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Pareto optimal approach in Multi-Objective Chaotic Mutation Immune Evolutionary Programming (MOCMIEP) for optimal Distributed Generation Photovoltaic (DGPV) integration in power system

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ABSTRACT

The latest advancement in the technology, including the integration of the renewable energy resources, has become a recent trend in the power system infrastructure. Although, this can bring many benefits, excessive integration without proper planning may lead to unwanted circumstances such as voltage instability and higher power losses. This paper proposes a new Pareto optimality based technique namely: Multi-objective Chaotic Mutation Immune Evolutionary Programming. The technique was developed to determines the optimal location and sizing of Distributed Generated Photovoltaic (DGPV) and minimizing the multiple objective functions, namely, the active power losses and Fast Voltage Stability Index (*FVSI*), simultaneously. The method was tested on the IEEE test system. The results revealed that the proposed technique had the ability to acquire a set of Pareto solutions. Furthermore, this paper also confirmed that Multi-objective Chaotic Mutation Immune Evolutionary Programming (MOCMIEP) outperformed the Multi-objective Evolutionary Programming and Multi-objective Artificial Immune System in most cases.

1. Introduction

In the last decade, the power generation by renewable energy resources has become a new trend to cater the rise of energy demand and provide less greenhouse emission with cleaner energy production. The renewable energy, in terms of its distributed generation (DG), is widely integrated in the distribution network, which is closer to the customer's side and can directly provide the energy to consumers. Therefore, it is capable of providing efficient energy usage and improving the performance of the distribution system network [1,2].

Besides that, the increment of load demand due to the exponential growth in economics also contributes to the growth of interest in the DG installation. There are many types of distributed generations such as hydro, wind turbine, biomass, and solar photovoltaic. Currently, Asian countries including Malaysia, are foreseeing the distributed generation photovoltaic (DGPV) as the emerging trend within the next few years. Referring to the Low Carbon Society Blueprint for Iskandar Malaysia 2025, the DGPV system was one of the recommendations for sustainable and clean energy production technologies in power system [3]. Other than the distribution network, the possibility of connecting DGPV into the large transmission network had also been considered due the space limitation of new transmission line expansion, enhancement of power reliability and awareness of the environmental pollution related to fossil fuels. In addition, through the employment of DGPV, the transmission congestion can be reduced significantly [4,5]. Despite all the benefits provided by the DGPV integration, appropriate location and sizing of the DGPV units are crucial to maintain a stable and secured power system operation. Therefore, voltage stability is one of the concerns in maintaining the system security. Voltage stability is defined as the ability of the power system to maintain the normal condition of voltage profile after being

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Nomenclature

Z	line impedance	P_G	generated power
X	line reactance	P_{DG}	DGPV size
Q	reactive power	P	active power
V	voltage	u	normalised factor
δ	voltage angle	M	non-dominated solution
n	Total number of buses	N	Number of objective function

subjected to disturbances. It can be classified into static and dynamic approaches. Static voltage stability assessment is suitable for power system planning problems. In this work, Fast Voltage Stability Index (*FVSI*) is used as one of the objective functions to determine the voltage stability of the system.

In obtaining the optimal location and sizing of integrated DGPV units, the objective function of the problem must be properly defined. The problem can be interpreted either as a single objective or multi-objectives problem. For simplicity, many studies are dealing with a single objective for solving the optimal allocation of DG in the power system [6,7]. Ananthapadmanabha. T et al. [6] proposed a forward-backward sweep algorithm for DG sizing and location that considers the minimization of voltage stability index (SI) in IEEE 33-bus distribution system. The hybrid particle swarm optimization algorithm was used for DG allocation in a distribution network for power loss minimization [7]. However, in the actual implementation of this technology, the problem often deals with several contracting objectives that have to be optimized simultaneously.

Recently, various metaheuristic techniques have been implemented to solve for multi-objectives optimal location and sizing of DGs in the distribution system [8–11]. B. Poornazaryan (2018) has proposed an Imperialistic Competitive Algorithm (ICA) in [12] for optimal location and sizing of DGs for loss minimization and voltage stability improvement. The finding of the research supported that the DG integration in the power system provides a measure for active power loss minimization. In [13], a multi-objective technique was used to combine the losses and voltage stability index using PSO to find the weakest bus for DG placement. In [14], multi-objective Shuffled Frog Leaping Algorithm (SFLA) technique was utilized for DG placement and sizing with three objective functions for minimizing losses, energy cost and total population. S. Biswas (2014) in [15] had developed a multi-objective Artificial Bee Colony (ABC) algorithm to determine the optimal location and sizing of multi-DGs in the distribution of radial network. Improvements of the multi-objective particle swarm optimization (PSO) were presented in [16,17] to determine the best locations for DG in the distribution network with minimization of power losses and cost. However, the main weakness of this technique is that their performance declines as the search space increases, and it may be stuck in local optima [18].

Taking power losses, voltage profile, and voltage stability indicator into consideration, the optimal location and size for different DG units is presented in [19] by using the weighted sum multi-objective ant lion optimization (ALO). In [20], once again, the weighted sum multi-objective was applied for the evaluation of optimal location and sizing of DG. In addition, in this research, the weighting factors are heuristically chosen and used to combine multiple criteria into one objective function. However, the drawbacks of this method are the inappropriate value of the weighted factor that often leads to imprecise solutions [21].

The Pareto-based multi-objective technique is applied in [22–24] for finding optimal location and size of DGPV in the distribution network. In this multi-objective technique, instead of one solution, a set of solutions known as Pareto optimal solutions was determined. In order to select the best solution, an intelligent fuzzy programming is introduced in the algorithm [25]. From the literature review conducted in the study, most researches were focused on the impact of DG placement in the radial network distribution power system. However, by considering the current situation of the transmission and generation demand expansion, this paper presents the study to be applied to the transmission power system.

In this paper, the application of a multi-objective algorithm for DGPV location and sizing having two contradicting objectives was presented. The objective functions are to minimize the power losses and voltage stability index. A newly developed technique, namely, MOCMIEP has been developed for optimal location and sizing of two units DGPV in the transmission system. The proposed algorithm was based on the Pareto optimality to solve the problem. The proposed algorithm is proposed to solve for two DGPV units in IEEE 57-bus system. The results from MOCMIEP are then compared with the multi-objective Evolutionary Programming (MOEP) and multi-objective Artificial Immune System (MOAIS). The results obtained show that the proposed method outperformed other algorithms in finding the precise solution. The findings from this research is valuable for the utility companies in power system's future planning.

This paper is organized as follows: in Section 2, problem formulation is introduced; Section 3 presents the constraints of the problem formulations, Section 4 provides the concept of Pareto optimally in multi-objective problems; Section 5 derives the formulation of the best compromise index. Section 6 explains the step-by-step implementation of MOCMIEP for optimal location and size of DGPV problem. Section 7 discusses the results; and finally, Section 8 concludes the findings and contributions of the paper.

2. Problem formulation

The proposed MOCMIEP is applied to a test system, which is IEEE 57-bus RTS. The experiments are implemented in MATLAB® R2016b. The experiment is simulated for 20 runs and the best compromise solution is then recorded. The optimal location and sizing of two units of DGPV are simulated with the objective function of the minimization of active power losses and voltage stability index, *FVSI*.

2.1. Objective functions

The issue of dealing with multi-objective optimization is to optimize two contradicting objective functions. In this study, the aim is to minimize both objective functions simultaneously.

2.1.1. Minimization of Fast voltage stability index (FVSI)

The first objective, f_1 is to minimize the highest value of Fast Voltage Stability Index (*FVSI*), which was developed by I. Musirin in [26], as shown in Eq. (1):

$$f_1 = \min(FVSI_{\max}) = \min\left(\max\left(\frac{4Z^2Q_j}{V_i^2X}\right)\right) \tag{1}$$

where, ith and jth are the sending and receiving end, respectively.

2.1.2. Minimization of active power losses

The total active power losses in the system, P_{loss} is the second objective function, f_2 for the problem. The losses can be expressed by Eq.(2):

$$f_2 = P_{loss}$$
$$P_{loss} = \sum_{i=1}^{N}\sum_{j=1}^{N}\left[\alpha_{ij}\left(P_iP_j + Q_iQ_j\right) + \beta_{ij}\left(Q_iP_j - P_iQ_j\right)\right] \quad (2)$$
$$\alpha_{ij} = \frac{r_{ij}}{|V_i||V_j|}\cos\left(\delta_i + \delta_j\right); \beta_{ij} = \frac{r_{ij}}{|V_i||V_j|}\sin\left(\delta_i + \delta_j\right)$$

$|V_i|\angle\delta_i$ is complex voltage at bus, ith

$r_{ij} + jx_{ij} = Z_{ij}$ is the ijth element of $[Z_{bus}]$ the impedance matrix

P_i and P_j are active power injections at bus ith and jth, respectively

Q_i and Q_j are reactive power injections at bus ith and jth, respectively

For multi-objective problem with two objective functions, namely, *FVSI* and active power losses, they are to be minimized simultaneously while satisfying all of the inequality constraints. This problem is formulated as a multi-objective optimization problem with non-linear constrained optimization, as shown in Eq. (3):

$$min\ F = [f_1, f_2] \quad (3)$$

3. Constraints

In solving a multi-objective problem, there are the equality and inequality constraints that need to be satisfied. In this section, these constraints are presented in details.

3.1. Inequality constraint

Inequality constraints refer to equations that are not compulsory to be fulfilled. Normally, the inequality equation is defined by the minimum and maximum range. Therefore, the solution may be located in between the range said.

3.1.1. DGPV capacity

The first inequality constraint is the DGPV generating capacity. The sizing varies and is based on the renewable energy policies of countries and the solar irradiance [27]. It can be expressed as:

$$P_{DG,i}^{\min} \leqslant P_{DG,i} \leqslant P_{DG,i}^{\max} \forall i \in n \quad (4)$$

where, $P_{DG,i}^{\min}$ is the minimum output and $P_{DG,i}^{\max}$ is the maximum output of DGPV at the ith bus with DGPV unit.

3.1.2. Position of DGPV

The position of DGPV is based on the number of units that need to be installed, and is given by:

$$1 \leqslant DG_{position} \leqslant n_{buses} \quad (5)$$

$$P_{DG,1} \neq P_{DG,2} \neq P_{DG,3} \quad (6)$$

3.1.3. Bus voltage

In order to avoid voltage instability, the voltage of each bus, i in the system, V_i, should be the limit between its minimum and maximum values, and is expressed as:

$$v_{\min} \leqslant v_i \leqslant v_{\max} \quad \forall i \in n \quad (7)$$

where, v_{min} is the minimum value and v_{max} is the maximum value of the bus voltage limit.

3.2.4. Voltage stability

The voltage stability of the power system can be monitored using a pre-developed index. Generally, to be in a stable condition, the index must be in between the minimum and maximum limit, and is defined as follows:

$$0 < FVSI \leqslant 0.95 \quad (8)$$

3.2. Equality constraints

Equality constraints refer to the constraint that is compulsory to be imposed. In the power system, the real power balance equations in the system must be constantly fulfilled within a specific tolerance.

3.2.1. Power balance

The total power generation by both the generator and DGPV should be equal to the total consumption. The power balance constraint is shown in Eq. (9):

$$\sum_{i=1}^{G} P_{G,i} - P_{D,i} + \sum_{i=1}^{k} P_{DG,i} - P_{loss} = 0 \forall i \in n \quad (9)$$

where, $P_{G,i}$, $P_{D,i}$, $P_{DG,i}$, and P_{loss} are the active power generated by generator, total demand, active power generated by DGPV and active power losses for ith bus, respectively. G is the total number of generation units and k is the total number of DGPV units.

4. Pareto optimal solutions

The concept of Pareto optimality is based on the evaluation of the non-dominated solution, also known as a set of best compromise solutions. In other words, other solutions do not dominate any individual in this set. Based on Fig. 1, the concept of dominance and Pareto optimality are explained. In domination concept for minimization of two objective functions, a solution x_1 dominates solution x_2 if the objective function for x_1, which is $f(x_1)$ is better than the objective function for x_2, $f(x_2)$ and x_1 is no worse than x_2 in at least one objective [28]. Therefore, x_1 is known as a non-dominated solution. In optimization, the test will be applied for all individuals in the population to come out with a set of solutions that are non-dominated in the entire search space, known as the Pareto optimal solution or optimal front. The mathematical expression of this is shown in Eq.(10):

$$\begin{gathered} x_1 \succ x_2 if \\ \forall i : f_i(x_1) \leqslant f_i(x_2) \wedge \exists j : f_j(x_1) < f_j(x_2) \end{gathered} \quad (10)$$

where, $j = 1,2,\ldots M$, which is the number of objective functions.

5. Best compromise solution (BCS)

In multi-objective optimization with non-dominance approach, the algorithm generated a set of best solutions known as the Pareto optimal front. The linear membership u_i^k is introduced for every solution in ith Pareto-front, which represents the proper goal of kth objective function. In reality, the best solution among these solutions is defined based on the decision maker's experience and intuitive knowledge. On the other hand, a decision can also be made by using the formulation of the best compromise index [29], as shown in Eq. (11), to choose only one best solution.

$$u_i = \frac{\sum_{k=1}^{N} u_{f_i}^k}{\sum_{i=1}^{M}\sum_{k=1}^{N} u_{f_i}^k} \quad (11)$$

The variation of u_i^k is determined by the following equations:

$$u_{f_i}^k = 1 \quad if \quad \left(f_i^k < f_{\min}^k\right) \quad (12)$$

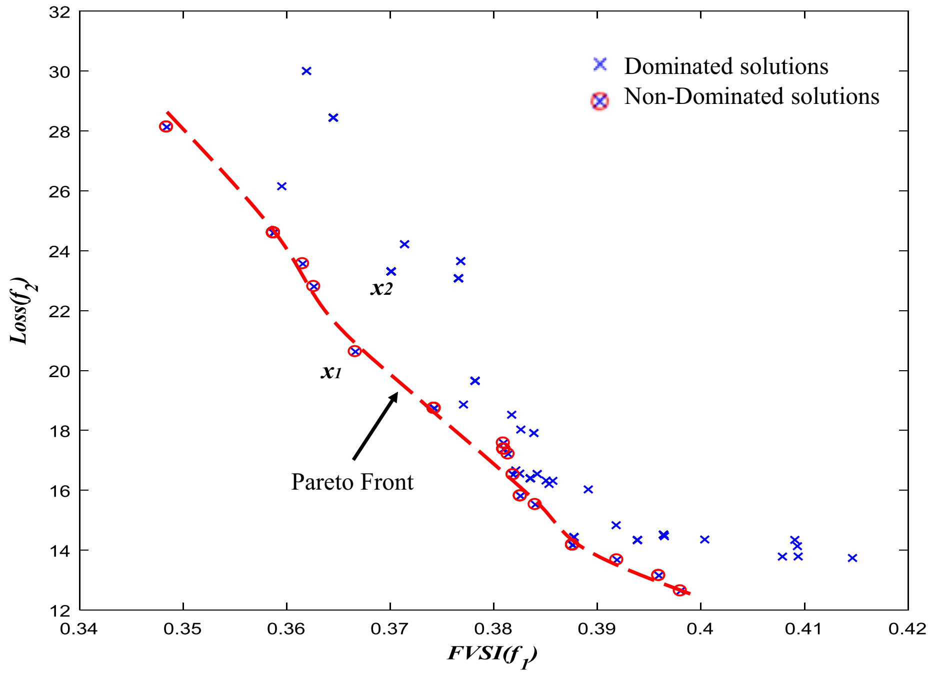

Fig. 1. Pareto optimal front for multi-objective optimization.

$$u_{f_i}^k = \frac{f_{\max}^k - f_i^k}{f_{\max}^k - f_{\min}^k} \quad if \quad \left(f_{\min}^k < f_i < f_{\max}^k\right) \tag{13}$$

$$u_{f_i}^k = 0 \quad if \quad \left(f_i^k > f_{\max}^k\right) \tag{14}$$

where, $f_{\min}^k$ and $f_{\max}^k$ are the minimum and maximum values of kth objective function in kth non-dominated solution, respectively. $u_{f_i}^k$ is the fitness value for all ith non-dominated solutions for all kth objective functions.

6. Implementation of Multi-Objective chaotic mutation Immune evolutionary programming (MOCMIEP) for DGPV sizing and location

Original evolutionary programming (EP) algorithm has a problem in finding appropriate solutions in some cases and would always fall into local optima. To improve the search ability and convergence of this algorithm, some modifications are applied at the mutation process. The newly proposed algorithm, known as MOCMIEP, is implemented for solving optimal location and sizing of the DGPV in the transmission system. The flowchart of this technique is depicted in Fig. 2.

The steps of the location and size of DGPV problem using MOCMIEP algorithm are as follows:

Step 1: Initialization of data, constraints and control variables.
Step 2: Randomize the number of individuals in 1x N vector [x_1, x_2, $\boldsymbol{x_3}$, $\boldsymbol{x_4}$, …, x_N] that represents random DGPV (x_1, x_2) position and DGPV sizes ($\boldsymbol{x_3}$, $\boldsymbol{x_4}$)
Step 3: Calculate the fitness functions for kth fitness function [$f_1(x)$, $f_2(x)$,$f_3(x)$, …, $f_K(x)$]
Step 4: Check whether the fitness function satisfies all of the constraints or otherwise. If yes, proceed to Step 5. If not, go back to Step 2.
Step 5: Fill in the individuals in the parent population, N_p set.
Step 6: Check whether the population is full. If yes, go to Step 7. If not, go back to Step 2.
Step 7: Cloning all the individuals in the population.
Step 8: Classification of population based on non-dominated sorting.
Step 9: Calculation of Fitness 1.
Step 10: Mutation of population by using the chaotic mutation to produce offsprings, N_f.
Step 11: Calculation of Fitness 2.
Step 12: Combination of parents, N_p and offspring, N_f.
Step 13: Identification of the non-dominated solutions.
for i = 1:2 * N
Determine the number of individuals that is dominated by "i" in the combination set
end
Sort based on the non-dominated value (highest to lowest)
Select the top N individuals as the new generation.
Step 14: Check the stopping criteria
if the *iteration number* > *maximum iteration*, then
show the non-dominated solutions or Pareto front
else, continue to Step 7
End.

7. Results and analysis

In this work, the placement and sizing of multi-DGPV, as discussed previously, are considered for the analysis. Optimization techniques and best compromise calculation were performed to select the sizing of DGPV and to ensure its optimal location that can enhance the voltage stability and to reduce the active power loss. The reactive power loading is performed on bus 19, which is a load bus. There are two cases considered in this study, namely, single DGPV and two units DGPV installation. In order to validate the performance of the proposed method, the results are compared with classical multi-objective evolutionary programming (MOEP)

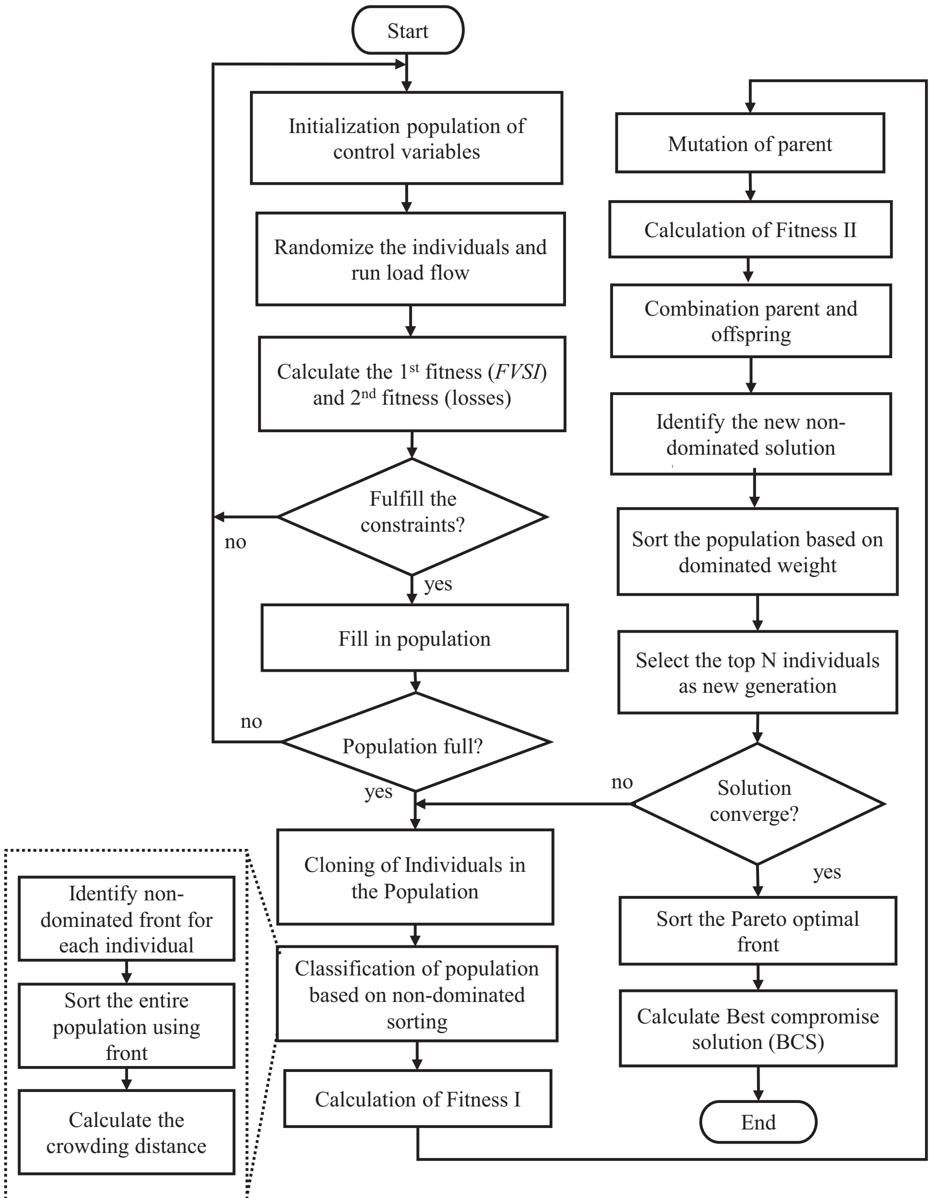

Fig. 2. Flowchart of MOCMIEP for optimal DGPV location and sizing.

and multi-objective artificial immune system (MOAIS). Table 1 tabulates the pre-DGPV installation data for the test system with reactive power loading variations. It can be seen that the increase in losses as the loading increases is mainly due to an increase in the thermal heat in the transmission line. Furthermore, the *FVSI* of the system increases tremendously with the increase of the loading from 0.4058 to 0.8294 for 10 MVAR and 30 MVAR loads, respectively. It implies that the increment of reactive power loading at the chosen load will cause voltage drop which leads to current increment and *FVSI* value increment in the system. Any attempt to increase reactive power loading higher than 30 MVAR can possibly force the system to reach *FVSI* value close to unity which indicates unstable condition to the whole system. The losses value increases from 27.85 MW at 10 MVAR to 32.88 MW at 30 MVAR when load was connected to bus 19. Increment of reactive power loading has big impact to the losses in the system. This phenomenon was due to the increase of current that flows through the transmission lines, which causes I^2R value to increase. The increment of losses in the system can also cause temperature rise on the transmission cable. This needs to be avoided so that the system can still operate within the acceptable limit.

Table 1
Pre-DGPV Installation Data.

	Reactive Power Loading, Q_{d19} (MVAR)	*FVSI*	Losses (MW)
Pre-Installation	10	0.4058	27.85
	20	0.5357	29.73
	30	0.8294	32.88

7.1. Case 1: Single unit DGPV installation

Table 2 tabulates the results of location and sizing for single-unit DGPV installation in IEEE 57-Bus RTS. At reactive power loading of 10 MVAR, MOCMIEP gives bus 49 as the optimal location to install 59.66 MW for the sizing of DGPV. On the other hand, MOEP gives bus 38 with DGPV sizing of 45.62 MW while MOAIS gives bus

Table 2
Location and Size of Single-Unit DGPV Installation.

Reactive Power Loading, Q_{d19} (MVAR)	Techniques	Location (Bus)	Size (MW)
10	MOCMIEP	49	59.66
	MOEP	38	45.62
	MOAIS	49	55.22
20	MOCMIEP	38	59.39
	MOEP	23	53.63
	MOAIS	38	51.67
30	MOCMIEP	38	57.14
	MOEP	38	52.70
	MOAIS	38	52.70

39 for the optimal location to install 52.22 MW. At reactive power loading of 20 MVAR, MOCMIEP gives bus 38, MOEP gives bus 23 and MOAIS gives bus 38 for the optimal location. The sizing of the DGPV can be referred to the same table. For 30 MVAR reactive power loading connected to bus 19, all the three techniques exhibit bus 38 as the optimal locations with 27.14 MW for the MOCMIEP, 52.70 MW for both MOEP and MOAIS. It reflects that all the three optimization techniques agree each other in term of identifying the optimal locations. Thus, we can choose any reactive power loading to perform compensation scheme using DGPV as the compensating device. Apparently, bus 38 is the most suitable location for performing the DGPV installation in this system for reactive power loading of 20 MVAR or 30 MVAR.

The percentage of improvement of *FVSI* and power loss for single unit DGPV installation can be referred to Table 3. In general, the implementation of DGPV installation to the system has significantly reduced the *FVSI* value for all reactive power loadings. This phenomenon has also agreed with the finding reported by B. Singh and S.A.A Kazmi in [30] and [31], respectively.. The proposed multi-objective optimization technique has also reduced the losses in the system at all the reactive power loadings. The values for *FVSI* and losses prior to the DGPV installation can be referred to Table 1. For instance, at 10 MVAR reactive power loading; MOCMIEP managed to reduce *FVSI* value to 0.3881 with the DGPV installation for its original value of 0.4058 as shown in Table 1. This leads to 4.36% reduction, implying improvement of voltage stability. The losses have been significantly reduced to 17.69 MW from its original value (without DGPV installation in Table 1). This implies a loss reduction of 21.19%. Apparently, the proposed MOCMIEP outperformed MOEP and MOAIS in terms of reduction in *FVSI* and loss values. At higher reactive power loading worth 30 MVAR, the *FVSI* value has been reduced from 0.8294 (in Table 1) to 0.8168. This phenomenon leads to 1.52% *FVSI* reduction. On the other hand, the losses have been reduced to 25.54 MW which gives 22.32% reduction. From the table, MOCMIEP shows its superiority in terms of percentage of loss reduction for all reactive power loading as compared to MOEP and MOAIS.

7.2. Case 2: Two units DGPV installation

In Case 2, two units of DGPV installation have been conducted to the system. The main reason for this case is to make a comparison of performance with the single-unit DGPV installation. At reactive power loading of 10 MVAR, MOCMIEP exhibits buses 49 and 51 as the optimal locations for DGPV installation with the sizing of 59.41 MW and 53.94 MW, respectively. This leads to total sizing of 113.35 MW. On the other hand, MOEP gives buses 50 and 23 for the two units DGPV installation with the sizing of 59.49 MW and 44.62 MW, respectively. This gives total DGPV sizing of 104.11 MW. For MOAIS, buses 50 and 49 are the optimized locations. The sizing for the two units DGPV are 536.58 MW and 53.62 MW, respectively. This gives total DGPV sizing of 90.20 MW. At higher reactive power loading, i.e. 20 MVAR, both MOCMIEP and MOEP give buses 49 and 18 for the optimal locations, while MOAIS exhibits buses 57 and 18. The values for the sizing for all the techniques can be referred to the table. Apparently, both techniques are comparable. Results for reactive power loading of 30 MVAR can be referred to the same table. Results from this table can be beneficial to the power system operator at the Planning Department of the utility for the offline studies and future remedial action.

Further detail for Case 2 in terms of percentage of improvement of *FVSI* and power loss for two units DGPVs installation are tabulated in Table 5. This table gives the performance of *FVSI* and loss reductions. In general, the proposed MOCMIEP outperformed MOEP and MOAIS in terms of giving the highest reduction of *FVSI* and loss. At 30 MVAR reactive power loading, the *FVSI* value has been reduced from 0.8294 without DGPV installation (in Table 1) to 0.7365 with two units DGPV installation to the system, with the location indicated in Table 4. MOCMIEP is outstanding as compared to MOEP and MOAIS with the percentage of *FVSI* reduction worth 11.20%; MOEP only managed to achieve 2.09%, while MOAIS capable to achieve 1.00%. Percentage of reduction for losses value using MOCMIEP is 27.18%, while MOEP and MOAIS give 28.98% and 34.54%, respectively. It is observed that MOEP and MOAIS outperformed MOCMIEP. Nevertheless, the difference between MOCMIEP and MOEP is not significant. Percentage of loss reduction for 10 MVAR and 20 MVAR reactive power loading are higher for the optimization process using MOCMIEP as compared to MOEP and MOAIS. This result indicates MOCMIEP is considered performing well in most reactive power loadings. In term of percentage of *FVSI* reduction, the proposed MOCMIEP has consistently exhibited the best technique.

7.3. Comparative studies

Comparative studies have been performed to highlight the effect of single and multi-unit DGPV installation. In this study, multi-unit refers to two units of DGPV. The results for comparative studies for single DGPV and two units DGPV are tabulated in

Table 3
Percentage of Improvement of *FVSI* and power loss for Single-Unit DGPV Installation.

Reactive Power Loading, Q_{d19} (MVAR)	Techniques	*FVSI*	Losses (MW)	*FVSI* Improvement(%)	Loss Reduction(%)
10	MOCMIEP	0.3950	21.95	2.65	21.19
	MOEP	0.4033	22.29	0.61	19.98
	MOAIS	0.3955	22.20	2.53	20.31
20	MOCMIEP	0.5229	23.62	2.39	20.56
	MOEP	0.5235	23.92	2.27	19.55
	MOAIS	0.5287	23.11	1.31	22.27
30	MOCMIEP	0.8168	25.54	1.52	22.32
	MOEP	0.8173	25.86	1.46	21.34
	MOAIS	0.8173	25.86	1.46	21.34

Table 4
Location and Size of Two-Unit DGPV Installation.

Reactive Power Loading, Q_{d19} (MVAR)	Techniques	Location (Bus)		Sizing (MW)		Total Size (MW)
10	MOCMIEP	49	51	59.41	53.94	113.35
	MOEP	50	23	59.49	44.62	104.11
	MOAIS	50	49	36.58	53.62	90.20
20	MOCMIEP	49	18	55.96	43.39	99.36
	MOEP	49	18	49.41	14.88	64.29
	MOAIS	57	18	37.03	15.80	52.83
30	MOCMIEP	18	47	52.64	56.80	109.44
	MOEP	38	56	54.34	19.81	74.15
	MOAIS	16	38	50.54	51.57	102.11

Table 5
Percentage of Improvement of *FVSI* and power loss for Two-Unit DGPVs installation.

Reactive Power Loading, Q_{d19} (MVAR)	Techniques	*FVSI*	Losses (MW)	*FVSI* Improvement (%)	Loss Reduction (%)
10	MOCMIEP	0.3881	17.69	4.36	36.48
	MOEP	0.3952	18.46	2.60	33.73
	MOAIS	0.3895	19.15	4.02	31.19
20	MOCMIEP	0.3947	17.89	10.97	30.30
	MOEP	0.4833	21.49	9.78	27.72
	MOAIS	0.4770	24.15	10.97	18.77
30	MOCMIEP	0.7365	23.94	11.20	27.18
	MOEP	0.8121	23.35	2.09	28.98
	MOAIS	0.8211	21.52	1.00	34.54

Table 6
Comparison of single-unit and Two-Unit DGPV installation for MOCMIEP.

Reactive Power Loading, Q_{d19} (MVAR)	Single DGPV		Two DGPVs	
	% *FVSI*	% Loss	% *FVSI*	% Loss
10	2.65	21.19	4.36	36.48
20	2.39	20.56	10.97	30.30
30	1.52	22.32	11.20	34.54

Table 6. In general, the percentage of *FVSI* and loss reductions are higher with two units DGPV installations as compared to single DGPV installation for all reactive power loading. For instance, at 10 MVAR reactive power loading value, the percentage of *FVSI* reduction is only 2.65% for single DGPV installation; while, with two units DGPV installations MOCMIEP manage to achieve a significantly high percentage of *FVSI* reduction worth 4.36%. Apparently, two units DGPV installation has shown a profound impact in terms of voltage stability improvement indicated by a reduction in *FVSI* value. The percentage of reduction in losses experienced by the system through the installation of two units DGPV is also very promising as can be referred to the same table. With two units DGPV installation, the percentage of loss reduction is 36.48%; while, single DGPV can only manage to achieve 21.19%. Apparently, two units DGPV installation has shown 15.29% higher in terms of loss reduction as compared to single unit DGPV installation. The results can be taken as a benchmark by the power system operator to manage DGPV installation scheme in this system. The same scenario can be observed for other reactive power loading i.e. 20 MVAR and 30 MVAR. For two DGPVs installation at 30 MVAR reactive power loading has shown outstanding results. The reduction of *FVSI* is only 1.52% for single DGPV while 11.20% of *FVSI* reduction has been achieved with two units DGPV installation. From the results it is worth to mention that two DGPVs installation scheme has given good impact to the system in terms of percentage of FVSI and loss reductions. That means, voltage stability has been improved while losses have been reduced which lead to temperature rise avoidance.

The results for Pareto optimal solutions for single unit DGPV installation with 10 MVAR reactive power loading subjected to bus 19 in IEEE 57-Bus RTS, performed using MOCMIEP, MOEP and MOAIS are illustrated in Fig. 3 to Fig. 5. The results are given in terms of solutions, known as the non-dominated or Pareto optimal solutions, and marked as the red circle. In Fig. 3, MOCMIEP is capable to achieve the highest number of non-dominated solutions worth 175. The best compromise solution is chosen based on Eq. (11) and given as 0.3950 for *FVSI* and 21.95 MW for losses. However, some of the solutions are overlapping each other. The Pareto solutions for MOCMIEP are well distributed to form a trade-off curve. The best compromise value for *FVSI* and loss is 0.3950 and 21.95 MW, respectively. On the other hand, Fig. 4 and Fig. 5 show the results for the non-dominated solutions performed using MOEP and MOAIS. MOEP managed to achieved 80 non-dominated solutions while MOAIS exhibits 58 solutions. The best compromise solution for MOEP is 0.4033 and 22.29 MW for *FVSI* and loss, respectively. The best compromise solution MOAIS is 0.3955 and 22.20 MW for *FVSI* and loss, respectively.

Similarly, Fig. 6 to Fig. 8 demonstrated the Pareto optimal solutions for two units DGPV installation with 10 MVAR reactive power loading at bus 19 in the same system using MOCMIEP, MOEP and MOAIS, respectively. In Fig. 6, the non-dominated solutions achieved by MOCMIEP is 150 with the best compromise solution of 0.3881 and 17.69 MW for *FVSI* and loss, respectively. Meanwhile, Fig. 7 and Fig. 8 illustrated the results for non-dominated solutions achieved by MOEP and MOAIS, respectively. MOEP managed to attain 70 non-dominated solutions while MOAIS exhibits 80 solu-

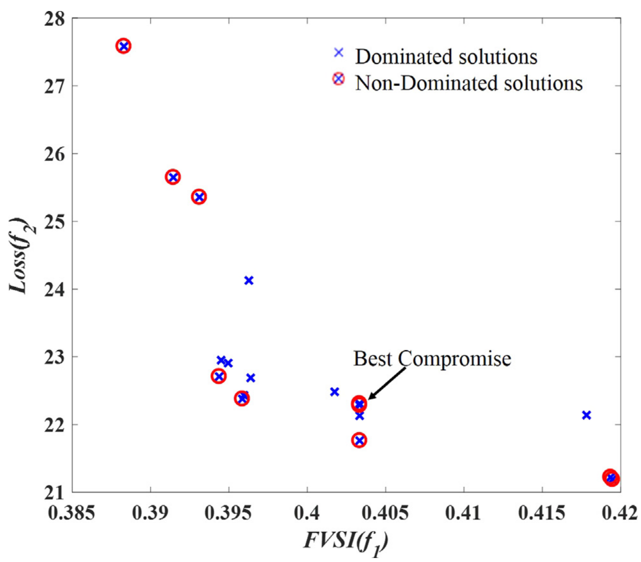

Fig. 3. Pareto fronts for Single-unit DGPV Installation obtained using MOCMIEP.

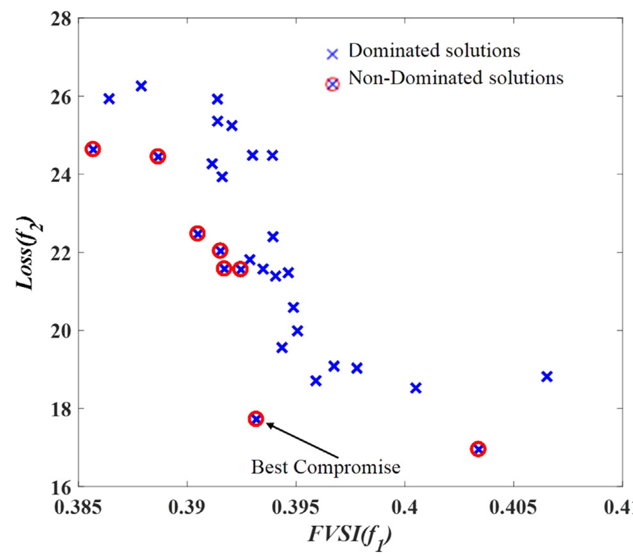

Fig. 6. Pareto fronts for Two units DGPV Installation obtained using MOCMIEP.

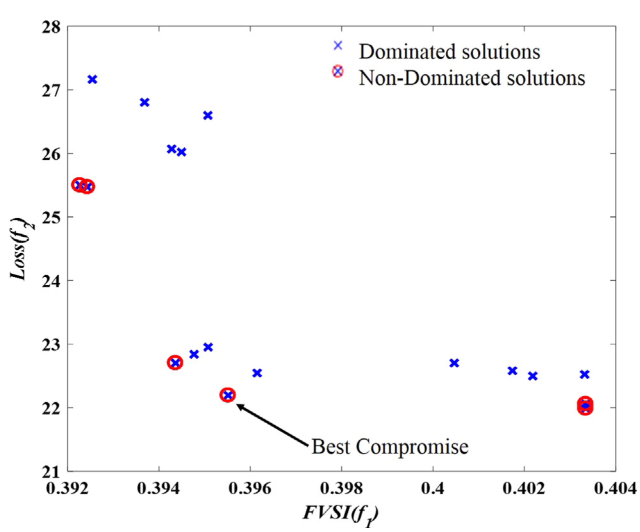

Fig. 4. Pareto fronts for Single-unit DGPV Installation obtained using MOEP.

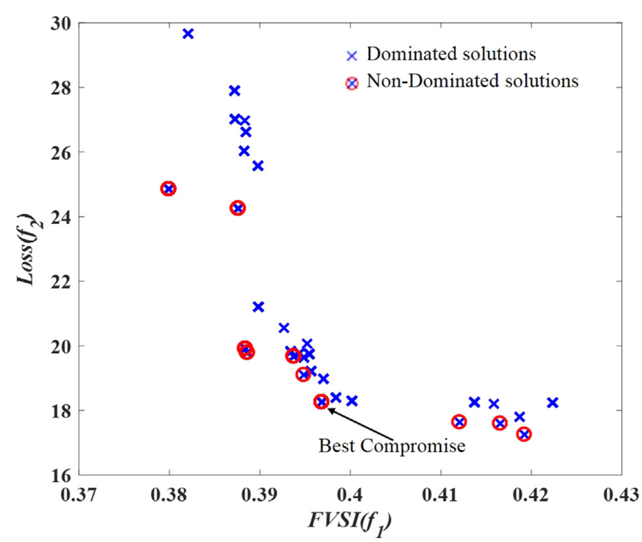

Fig. 7. Pareto fronts for Two units DGPV Installation obtained using MOEP.

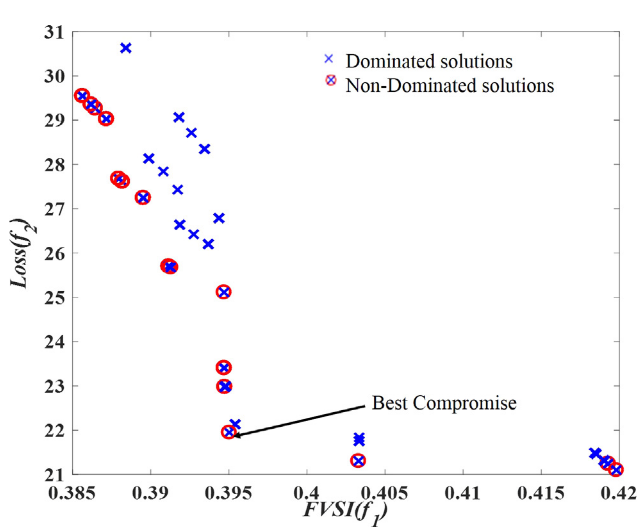

Fig. 5. Pareto fronts for Single-unit DGPV Installation obtained using MOAIS.

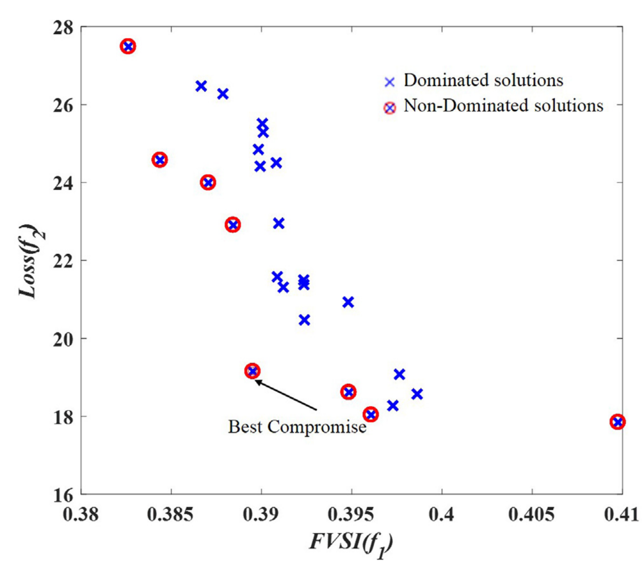

Fig. 8. Pareto fronts for Two units DGPV Installation obtained using MOAIS.

tions. The best compromise solution for MOEP is 0.3952 and 18.46 MW for *FVSI* and loss, respectively. The best compromise solution MOAIS is 0.3895 and 19.15 MW for *FVSI* and loss, respectively.

8. Conclusion

This paper has presented Pareto optimal approach in multi-objective chaotic mutation immune evolutionary programming (MOCMIEP) for optimal distributed generation photovoltaic (DGPV) integration in power system. In this study, MOCMIEP algorithm has been developed which integrates the elements of chaotic, immune and evolutionary to optimally determine the location and sizing of DGPVs. The objective functions include the minimization of maximum system *FVSI* and power loss. The Pareto optimality is used to solve the multi-objective optimization problem. This technique provides a set of solutions, where the decision maker can select an option based on the desirable result. On the other hand, the best solution can also be obtained using the best compromise index approach. Two cases with different reactive power loading have been considered in this study and applied on the IEEE 57-Bus RTS. The proposed MOCMIEP technique has successfully achieved 22.32% in loss reduction and 1.52% in *FVSI* reduction for single unit DGPV installation at 30 MVAR reactive power loading. This is the maximum achievable values in the study. For two unit DGPV installation, MOCMIEP has successfully achieved 4.36% in *FVSI* reduction and 36.48% loss reduction, experienced at 10 MVAR reactive power loading. It is worth to mention that the proposed method is capable of achieving the best solution in most cases, compared to the other methods in this study. The main contribution of this work is the development of MOCMIEP technique which has effectively solved optimization problem while considering all of the constraints in the optimal location and sizing for the DGPV installation. It can be concluded that the MOCMIEP is a reliable optimization method for solving different multi-objective optimization problems in the power system. The developed MOCMIEP technique can help the power system operators to perform their offline studies and planning which in turn can give benefits in terms of economic investment. Further exploration can be done to solve more complex problems by conducting minor modification on the developed algorithm.

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References

[1] Ehsan A, Yang Q. Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques. Appl Energy 2018;210:44–59.
[2] Bahrami S, Amini MH, Shafie-khah M, Catalao JPS. A Decentralized renewable generation management and demand response in power distribution networks. IEEE Trans Sustain Energy 2018;9. 1 1.
[3] Theo WL, Lim JS, Ho WS, Hashim H, Lee CT. Review of distributed generation (DG) system planning and optimisation techniques: comparison of numerical and mathematical modelling methods. Renew Sustain Energy Rev 2017;67:531–73.
[4] Badran O, Mekhilef S, Mokhlis H, Dahalan W. Optimal reconfiguration of distribution system connected with distributed generations: A review of different methodologies. Renew Sustain Energy Rev 2017;73:854–67.
[5] Balachennaiah P, Suryakalavathi M, Nagendra P. Firefly algorithm based solution to minimize the real power loss in a power system. Ain Shams Eng J 2015;9:89–100.
[6] Ananthapadmanabha T, Rani DNS. Optimal allocation of combined DG and capacitor units for voltage stability enhancement. Procedia Technology 2015;21:216–23.
[7] Aman MM, Jasmon GB, Bakar AHA, Mokhlis H. A new approach for optimum simultaneous multi-DG distributed generation units placement and sizing based on maximization of system loadability using HPSO (hybrid particle swarm optimization) algorithm. Energy 2014;66:202–15.
[8] Pesaran HAM, Huy PD. Ramachandaramurthy VK. A review of the optimal allocation of distributed generation: Objectives, constraints, methods, and algorithms. Renew Sustain Energy Rev 2017;75:293–312.
[9] Prakash P, Khatod DK. Optimal sizing and siting techniques for distributed generation in distribution systems : a review. Renew Sustain Energy Rev 2016;57:111–30.
[10] Mehta P, Bhatt P, Pandya V. Optimal selection of distributed generating units and its placement for voltage stability enhancement and energy loss minimization. Ain Shams Eng J 2015;9:187–201.
[11] Moazenzadeh R, Mohammadi B, Shamshirband S, Chau K. Coupling a firefly algorithm with support vector regression to predict evaporation in northern Iran. Eng Appl Comput Fluid Mech 2018;12:584–97.
[12] Poornazaryan B, Karimyan P, Gharehpetian GB, Abedi M. Optimal allocation and sizing of DG units considering voltage stability, losses and load variations. Int J Electr Power Energy Syst 2016;79:42–52.
[13] Aman MM, Jasmon GB, Bakar AHA, Mokhlis H. A new approach for optimum DG placement and sizing based on voltage stability maximization and minimization of power losses. Energy Convers Manage 2013;70:202–10.
[14] Doagou-Mojarrad H, Gharehpetian GB, Rastegar H, Olamaei J. Optimal placement and sizing of DG (distributed generation) units in distribution networks by novel hybrid evolutionary algorithm. Energy 2013;54:129–38.
[15] Biswas S, Chatterjee A, An Goswami SK. artificial bee colony based optimal placement and sizing of distributed generation. In: Proceedings of The 2014 International Conference on Control, Instrumentation, Energy and Communication (CIEC). p. 356–60.
[16] Cheng S, Chen MY, Fleming PJ. Improved multi-objective particle swarm optimization with preference strategy for optimal DG integration into the distribution system. Neurocomputing 2015;148:23–9.
[17] Azizivahed A, Narimani H, Naderi E, Fathi M, Narimani MR. A hybrid evolutionary algorithm for secure multi-objective distribution feeder reconfiguration. Energy 2017;138:355–73.
[18] Shaghaghi S, Bonakdari H, Gholami A, Ebtehaj I, Zeinolabedini M. Comparative analysis of GMDH neural network based on genetic algorithm and particle swarm optimization in stable channel design. Appl Math Comput 2017;313:271–86.
[19] Ali ES, Abd Elazim SM, Abdelaziz AY. Ant lion optimization algorithm for renewable distributed generations. Energy 2016;116:445–58.
[20] Mohandas N, Balamurugan R, Lakshminarasimman L. Optimal location and sizing of real power DG units to improve the voltage stability in the distribution system using ABC algorithm united with chaos. Int J Electr Power Energy Syst 2015;66:41–52.
[21] Chiandussi G, Codegone M, Ferrero S, Varesio FE. Comparison of multi-objective optimization methodologies for engineering applications. Elsevier Ltd; 2012.
[22] Mahesh K, Nallagownden P, Elamvazuthi I. Advanced Pareto front non-dominated sorting multi-objective particle swarm optimization for optimal placement and sizing of distributed generation. Energies 2016;9:982.
[23] Injeti SKA. Pareto optimal approach for allocation of distributed generators in radial distribution systems using improved differential search algorithm. J Electr Syst Inf Technol 2017.
[24] Velásquez MA, Morillo JL, Barco JE, Cadena ÁI. Pareto-based multi-stage and multi-objective planning of DG enhanced distribution system. Int J Elect Energy 2014;2:45–52.
[25] Razmi J, Jafarian E, Amin SH. An intuitionistic fuzzy goal programming approach for finding pareto-optimal solutions to multi-objective programming problems. Expert Syst Appl 2016;65:181–93.
[26] Musirin I, Rahman TKA. Estimation of maximum loadability in power systems by using fast voltage stability index. Int J Power Energy Syst 2005;25:181–9.
[27] Sie AWH, Abidin IZ, Hashim H. A methodology to determine suitable placement of solar photovoltaic sources in the transmission system taking into account Voltage Stability Index (VSI). In: Conference Proceeding - 2014 IEEE International Conference on Power and Energy, PECon 2014. p. 226–30.
[28] Cheikh M, Jarboui B, Loukil T, Siarry P. A method for selecting Pareto optimal solutions in multiobjective optimization. J Informat Mathemat Sci 2010;2:51–62.
[29] Zare M, Niknam T, Azizipanah-Abarghooee R, Amiri B. Multi-objective probabilistic reactive power and voltage control with wind site correlations. Energy 2014;66:810–22.
[30] Singh B, Mishra DK. A survey on enhancement of power system performances by optimally placed DG in distribution networks. Energy Rep 2018;4:129–58.
[31] Ali S, Kazmi A, Shin DR. DG placement in loop distribution network with new voltage stability index and loss minimization condition based planning approach under load growth. Energies 2017;10:1203.

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