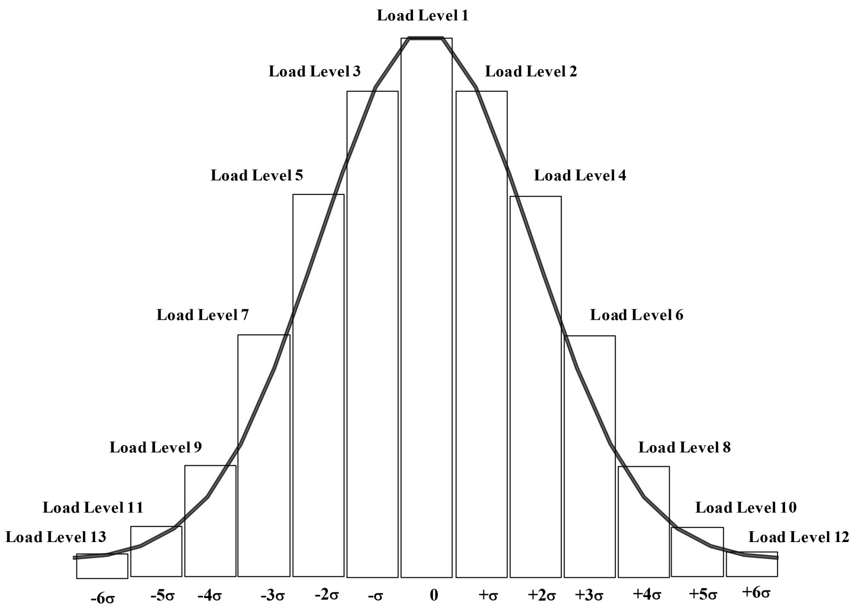

Figure 3: Load approximation with discontinuous normal PDF

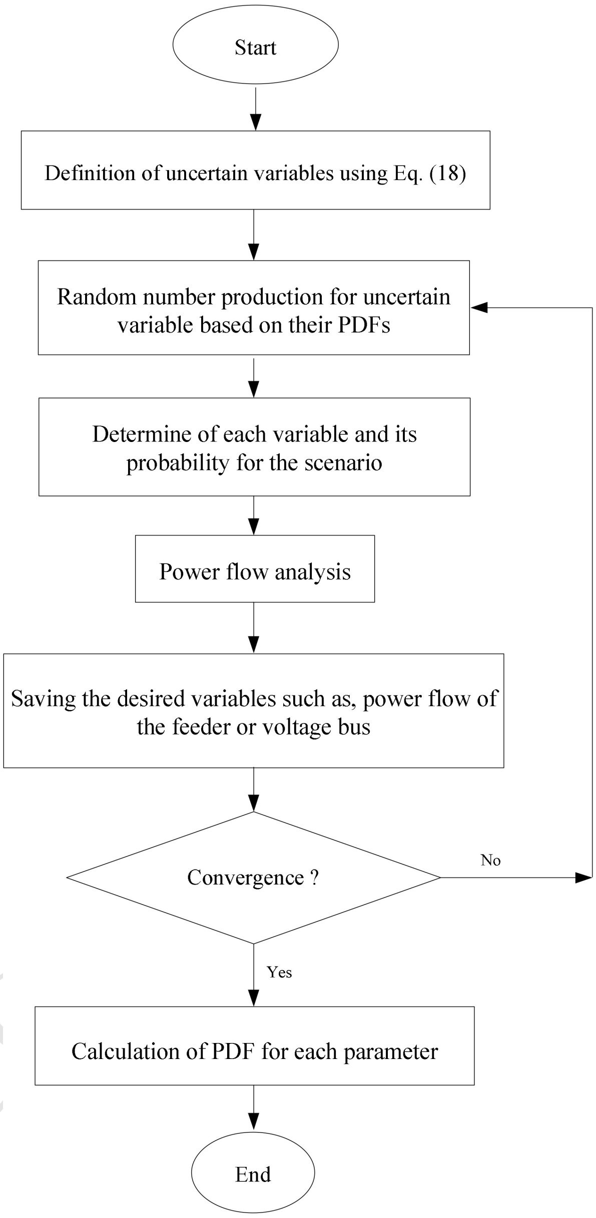

Figure 4: The flowchart of the proposed MCS

Algorithm Pseudo code of the Harmony Search Algorithm

Begin HSA
Define fitness function $fitness(x)=f(x)$, $x=(x_1,x_2,\ldots,x_N)$
Define the lower and upper boundaries: ***LB,UB***
Set algorithm parameters: harmony memory size (HMS),
harmony memory consideration rate ($HMCR$),
pitch adjustment rate (PAR) and the bandwidth (BW),
set maximum number of iteration NI,
HM$\leftarrow$ Generate initial population
Set $t=0$
while $t < NI$ *do*
    for $j=1$ *to* N / *N denotes the number of variables * / **do**
        if $r_1 < HMCR$ /*r_1,r_2,r_3 and r_4 are unimormly distributed continious random number between [0,1]*/ **then**
            $x_{jnew}=\boldsymbol{HM}(a,j), a \in \{1,2,\ldots, HMS\}$ / *Choose a value from ***HM*** for j * /
            if $r_2 < PAR$ **then**
                $x_{(j)new}= x_{(j)new.} \pm r_3 \times BW$ / *Pitch adjustment */
            else
                $x_{(j)new}= LB^j + r_4 \times (UB^j - LB^j)$ /*Randomly generate a value*/
            end if
        end if
    end for
    if $fitness\ (x_{new}) \leq worst\ (fitness)(\boldsymbol{HM})$ **then**
    HM$\leftarrow x_{new}$ / *Update the ***HM*** */
    end if
    $t=t+1$
end while
end

Figure 5: The pseudo code of HSA [59]

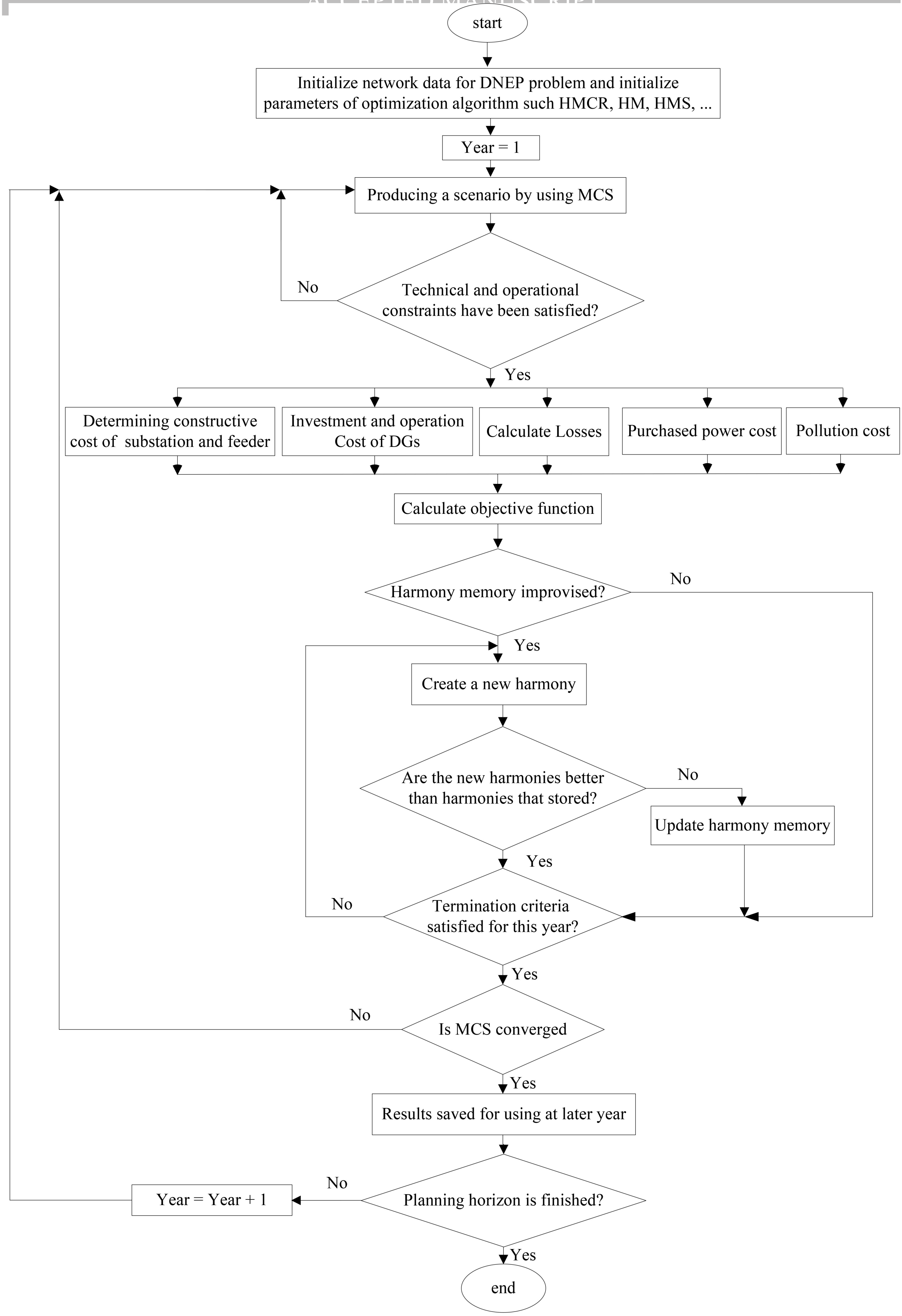

Figure 6: The flowchart of the proposed expansion planning

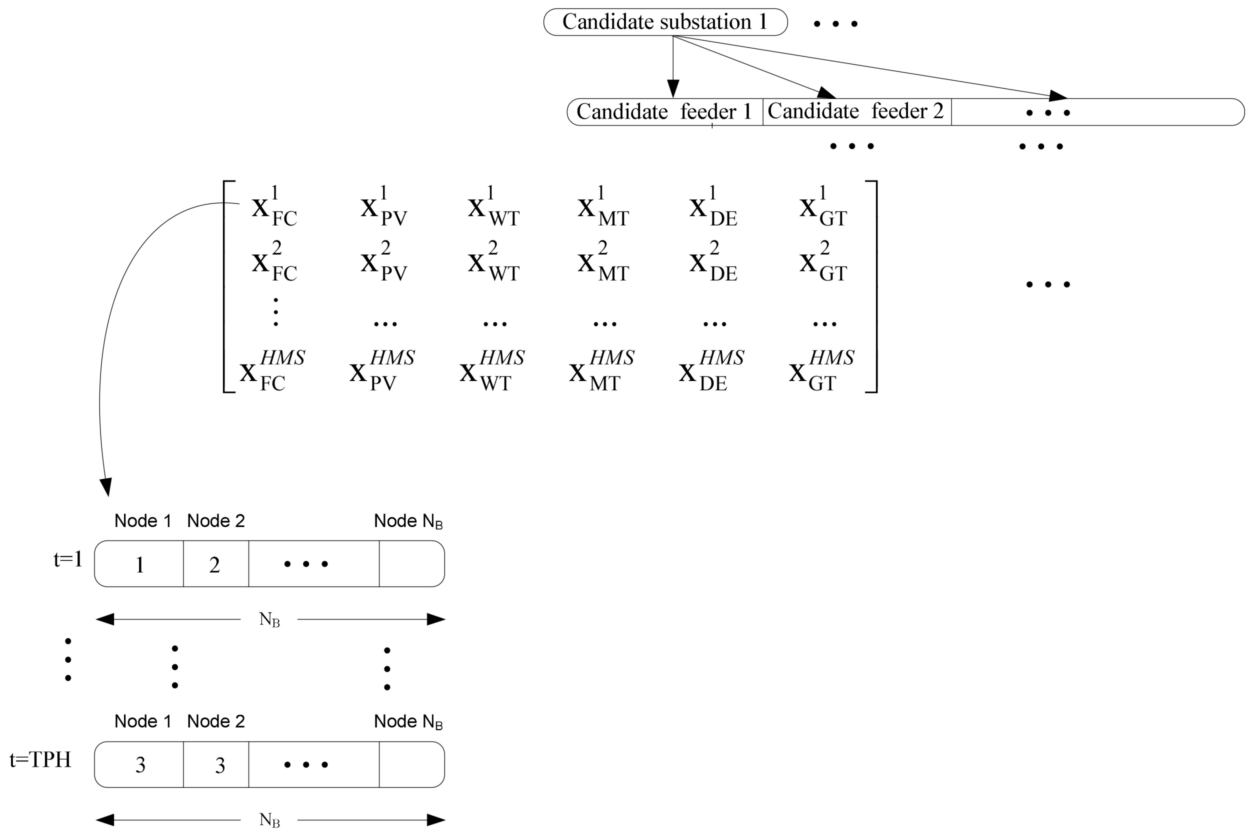

Figure 7: The proposed coding in applied modified HSA

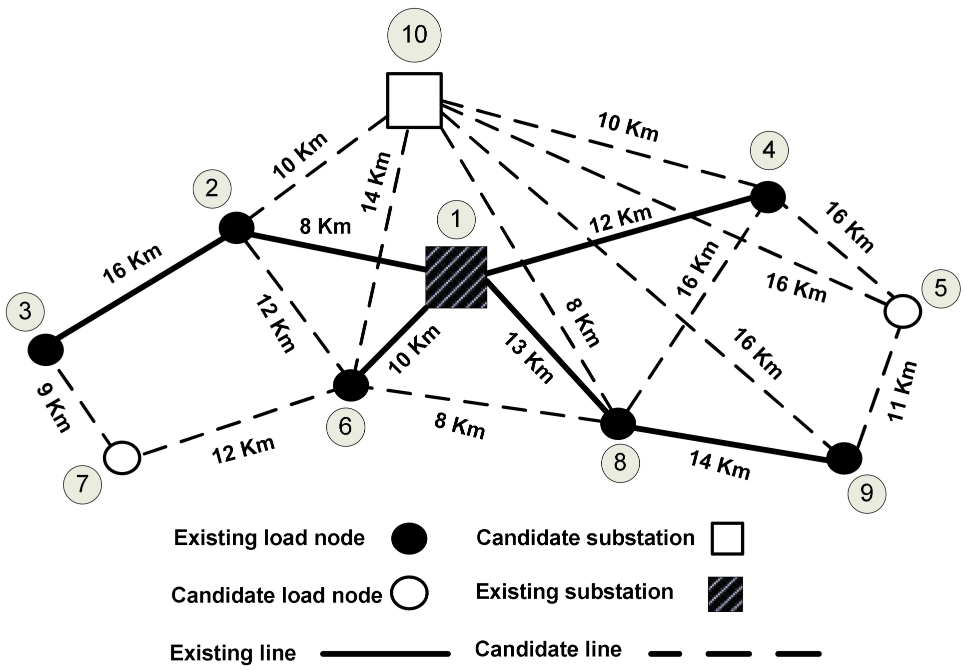

Figure 8: The initial topology of the 9-node primary distribution system

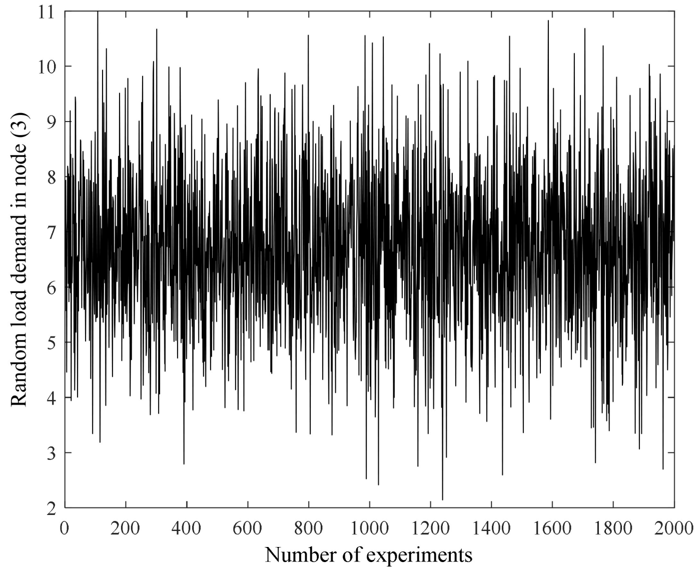

Figure 9: Total random of demand load in system (2) in node (3)

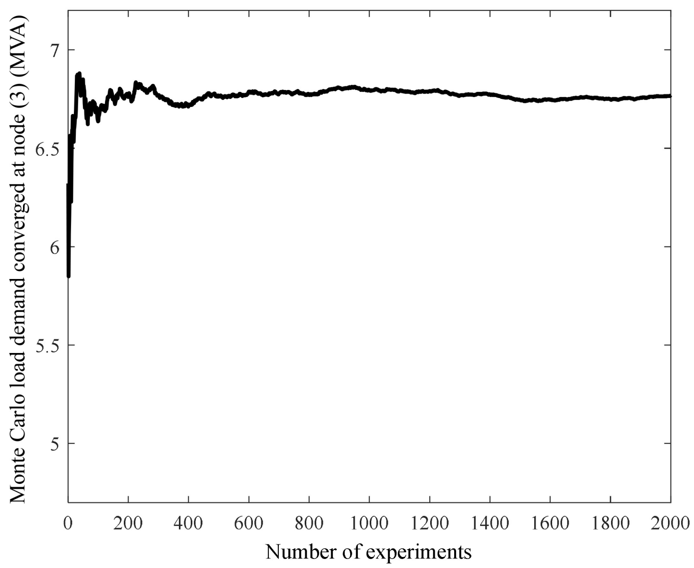

Figure 10: Converged load demand in system (2) in node (3)

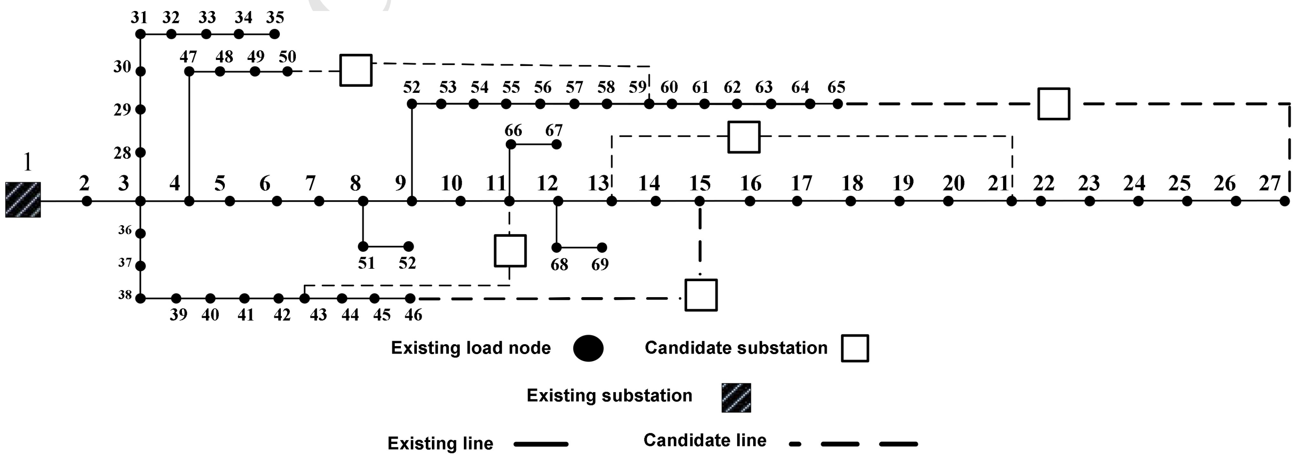

Figure 11: The initial topology of the 69-node distribution system

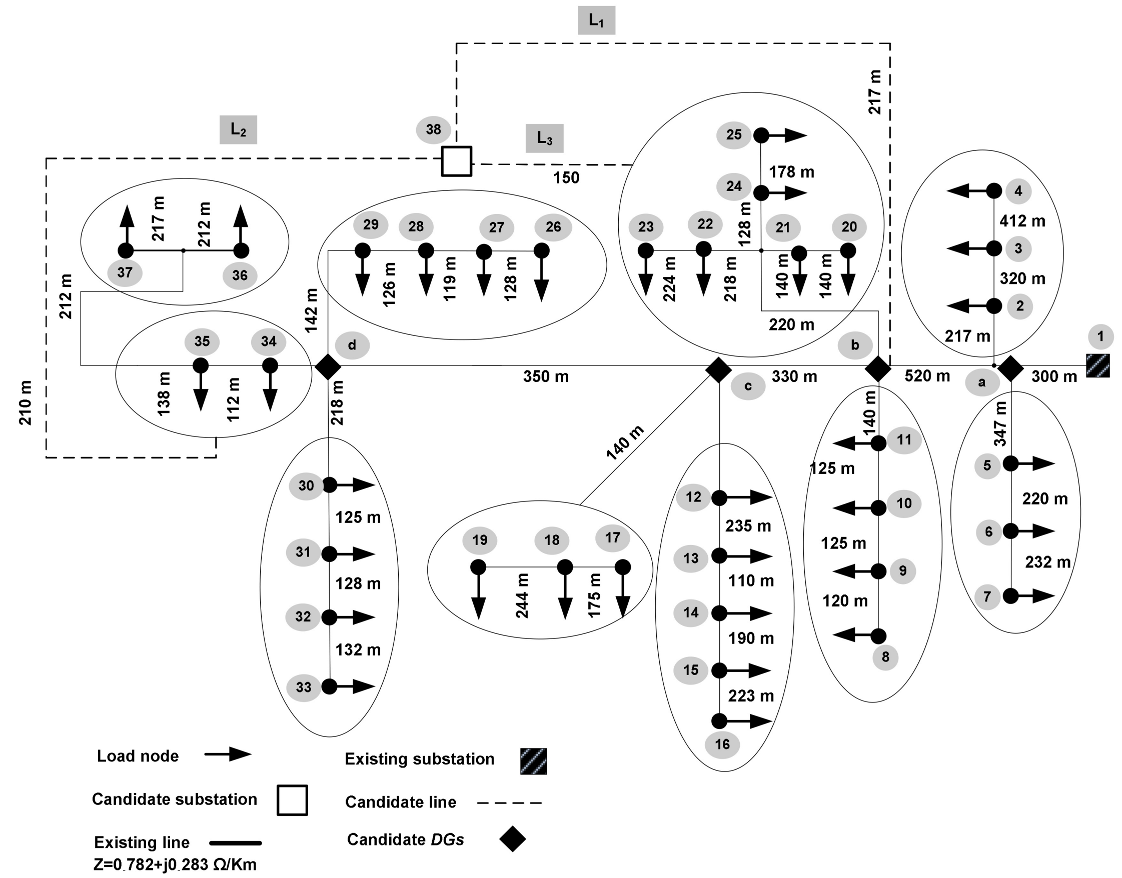

Figure 12: Single line diagram of part of 20 kV distribution network Farhangian-Kangavar

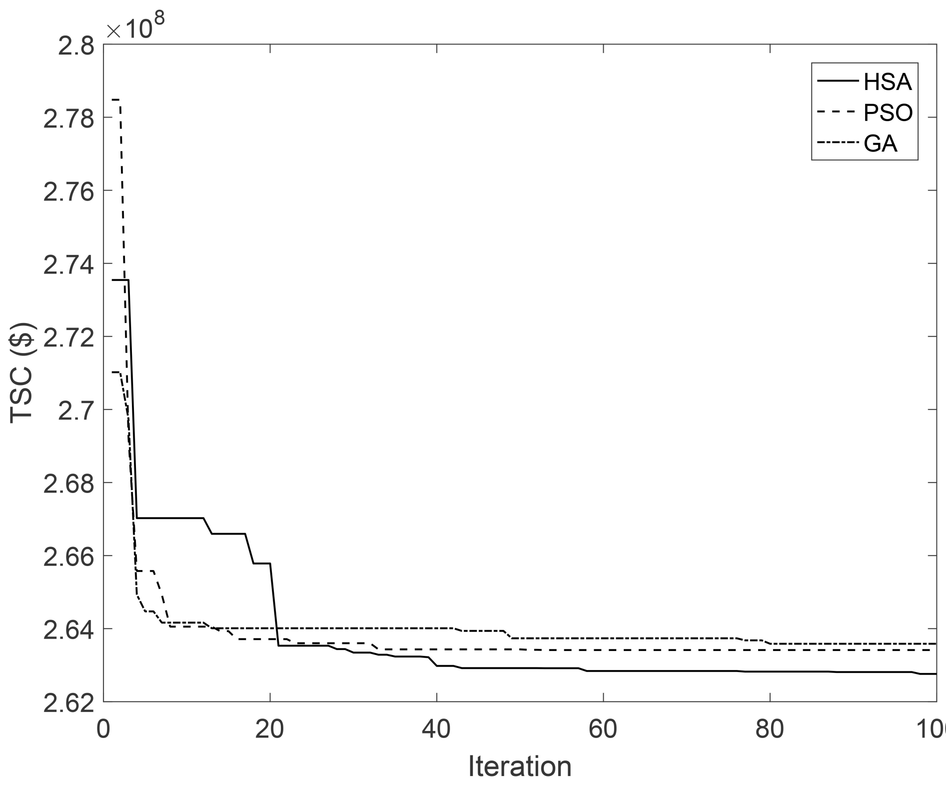

Figure 13: The convergence procedures of IHSA, PSO, and GA for proposed DNEP problem for system (1)

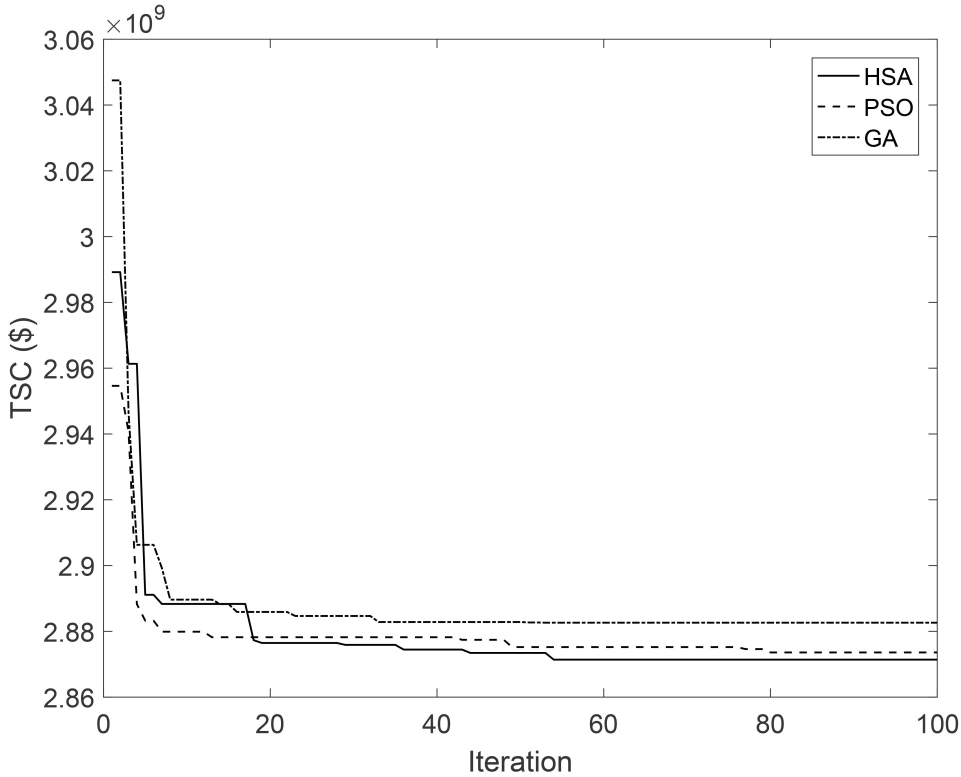

Figure 14: The convergence procedures of IHSA, PSO, and GA for proposed DNEP problem for system (2)

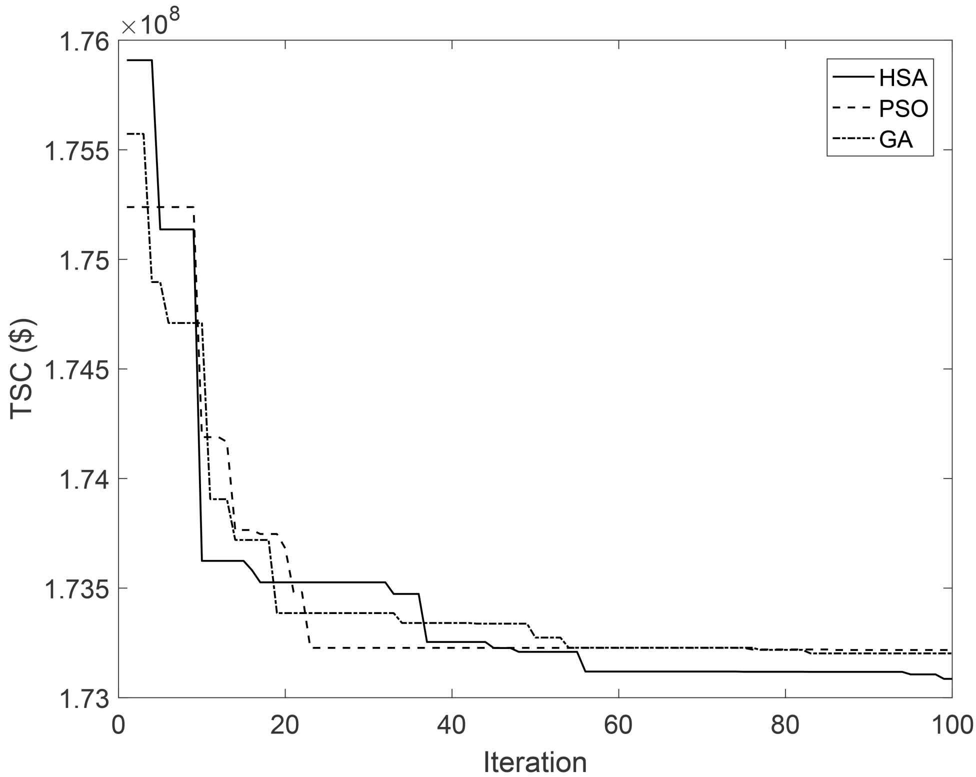

Figure 15: The convergence procedures of IHSA, PSO, GA for proposed DNEP problem for system (5)

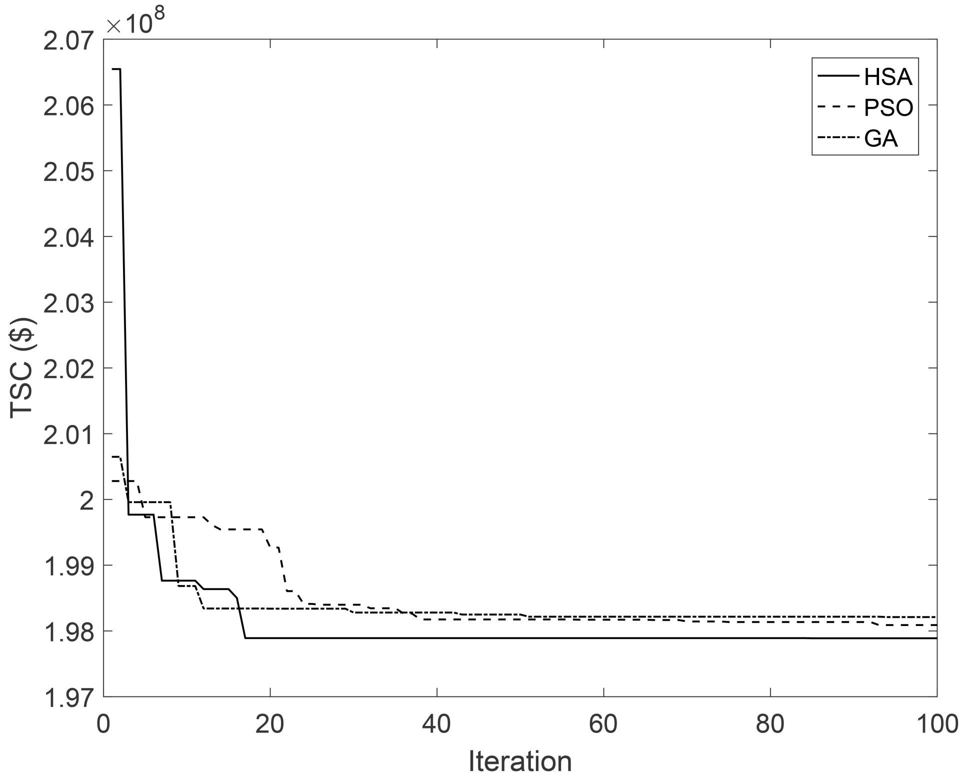

Figure 16: The convergence procedure of IHSA, PSO, and GA for proposed DNEP problem for system (6)

Highlights

- Modeling distribution network planning in the presence of distributed generators
- Modeling pollution emission of distributed generators in the objective function
- Using Monte-Carlo simulation to handle the uncertainties
- Applying the improved search harmony algorithm to solve the problem
- The proposed algorithm has the better performance in comparison with other methods