An Improved Multi-Objective Harmony Search for Optimal Placement of DGs in Distribution Systems

Komail Nekooei, Malihe M. Farsangi, Hossein Nezamabadi-Pour, and Kwang Y. Lee, *Fellow, IEEE*

***Abstract*—In this paper a new approach using Harmony Search (HS) algorithm is presented for placing Distributed Generators (DGs) in radial distribution systems. The approach is making use of a multiple objective planning framework, named an Improved Multi-objective HS (IMOHS), to evaluate the impact of DG placement and sizing for an optimal development of the distribution system. In this study, the optimum sizes and locations of DG units are found by considering the power losses and voltage profile as objective functions. The feasibility of the proposed technique is demonstrated in two distribution networks, where the qualitative comparisons are made against a well-known technique, known as Non-dominated Sorting Genetic Algorithm II (NSGA-II). Furthermore, the results obtained are compared with those available in the literature.**

***Index Terms*—Distributed generation, harmony search algorithm, multi-objective optimization.**

I. Introduction

RECENTLY, there has been a great interest in the integration of distributed generation (DG) units at the distribution level. In addition to environmental protection, DG could effectively improve power system stability, power quality and energy efficiency [1], [2]. Taking advantages of DGs [3] depends largely on how these devices are placed in the power system, namely on their location and size.

The optimal DG allocation is a complex problem with nonlinear objective function and nonlinear constraints, in which heuristic algorithms are a good choice for placing DGs. A range of techniques has been proposed to define the optimal locations and capacities of DGs [3]–[37]. Furthermore, a wide range of objectives and a variety of constraints are suggested in the literature, where two distinct approaches in solving the problem can be identified: 1) Finding optimal locations and sizes by using a weighted sum approach, and 2) Finding optimal locations and sizes based on Pareto-optimal front.

The first approaches aim to site DGs, by using multi-objective technique to optimize more than one objective functions simultaneously, which can be solved by using the weighting factors for maximizing the benefits of DG. In this approach, a combination of all objectives are considered as a single one, by using a weighted sum of multiple objective functions, such as the work carried out in [23]–[31].

The second approach aims to site DGs by optimizing all objective functions simultaneously, based on the Pareto front to yield non-dominated solutions [32]–[37].

The main drawback of the first approach is that it generates only one solution, which depends on the selected weights for each objective function. This solution could be one of the non-dominated solutions found by the second approach, i.e., the Pareto front.

However, the literature on Pareto front only reported the non-dominated solutions and the best non-dominated solution without comparing the quality of obtained non-dominated solutions. The quality comparison should be made between different multi-objective algorithms in order to choose the most effective one. Otherwise, this may lead us to a non-optimum solution for the problem at hand.

In this paper, the harmony search (HS) is selected as a tool for optimal DG allocation in two study systems. The standard HS is performing well but has some drawbacks that make the algorithm fails in finding the optimum solution in some problems. In view of these drawbacks, two improved versions of the HS algorithm are reported in the literature: Improved Harmony Search (IHS) and Novel Global Harmony Search (NGHS). These versions have improved the performance of the basic HS with some benefits and drawbacks.

This paper takes the benefit of the NGHS version and proposes additional improvement to overcome its drawbacks. Then, based on the improved NGHS algorithm, an improved multi-objective HS (IMOHS) is developed. The proposed IMOHS is different from other version of the multi-objective HS [38] in the improvisation, updating step and saving the non-dominated harmonies at each iteration with additional memory.

The proposed IMOHS is used to evaluate the impact of DG placement in developing optimal distribution system. A wide range of objectives and a variety of constraints are suggested in the literature for the placement of DGs, such as loss reduction, voltage improvement, reliability improvement [3]–[37], etc. This paper has considered the primary objectives that have led to an increasing interest in placing DGs, that is, the minimization of power losses and voltage deviations. It should be noted that there are varieties of DGs available in the market; some of them are variable power DG sources such as wind and photovoltaic (PV). In practice, the site of such DG sources may be mainly determined by meteorological and geographic factors. However, DG sources with predictable output power such as fuel cells and microturbines can be placed at any bus in the

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K. Nekooei, M. M. Farsangi, and H. Nezamabadi-Pour are with Kerman University, Kerman, Iran. (e-mail: komailnekooei@gmail.com, mmaghfoori@mail.uk.ac.ir, nezam@mail.uk.ac.ir).

K. Y. Lee is with the Department of Electrical and Computer Engineering, Baylor University, Waco, TX 76798-7356 USA. (e-mail: Kwang_Y_Lee@baylor.edu).

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distribution system to achieve optimal result. Without the loss of generality, the proposed algorithm can be applied for specified DG(s) in a practical power system. It should be noted that the placing problem of DGs is in two parts. The first part is choosing the objectives and the types of DGs and the second part is choosing a powerful algorithm for finding the optimal solution, which is the main focus of the paper. Nevertheless, the method presented in this paper can be effective and helpful to system designers in selecting proper sites to place DGs.

Feasibility of the proposed technique is demonstrated for two typical distribution networks and is compared against a well known technique known as NSGA-II [37], [39], [40] method and other algorithms available in the literatures.

To make sure that a proper algorithm is chosen, the comparison is made based on qualitative observation by plotting the Pareto front and by considering comparison metrics known as convergence metric (C-metric), spacing metric (SP-metric) and diversity metric (D-metric). Obtained results show that the proposed IMOHS performs much better than NSGA-II.

The main contributions of the paper can be summarized as follows:

1. An improvement is made on the improved version of HS algorithm (NGHS).
2. Apart from the improvement of the HS, a new version of multi-objective HS (IMOHS) is introduced.
3. The comparison is made qualitatively by plotting the Pareto front and considering comparison metrics.

The paper is organized as follows: to make a proper background, the basic concept of the HS and two improved versions of the HS algorithm reported in the literature (known as IHS and NGHS) are briefly explained in Section II. Also, in Section II, we propose NGHS-II algorithm as an improvement of NGHS. The proposed multi-objective HS is explained in Section III. The optimization problem is formulated in Section IV. Results obtained are given in Section V and some conclusions are drawn in Section VI.

II. Harmony Search Algorithms

An overview of the basic Harmony Search (HS) algorithm is presented in this section, followed by two improved versions of the HS algorithm reported in the literature, Improved Harmony Search (IHS) and Novel Global Harmony Search (NGHS). We then propose NGHS-II algorithm as an improvement of the NGHS.

A. Harmony Search (HS)

The HS is based on the natural musical process which searches for a perfect state of harmony. The HS algorithm does not require initial values for the decision variables and uses a stochastic random search. In general, the HS algorithm works as follows [41], [42]:

Step 1. Define the objective function and decision variables. Input the system parameters and the boundaries of the decision variables.

The optimization problem can be defined as:

$$\text{Minimize } f(x)$$
$$\text{subject to } x_{iL} \leq x_i \leq x_{iU} \ (i = 1, 2, \ldots, N)$$

where x_{iL} and x_{iU} are the lower and upper bounds for decision variables.

The HS algorithm parameters are specified in this step. They are the harmony memory size (HMS) or the number of solution vectors in harmony memory, the harmony memory considering rate (HMCR), the distance bandwidth (bw), the pitch adjusting rate (PAR), and the number of improvisations (K) or stopping criterion, where K is the same as the total number of function evaluations.

Step 2. Initialize the harmony memory (HM). The harmony memory is a memory location where all the solution vectors (sets of decision variables) are stored. The initial harmony memory is randomly generated in the region $[x_{iL}, x_{iU}] (i = 1, 2, \cdots, N)$. This is done based on the following equation:

$$x_i^j = x_{iL} + \text{rand}() \times (x_{iU} - x_{iL}) \; j = 1, 2, \ldots, \text{HMS} \quad (1)$$

where $\text{rand}()$ is a random number from a uniform distribution of [0, 1].

Step 3. Improvise a new harmony from the harmony memory. Generating a new harmony x^{new} is called improvisation, which is based on 3 rules: memory consideration, pitch adjustment, and random selection. First of all, a uniform random number r is generated in the range [0, 1]. If r is less than the HMCR, the decision variable x_i^{new} is generated by the memory consideration; otherwise, x_i^{new} is obtained by a random selection. Then, each decision variable x_i^{new} will undergo a pitch adjustment with a probability of PAR if it is produced by the memory consideration. The pitch adjustment rule is given as follows:

$$x_i^{\text{new}} = x_i^{\text{new}} \pm r \times \text{bw} \quad (2)$$

Step 4. Update harmony memory. After generating a new harmony vector x^{new}, the harmony memory will be updated. If the fitness of the improvised harmony vector $x^{\text{new}} = (x_1^{\text{new}}, x_2^{\text{new}}, \ldots, x_N^{\text{new}})$ is better than that of the worst harmony, the worst harmony in the HM will be replaced with x^{new} and become a new member of the HM.

Step 5. Repeat *Steps 3–4* until the stopping criterion (maximum number of improvisations, K) is met.

B. The Improved Harmony Search (IHS)

An improved harmony search algorithm (IHS) is proposed in [43], in which the key modifications are about PAR and bw. In the HS, PAR, and bw are all constants, but the IHS updated them dynamically as follows:

$$\text{PAR}(k) = \text{PAR}_{\min} + \left(\frac{\text{PAR}_{\max} - \text{PAR}_{\min}}{K}\right) k \quad (3)$$

$$\text{bw}(k) = \text{bw}_{\max} \exp\left(\frac{\ln\left(\frac{\text{bw}_{\min}}{\text{bw}_{\max}}\right)}{K}\right) k \quad (4)$$

where k is current number of improvisations, and K is maximum number of improvisations. Numerical results on engineering optimization problems reveal that the IHS can find better solutions compared to the HS.

In IHS, the numbers of parameters are increased, which is not good, and this is the main drawback of the IHS. It should be noted that in order to get the optimum point by heuristic algorithms, the parameters of the algorithm must be tuned for the problem at hand.

C. A Novel Global Harmony Search (NGHS)

The NGHS proposed by Zou [44] is different from HS in three aspects as follows:

1) Mutation operator is added. Instead of parameters HMCR, bw and PAR in the basic HS, a genetic mutation probability (p_m) is considered in the NGHS. Therefore, the number of parameters is decreased.

2) The NGHS modifies the improvisation step of the HS, and it works as follows [44]:

for $i = 1 : N$ *do*
  $\mathrm{step}_i = |x_i^{\mathrm{best}} - x_i^{\mathrm{worst}}|$ *% calculate the adaptive step*

$$x_i^{\mathrm{new}} = x_i^{\mathrm{best}} \pm r \times \mathrm{step}_i \text{ \% } \textit{position updating} \quad (5)$$

  if $\mathrm{rand}() \leq p_m$
    $x_i^{\mathrm{new}} = x_{iL} + \mathrm{rand}() \times (x_{iU} - x_{iL})$ *% genetic mutation*
  end
end for

Here, "best" and "worst" are the indices of the global best harmony and the worst harmony in the HM, respectively, and r and $\mathrm{rand}()$ are all uniformly generated random numbers in [0, 1].

The *adaptive step* (step_i) can guarantee that the algorithm has strong local search ability in the late stage of optimization and has strong global search ability in the early stage of optimization.

To prevent the premature convergence of the NGHS, the genetic mutation operation is carried out for the worst harmony in the harmony memory (HM) after updating the position.

3) After improvisation, the NGHS replaces the worst harmony x^{worst} in the HM with the new harmony x^{new} even if x^{new} is worse than x^{worst}.

The NGHS has some drawbacks. In the next section, we propose NGHS-II algorithm as an improvement of NGHS.

D. The Proposed NGHS-II

In the NGHS, the original structure of harmony search is changed by excluding the HMCR parameter and including a mutation probability, p_m. With a careful observation, we can find that the role of the mutation probability is the same as (1-HMCR), i.e., the complement of HMCR. Therefore, in this paper, the genetic mutation probability (p_m) is removed and the HMCR is used to preserve the original structure of the harmony search and the improvisation step becomes as follows [45]:

for $i = 1 : N$ *do*
  if $\mathrm{rand}() \leq \mathrm{HMCR}$
  $\mathrm{step}_i = |x_i^{\mathrm{best}} - x_i^{\mathrm{worst}}|$ *% calculate the adaptive step*

$$x_i^{new} = x_i^{best} \pm r \times step_i \text{ \% } \textit{position updating} \quad (6)$$

$$x_i^{\mathrm{new}} = \max(x_{iL}, \min(x_{iU}, x_i^{\mathrm{new}}))$$

  else
    $x_i^{\mathrm{new}} = x_{iL} + \mathrm{rand}() \times (x_{iU} - x_{iL})$ *% genetic mutation*
  end
end for

In the NGHS-II, a new harmony is inclined to mimic the global best harmony in the HM, similar to the NGHS. Since the parameter (1-HMCR) determines the randomness of the new harmony, large HMCR results in premature convergence. To maintain the diversity of the HM, HMCR must be small. But small HMCR decreases convergence speed, and also results in producing new harmonies which are infeasible.

In this paper HMCR is adjusted close to one to produce feasible solutions and have a good exploitation. After some evaluations, the algorithm may reach to a local solution and *the adaptive step* (step_i) goes to zero. At this step the algorithm is stagnated. Therefore, to prevent the stagnation, we generate a few harmonies randomly and replace the worse harmonies with them in the HM. The number of new random harmonies depends on the problem and the size of the HM. The new random harmonies cause the step_i to increase and the algorithm starts new exploration to find a better solution.

In the NGHS, the worst harmony x^{worst} in the HM will be replaced with the new harmony x^{new} even if x^{new} is worse than x^{worst}. This replacement is not good since it makes the algorithm not to converge. Therefore, in this paper, the worst harmony x^{worst} in the HM will be replaced with the new harmony x^{new} only if x^{new} is better than x^{worst}.

It should be noted that in the NGHS and NGHS-II the number of parameters is decreased compared to IHS.

III. The Improved Multi-Objective Harmony Search

There is only one multi-objective harmony search (MOHS) in literature, which is reported in [38] and it is based on IHS.

In this paper, an improved multi-objective harmony search (IMOHS) is proposed. In the IMOHS, the search process of the proposed NGHS-II is applied on harmonies, which are ranked based on the non-dominated sorting and distance crowding strategies [39] to find new harmonies based on the following definitions:

Domination rank. A multi-objective optimization problem can be defined as follows:

$$\begin{aligned} &\text{minimize } \{f_1(X), f_2(X), \ldots, f_m(X)\} \\ &\text{subject to, } X \in T \end{aligned} \quad (7)$$

where $m \geq 2$. The objective functions $f_i(X) : R^n \rightarrow R$ are conflicting to one another and the aim is optimizing them simultaneously (without loss of generality it is assumed that the objective functions are to be minimized). The decision vectors $X = (x_1, x_2, \ldots, x_n)^T$ belong to the feasible region $T \subset R^n$ which is formed by the constraints.

The feasible region for objective functions f is denoted by $H \subset R^m$ and is called as the feasible objective region. The elements of H are called objective vectors and they consist of the values of the objective functions, $f(X) = (f_1(X), f_2(X), \ldots, f_m(X))$.

A decision vector $X_1 \in T$ is said to *dominate* a decision vector $X_2 \in T$ (denoted by $X_1 \prec X_2$), if and only if:

$$\text{I.} \quad \forall i: f_i(X_1) \le f_i(X_2), \quad i = 1, \ldots, m. \tag{8}$$
$$\text{II.} \quad \exists i | f_i(X_1) < f_i(X_2), \quad i = 1, \ldots, m \tag{9}$$

This means that the decision vector X_1 is not worse than X_2 in all objectives and is strictly better than X_2 in at least one objective.

Also X_1 *weakly dominates* X_2 (denoted by $X_1 \preceq X_2$), if and only if

$$\forall i: f_i(X_1) \le f_i(X_2), \tag{10}$$

Finding the non-dominated members in population P is based on the following steps:

1. Define a rank counter l to be 0.
2. Increase: $l = l + 1$.
3. Based on the definition of domination, find the non-dominated harmonies from population P.
4. Assign rank l to these harmonies.
5. Remove these harmonies from population P.
6. If population P is empty, stop. Otherwise, go to Step 2.

Crowding distance. The density of solutions can be measured by a crowding distance. The value of the crowding distance shows an estimate of the density of solutions surrounding a particular solution.

Based on the above definitions, if a solution X_1 is better than another harmony X_2, one of the following conditions has happened: (a) the domination rank of solution X_1 is smaller than that of solution X_2, or (b) their domination ranks are equal and the crowding distance of harmony X_1 is larger than that of harmony X_2.

In the proposed IMOHS, an additional memory is used to save the non-dominated harmonies at each iteration, which is called *Archive* while the dominated harmonies remain in the HM.

To keep the diversity of the HM, dominated harmonies are not discarded and they are given a chance to participate in the improvisation process. Based on the definition of domination the harmonies in Archive have the rank of 1 while the dominated harmonies in the HM have the ranks of 2, 3,…. Among harmonies in the HM, those harmonies with ranks 2 and 3 are the ones who can help the algorithm for exploitation since they are close to those harmonies in the Archive. The harmonies with other ranks can be used in exploration. Therefore, to prevent discarding the weak-dominated harmonies (harmonies with ranks of 4, 5,…) in the earlier iterations and preserve the diversity of the HM, updating process is improved as follows:

To generate a new harmony X^{new}, a dominated harmony (X^d) and a non-dominated harmony (X^{Nd}) is selected randomly from the HM and archive, respectively. Then the new harmony is produced as follows:

$$X^{\text{new}} = X^{\text{Nd}} \pm \text{rand}() \times |X^{\text{Nd}} - X^d| \tag{11}$$

The HM is updated by new harmony. The dominated harmony X^d will be replaced by X^{new} if X^{new} dominates X^d. Generation of a new harmony and updating the HM are repeated for HMS times in each iteration.

At the end of iterations, the Archive is updated so that the harmonies of the HM are sorted according to the definition of domination, and the non-dominated harmonies of the HM are transferred to Archive. Also, the harmonies of Archive which are dominated by the new non-dominated harmonies (transferred from the HM) return to the HM.

Based on the above descriptions, the details of proposed IMOHS are as follows:

Step 1. Define objective functions and decision variables, and input the system parameters and the boundaries of the decision variables.

Step 2. Initialize the harmony memory (HM) and Archive.

2-1. Initial population is produced randomly within the range of the boundaries of the decision variables in the HM so that none of them are repeatable.

2-2. Evaluate the population of the HM and rank the evaluated population based on the non-dominated sorting scheme.

2-3. The non-dominated solutions (harmonies with rank 1) are moved to the Archive. Harmonies with other ranks remain in the HM.

Step 3. Generate new harmonies and update the HM.

3-1. Select a harmony randomly from the Archive (X^{Nd}).

3-2. Select a harmony randomly from the HM (X^d).

3-3. Find the distance between the selected non-dominated harmony and dominated harmony and consider it as a search radius.

3-4. Generate a new harmony based on (11). The X^d will be replaced by the X^{new} if the X^{new} dominates the X^d.

3-5. Repeat steps 3-1 to 3-4 for HMS times.

Step 4. Update the Archive.

At the end of each iteration, the harmonies in the HM are sorted according to the definition of domination, and the non-dominated harmonies in the HM are transferred to Archive. Also, the harmonies in the Archive which are dominated by the new non-dominated harmonies return to the HM. If the number of candidate harmonies to transfer to the *Archive* is greater than the size of the Archive, the *crowding distance* is calculated and those with higher crowding distance are moved to the Archive.

Step 5. Check for stopping conditions. If the number of improvisations has been reached to the maximum, go to the next step. Otherwise, return to *step 3*.

Step 6. The harmonies in the Archive (or non-dominated solution vectors) are Pareto front. The best compromise solution is obtained by using the *max-min* [7], [35] method as follows:

$$\max\left\{\min_t\left\{\ldots, \frac{f_j^{\max} - f_{i,j}}{f_j^{\max} - f_j^{\min}}, \ldots\right\}\right\} \tag{12}$$

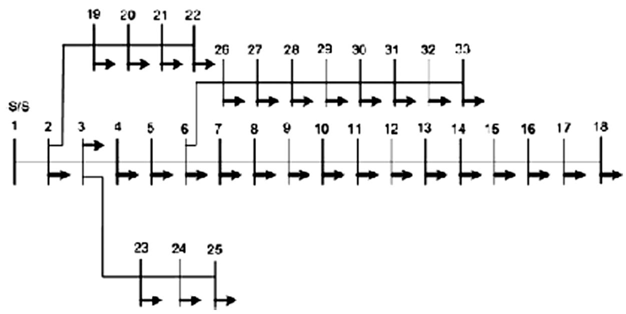

Fig. 1. The study system-1.

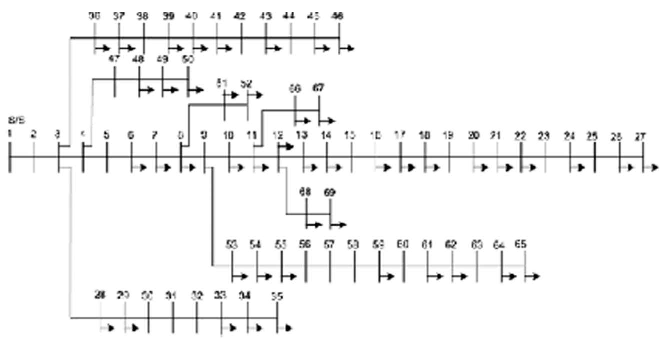

Fig. 2. The study system-2.

where i refers to the i-th solution of the non-dominated set, $f_j^{\max}$ and $f_j^{\min}$ are the maximum and minimum values of the j-th objective function, respectively.

IV. Study System and Problem Formulation

Two study systems are used in this paper.

1) Study System-1: This test system is illustrated in Fig. 1 which is a radial distribution system with the total load of 3.72 MW, 2.3 MVar, 33 bus, and 32 branches and the power loss of 210.998 kW [23]. A PV model is considered for DGs in this study system.

2) Study System-2: The system shown in Fig. 2 is also a radial distribution system, which consists of 69 bus and 68 branches with the total load of 3.8 MW, 2.69 MVar, and power loss of 225 kW [9].

A PQ model is considered for DGs in this study system. The DGs are considered to be working at a specified power factor (0.85 lagging).

In practice, in the distribution network, load pattern is varying with time. The optimal location and size of DG determined under invariant loads may not be optimal under time-varying loads and the optimal DG size may vary with varying load demand. But in practice, it is not economically feasible to change the DG size with changing load demand. Therefore, for planning purpose, an optimal size and location of DGs can be determined by considering peak, average, or combination of the two loading conditions to get the maximum benefit of DGs. In this paper, we have considered the two prototype systems with existing loading conditions and studied the impact of DGs by comparing the case with and without DGs.

It should be noted that in PQ model, the DG is considered as negative load. The PV model regulates the terminal bus voltage by adjusting their reactive power output. However, it is preferred to not to use a PV model, since injecting a great amounts of reactive power in order to raise the bus voltage may result in high field currents and overheating for the generator, triggering the excitation limit and disconnecting the generator from the network.

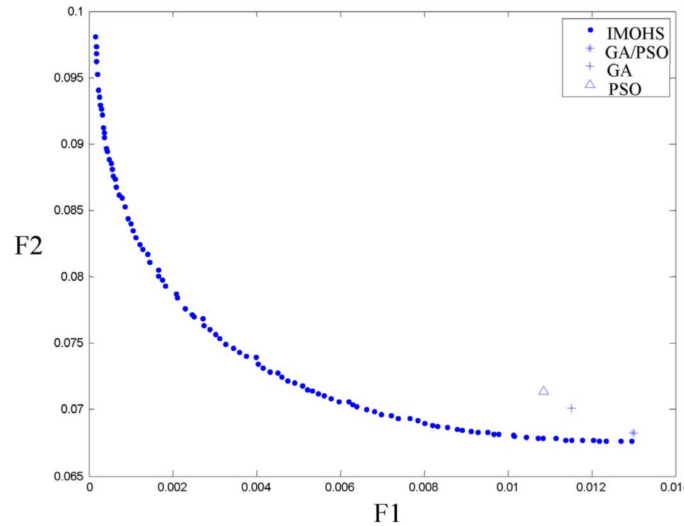

Fig. 3. Pareto front of the IMOHS and the obtained results by [23].

TABLE I
The Obtained Solutions by GA, PSO and GA/PSO in [23]

Method	DG Locations (bus number) and DG Sizes (MW)				Worst Voltage (p.u)	Loss (p.u)
GA/PSO	24	26	14	32	0.9703	0.0682
	1.0232	0.8671	0.6628	0.6639		
GA	24	6	13	30	0.9674	0.0701
	0.8571	0.6429	0.8571	0.7382		
PSO	25	6	15	31	0.9696	0.0713
	0.5413	0.8301	0.8330	0.6478		

The penetration level of distributed generation is increasing in distribution network. Therefore, distribution networks are no longer passive in nature, and their characteristics are becoming similar to an active transmission network. Therefore, considering power losses as an objective function in distribution network is very common in the literature [10]–[21].

In this paper, the objective is to minimize the network power loss and maximize the voltage regulation in the study systems as follows [23]–[25]:

$$\text{Min } f_1 = (P_{\text{loss}}) \tag{13}$$

$$\text{Min } f_2 = \sum_{i=1}^{n} (V_i - 1)^2 \tag{14}$$

subject to

$$0 < P_{\text{DG}} < P_{\text{DG}}^{\max} \tag{15}$$

$$V_{\min} < V_i < V_{\max} \tag{16}$$

where n is the total number of nodes, V_i is voltage magnitude of node i. P_{DG} is the power of DG and $P_{\text{DG}}^{\max}$ is the maximum power of DG. $P_{\text{DG}}^{\max}$ is 1.2 MW and 2 MW for the study system-1 [23] and system-2 [9], respectively.

TABLE II
SOLUTIONS OBTAINED BY IMOHS THAT DOMINATE THE SOLUTIONS OBTAINED BY GA, PSO, AND GA/PSO IN [23] FOR STUDY SYSTEM-1

DG Sizes (MW)				Sum(DG Sizes)	DG Locations (bus number)				Voltage Deviation (p.u.)	Worst Voltage (p.u)	Loss (p.u)
0.9291	0.6481	0.9713	0.6846	3.2331	6	14	24	31	0.012962	0.970379	0.067631
0.8911	0.6595	0.9630	0.7071	3.2207	6	14	24	31	0.012699	0.970769	0.06765
0.9320	0.6580	0.9692	0.6980	3.2572	6	14	24	31	0.012331	0.971149	0.067652
0.9341	0.6585	1.0022	0.6966	3.2914	6	14	24	31	0.012174	0.971307	0.067675
0.8835	0.6695	0.9869	0.7241	3.2640	6	14	24	31	0.012037	0.97154	0.067703
0.9225	0.6810	0.9991	0.6899	3.2925	6	14	24	31	0.011772	0.972155	0.06772
0.9316	0.6733	0.9549	0.7181	3.2780	6	14	24	31	0.011515	0.972214	0.067741
0.9495	0.6821	0.9611	0.6978	3.2906	6	14	24	31	0.011376	0.972693	0.067755
0.9369	**0.6672**	**1.0117**	**0.7312**	3.3470	**6**	**14**	**24**	**31**	**0.011146**	**0.972341**	**0.067831**
0.9325	0.6952	0.9749	0.7141	3.3166	6	14	24	31	0.010839	0.973319	0.067853
0.9357	0.7049	0.9570	0.7073	3.3049	6	14	24	31	0.010713	0.973169	0.067894
0.9667	0.6946	0.9574	0.7168	3.3355	6	14	24	31	0.010434	0.973818	0.067943
0.9835	0.6855	0.9697	0.7326	3.3712	6	14	24	31	0.010145	0.973854	0.068034
0.9084	0.7209	0.9311	0.7385	3.2988	6	14	24	31	0.010122	0.974104	0.068092
0.9963	0.7044	0.9625	0.7159	3.3791	6	14	24	31	0.009781	0.974345	0.068135
0.9573	0.7127	1.0082	0.7264	3.4046	6	14	24	31	0.009666	0.974492	0.068184

In general, optimal placement of DGs can be formulated by considering other factors, such as economic and geographic considerations. In this paper, only two factors, power loss and voltage regulation, are taken into account, and the optimal placement of DGs is found by considering these two objectives. However, any other objectives can be added to the problem and optimized by the proposed algorithm.

V. IMPLEMENTATION OF IMOHS

In order to find the effectiveness and superiority of the IMOHS, the test results are compared with the results obtained by other algorithms available in the literature. To compare the result of IMOHS and its improvement in results over other heuristic approaches, all conditions must be the same. Therefore, four DGs are placed in the study system-1. The goal of the optimization is to find the best location and size of each DG. Therefore, each harmony is a d-dimensional vector, in which $d = 2 \times 4 = 8$. The HMS, HMCR and maximum number of improvisations are set to be 100, 0.9, and 500, respectively.

In searching for the harmony associated with non-dominated solutions, each harmony in the population is evaluated using the objective function defined by (13)–(14) subject to (15)–(16). To find the best location and size, the IMOHS is run for 50 independent runs under different random seeds. It should be noted that the archive size is fixed to M members of all the non-dominated solutions obtained, where M is selected to be 100.

Fig. 3 shows the obtained Pareto front by IMOHS. In [23] the location and size of the DGs are found by Genetic Algorithm (GA), Particle Swarm optimization (PSO), and a combination of GA/PSO. The results in [23] are obtained by the weighted-sum approach which only gives one solution. This figure shows the difference between the obtained solutions by IMOHS and other approaches in [23]. Table I shows the obtained location of the DGs in [23]. Table II shows the 16 Pareto solutions obtained by IMOHS that dominate the solutions obtained by GA, PSO, and GA/PSO in [23].

Among the 16 Pareto solutions obtained, one solution with the best compromise between the two objective functions is explored by using *max-min* approach [7], [35] from the Pareto front. Based on the max-min approach, the bolded solution in Table II is selected for DGs location. The DGs are placed at busses 6, 14, 24, and 31 with the size of 0.9369, 0.6672, 1.0117, and 0.7312 MW, respectively. As the table shows, if we select the solutions above the bolded solution, the voltage deviation (the first objective function) is getting worse but the loss (the second objective function) is getting better. Also, if we select the solutions below the bolded solution, the voltage deviation (the first objective function) is getting better but the loss (the second objective function) is getting worse. Fig. 4 shows the voltage magnitude of the busses of the study system-1 before and after the placement of DGs.

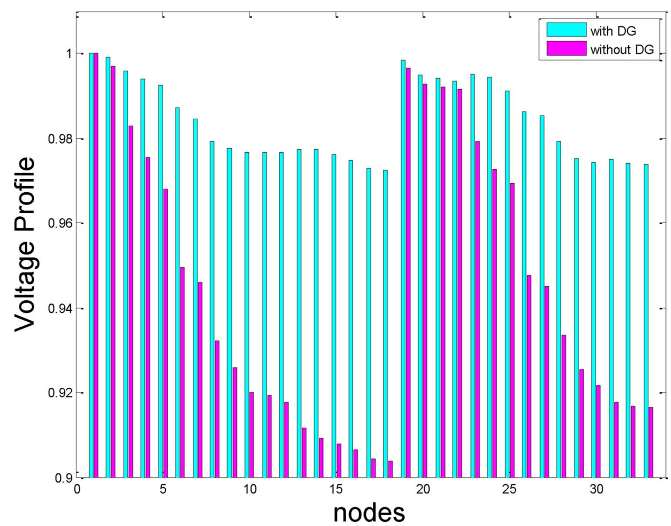

Fig. 4. Voltage magnitude of the busses of the study system-1 with and without DGs.

To investigate the ability of the IMOHS in finding the solution and convergence characteristics of the algorithm, the same study is carried out on the second study system, which is a larger system. For this system, based on [9], three DGs are placed in the system. Therefore, $d = 6$ and other settings are the same as in the system-1.

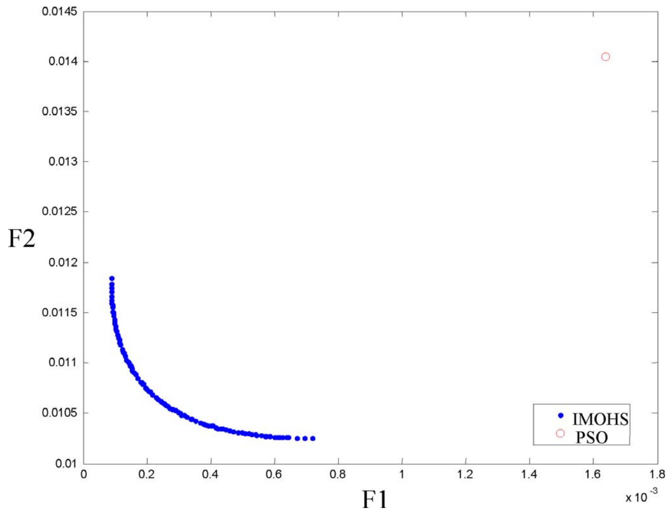

Fig. 5. Pareto front of the IMOHS and the obtained results by [9].

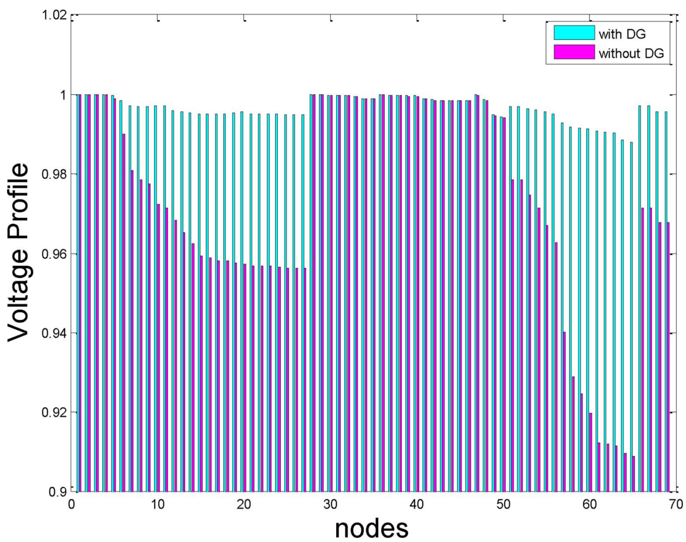

Fig. 6. Voltage magnitude of the busses of the study system-2 with and without DGs.

TABLE III
PSO [9] AND IMOHS RESULTS FOR STUDY SYSTEM-2

Method	DG Locations (bus number) and DG sizes (MW)			Worst Voltage (p.u)	Loss (p.u)
PSO	61	64	21	0.9879	0.0128
	1.278	0.301	0.324		
IMOHS	61	11	21	0.9937	0.0105
	1.4552	0.4769	0.3124		

The results obtained are compared with those obtained in [9] in which PSO is applied to find the location of three DGs by minimizing P_{loss}. The obtained results by the IMOHS and PSO in [9] are shown in Fig. 5. Once again, the max-min approach is used to find the best solution from the Pareto front obtained. The selected location by the max-min approach is given in Table III with the result given by PSO in [9]. Based on Table III, three DGs are placed at busses 61, 11, and 21 with the size of 1.4552, 0.4769, and 0.3124 MW, respectively. Fig. 6 shows the voltage magnitude of the busses of the study system-2 before and after placement of DGs.

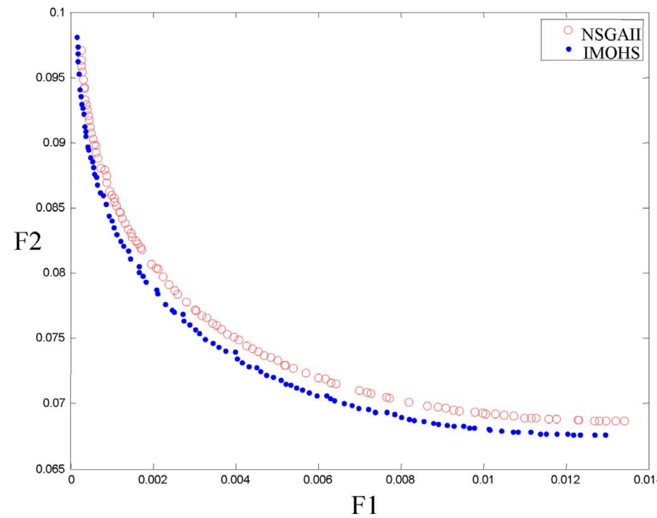

Fig. 7. Pareto front of IMOHS and NSGA-II for study system-1.

VI. COMPARISON OF IMOHS WITH NSGA-II

The IMOHS is compared with one outstanding evolutionary multi-objective optimization algorithm, NSGA-II. The two multi-objective algorithms are executed 50 times, where the population was monitored for non-dominated solutions and the resulting non-dominated set is taken as the outcome of one optimization run. The number of fitness evaluations is the same for both algorithms. The comparison is made qualitatively. In the case of multi-objective optimization, the definition of quality is more complex than in the single-objective optimization. For a powerful multi-objective optimization algorithm, the distance of the obtained non-dominated set to the Pareto front should be minimized. Also, a proper distribution is desirable for the obtained solutions. Furthermore, for each objective, a wide range of values should be covered by the non-dominated solutions. In view of these, the quality of the multi-objective algorithm can be checked by some comparison metrics such as error ratio, convergence metric, generational distance, diversity metric, spaced metric, relative convergence metric, etc. [46]–[50]. The first three metrics need the true Pareto-optimal front of the problem.

Since for engineering problem, the true Pareto-optimal front is unknown, therefore, in this paper, the comparison is made by plotting the Pareto front and considering relative convergence metric (C-metric) [46], [47], [49], spacing metric (SP-metric) [47]–[53], and diversity metric [47], [48], [50]. Since the two multi-objective algorithms are executed 50 times, *box-plot* and *t-test* tools are used to show the quality of obtained results by these metrics.

Comparison of the Pareto front. The obtained Pareto front with the IMOHS and NSGA-II in placing the DGs is shown in Figs. 7 and 8 for study system-1 and system-2, respectively. The figures show that the Pareto front of IMOHS dominates the NSGA-II's, which shows the superiority of the proposed algorithm.

Convergence metric (C-metric). The quality of two given sets of non-dominated solutions is compared with *C-metric*. For two

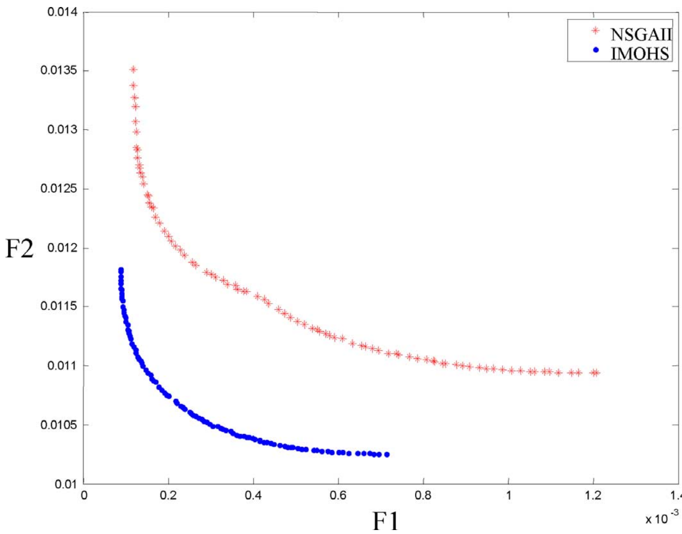

Fig. 8. Pareto front of IMOHS and NSGA-II for study system-2.

given Pareto sets, the function I_C maps the ordered pair (A, B) to the interval [0, 1] as follows:

$$I_C(A,B) = \frac{\text{size}(\{b \in B, \exists a \in A : a \preceq b\})}{|B|} \tag{17}$$

where $\text{size}(x)$ is the number of elements in the specified set x, $\preceq$ means weakly dominated, $|B|$ is the size of the Pareto set B.

A value of 1 for $I_C(A,B)$ indicates that all the decision vectors in B are weakly dominated by A, and $I_C(A,B) = 0$ indicates that no decision vectors in B is weakly dominated by ones in A. Since $I_C(A,B)$ is not necessarily equal to $1 - I_C(B,A)$, both directions always have to be considered.

The *box-plot* and *t-test* can be used to show the quality of the solutions obtained by IMOHS with respect to NSGA-II as follows:

a) *Box-plot*. For a pair (A, B) there is a sample set of 50 C-metric average values according to the 50 runs performed. The box-plot can be used to visualize the distribution of these samples.

The upper and lower ends of the box are the upper and lower quartiles. In other words, on each box, the edges of the box are the 25th and 75th percentiles and the central mark is the median.

Figs. 9–10 illustrate the box-plots for two study systems. These figures show that the left boxes I_C(IMOHS, NSGA-II) are higher than the right box I_C(NSGA-II, IMOHS) in all 50 runs. According to the definition of the C-metric, I_C (IMOHS, NSGA-II) represents the ratio of solutions in NSGA-II that are weakly dominated by the Pareto set of IMOHS. In other words, the higher I_C(IMOHS, NSGA-II) means the better approximate Pareto-optimal set is found by IMOHS than by NSGA-II. The figures show that the proposed method is performing well in finding the approximate Pareto-optimal front.

b) *t-test*. The *unpaired t-test* is a statistical test applied to data containing two or more groups. The test shows whether the means of two groups are statistically different from each other or not. Tables IV–V show mean value, standard deviation (Std) and the results of an unpaired *t-test* between IMOHS and NSGA-II (p-value) [51]–[53]. These tables reveal that there is statistically significant difference between IMOHS and NSGA-II for both study systems.

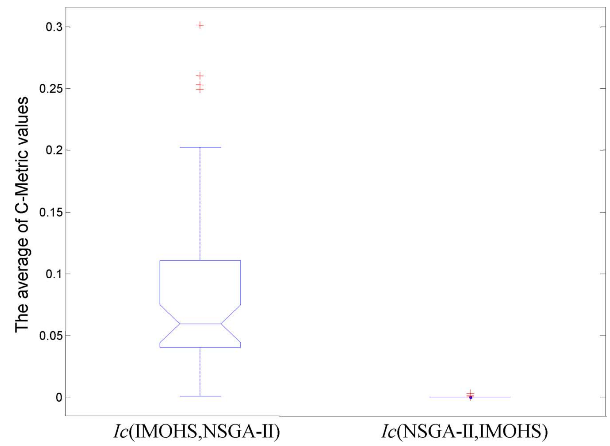

Fig. 9. Box-plot: C-metric values of 50 runs for study system-1.

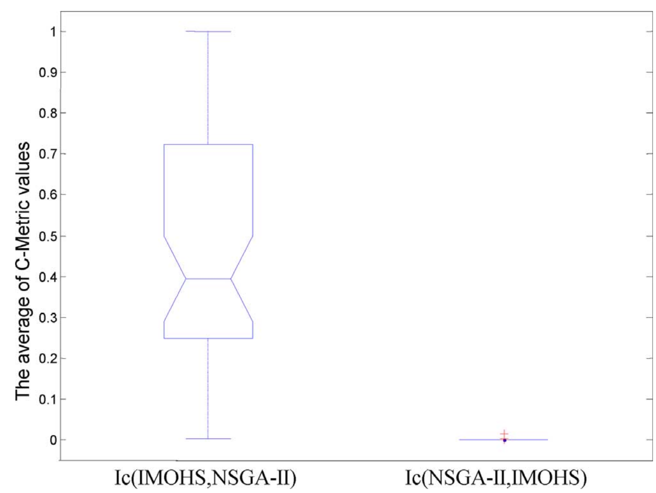

Fig. 10. Box plot: C-metric values of 50 runs for study system-2.

TABLE IV
C-METRIC: THE MEAN VALUE, STANDARD DEVIATION (STD) AND THE RESULTS OF UNPAIRED *T-TEST* BETWEEN IMOHS AND NSGA-II FOR STUDY SYSTEM-1

Ave C-Metric	IMOHS	NSGA-II
Mean	0.086588	0.000176
Std	0.07301	0.000542
p-value (t-test)	5.64E-11	
Difference	Extremely Significant	

TABLE V
C-METRIC : THE MEAN VALUE, STANDARD DEVIATION (STD) AND THE RESULTS OF UNPAIRED *T-TEST* BETWEEN IMOHS AND NSGA-II FOR STUDY SYSTEM-2

Ave C-Metric	IMOHS	NSGA-II
Mean	0.480136	0.000342
Std	0.352062	0.001904
p-value (t-test)	7.08E-13	
Difference	Extremely Significant	

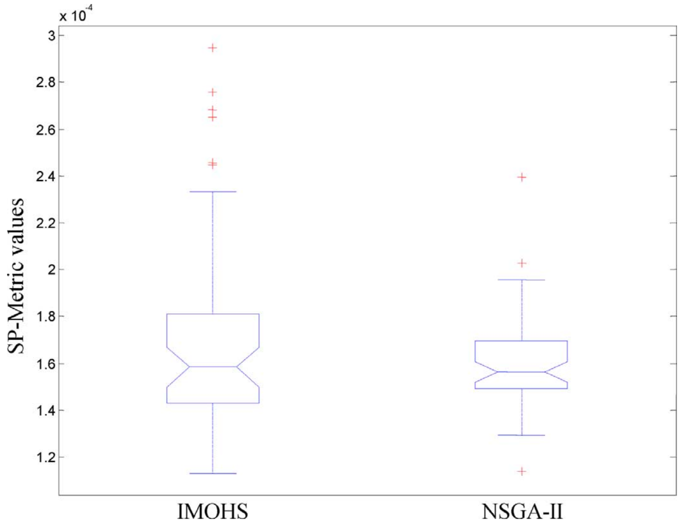

Fig. 11. Box-plot: SP-metric values of 50 runs for study system-1.

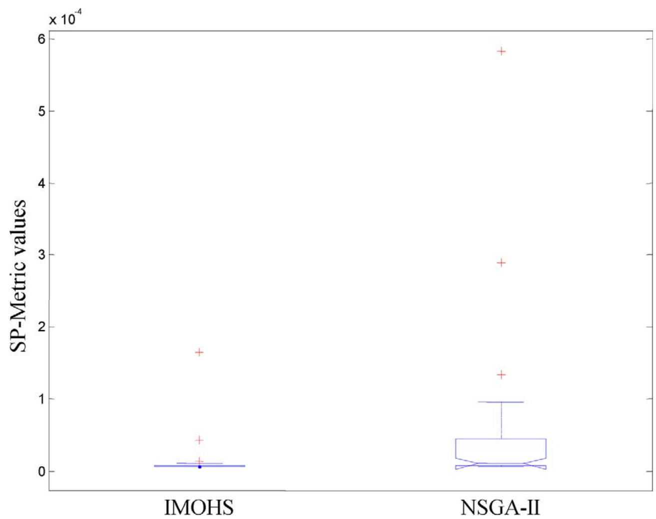

Fig. 12. Box-plot: SP-metric values of 50 runs for study system-2.

TABLE VI
SP-METRIC: THE MEAN VALUE, STANDARD DEVIATION (STD) AND THE RESULTS OF UNPAIRED *T-TEST* BETWEEN IMOHS AND NSGA-II FOR STUDY SYSTEM-1

Spacing Metric	IMOHS	NSGA-II
Mean	0.000171	0.00016
Std	4.15E-05	2.10E-05
p-value (t-test)	0.039407	
Difference	Non-Significant	

Spacing metric (SP-metric). The range (distance) variance of neighboring vectors in the Pareto front is measured by spacing metric and is defined as:

$$\mathrm{SP} = \sqrt{\frac{1}{n-1}\sum\nolimits_{i=1}^{n}(\overline{d}-d_i)^2} \qquad (18)$$

where $d_i = \min(\sum_{k=1}^{m}|f_k^i - f_k^j|), i,j = 1,\ldots,n$ where m is the number of objectives, $\overline{d}$ is the mean of all d_i, and n is the number of vectors in the Pareto front found by the algorithm.

If SP-metric takes a value of zero, it shows that all the non-dominated solutions found are equidistantly spaced. The obtained results for SP-metric are given by Figs. 11–12 and Tables VI–VII. The results show that two algorithms are performing similar in study system 1 while in study system 2 which is a larger system, the difference is significant between the two.

TABLE VII
SP-METRIC: THE MEAN VALUE, STANDARD DEVIATION (STD) AND THE RESULTS OF UNPAIRED *T-TEST* BETWEEN IMOHS AND NSGA-II FOR STUDY SYSTEM-2

Spacing Metric	IMOHS	NSGA-II
Mean	1.18E-05	4.27E-05
Std	2.28E-05	9.11E-05
p-value (t-test)	0.026189	
Difference	Significant	

TABLE VIII
D-METRIC: THE MEAN VALUE, STANDARD DEVIATION (STD) AND THE RESULTS OF UNPAIRED *T-TEST* BETWEEN IMOHS AND NSGA-II FOR STUDY SYSTEM-1

Diversification Metric	IMOHS	NSGA-II
Mean	319.7656	323.037
Std	4.071693	37.42144
p-value (t-test)	0.535407	
Difference	Non-Significant	

TABLE IX
D-METRIC: THE MEAN VALUE, STANDARD DEVIATION (STD) AND THE RESULTS OF UNPAIRED *T-TEST* BETWEEN IMOHS AND NSGA-II FOR STUDY SYSTEM-2

Diversification Metric	IMOHS	NSGA-II
Mean	125.2956	222.802
Std	7.853399	141.779
p-value (t-test)	1.18E-05	
Difference	Non-Significant	

Diversification metric. The diversification metric is used to measure the spread of the solution set. Its definition is:

$$D = \sqrt{\sum_{i=1}^{n}\max\left(\|X_i' - Y_i'|\right)} \qquad (19)$$

where $\|X_i' - Y_i'\|$ is the Euclidean distance between of the non-dominated solution $X_i^{'}$ and the non-dominated solution $Y_i^{'}$.

The results are given in Tables VIII–IX. The results show that NSGA-II has more diversity than the IMOHS in its obtained Pareto front. This is obvious since as it is shown in Figs. 7–8, the IMOHS dominates the NSGA-II and all solutions found in IMOHS are closer to Pareto-optimal front which we expect to have less diversity.

Therefore, we can come to the conclusion that the proposed IMOHS can maintain superior approximate Pareto-optimal set than the NSGA-II in dealing with the 50 independent runs.

VII. CONCLUSION

In this paper a new multiple objective planning framework, namely improved multi-objective harmony search (IMOHS), is developed, which is able to evaluate the impact of DG placement for an optimal planning of a distribution system. The feasibility of the proposed technique is demonstrated for a two typical distribution networks and is compared with a well known

NSGA-II method. The comparison is made quantitatively by plotting the Pareto front, convergence metric (C-metric), the spacing metric (SP-metric), and the diversity metric (D-metric). The Pareto front of the IMOHS and other three metrics represent that the IMOHS has superior performance in both convergence and uniform diversity.

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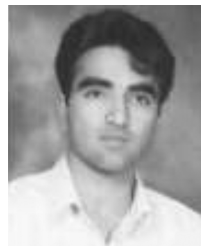
Komail Nokooei received the B.S. degree in electrical engineering from Kerman University, Iran, in 2003. Currently he is working toward the M.Sc. degree at Kerman University. His interests include power system control and stability and evolutionary computation.

M. M. Farsangi received the B.S. degree in electrical engineering from Ferdousi University, Iran, in 1995, and the Ph.D. degree in electrical engineering from Brunel Institute of Power Systems, Brunel University, U.K., in 2003.

Since 2003, she has been with Kerman University, Kerman, Iran, where she is currently an Associate Professor of Electrical Engineering. Her research interests include power system control and stability and computational intelligence.



Hossein Nezamabadi-Pour received the B.S. degree in electrical engineering from Shahid Bahonar University of Kerman, Kerman, Iran in 1998, and the M.Sc. and Ph.D. degrees in electrical engineering from Tarbait Moderres University, Iran, in 2000 and 2004, respectively.

In 2004, he joined the Department of Electrical Engineering at Shahid Bahonar University of Kerman, as an Assistant Professor, and was promoted to Associate Professor in 2008. He is the author and co-author of more than 170 peer reviewed journal and conference papers. His interests include image processing, pattern recognition, soft computing, and evolutionary computation.

Kwang Y. Lee (LF'08) received the B.S. degree in electrical engineering from Seoul National University, Korea, in 1964, the M.S. degree in electrical engineering from North Dakota State University, Fargo, in 1968, and the Ph.D. degree in systems science from Michigan State University, East Lansing, in 1971.

He has been with Michigan State, Oregon State, the University of Houston, the Pennsylvania State University, and Baylor University, Waco, TX, where he is currently Professor and Chair of Electrical and Computer Engineering and Director of Power and Energy Systems Laboratory. His interests include power systems control, operation, planning, and intelligent system applications to power systems.

Dr. Lee is a Past Associate Editor of IEEE Transactions on Neural Networks, and Editor of IEEE Transactions on Energy Conversion. He is also a registered Professional Engineer.