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Multiple DG Planning Considering Distribution Loss and Penetration Level using EMEFA-ANN Method

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Abstract

This paper presents the implementation of multiple distributed generations planning in distribution system using computational intelligence technique. A pre-developed computational intelligence optimization technique named as Embedded Meta EP-Firefly Algorithm (EMEFA) was utilized to determine distribution loss and penetration level for the purpose of distributed generation (DG) installation. In this study, the Artificial Neural Network (ANN) was used in order to solve the complexity of the multiple DG concepts. EMEFA-ANN was developed to optimize the weight of the ANN to minimize the mean squared error. The proposed method was validated on IEEE 69 Bus distribution system with several load variations scenario. The case study was conducted based on the multiple unit of DG in distribution system by considering the DGs are modeled as type I which is capable of injecting real power. Results obtained from the study could be utilized by the utility and energy commission for loss reduction scheme in distribution system.

Keywords: *artificial neural network, DG planning, distributed generation, embedded Meta EP-firefly algorithm, penetration level, distribution loss*

1. Introduction

DG is an emerging approach that is well known in electric power system recently. Nevertheless, the researcher and utility engineer have a lot of problem that need to be concerned in the DG allocation problem. DG units need to be strategically placed in distribution systems in order to obtain the maximum output from the DG installation. Improper sizing and placement of DG may result overcompensation or under compensation [1-2]. Consequently, the factors of the best location and sizing are among the crucial issues in the implementation of distributed generation in the distribution system. Therefore, it is necessary to develop an optimization or heuristic technique based methodology to identify the optimal placement of distributed renewable generation for a given system that can provide economic, environmental and technical advantages [3-5]. There are several researches that study on the optimal distributed renewable generation location by their imposed constraints and objectives. However, the systematic principle for this issue is still an unsolved problem [6]. The integration of multiple-DG units cannot be handled simply as well as single-DG because of the complex structures of power networks, despite of these different techniques. Consequently, researchers have started to use intelligent techniques such as Genetic Algorithm [7], Evolutionary Programming (EP) [8], Particle Swarm Optimization [9] and Firefly Algorithm (FA) [10], fuzzy logic [11] and ANN [12] to solve the problem.

This paper presents the effect of multiple DG installation considering loss minimization and the penetration level in distribution system. The proposed EMEFA-ANN was utilized to optimize the weight of the ANN to minimize the mean squared error (MSE). Results indicated that the proposed EMEFA-ANN has achieved better MSE error. The loss equation is used to determine the optimal size of DG by using the computational intelligence technique and it is necessary to consider the reduction of I^2R loss in order to obtain the efficient power delivery in

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the distribution system. The loss associated with the active and reactive power components of branch currents is given by (1).

$$P_{loss} = \sum_{i=1}^{n}\sum_{j=1}^{n}\left(\frac{R_{ij}\cos(\delta_i)}{V_iV_j}\right)\left(P_iP_j + Q_iQ_j\right) + \left(\frac{R_{ij}\sin(\delta = \delta_i - \delta_j)}{V_iV_j}\right)\left(Q_iP_j - P_iQ_j\right) \quad (1)$$

Where P_i and Q_i are the real and reactive power of bus *i* respectively, P_j and Q_j are the real and reactive power of bus *j* respectively, R_{ij} is the line resistance between bus *i* and bus *j*, V_i and V_j are the voltage magnitude of bus *i* and bus *j* respectively, and δ_i and δ_j are the voltage angle of bus *i* and bus *j* respectively. Table 1 indicates the DG type and the variable of the DG modelling for optimization. Equation (2) and (3) shows the setting of voltage limit and loss reduction limit respectively. The results of power losses must be less than without DG sources or in base case.

$$0.95p.u \le V_{\min} \le 1.05p.u \quad (2)$$

$$P_{loss}^{with\ DG} < P_{loss}^{without\ DG} \quad (3)$$

$$\delta_{loss} = P_{loss} \quad (4)$$

$$\sum_{i}^{nDG} p_{loss} \le P_{DG}^{Max} \quad (5)$$

$$P_{DG}^{Max} < 80\% \times \sum_{i}^{nbus} P_{demand}^{i} \quad (6)$$

Table 1. DG Type and The Variable Of The DG Modelling For Optimization

DG Type	DG Modelling
Type I: DG capable of injecting real power only, like photovoltaic, fuel cells etc. is the good examples of type-I DG.	$x_i = P_g$ (MW)
Type II: DG capable of injecting reactive power only to improve the voltage profile fall in type-II DG, e.g. kvar compensator, synchronous compensator, capacitors etc.	$x_i = Q_g$ (MVAr)
Type III: DG capable of injecting both real and reactive power, e.g. synchronous machines.	$x_i = P_g$ (MW) $Q_g = P_g \times \tan^{-1}\theta$ (MVAr)
Type IV: DG capable of injecting real but consuming reactive power, e.g. induction generators used in the wind farms.	$x_i = P_g$ (MW) $Q_g = -P_g \times \tan^{-1}\theta$ (MVAr)

The proposed technique was tested on the IEEE 69 bus test systems in order to validate the technique. The case study was conducted based on the multiple unit of DG in distribution system by considering the DGs are modelled as type I. The power factor of the system was set to be 0.85 based on IEEE standard and energy commission [13]. The analysis was done by setting the voltage limit to an acceptable value. The P_{loss} is also refer as δ_{loss} to demonstrate the total loss in the system. With regard to DG penetration, the total amount of DG active power in the network must not exceed 0.8 times the total system demand. In this study, the variation of active and reactive load as shown in (7) and (8) with respect to the load factor k. The penetration level sensitivity index (PLSI) was derived from the loss equation and penetration level calculated in the system. Penetration level refers to the capacity of DG to be installed with respect to the total load in the system. The general mathematical equation is given by (9). Equation (10) shows the formulation of the penetration level of DG at bus *n*. In this study, the new penetration level sensitivity index (PLSI) was derived from the loss equation and penetration level calculated in the system. The PLSI index is shown in (12). The objective function is to minimize the PLSI value in (13). A penetration level sensitivity index (PLSI) was developed in order to determine the proper location for the distributed generation planning. This index was calculated based on the change in total losses with respect to the changes in penetration level in the entire system.

$$P_{load_{new}} = P_{load_i} \times k \tag{7}$$

$$Q_{load_{new}} = Q_{load_i} \times k \tag{8}$$

(for i=1,2,3,..,$n_{bus\ no}$ and load factor,k=0.6,0.8,1.0,1.2,1.4)

$$P_L = \frac{InstalledDG_{Power}}{TotalLoad} \tag{9}$$

$$PL_n = \frac{P_{DG_n} + Q_{DG_n}}{P_{TotalLoad} + Q_{TotalLoad}} \tag{10}$$

$$(\text{for } n = 1,2,3,\ldots, n_{bus})$$

$$PLSI_n = \frac{\delta_{loss_n}}{\delta_{PL_n}} \tag{11}$$

$$PLSI_n = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} A_{ij}\left(P_iP_j + Q_iQ_j\right) + B_{ij}\left(Q_iP_j - P_iQ_j\right)}{\left(\frac{P_{DG_n} + Q_{DG_n}}{P_{TotalLoad} + Q_{TotalLoad}}\right)} \tag{12}$$

$$Of_1 = Minimize \sum_{n=1} PLSI_n \tag{13}$$

Figure 1 summarizes the description of multiple DG optimizations using proposed EMEFA-ANN method. This method was utilized to optimize the weight of the ANN to minimize the mean squared error (MSE). The proposed method involving two stages. The first stage is optimization of DG size and the location in the system. During this process, the load condition also varying due to the consideration of sudden increase of loads. The second stage is ANN method which is use to predict total losses. The input data for the ANN are the active and reactive load ($Pd_{6\text{-}10}$, $Qd_{6\text{-}10}$), the variation of load (k), the location of DG ($DGL_{1\text{-}n}$) and the active power of DG unit ($PDG_{1\text{-}n}$) where n is number of maximum DG unit. The output data of ANN1 and ANN2 is total loss and PLSI respectively. The network will be trained with Levenberg-Marquardt backpropagation algorithm. The proposed method started by generating control variable of $X_{i,\alpha}$ which depends on the number of population size and control variables**.** A new population is bred by mutating the initial existing population by implementing the mutation operator. Mutation is the only variation operator used for generating the offspring from each individual. The fitness of the offspring was calculated by calling the load flow program. The selection process was done by the tournament scheme. The individual is to compete with other randomly selected individuals and the winning criteria was based on fitness values. For each evaluation, the individual that obtained the most numbers of wins will be selected for the new generation. The competition scheme must be such that the fittest individuals will have a greater chance to survive, while weaker individuals will be eliminated. Through this, the population evolves towards the global optimal solution. Based on the sorted fitness value, the current best value is selected from the first half value and set as the initial locations of fireflies. Consequently, the FA operation was embedded in this method by comparing the initial location of i_{th} solution with its j_{th} neighboring solution. The value of β_0, γ and r are the predefined attractiveness, light absorption coefficient, and distance respectively [14].

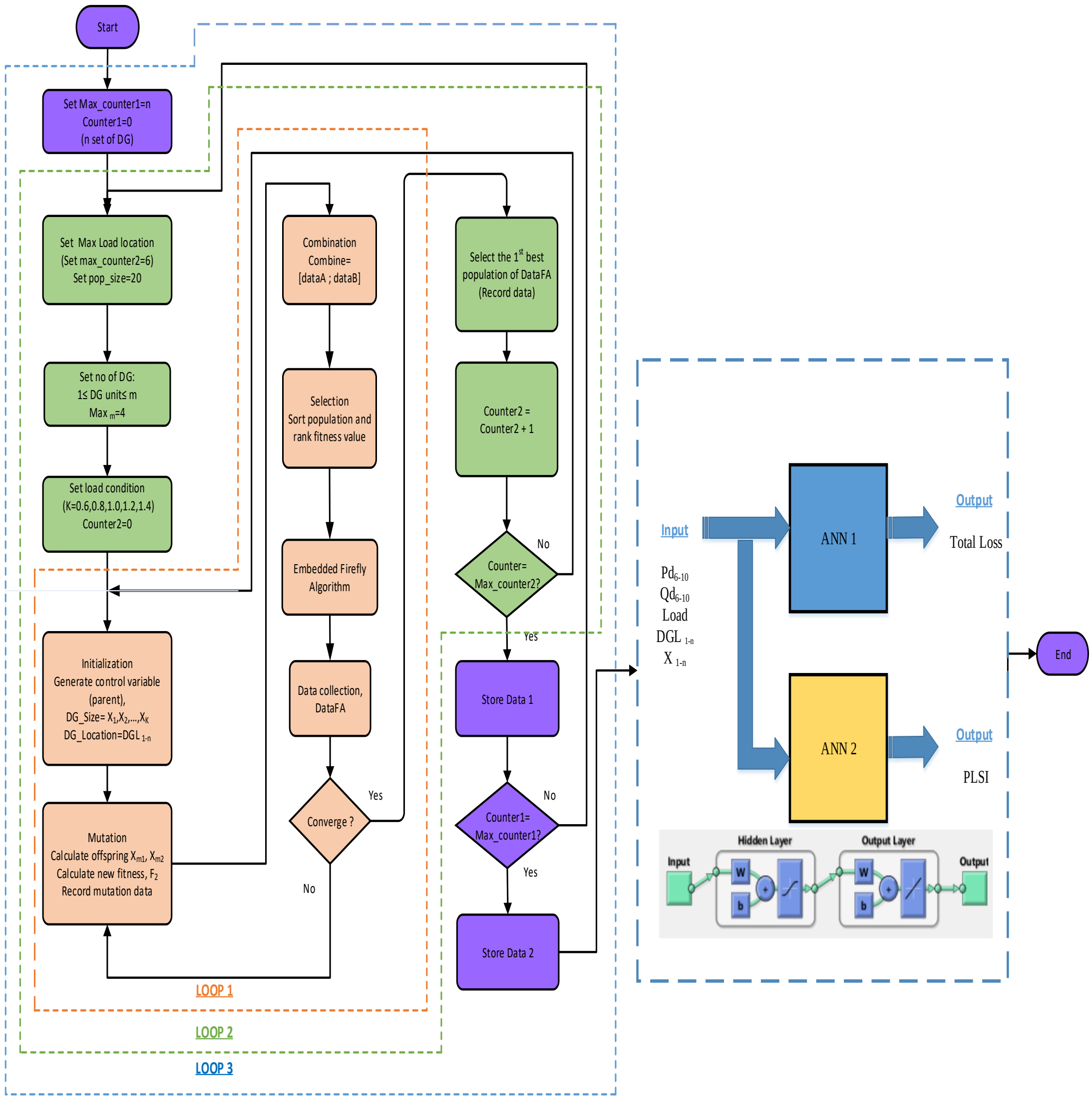

Figure 1. Flowchart for Multiple DG optimization using EMEFA-ANN Method

2. Results and Discussion

The proposed EMEFA-ANN technique was simulated and tested on the IEEE 69-bus test system. Firstly, the effect of the multi-DG installation using different types of DG is observed by setting the location for DG_1 at bus 61. The location of DG_2-DG_n is dependent upon the selected location from random number. The idea is to minimize distribution losses with the proposed EMEFA. In the simulations, two conditions are addressed which are without DG and with DG installed in the system. The analysis was conducted based on two cases which are discussed below. The total losses before DG installation is tabulated in Table 2 for various loading condition. Table 3 list the number of sample for training, validation and testing for the study.

Table 2. Total Losses Before Dg Installation

Loading,k (%)	Ploss(MW)	Qloss (MVAR)	Vmin (P.U)
0.6	0.0755	0.0344	0.9476
0.8	0.1389	0.0632	0.9288
1	0.2249	0.1021	0.9092
1.2	0.3366	0.1525	0.8887
1.4	0.4776	0.2158	0.8672

Table 3. Number Of Samples For Training, Validation And Testing

	Samples
Training	70
Validation	15
Testing	15

2.1. Effect of Multiple DG for ANN1

The effect of DG type I for the output ANN1 which is total loss was analyzed in this section. The analysis was conducted by looking into variation in loading conditions at the load buses ranging from 60% to 140%of the base load condition. In this study, the total loss was calculated while optimal output of DGs is determined using EMEFA technique. Table 4 shows the results for output power, total losses, PLSI index and the minimum voltage for different loading condition. The output data of ANN method which is total loss is collected and used as target data for ANN model. Figure 2 illustrate the performance of ANN1 for 3 unit of DG while the regression analysis was plotted in Figure 3. The results show the target R=0.98348 for installation of 3 units of DG. Similar study was performed for optimal DG allocation for 4 units of DG. The results are shown in Figure 4 and Figure 5 for the best performance and regression analysis respectively. The results show the R=0.9252 for installation of 4 units of DG. Regression, R Values measure the correlation between outputs and targets. An R value of 1 means a close relationship, 0 a random relationship.

2.2. Effect of Multiple DG for ANN2

Comparable study was performed for the output of ANN2 which represent the PLSI index. The results are shown in Figure 6 and Figure 7 for the best performance and Figure 8 and Figure 9 for regression analysis respectively. The results show the R=0.9947 (3 Units) and R=0.9803(4 Units) for installation of multi-units of DG. Results obtained from the study indicated that there is a good correlation between the results of ANN output and target values for DG planning. The allocation of total DG capacity considerably changes according to the load allocation and total DG sizing. Table V shows the results for MSE and R for ANN1 and ANN2. The MSE is the average squared difference between outputs and targets where the lower value indicates better results. The R values measure the correlation between outputs and targets. An R value of '1' indicates a close relationship, while '0' a random relationship. As can be seen from the table above, there was significant correlation R, for ANN2 compared to ANN1.

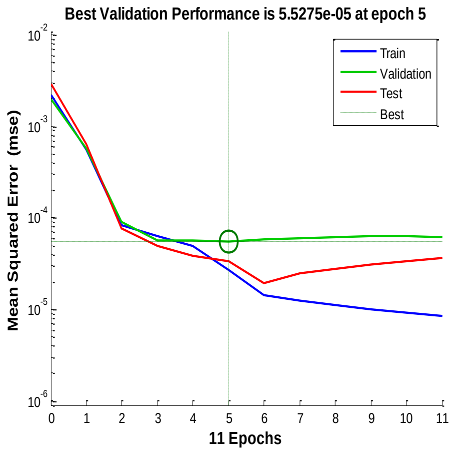

Figure 2. Performance for ANN1 (3 DG units)

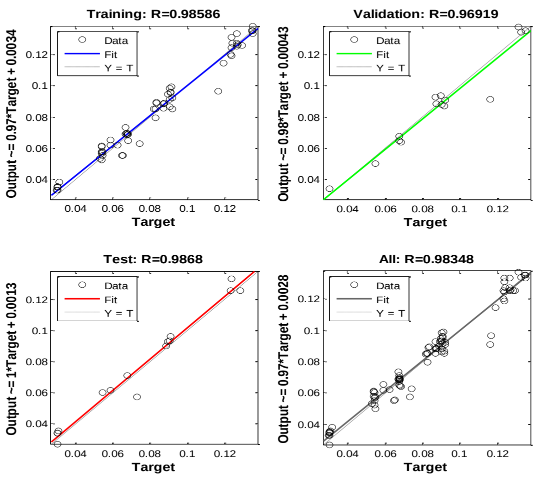

Figure 3. Regression analysis for ANN1 (3 DG units)

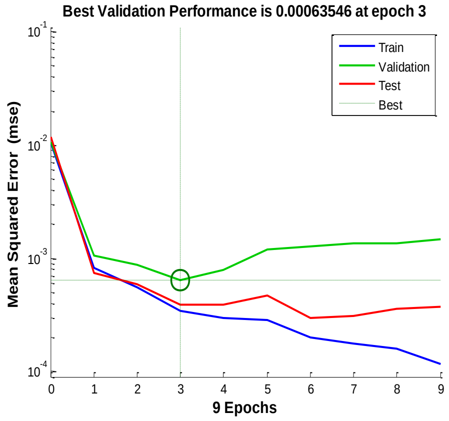

Figure 4. Performance for ANN1 (4 DG units)

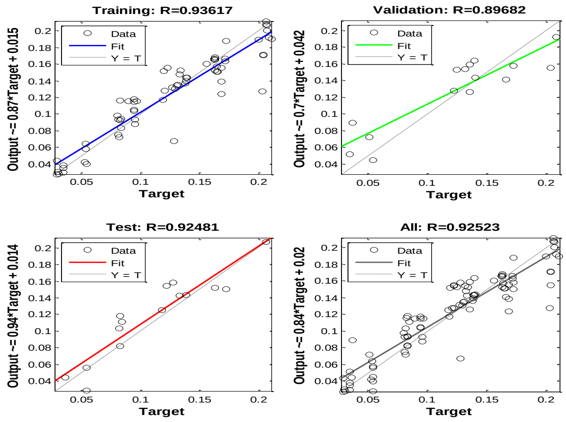

Figure 5. Regression analysis for ANN1 (4 DG units)

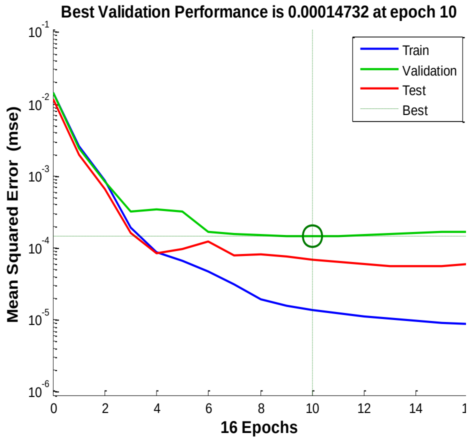

Figure 6. Performance for ANN2 (3 DG units)

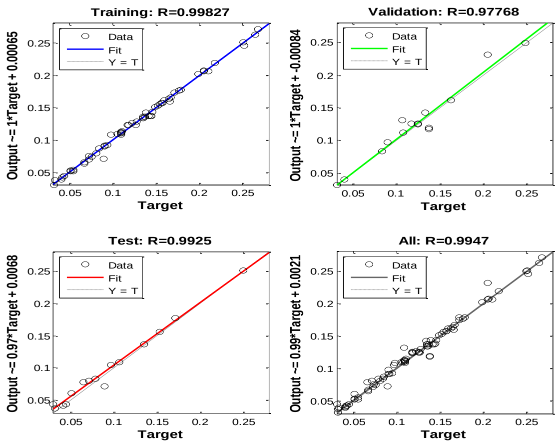

Figure 7. Regression analysis for ANN2 (3 DG units)

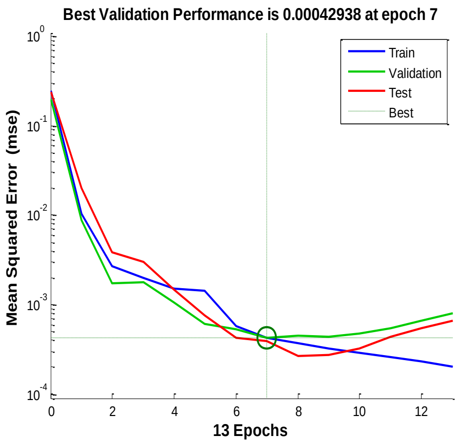

Figure 8. Performance for ANN2 (4 DG units)

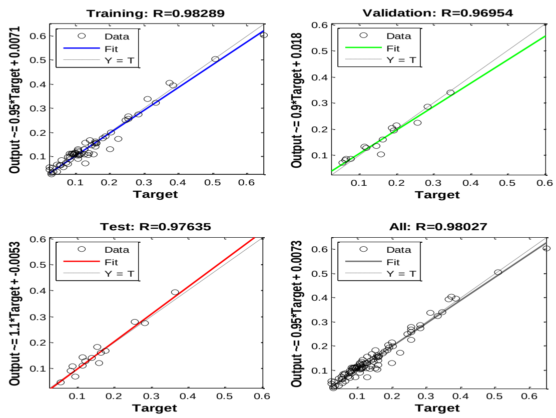

Figure 9. Regression analysis for ANN2 (4 DG units)

Table 4. Result For Optimal DG Type 1

						3DG						
k	P_{DG1}	P_{DG2}	P_{DG3}	P_{DG4}	P_{Loss} (MW)	Q_{Loss} (MVAr)	V_{min} (p.u)	PLSI	DG_{LOC1}	DG_{LOC1}	DG_{LOC1}	DG_{LOC1}
0.6	1.0204	0.4486	1.4761	0	0.0315	0.0171	0.9807	0.0299	61	50	39	26
0.8	1.4429	1.1588	1.0755	0	0.0540	0.0276	0.9745	0.0547	61	50	39	26
1	1.7617	0.6054	0.1204	0	0.0821	0.0372	0.9677	0.1538	61	50	39	26
1.2	2.1373	2.0460	1.8655	0	0.1270	0.0695	0.9611	0.1174	61	50	39	26
1.4	2.5046	1.6902	2.1855	0	0.1705	0.0852	0.9543	0.1743	61	50	39	26
						4DG						
k	P_{DG1}	P_{DG2}	P_{DG3}	P_{DG4}	P_{Loss} (MW)	Q_{Loss} (MVAr)	V_{min} (p.u)	PLSI	DG_{LOC1}	DG_{LOC1}	DG_{LOC1}	DG_{LOC1}
0.6	1.6539	0.0545	1.6112	1.6112	0.0530	0.0353	0.9846	0.0300	61	52	41	35
0.8	1.7498	1.6626	0.4605	0.4605	0.0692	0.0334	0.9854	0.0595	61	52	41	35
1	1.8368	0.7379	0.4331	0.4331	0.0804	0.0392	0.9722	0.1088	61	52	41	35
1.2	1.7809	1.9945	0.9840	0.9840	0.1315	0.0668	0.9691	0.1281	61	52	41	35
1.4	2.1039	1.2329	0.2116	0.2116	0.1635	0.0786	0.9583	0.2838	61	52	41	35

Table 5. Results for MSE and R for ANN1

	ANN1				ANN2			
	3 DG		4 DG		3 DG		4 DG	
	MSE	R	MSE	R	MSE	R	MSE	R
Training	2.6858×10^{-5}	0.9859	3.4702×10^{-4}	0.9362	1.3650×10^{-5}	0.9983	4.2557×10^{-4}	0.9829
Validation	5.5275×10^{-4}	0.9619	1.3546×10^{-4}	0.8968	1.4732×10^{-5}	0.9777	4.2938×10^{-4}	0.9695
Testing	3.3579×10^{-5}	0.9868	3.8622×10^{-4}	0.9248	6.9178×10^{-5}	0.9925	3.8885×10^{-4}	0.9763

3. Conclusion

In conclusion, the penetration level for multi-DG installation for DG planning in distribution system using EMEFA-ANN technique was successfully implemented and tested on 69 bus test system. Results obtained from the study indicated that there is a good correlation between the results of ANN2 output and target values for DG planning compared to ANN1. The allocation of total DG capacity considerably changes according to the load allocation and total DG sizing. The result shows the capability of the technique to perform DG planning and to ensure the proper placement and sizing of the DG unit by considering the penetration level. Results from the study would be beneficial for the energy commission and utility in ensuring the proper placement and sizing for the benefit of powerful system utility as a compensating technique as well as to support the green agenda and clean energy.

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