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Probabilistic Power Distribution Planning Using Multi-Objective Harmony Search Algorithm

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Abstract- *In this paper, power distribution planning (PDP) considering distributed generators (DGs) is investigated as a dynamic multi-objective optimization problem. Moreover, Monte Carlo simulation (MCS) is applied to handle the uncertainty in electricity price and load demand. In the proposed model, investment and operation costs, losses and purchased power from the main grid are incorporated in the first objective function, while pollution emission due to DGs and the grid is considered in the second objective function. One of the important advantages of the proposed objective function is a feeder and substation expansion in addition to an optimal placement of DGs. The resulted model is a mixed-integer non-linear one, which is solved using a non-dominated sorting improved harmony search algorithm (NSIHSA). As multi-objective optimization problems do not have a unique solution, to obtain the final optimum solution, fuzzy decision making analysis tagged with planner criteria is applied. To show the effectiveness of the proposed model and its solution, it is applied to a 9-node distribution system.*

Keyword: Fuzzy decision-making, Harmony search algorithm, Monte Carlo simulation, Power distribution planning.

NOMENCLATURE

Indices and sets

$t\ /\ \Omega^{t}$	Index/Set of time period
$y\ /\ \Omega^{\mathrm{CDS}}$	Index/Set of candidate distribution substations
$\lambda\ /\ \Omega^{F}$	Index/Set of existing and candidate lines/feeders
$i, j\ /\ \Omega^{N_B}$	Index/Set of nodes
$k\ /\ \Omega^{\mathrm{DG}}$	Index/Set of DGs
$h\ /\ \Omega^{\mathrm{EDS}}$	Index/Set of existing distribution substation
$m\ /\ \Omega^{\mathrm{GE}}$	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 kth DG technology ($/kW)
C_k^{OP}	Operation cost of kth DG technology ($/kWh)
pf	Penalty factor
$E_{k,m}^{\mathrm{DG}}$	Emission factor of type m in kth DG technology (kg/kWh)
E_m^{G}	Emission factor of type m associated with electricity taken from the grid (kg/kWh)
π_s	Electricity market Price ($/kWh)
TPH	Total planning horizon
P_k^{CAP}	Capacity limit of kth DG technology (kW)
U_i^{Min}	Minimum voltage at node i
U_i^{Max}	Maximum voltage at node i
$P_h^{\mathrm{SS\text{-}Max}}$	Distribution substation capacity limit (MVA)
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
R	Resistance of the feeder (Ω/phase/km)
X	Reactance of the feeder (Ω/phase/km)
$D_{i,t}$	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

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$n_{t.y}$	Number of substations must be installed in time period t
$P_{t,i,k}^{\mathrm{OP}}$	Operation generation of kth DG technology at node i in time period t (kW)
$P_{t,h}^{\mathrm{PS}}$	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)
$U_{t,i}$	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 ($)
CPP	Cost of purchased power from main grid ($)
PEA	Pollution emission amount (ton/h)
TSC	Total social cost ($)

1. INTRODUCTION

1.1 Motivation and aim

The power distribution system, in the context of power distribution planning (PDP), is designed with a primary goal to design the distribution network so as to timely meet the electrical load growth in the most economical, reliable, and safe way. This is not straightforward, because of the very large extension of the power distribution network, as well as the fact that this network is responsible for most of the electrical energy losses and most of the interruptions due to faults. In the last years, the distribution planning function is further complicated by the high penetration of distributed generators (DGs) technologies [1, 2]. Optimal planning of DGs is an optimization problem to determine the optimal location, type, and size of DGs in order to decrease the peak demand and power losses and increase the reliability [3]. Therefore, in the presence of DGs, the PDP is changed. The aim of this paper is to model the PDP in the presence of uncertainties and DGs as a dynamic multi-objective optimization problem by a non-dominated sorting improved harmony search algorithm (NSIHSA).

1.2. Literature review and contributions

Based on the treatment of the planning horizon, the PDP problem can be traditionally classified into two categories, namely static and dynamic planning horizon. In the static planning horizon, only a single period is investigated as a planning horizon. In contrast, the dynamic expansion planning considers the planning horizon by the detachment of the study period into multiple stages. For the static planning horizon, the planner searches for a suitable number of new feeders or substations, which should be added to the system and in this case, the planner is unwilling to schedule when the new feeders or substations should be constructed and the total expansion investment is considered at the beginning of the planning horizon. From the viewpoint of power system structures, PDP approaches can be categorized into regulated and deregulated environments. The main objective function of the PDP problem in the regulated structure is to meet the load demand, while maintaining service quality and reliability of the system. Uncertainty is low in this structure. Deregulation has changed the objective of the PDP and increased uncertainties of the system. Due to these changes, new approaches are required for the PDP problem and also, the uncertainty is an important issue in this environment. Here, due to uncertainties, the prepared plan does not correspond to the real planning. Therefore, an appropriate tool for handling uncertainties in the PDP problem is inevitable. In this paper, the uncertainty of demand and electricity price is modeled in the proposed model using Monte Carlo simulation (MCS). As the PDP problem is mixed integer nonlinear in nature , many methodologies including mathematical and meta-heuristic approches have been incorporated to solve the problem. Dynamic programming (DP), linear programming (LP), and benders decomposition, which are based on mathematical approaches, as well as simulated annealing (SA), Tabu search (TS), particle swarm optimization (PSO), genetic algorithm (GA), artificial immune system (AIS), bacterial foraging (BF), ant colony system (ACS), ant lion optimization algorithm (ALOA), artificial bee colony (ABC), grey wolf optimizer (GWO), binary chaotic shark smell optimization (BCSSO), learning automat (LA), big bang-big crunch (BB-BC) and shuffled frog leaping algorithm (SFLA), which are based on meta-heuristic approaches, have been applied to solve the PDP problem. For clarity, the proposed model in this paper is compared with those proposed in other studies from different aspects, as shown in Table 1. In this paper, a new multi-objective framework is presented for the PDP problem considering uncertainty in demand in the presence of DGs. The MCS is used to model the uncertainty of load and electricity price into the algorithm. One of the important advantages of the proposed model is the optimal placement of DGs including wind turbine (WT), gas turbine (GT), micro turbine (MT), photovoltaic (PV), fuel cell (FC) and diesel engine (DE) in the presence of expansion lines/feeders and distribution substations. In the objective function with regard to pollution, type of the pollution is also intended.

Table 1. A review of previous studies on the PDP problem and their solving methods

Ref	Static/ Dynamic	Uncertainty	Considering DGs	Pollution	Variable	Objective function	Solving method
[4]	Static	No	Yes	No	Size and location of DGs	Power losses	LA
[5]	Static	DGs	Yes	No	Size and location of DGs	Minimizing load consumption	GA
[6]	Static	No	Yes	No	Size and location of DGs	Minimizing voltage variations	GA
[7]	Static	No	Yes	No	Size and location of DGs	Power losses	ALOL
[8]	Static	Load	Yes	Yes	Size and location of DGs	Power losses, pollution emission	BB-BC
[9]	Dynamic	No	Yes	No	Size and location of DGs	Investment and operation costs	BCSSO
[10]	Static	No	No	No	Feeders location	Feeders installation cost	BFT
[11]	Static	No	No	No	Substations and feeders location	Energy cost and interruption cost	GA
[12]	Dynamic	No	Yes	No	Substations, DGs and feeders location & size	Cost of DGs and substations	GA
[13]	Static	No	No	No	Sizing and siting of substations	Cost of substations	LA
[14]	Dynamic	Load	Yes	No	capacity and location of MV substation and DGs	Cost of DGs and substations	GSO
[15]	Static	No	Yes	No	Substations, DGs and feeders location & size	Cost of DGs and substations	LP
[16]	Dynamic	No	Yes	No	Substations, DGs and feeders location & size	Investment and operational costs	GA
[17]	Static	No	Yes	No	DGs location or size, feeders location	Voltage deviation, losses, DGs cost	GA
[18]	Dynamic	No	Yes	No	Substations, DGs and feeders location & size	Cost of DGs and reliability	PSO
[19]	Dynamic	No	Yes	No	Substations, DGs and feeders location & size	Cost of losses and DGs	ABC
[20]	Dynamic	Load	Yes	No	Substations, DGs and feeders location & size	Max a return-per-risk index	PSO
[21]	Static	Load	No	No	Feeders location & size	Losses and feeders cost	AIS
[22]	Dynamic	Load	Yes	No	Feeders location, DGs location	Losses and reliability cost	GA
[23]	Dynamic	Load	Yes	Yes	Feeders location, DGs location	Cost of DGs, feeders and losses	GA
[24]	Dynamic	No	Yes	No	Substations, DGs, and feeders size	Min total costs minus total revenues	ACS
[25]	Static	No	Yes	No	Feeders location & size	Cost of DGs, losses and feeders	SA
[26]	Static	Load	Yes	No	Feeders location & size	Cost of DGs and feeders	TS
[27]	static	Load	Yes	No	Feeders & DGs location	Cost of DGs	PSO
[28]	Static	Load	Yes	No	Feeders & DGs location	Cost of DGs and feeders	GA
[29]	Static	No	Yes	No	DGs location & size	Min of losses & voltage deviation	GWO
[30]	Static	No	Yes	Yes	DGs location & size	Cost of DGs and losses	SFLA
This paper	Dynamic	Load and energy price	Yes	Yes	Location of substation and feeders, location and size of DGs, voltage of nodes	New construction of substations and feeders, purchased power from main grid, losses, pollution, investment and operation cost of DGs	NSIHSA-II

To solve the PDP problem, the NSIHSA-II is used. As multi objective optimization problems do not have a unique answer, fuzzy decision-making analysis is applied to obtain the final optimal solution. To show the effectiveness of the proposed methodology, it is compared with other multi-objective optimization problem solvers like the strength Pareto evolutionary algorithm (SPEA), multi-objective evolutionary algorithm-decomposition (MOEA-D), non-dominated sorting genetic algorithm-II (NSGA-II) and multi-objective particle swarm optimization (MOPSO), which are well-known techniques in solving multi-objective optimization problems. Therefore, the main contributions of this paper are as follows:

- Modelling the PDP problem as a dynamic multi-objective optimization (including new construction of substations and feeders, purchased power from the main grid, losses, pollution, investment and operation costs) including the uncertainties of demand and electricity price in the presence of six types of conventional DGs.
- To solve the proposed model, multi-objective improved harmony search algorithm is applied.
- Determining optimal location and size of the six types of DGs which will be installed in the distribution network in the planning horizon.
- Analyzing each Pareto solution and applying the fuzzy decision-making as a popular technique to obtain the final optimum solution tagged with the planner criteria.

1.3. Paper organization

This paper is organized as follows: Section 2 formulates the proposed PDP problem. In Section 3, the solution methodology is discussed. Section 4 conducts the numerical results and presents comparison among various solving methods for the problem. Finally, concluding remarks are discussed in Section 5.

2. MATHEMATICAL MODELLING

2.1. Objective functions

The proposed model as a total social cost (TSC) and pollution emmision amount (PEA) for the PDP problem in the presence of DGs is formulated as the following optimization problem:

$$\begin{aligned}\text{Min TSC} &= \text{COF}+\text{CDS}+\text{ICD}+(365\times 24\times \text{OCD})\\ &+(365\times 24\times \text{COL})+(365\times 24\times \text{CPP})\end{aligned} \tag{1}$$

$$\begin{aligned}\text{Min PEA} = &\Bigg\{\Bigg(\sum_{i\in\Omega^{N_B}}\sum_{k\in\Omega^{DG}} \mathrm{P}_{t,i,k}^{\mathrm{OP}}\times C_B\times\sum_{m\in\Omega^{GE}} E_{k,m}^{\mathrm{DG}}\Bigg)\\ &+\Bigg(\sum_{h\in\Omega^{\mathrm{EDS}}} P_{t,h}^{\mathrm{PS}}\times C_B\times\sum_{m\in\Omega^{\mathrm{GE}}} E_m^{G}\Bigg)\Bigg\}\end{aligned} \tag{2}$$

$$\text{COF}=\sum_{t\in\Omega^t}\sum_{\lambda\in\Omega^F}(1+\mathrm{d})^{-t}\times(C_\lambda\times n_{t,\lambda}) \tag{3}$$

$$\text{CDS}=\sum_{t\in\Omega^t}\sum_{y\in\Omega^{CDS}}(1+\mathrm{d})^{-t}\times(C_y\times n_{t,y}) \tag{4}$$

$$\text{ICD}=\sum_{t\in\Omega^t}\sum_{i\in\Omega^{N_B}}\sum_{k\in\Omega^{\mathrm{DG}}}(1+\mathrm{d})^{-t}\times(\mathrm{C}_k^{\mathrm{INV}}\times C_B\times P_{t,i,k}^{\mathrm{OP}}) \tag{5}$$

$$\text{OCD}=\sum_{t\in\Omega^t}\sum_{i\in\Omega^{N_B}}\sum_{k\in\Omega^{\mathrm{DG}}}(1+\mathrm{d})^{-t}\times(\mathrm{C}_k^{\mathrm{OP}}\times C_B\times P_{t,i,k}^{\mathrm{OP}}) \tag{6}$$

$$\begin{aligned}&\text{COL}=\sum_{t\in\Omega^t}(1+\mathrm{d})^{-t}\,(\text{Losses}\times C_B\times\pi_s)\ ,\\ &\text{Losses}=\sum_{\substack{i\in\Omega^{N_B}\\ i\neq j}}\sum_{\substack{j\in\Omega^{N_B}\\ i\neq j}}\Big(\frac{(|U_{t,i}|-|U_{t,j}|)^2}{|Z_{ij}|}\Big)\times\cos\varphi\end{aligned} \tag{7}$$

$$\text{CPP}=\sum_{t\in\Omega^t}(1+\mathrm{d})^{-t}\times\sum_{h\in\Omega^{EDS}} P_{t,h}^{\mathrm{PS}}\times C_B\times\pi_s \tag{8}$$

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

2.2. Constraints

The constraints of the proposed multi-objective optimization problem are mainly those of optimal power flow in normal operating conditions as follows:

$$\begin{aligned}&P_{t,i,k}^{\mathrm{OP}}\times C_B\leq P_k^{\mathrm{CAP}}\\ &\forall t\in\Omega^t,\ \forall i\in\Omega^{N_B},\ \forall k\in\Omega^{\mathrm{DG}}\end{aligned} \tag{9}$$

$$\begin{aligned}&U_i^{\mathrm{Min}}\leq U_{t,i}\leq U_i^{\mathrm{Max}}\\ &\forall t\in\Omega^t,\ \ \forall i\in\Omega^{N_B}\end{aligned} \tag{10}$$

$$\begin{aligned}&P_{t,h}^{\mathrm{PS}}\leq P_h^{\mathrm{PS\text{-}Max}}\\ &\forall t\in\Omega^t,\ \forall h\in\Omega^{\mathrm{EDS}}\end{aligned} \tag{11}$$

$$\begin{aligned}&P_{t,ij}\times C_B\leq P_{ij}^{\mathrm{Max}}\\ &\forall t\in\Omega^t,\ \underset{i\neq j}{\forall}\, i,j\in\Omega^{N_B}\end{aligned} \tag{12}$$

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

Radial structure of distribution network = 1 (14)

The constraint of Eq. (9) shows the limitation of operational capacity of DGs; the constraint of Eq. (10) represents a limitation of voltage which, in this paper, the minimum and maximum voltage of nodes is assumed to be 0.95 p.u and 1.05 p.u, respectively; the constraint of Eq. (11) represents the limitation in distribution substation capacity; the constraint of Eq. (12) denotes the limitation in thermal capacity of the distribution feeder; the constraint of Eq. (13) represents the power balance constraint in which the term I' is the total loss power in the feeder connecting node i to the node j; and the constraint of Eq. (14) is applied to keep the radial structure of the distribution network. In this paper, node encoding based on Prufer number in genetic algorithm is applied to obtain a radial structure for the system. Therefore, in order to evaluate the system radially, the following constraints must be satisfied, simultaneously [31]:

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

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

Where A is a node-branch matrix with size $N_B\times N_B$, in which elements are either 1 or 0. The operator *det(.)* denotes determinant of the matrix. The constraint that is modelled as Eq. (16) is a condition of the establishment of a tree in graphs theory, where N_B is the number of nodes and q is the number of branches.

3. SOLUTION METHODOLOGY

3.1. Modelling uncertainties

Since electrical load and electricity price are estimated, they are faced with uncertainty. Considering the uncertainty in the planning problem makes it more robust and flexible. Through observing the past behavior, the planner can estimate the probability distribution function (PDF) of these uncertainties; thus, they are categorized in random uncertainties. One of the appropriate tools for analyzing and considering random uncertainties is the MCS. Generally, the load and price are estimated by normal PDF [32].

Therefore, in this paper, the load and price are considered by this PDF. Suppose, one of the loads has normal PDF with the mean of 50 and standard deviation of 10%. As this normal PDF is a continuous function, therefore, it does not demonstrate the probability of each point of load, and only shows the probability density. In order to determine the probability of various load levels, the continuous function must be estimated with a normal discontinuous function. In this approximation, smaller steps lead to smaller error of approximation. The above normal PDF and its approximation with 16 steps is shown in Fig. 1. In this figure, the horizontal axis shows the value of the load level and the vertical axis shows the probability of each load level. Therefore, Fig. 1 is shown in Eq. (17) where the vector P shows the probability of each load level. In other words, the variables $p_1,p_2,...,p_n$ show the load levels $I_1,I_2,...,I_n$, problem, the next step is to develop scenarios based on these uncertainties. In this step, a random number for each uncertain variable is produced based on its PDF. After the generation of a random number, the probability of this load level is calculated using Eq. (17). Therefore, in this scenario, both load level and its probability are calculated for all the network loads. The same process is also used for other network uncertainties until, in each scenario, each uncertain variable with a value and its occurrence probability is specified. The flowchart of this process is shown in Fig 2. In the first step, all the uncertain variables are defined according to Eq. (17) and for any variable, a random number is produced. Then, the value of the variable and its probability in each scenario is specified Thus, the power flow analysis is performed to obtain

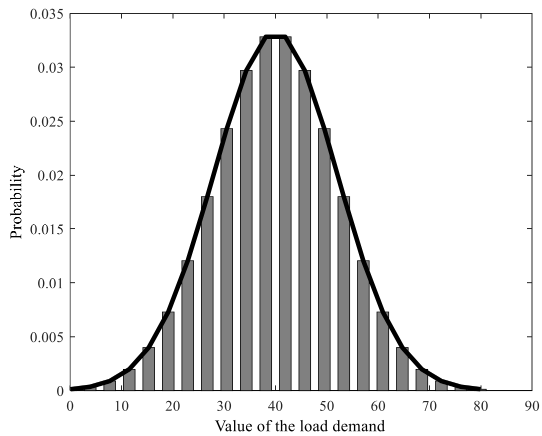

Fig. 1. Load approximation with discontinuous normal PDF

$$P=\begin{cases} p_1, & \text{Load}=I_1.\\ p_2, & \text{Load}=I_2.\\ \vdots & \vdots\\ p_n, & \text{Load}=I_n.\end{cases} \tag{17}$$

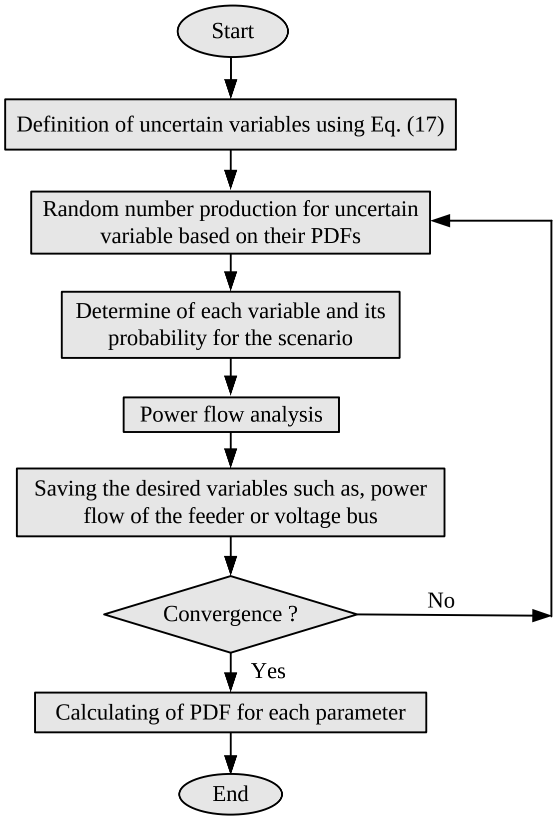

Fig. 2. Flowchart of the proposed MCS

parameters such as the voltage of nodes, flow of feeders and power losses. As a result, the MCS convergence is considered. The MCS convergence can be the variance of the output variables. This means that, if the variance of the output variable is less than the specified limit, the algorithm is finished; otherwise, the algorithm is repeated and a new scenario is produced. Finally, with increasing scenarios, there are a number of scenarios that contain the value of the variable and its probability. Therefore, the planner can plot the value of the output variable in terms of its probability. With this approach, the effect of the uncertainty in the input data appears in the output and the PDF of the output variable can be specified.

3.2. Non-dominated sorting improved harmony search algorithm (NSIHSA)

One of the appropriate tools for managing and solving various incommensurable objective functions with compatible/incompatible relations and also, for solving non-linear, non-convex and mixed-integer multi-objective optimization problems is NSIHSA, which is based on the harmony search algorithm (HAS). The HSA was derived by adopting the idea that the existing meta-heuristic algorithms are found in the paradigm of natural phenomena [33]. The HSA has so far elucidated in practice a great potential and efficiency in comparison with other meta-heuristic methods in a wide spectrum of real applications. Although this meta-heuristic algorithm possesses a similar structure to other existing population-based meta-heuristic algorithms, it uses some distinctive features that make it widely applied in the literature [34]. The general steps of the procedure of this algorithm are as follows [33]:

1. Initializing 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. Improvising a new harmony from the HM.
4. Updating the HM.
5. Repeating the steps 3 and 4 until the termination criterion is satisfied.

To improve the performance of the HSA and eliminate the drawbacks lying with fixed values of the pitch adjustment rate (*PAR*) and bandwidth (*bw*), the improved HSA method, which uses the variables *PAR* and *bw*, is used. The parameters *PAR* and *bw* change dynamically with the generation number expressed as follows [35]:

$$PAR(gn) = PAR_{\min} + \frac{PAR_{\max} - PAR_{\min}}{NI} \times gn \tag{18}$$

$$bw(gn) = bw_{\max} \times e^{\left(\frac{Ln\left(\frac{bw_{\min}}{bw_{\max}}\right)}{NI} \times gn \right)} \tag{19}$$

Where PAR_{min}, PAR_{max}, NI, bw_{gn}, bw_{min}, bw_{max}, and gn are the minimum pitch adjusting rate, maximum pitch adjusting rate, number of solution vector generations, bandwidth for each generation, minimum bandwidth, maximum bandwidth and generation number, respectively. In this paper, the search process of the novel global harmony search algorithm is applied on harmonies, which are ranked based on non-dominated sorting and distance crowding strategies [36] that are subsequently explained. The basic of the technique is to categorize a harmony of solutions into the number of Pareto levels. The level 1 is a set of Pareto solutions in the entire harmony memory and level 2 is a set of Pareto solutions in the harmony memory except the level 1, which continues until the entire harmony memory is categorized into *k* levels. Highest fitness will be assigned for solutions on the first level and then, for those on the second level and so on. Moreover, crowding distance is used as a control agent and actually, as a secondary criterion for classification and dedicated fitness of levels

[37]. After ranking, new harmonies are generated. It should be noted that for handling the constraints, Deb's method [37] is employed, in which any feasible solution is preferred to any infeasible solution; accordingly, between two feasible solutions, one having the better objective value is preferred and, between two infeasible solutions, one having the smaller constraint violation is preferred.

3.3. Final decision-making

In fuzzy decision-making, a strictly monotonically decreasing and continious membership function is specified to each objective function. The value of the membership function shows to what extend a solution is satisfying the objective f_i. The decision maker is fully satisfied with the objective value of $f_i(X)$ if $\mu_{f_i(X)}=1$ and not satisfied at all if $\mu_{f_i(X)}=0$. In this paper, the linear membership function is applied for entire objective functions as Eq. (20):

$$\mu_{f_i(X)}=\begin{cases} 0, & f_i(X)>f_i^{\max} \\ \dfrac{f_i^{\max}-f_i(X)}{f_i^{\max}-f_i^{\min}}, & f_i^{\min}\le f_i(X)\le f_i^{\max} \\ 1, & f_i(X)<f_i^{\min} \end{cases} \tag{20}$$

Where $f_i^{\max}$ and $f_i^{\min}$ are the maximum and minimum of the objective function among the Pareto solutions, respectively. After determining any membership functions, the planner will be questioned to select the favorable level of prosperity of each objective. Favorable levels of prosperity are named satisfaction levels or reference levels of prosperity and are represented by μ_{ri}. Using the distance metric technique, the ultimate answer can be specified by Eq. (21):

$$\min_{X\in\Phi}\sum_{i=1}^{2}\left|\mu_{ri}-\mu_{fi}(X)\right|^{p} \tag{21}$$

where $1\le p\le\infty$ and Φ is the non-dominated solutions (X).

3.4. Proposed expansion planning

The flowchart of the proposed model is shown in Fig. 3. In the first step, an initial random HM is generated. Fig. 4 shows the coding of the solutions. As illustrated, each solution is shown via a $t\times\ell$ matrix regarding the t planning stages and six types of DGs in the N_B nodes. The matrix elements show some of DGs added for connecting to the node. As shown in Fig. 3, in $t=TPH$ in the nodes 1 and 2, one fuel cell must be installed. After structuring the HM, the way the constraints are handled should be specified. The method used for dealing with the non-

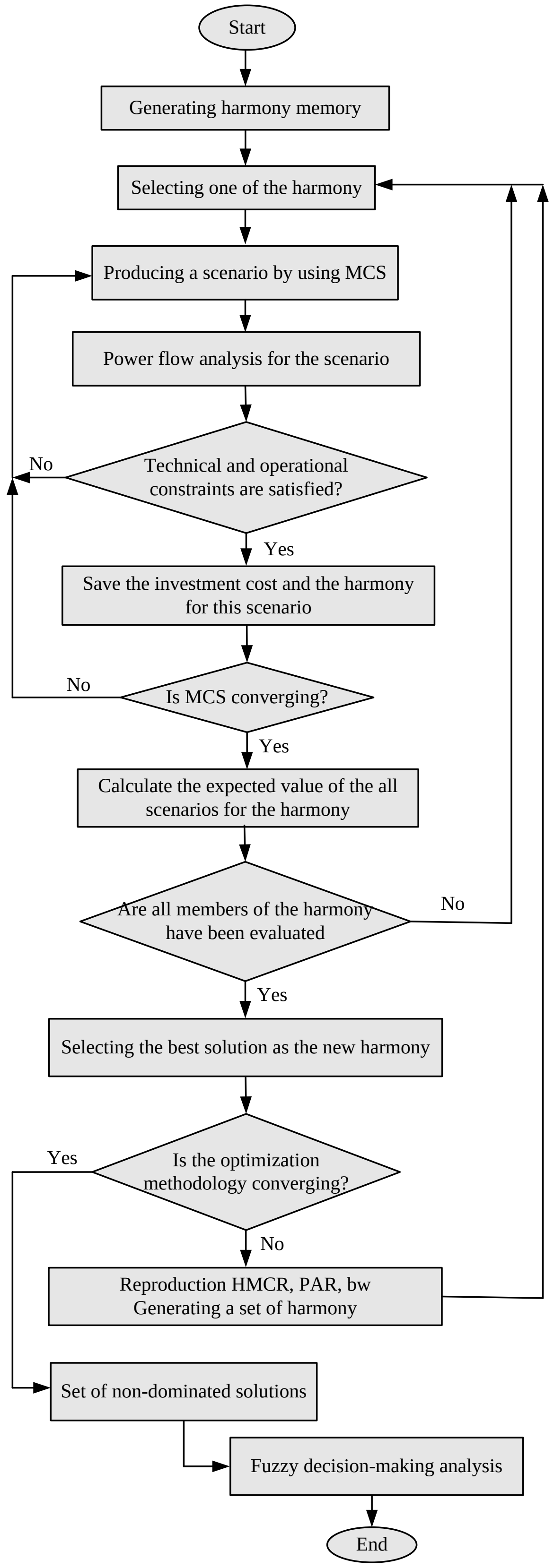

Fig. 3. Flowchart of the proposed expansion planning

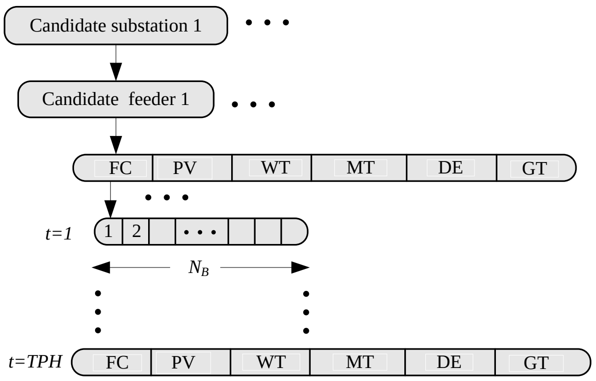

Fig. 4. The proposed coding in the applied HAS

technical constraints are the rejecting technique, in which the infeasible harmonies are discarded all over the generations. For technical constraints, the penalty method is used, in which a penalty is added to the objective function of the problem for violation of any constraint. The value of the penalty varies depending on the importance of the violated constraint. Designing the basic operators and control parameters of the HSA is the next step. For the *HMS*, *HMCR*, PAR_{min} and bw_{min} rates, typical values are selected in the intervals (10,50), (0,0.99), (0.001,0.5) and (0.0001,0.5), respectively. For stopping the algorithm, several criteria such as the number of generations can be used. As illustrated in Fig. 3, at first, an initial harmony memory is randomly produced for the algorithm. Then, a vector in the harmony memory is selected. In the next step, the MCS is applied to handle the system uncertainty. For each scenario of the MCS, uncertain parameters such as electricity price and electrical load demand are randomly produced based on their defined PDF. Subsequently, the objective functions are calculated and then the constraints are considered. If there is a violation in the constraints, the current scenario is not included in the procedure; otherwise, the cost is saved and the MCS is reiterated. The proposed flowchart clearly illustrates that the methodology solves the problem including the constraints and the constraints are considered for each scenario. Then, the expected value of cost and amount of pollution are calculated as the final answer for the current vector. This procedure is applied to calculate the costs for all vectors in the harmony memory. Then, the vector with the minimum cost is chosen. In the next step, the convergence of the NSIHSA methodology is considered and if the stop criterion is met, the algorithm will be ended and the best vector is considered as the output of planning; otherwise, the harmony memory is updated based on the NSIHSA rules and the algorithm is repeated from the beginning. Finally, the planner will be asked to determine his satisfaction levels and by applying the fuzzy satisfying method, the final solution will be obtained.

4. NUMERICAL RESULTS

Figure 5 shows the 9-node primary distribution test system. This system has 9 nodes, in which one is a 132/33 kV substation in the node 9 with capacity of 40 MVA and other nodes are the load points that should be served. This case study has 6 existing lines as shown in Fig. 5. Further, this case study has a candidate distrubution substation with 40 MVA capacity, 13 candidate lines and two candidate load nodes, which must be served for expansion planning as shown. In the proposed planning, six types of DGs consisting of WT, GT, PV, MT, FC and DE are investigated. In Table 2, the data of size, installed capacity limit, investment and operation cost of these resources can be found, and pollutant emission rates of these technologies are shown in Table 3. Moreover, according to Table 2, due to limited installed capacity, it is assumed that these resources are able to produce their maximum power. Other network data including economic and technical characteristics for this system can be found [38]. The initial load demand in peak time for this system is shown in Table 4. Moreover, in this case, the power factor (cosφ) and discount rate are considered to be equal to 0.8 and 3%, respectively. It should be noted that all the load nodes are candidate for installing DGs and also, the rated voltage is included 33 kV. The data of the candidate lines for expansion are shown in Table 5. It is assumed that the system should be expanded for a 5-year planning horizon with the load growth of 5%. The electricity price is considered 85 \$/MWh with the standard deviation of 10%; here, the standard deviation of the load demand in each node in the peak time is 10%. Fig. 6 shows a sample of the number of the performed experiments. Furthermore, Fig. 7 shows the converged load demand in the node (3) in 2000 iterations of the MCS. It should be noted that, unlike the

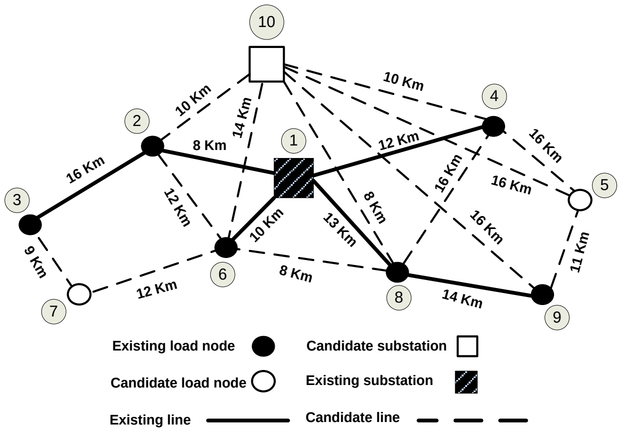

Fig. 5. Initial topology of the 9-node primary distribution system

Table 2. Data of the six DG technologies

DG	Size (kW)	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 3. Emission of pollutant rates of the six DG technologies

DG	NO_X	SO_2	CO_2	CO	PM_{10}
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	0.0004	0.00004
MT	0.0002	0.000037	0.725	0.0005	0.00004
PV	0	0	0	0	0
WT	0	0	0	0	0
Grid	0.0022952	0.0035834	0.92125	-	-

Table 4. Initial load demand in peak time for the 9-node distribution system

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

deterministic approaches, executation of the MCS does not require any additional calculations. With considering 2000 iterations of the MCS and the initial harmony size of 200 and 100 iterations for the NSIHSA, the Pareto solutions are determined, as shown in Fig. 8. The placement of DGs with the planned capacity of the 9-node distribution system, costs of the planning and voltage of the nodes for this case study are shown in Tables 6-8, respectively. Suppose that the reference value is 65% for the objective function of pollution, and 65% for the total planning cost; therefore, with this satisfaction level and by considering *p=2* according to Eq. (21), the ultimate answer could be obtained using the fuzzy decision making, and as shown in Table 7, the Pareto solution 13 is the best solution for this satisfaction level of objective functions. Table 9 shows the best Pareto solution for the 9-node distribution system for various satisfaction levels considering uncertainties. In the Pareto solution 13, 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 19.74%. Moreover, in this solution, according to Table 7, the deployment of DGs decreases both the ultimate planning cost by 6.25% and losses by 36.61%. In addition, there is no need to build a new substation, and only it is needed to build a new line between the nodes 6 and 7 as well as between the nodes 4 and 5. It is obvious that considering the uncertainties of the system leads to increased investment cost; however, considering these uncertainties in the planning makes the plan a more robust and flexible one, which can meet the network requirement. A comparison between the proposed model and its solving methodology and Refs. [27], [38-41] is shown in Table 10 for the first year; it can be seen that the proposed algorithm has better performance than the other methods from different aspects, leading to a lower-cost plan. In order to evaluate the applied methodology, the SPEA, MOEA-D, NSGA-II and MOPSO, which are well-known techniques in solving multi-objective optimization problems, are implemented. Table 11 shows the parameters of the SPEA, MOEA-D, NSGA-II and MOPSO techniques. The results are shown in Fig. 9. In order to evaluate the performance and quality of Pareto solutions in multi-objective optimization problem, several performance indices are presented in the literature. In this paper, diversification metric (DM) and mean ideal distance (MID) indices are applied. The DM index specifies the diversity of Pareto solutions. In this metric, the algorithm with a higher DM value has a better capability, which is defined as Eq. (22) [42]:

$$DM = \sqrt{\sum_{i=1}^{M}\left(\max_{j=1,\dots,N_P}\{f_i^{\,j}\} - \min\{f_i^{\,j}\}\right)^2} \qquad (22)$$

$$MID = \frac{\sum_{j=1}^{N_P} C_j}{N_P}, \; C_j = \sqrt{\sum_{i=1}^{M}\left(f_i^{\,j} - f_{i,m}\right)^2} \qquad (23)$$

Where $f_i^{\,j}$ is the ith objective of the *j*th Pareto solution in the Pareto front, N_p is the number of Pareto solutions and *M* is the number of objective functions. The MID index specifies the distance between optimal Pareto solutions as shown in Eq. (23) and the best optimal solution for each objective function, in which a solution with smaller MID represents a better quality. Here, $f_{i,m}$ is the optimal value of the *i*th objective functions, which can be obtained by single objective optimization. Table 12 shows the DM and MID indices for the NSIHSA, NSGA-II, SPEA, MOPSO and MOEA-D methods. As is known, the NSIHSA is better in performance than the NSGA-II, SPEA, MPEA-D and MOPSO algorithms. It is noteworthy that there is no necessity to obtain results under the same conditions to have a comparison. In fact, the DM and MID indices denote a view about how the Pareto solutions are spread and how they are near to their ideal solutions. These comparisons demonstrate the capability of the NSIHSA method in obtaining more diverse and qualified Pareto solutions.

5. CONCLUSION

In this paper, a probabilistic multi-objective framework for the power distribution planning problem in distribution electricity systems is proposed. The main output of the proposed framework is to determine the location, type, and capacity of the six conventional distributed generators, feeders and distribution substations while considering monetary cost (including DGs investment and operating cost and purchased power from the network) and emission considerations as well as load and electricity price uncertainties. The proposed probabilistic multi-objective optimization method is applied to the 9-bus distribution system to assess the ability and performance of the proposed model and its solution with respect to previous ones. One of the most important advantages of the proposed framework is that by proposing several Pareto solutions, it allows the planner to consider its own preference for making the correct decision among those solutions based on the market's working strategies.

Table 5. Lines data of the 9-node distribution system

From node	To node	*R* (p.u)	*X* (p.u)	C_l (M$)
1	2	0.02082	0.02868	0.31
1	4	0.02748	0.03654	0.42
1	6	0.02500	0.03322	0.31
1	8	0.03331	0.04430	0.31
2	3	0.04997	0.06644	0.82
8	9	0.04664	0.06201	0.31
3	7	0.02332	0.03310	0.31
6	7	0.02748	0.03654	0.42
2	6	0.02748	0.03654	0.42
6	8	0.02082	0.02768	0.31
4	8	0.04997	0.06644	0.82
4	5	0.04997	0.06644	0.82
5	9	0.02665	0.03543	0.31
10	2	0.02500	0.03322	0.31
10	6	0.04664	0.06201	0.63
10	4	0.02500	0.03322	0.31
10	5	0.04997	0.06644	0.82
10	8	0.02082	0.02768	0.31
10	9	0.04997	0.06644	0.82

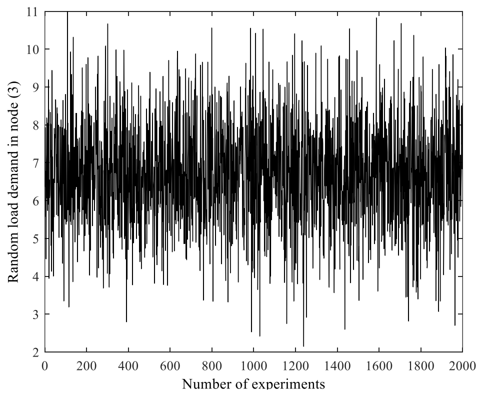

Fig. 6. Total random demand load in the node (3)

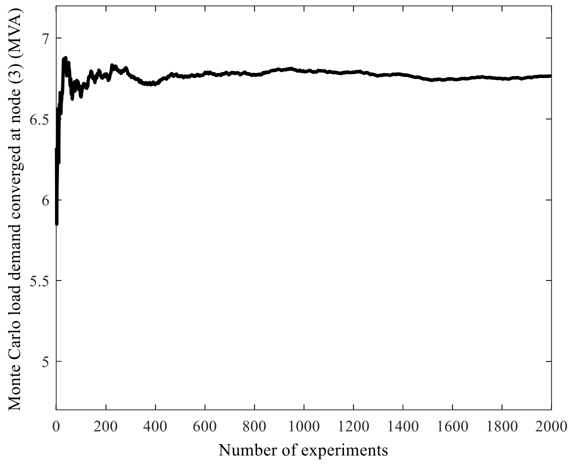

Fig. 7. Converged load demand in the node (3)

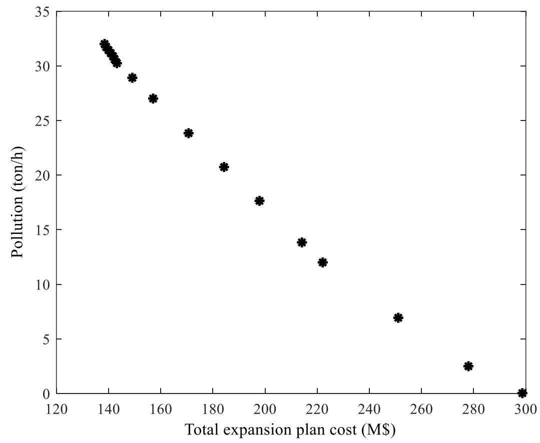

Fig. 8. Non-dominated solutions for the 9-node distribution system considering uncertainties

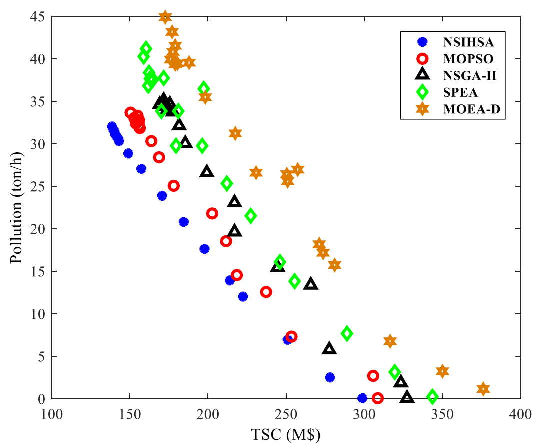

Fig. 9. Comparison of Pareto solutions in the NSIHSA, MOPSO, NSGA-II, SPEA and MOEA-D algorithms

Table 6. DGs planning results of the 9-node distribution system considering uncertainties

Pareto solution		Type, size (kW) and location of planned DGs						Pollution (ton/h)
		WT	PV	FC	MT	GT	DE	
1	PC*	-	-	-	2,2,1,2,2,1,1,1,1	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	32.017
	Node	-	-	-	@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	PC	-	-	-	2,1,0,2,2,1,1,1,1	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	31.726
	Node	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
3	PC	-	-	-	2,1,0,1,2,1,1,1,0	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	31.436
	Node	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
4	PC	-	-	-	1,1,0,0,2,1,1,1,0	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	31.146
	Node	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
5	PC	-	-	-	1,0,0,0,1,1,1,1,0	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	30.855
	Node	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
6	PC	-	-	-	1,0,0,0,1,0,1,0,0	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	30.565
	Node	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
7	PC	-	-	-	0,0,0,0,0,0,1,0,0	4,4,4,4,4,4,4,4	2,2,2,2,2,2,2,2	30.275
	Node	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
8	PC	-	-	-	-	4,3,4,4,3,4,4,4	2,2,2,2,2,2,2,2	28.878
	Node	-	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
9	PC	-	-	-	-	4,1,4,3,3,4,4,4	2,2,2,2,2,2,2,2	27.000
	Node	-	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
10	PC	-	-	-	-	4,1,2,3,1,3,4,4	2,2,2,2,2,2,2,2	23.872
	Node	-	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
11	PC	-	-	-	-	4,1,1,3,1,3,2,2	2,2,2,2,2,2,2,2	20.743
	Node	-	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
12	PC	-	-	-	-	2,1,0,3,0,2,2,2	2,2,2,2,2,2,2,2	17.614
	Node	-	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
13	PC	-	-	-	-	2,0,0,0,0,1,1,2	2,2,2,2,2,2,2,2	13.859
	Node	-	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
14	PC	-	-	-	-	0,0,0,0,0,0,1,2	2,2,2,2,2,2,2,2	11.982
	Node	-	-	-	-	@2,3,4,5,6,7,8,9	@2,3,4,5,6,7,8,9	
15	PC	2,2	-	-	-	-	1,0,2,2,1,1,2,2	6.947
	Node	@5,7	-	-	-	-	@2,3,4,5,6,7,8,9	
16	PC	2,3,3	-	-	-	-	1,0,0,0,1,1,0,1	2.526
	Node	@ 5,7,8	-	-	-	-	@2,3,4,5,6,7,8,9	
17	PC	2,3,2,2,2,1,2	-	-	-	-	-	0
	Node	@1,2,3,4,5,7,8	-	-	-	-	-	

* PC: Planed capacity

Table 7. Costs of planning for the 9-node distribution system considering uncertainties

Item	Without DGs	Pareto solution							
		1	2	3	4	5	6	7	8
DGs investment cost (M$)	0	43.9	43.3	42.7	42.1	41.5	40.9	40.3	38
DGs operation cost (M$)	0	93.2940	92.4180	91.5420	90.6660	89.7900	88.9140	88.0380	84.0960
Cost of purchased power (M$)	225.0367	0.1132	1.2884	2.6900	4.0916	5.4932	6.8948	8.2964	16.0052
Substation investment cost (M$)	1.5	0	0	0	0	0	0	0	0
Feeder investment cost (M$)	1.8	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2
$\mu_{f1}(X) = \mu_{EP}(\%)$	-	0	0.91	1.81	2.72	3.63	4.54	5.44	9.80
$\mu_{f2}(X) = \mu_{TEC}(\%)$	-	100	99.62	99.10	98.58	98.06	97.54	97.02	93.38
$\sum_i \lvert 0.65 - \mu_{fi}(X) \rvert^2$	-	54.5000	53.0607	51.5579	50.0641	48.5924	47.1426	45.7267	38.5246
Losses (p.u)	0.0054039	0.0025233	0.0026205	0.0026974	0.0027582	0.0028415	0.0028567	0.0029798	0.0030236
Total expansion cost (M$)	228.3367	138.5072	139.1164	139.9420	140.7776	141.6132	142.4488	143.2744	149.1012
Item	Pareto solution								
	9	10	11	12	13	14	15	16	17
DGs investment cost (M$)	35	30	25	20	14	11	23.5	38	63
DGs operation cost (M$)	78.8400	70.0800	61.3200	52.5600	42.0480	36.7920	23.4858	11.4936	6.3168
Cost of purchased power (M$)	26.5172	44.0372	61.5572	79.0772	100.1012	110.6132	124.6292	135.1412	128.1332
Substation investment cost (M$)	0	0	0	0	0	0	0	0	0
Feeder investment cost (M$)	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2	1.2
$\mu_{f1}(X) = \mu_{EP}(\%)$	15.67	25.44	35.21	44.98	56.71	62.58	78.30	92.11	100
$\mu_{f2}(X) = \mu_{TEC}(\%)$	88.31	79.86	71.41	62.96	52.82	47.75	29.68	12.93	0
$\sum_i \lvert 0.65 - \mu_{fi}(X) \rvert^2$	29.7681	17.8581	9.2853	4.0496	2.1708	3.0342	14.2439	34.4624	54.5000
Losses (p.u)	0.003106	0.0031758	0.0032622	0.0033423	0.0034519	0.0034253	0.0035409	0.0035157	0.0027952
Total expansion cost (M$)	157.2272	170.7572	184.2872	197.8172	214.0592	222.1852	251.1150	277.9448	298.6500

Table 8. Voltage of nodes in the 9-node distribution system in each Pareto solution considering uncertainties

Voltage	Without DGs	Pareto solution 1	2	3	4	5	6	7	8
node (1)	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
node (2)	0.9837	0.9851	0.9846	0.9842	0.9841	0.9836	0.9837	0.9836	0.9829
node (3)	0.9551	0.9575	0.9574	0.9571	0.9567	0.9565	0.9559	0.9557	0.9554
node (4)	0.9685	0.9867	0.9863	0.9862	0.9859	0.9857	0.9853	0.9849	0.9851
node (5)	0.9542	0.9854	0.9883	0.9852	0.9851	0.9843	0.9845	0.9839	0.9842
node (6)	0.9852	0.9882	0.9878	0.9875	0.9874	0.9872	0.9879	0.9872	0.9871
node (7)	0.9675	0.9779	0.9774	0.9768	0.9768	0.9765	0.9768	0.9757	0.9759
node (8)	0.9806	0.9871	0.9865	0.9867	0.9859	0.9858	0.9857	0.9849	0.9851
node (9)	0.9642	0.9786	0.9786	0.9782	0.9781	0.9776	0.9775	0.9771	0.9772
Standard deviation	0.0152	0.0115	0.0114	0.0116	0.0116	0.0117	0.0118	0.0119	0.0119
Voltage	Pareto solution 9	10	11	12	13	14	15	16	17
node (1)	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
node (2)	0.9831	0.9831	0.9827	0.9818	0.9817	0.9818	0.9815	0.9816	0.9841
node (3)	0.9549	0.9551	0.9541	0.9549	0.9539	0.9538	0.9541	0.9532	0.9569
node (4)	0.9842	0.9841	0.9839	0.9841	0.9841	0.9837	0.9829	0.9834	0.9864
node (5)	0.9841	0.9829	0.9829	0.9832	0.9814	0.9814	0.9817	0.9801	0.9848
node (6)	0.9872	0.9865	0.9871	0.9863	0.9858	0.9861	0.9853	0.9858	0.9881
node (7)	0.9758	0.9749	0.9752	0.9739	0.9742	0.9741	0.9741	0.9742	0.9759
node (8)	0.9847	0.9839	0.9834	0.9841	0.9827	0.9836	0.9831	0.9831	0.9858
node (9)	0.9762	0.9765	0.9758	0.9761	0.9753	0.9761	0.9746	0.9757	0.9756
Standard deviation	0.0121	0.0120	0.0123	0.0121	0.0122	0.0123	0.0122	0.0124	0.0118

Table 9. Best Pareto solution for the 9-node distribution system for various satisfaction levels considering uncertainties

$\mu_{f1}(X)=\mu_{FP}(\%)$	10	20	30	40	50	60	70	80	90
$\mu_{f2}(X)=\mu_{TEC}(\%)$	90	80	70	60	50	40	30	20	10
$\min_{X\in\Phi}\sum_{i=1}^{2}\left\|\mu_{ri}-\mu_{fi}(X)\right\|^2$	0.0011	0.0030	0.0029	0.0034	0.0053	0.0067	0.0069	0.0097	0.0013
Best Pareto solution	8	10	11	12	13	14	15	15	16

Table 10. Comparison of the proposed approach in the first year with other studies

Item	Investment cost (M$/year)	Losses (p.u)	Type of DGs	Pollution
planning without uncertainty	11.4	0.00269	specified	Considered
Planning with uncertainty	12.1	0.00268	specified	Considered
Ref. [39]	12.3856	0.00635	Non-specified	Not considered
Ref. [40]	13.5090	0.00529	Non-specified	Not considered
Ref. [27]	12.0423	0.00335	Non-specified	Not considered
Ref. [38]	48.54	0.00562	Non-specified	Not considered
Ref. [41]	100.46	0.00348	Non-specified	Not considered

Table 11. Parameters of the MOPSO, NSGA-II, SPEA and MOEA-D algorithms

MOPSO	Iteration	Population size	Weighting factors (c_1, c_2)	Inertia weight
	100	200	2, 2	0.5
NSGA-II	Iteration	Population size	Crossover rate	Mutation rate
	100	200	0.8	0.4
SPEA	Iteration	Population size	Number of clusters	Crossover, mutation
	100	200	5	1.0, 0.0
MOEA-D	Iteration	Population size	Number of Neighbours, number of Archive	Crossover
	100	200	8, 50	0.5

Table 12. MID and DM indices of Pareto solutions obtained by the NSIHSA, MOPSO and NSGA II

Algorithm	DM index	MID index
NSIHSA	163.312	59.3272
MOPSO	161.987	60.6121
NSGA-II	161.691	61.8124
SPEA	160.0125	63.156
MOEA-D	159.1291	64.321

REFERENCES

[1] A. Sadeghi Yazdankhah and R. Kazemzadeh, “Power management in a utility connected micro-grid with multiple renewable energy sources,” *J. Oper. Autom. Power Eng.*, vol. 5, no. 1, pp. 1-10, 2017.

[2] P. S. Georgilakis and N. D. Hatziargyriou, “A review of power distribution planning in the modern power systems era: Models, methods and future research,” *Electr. Power Syst. Res.*, vol. 121, pp. 89-100, 2015.

[3] M. Sadeghi and M. Kalantar, “Clean and polluting DG types planning in stochastic price conditions and DG unit uncertainties,” *J. Oper. Autom. Power Eng.*, vol. 4, no. 1, pp. 1-15, 2016.

[4] M. KN and J. EA, “Optimal integration of distributed generation (DG) resources in unbalanced distribution system considering uncertainty modelling,” *Int. Trans. Electr. Energy Syst.*, vol. 27, no. 1, 2017.

[5] Z. Wang, B. Chen, J. Wang, and M. M. Begovic, “Stochastic DG placement for conservation voltage reduction based on multiple replications procedure,” *IEEE Trans. Power Deliv.*, vol. 30, no. 3, pp. 1039-1047, 2015.

[6] I. Kim, “Optimal distributed generation allocation for reactive power control,” *IET Gener. Transm. Distrib.*, vol. 11, no. 6, pp. 1549-1556, 2017.

[7] E. Ali, S. A. Elazim, and A. Abdelaziz, “Ant lion optimization algorithm for renewable distributed generations,” *Energy*, vol. 116, pp. 445-458, 2016.

[8] M. Esmaeili, M. Sedighizadeh, and M. Esmaili, “Multi-objective optimal reconfiguration and DG (Distributed Generation) power allocation in distribution networks using big bang-big crunch algorithm considering load uncertainty,” *Energy*, vol. 103, pp. 86-99, 2016.

[9] M. Ahmadigorji and N. Amjady, “A multiyear DG-incorporated framework for expansion planning of distribution networks using binary chaotic shark smell optimization algorit hm,” *Energy*, vol. 102, pp. 199-215, 2016.

[10] S. Singh, T. Ghose, and S. Goswami, “Optimal feeder routing based on the bacterial foraging technique,” *IEEE Trans. Power Deliv.*, vol. 27, no. 1, pp. 70-78, 2012.

[11] A. Samui, S. Singh, T. Ghose, and S. Samantaray, “A direct approach to optimal feeder routing for radial distribution system,” *IEEE Trans. Power Deliv.*, vol. 27, no. 1, pp. 253-260, 2012.

[12] E. Naderi, H. Seifi, and M. S. Sepasian, “A dynamic approach for distribution system planning considering distributed generation,” *IEEE Trans. Power Deliv.*, vol. 27, no. 3, pp. 1313-1322, 2012.

[13] S. M. Mazhari, H. Monsef, and H. Falaghi, “A hybrid heuristic and learning automata- based algorithm for distribution substations siting, sizing and defining the associated service areas,” *Int. Trans. Electr. Energy Syst.*, vol. 24, no. 3, pp. 433-456, 2014.

[14] S. N. Ravadanegh, N. Jahanyari, A. Amini, and N. Taghizadeghan, “Smart distribution grid multistage expansion planning under load forecasting uncertainty,” *IET Gener. Transm. Distrib.*, vol. 10, no. 5, pp. 1136-1144, 2016.

[15] G. Celli, E. Ghiani, G. Soma, and F. Pilo, "Planning of reliable active distribution systems," in Proc. *CIGRE*, 2012, pp. 1-12.

[16] M. S. Nazar, M. R. Haghifam, and M. Nažar, “A scenario driven multiobjective primary–secondary distribution system expansion planning algorithm in the presence of wholesale–retail market,” *Int. J. Electr. Power Energy Syst.*, vol. 40, no. 1, pp. 29-45, 2012.

[17] T.-H. Chen, E.-H. Lin, N.-C. Yang, and T.-Y. Hsieh, “Multi-objective optimization for upgrading primary feeders with distributed generators from normally closed loop to mesh arrangement,” *Int J. Electr. Power Energy Syst.*, vol. 45, no. 1, pp. 413-419, 2013.

[18] I. Ziari, G. Ledwich, A. Ghosh, and G. Platt, “Optimal distribution network reinforcement considering load growth, line loss, and reliability,” *IEEE Trans. Power Syst.*, vol. 28, no. 2, pp. 587-597, 2013.

[19] A. M. El-Zonkoly, “Multistage expansion planning for distribution networks including unit commitment,” *IET Gener. Transm. Distrib.*, vol. 7, no. 7, pp. 766-778, 2013.

[20] M. E. Samper and A. Vargas, “Investment decisions in distribution networks under uncertainty with distributed generation—Part II: Implementation and results,” *IEEE Trans. Power Syst.*, vol. 28, no. 3, pp. 2341-2351, 2013.

[21] E. G. Carrano, F. G. Guimarães, R. H. Takahashi, O. M. Neto, and F. Campelo, “Electric distribution network expansion under load-evolution uncertainty using an immune system inspired algorithm,” *IEEE Trans. Power Syst.*, vol. 22, no. 2, pp. 851-861, 2007.

[22] C. L. T. Borges and V. F. Martins, “Multistage expansion planning for active distribution networks under demand and distributed generation uncertainties,” *Int. J. Electr. Power Energy Syst.*, vol. 36, no. 1, pp. 107-116, 2012.

[23] A. Zidan, M. F. Shaaban, and E. F. El-Saadany, “Long-term multi-objective distribution network planning by DG allocation and feeders’ reconfiguration,” *Electr. Power Syst. Res.*, vol. 105, pp. 95-104, 2013.

[24] S. Favuzza, G. Graditi, M. G. Ippolito, and E. R. Sanseverino, “Optimal electrical distribution systems reinforcement planning using gas micro turbines by dynamic ant colony search algorithm,” *IEEE Trans.Power Syst.*, vol. 22, no. 2, pp. 580-587, 2007.

[25] Ž. Popović, V. D. Kerleta, and D. Popović, “Hybrid simulated annealing and mixed integer linear programming algorithm for optimal planning of radial distribution networks with distributed generation,” *Electr. Power Syst. Res.*, vol. 108, pp. 211-222, 2014.

[26] N. Koutsoukis, P. Georgilakis, and N. Hatziargyriou, “A Tabu search method for distribution network planning considering distributed generation and uncertainties,” *Proc. Int. Conf. Probab. Methods Appl. Power Syst.*, 2014, pp. 1-6.

[27] R. Hemmati, R.-A. Hooshmand, and N. Taheri, “Distribution network expansion planning and DG placement in the presence of uncertainties,” *Int. J. Electr. Power Energy Syst.*, vol. 73, pp. 665-673, 2015.

[28] V. F. Martins and C. L. Borges, “Active distribution network integrated planning incorporating distributed generation and load response uncertainties,” *IEEE Trans. Power Syst.*, vol. 26, no. 4, pp. 2164-2172, 2011.

[29] U. Sultana, A. B. Khairuddin, A. Mokhtar, N. Zareen, and B. Sultana, "Grey wolf optimizer based placement and sizing of multiple distributed generation in the distribution system," *Energy,* vol. 111, pp. 525-536, 2016.
[30] H. Doagou-Mojarrad, G. Gharehpetian, H. Rastegar, and J. Olamaei, "Optimal placement and sizing of DG (distributed generation) units in distribution networks by novel hybrid evolutionary algorithm," *Energy,* vol. 54, pp. 129-138, 2013.
[31] Y.-Y. Hong and S.-Y. Ho, "Determination of network configuration considering multiobjective in distribution systems using genetic algorithms," *IEEE Transactions on Power Systems,* vol. 20, no. 2, pp. 1062-1069, 2005.
[32] X.-F. Wang, Y. Song, and M. Irving, *Modern power systems analysis*. Springer Science & Business Media, 2010.
[33] Z. W. Geem, J. H. Kim, and G. Loganathan, "A new heuristic optimization algorithm: harmony search," *Simulation,* vol. 76, no. 2, pp. 60-68, 2001.
[34] D. Manjarres, I. Landa-Torres, S. Gil-Lopez, J. D. Ser, M. N. Bilbao, S. S. Sanz and Z. W. Geem, "A survey on applications of the harmony search algorithm," *Engineering Applications of Artificial Intelligence,* vol. 26, no. 8, pp. 1818-1831, 2013.
[35] M. Mahdavi, M. Fesanghary, and E. Damangir, "An improved harmony search algorithm for solving optimization problems," *Applied mathematics and computation,* vol. 188, no. 2, pp. 1567-1579, 2007.
[36] B. Huang, B. Buckley, and T.-M. Kechadi, "Multi-objective feature selection by using NSGA-II for customer churn prediction in telecommunications," *Expert Systems with Applications,* vol. 37, no. 5, pp. 3638-3646, 2010.
[37] K. Deb, *Multi-objective optimization using evolutionary algorithms*. John Wiley & Sons, 2001.
[38] M. Haghifam, H. Falaghi, and O. Malik, "Risk-based distributed generation placement," *IET Generation Transmission and Distribution,* vol. 2, no. 2, pp. 252-260, 2008.
[39] H. Falaghi, C. Singh, M.-R. Haghifam, and M. Ramezani, "DG integrated multistage distribution system expansion planning," *International Journal of Electrical Power & Energy Systems,* vol. 33, no. 8, pp. 1489-1497, 2011.
[40] V. Quintana, H. Temraz, and K. Hipel, "Two-stage power system distribution planning algorithm," *IEE Proc. C (Gener., Trans. Distrib.)*, vol. 140, no. 1, pp. 17-29, 1993.
[41] H. Falaghi and M.-R. Haghifam, "ACO based algorithm for distributed generation sources allocation and sizing in distribution systems," in *Power Tech, 2007 IEEE Lausanne,* 2007, pp. 555-560.
[42] M. Rabiee, M. Zandieh, and P. Ramezani, "Bi-objective partial flexible job shop scheduling problem: NSGA-II, NRGA, MOGA and PAES approaches," *Int.l J. Produc. Res.,* vol. 50, no. 24, pp. 7327-7342, 2012.