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Applied TVA-PSO for optimal energy efficient integration of renewable energy sources based maximizing TEC levels

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Abstract

After the rapid increase in the population demography and industrial revolution, many researchers focus on maintaining the balance between the consumption and the production; in this regard, decentralized production plays an important role to achieve this balance, because of its technical economic aspect such as power losses reduction and voltage profile improvement. These advantages can better exploited through the optimal assessment of Distributed Generation (DG). This paper is interested in the study of the optimal location and size of one and multiple DG based on photovoltaic solar sources PV-DG in Radial Distribution Network (RDN) using the Time Varying Acceleration Particle Swarm Optimization Algorithm (TVA-PSO). This algorithm implemented to maximize the Multi-Objective Functions (MOF) based on the Environmental Pollution Reduction Level (EPRL), the Voltage Deviation Level (VDL), Active Power Loss Level (APLL), the Net Saving Level (NSL), and finlly the Short Circuit Level (SCL). The proposed method is tested on the standard IEEE 33-, 69-and 118-bus RDN. Outcomes proves that the proposed TVA-PSO is more efficient to solve the optimal allocation of multiple DGs with high convergence rate and minimum power loss reduction.

Keywords: Renewable distributed generation, Optimal energy efficient integration, Electric distribution networks, TEC levels, Time-varying acceleration particle swarm optimization.

1. Introduction

The global trend towards preserving the environment, and saving energy for all consumers has accelerated the search for new resources. In this regard the demand for renewable resources has significantly increased into RDN due of the operational and economic benefits such as reduction in energy purchase from the grid, the deferral in investment for building new lines, enhancement in system reliability and stability [1, 2]. The problem of DG assessment is, in general, a complex optimization problem. The implemented studies in this area fall into many categories depending on the solution algorithms, constraints, and considered objectives [3].

Mathematically numerous objective functions were formulated for the optimal assessment of DG units. These are: Minimization of active power loss [4], Minimization of reactive and active power losses [5], Minimization of power and energy loss [6], Minimization of voltage deviation [7], Minimization of total operational costs of DG units [8, 9], Minimization of total operational cost and minimization of risk factor [10], Minimization of environmental emissions [11], Minimization of pollutant emission [12], and Minimization of total harmonic distortion in distribution system [13]. Single objective function is considered to maximize the benefits of DG. These are: Maximization of voltage stability margin [14], Maximization of DG penetration [15], Maximization of network load ability due to the DG placement [16], Maximization of profit of a distribution company [17], Maximization of fossil fuel cost saving [18], Maximization of hosting capacity of renewable energy sources [19], and Maximization of the average interruption time in distribution system [20].

Practically, the problem of assessment of DGs in RDN becomes a complex multiobjective function (MOF) problem since it is quite hard to optimize multiple conflicting objectives in the same time. Determining the best suitable solution in view of all the objectives also becomes difficult since the optimization algorithms are originally designed to optimize a single objective. Therefore, researchers have usually considered a weighted sum approach to optimize multiple objectives of DG planning. For this, depending on the weights factor selected to each objective a single solution is obtained [21].

This paper presents optimal integration of multiple DG in RDN using TVA-PSO algorithm. In this regards, optimal incorporation of DG was installed in three different standard RDN. The optimal integration has been selected to maximize the five technical, economic and environmental levels. The effectiveness of the TVA-PSO is validated by comparing the obtained results with those reported in literature using other algorithms.

2. Multi-Objective Problem Formulation

2.1. Multi-Objective Function

The multi-objective level represented in eq. 1 with aim of maximize technical, economic and environmental levels by giving a specified weight to each index depending on the influences of each one. In this regard, w_1, w_2, w_3, w_4 and w_5 are the weighting factors. In this study, w_2, w_3 and w_4 is taken as 0.20, and w5 is taken as 0.10. Whereas due of the important of reduction of P_{Loss} w_1 is taken as 0.30:

$$MOF = \text{Max} \sum_{i=1}^{N_{BF}} \sum_{j=2}^{N_{BMr}} \begin{pmatrix} w_1 \cdot APLL_{i,j} + w_2 \cdot VDL_j \\ +w_3 \cdot ISCL_{i,j} + w_4 \cdot NSL_{i,j} \\ +w_5 \cdot EPRL_G \end{pmatrix} \quad (1)$$

The Mathematical description of the proposed levels composed the MOF, given as:

$$APLL = \frac{P_{\text{Loss}}^{\text{Without } DG}}{P_{\text{Loss}}^{\text{Withot } DG} + P_{\text{Loss}}^{\text{With } DG}} \times 100 \quad (2)$$

$$VDL = \frac{VD_{\text{Without } DG}}{VD_{\text{Without } DG} + VD_{\text{With } DG}} \times 100 \quad (3)$$

$$SCL = \frac{SC_{\text{With } DG} - SC_{\text{Without } DG}}{SC_{\text{Without } DG}} \times 100 \quad (4)$$

$$NSL = \frac{ALC_{\text{Without } DG} - ALC_{W_{\text{ith}} DG}}{ALC_{\text{Without } DG}} \times 100 \quad (5)$$

$$PRL = \frac{PE_{\text{With } DG}}{PE_{\text{Without } DG} + PE_{\text{AWith } DG}} \times 100 \quad (6)$$

The mathematical representation of the P_{Loss} can defined as [18-23]:

$$P_{\text{Loss}} = R_{ij} \frac{(P_{ij}^2 + Q_{ij}^2)}{V^2} \quad (7)$$

The economical aspect represented in ACL which considered following the P_{Loss} can be defined as [10, 11]:

$$C = P_{\text{Loss}} \times K_p \times T \quad (8)$$

The Short Circuit (SC) given by [24]:

$$CS = \frac{V_j}{Z_{ij}} \quad (9)$$

The Voltage Deviation (VD) is considered as follows [25]:

$$VD = |1 - V_j| \quad (10)$$

The Pollution of Emissions (PE) is given by [26]:

$$PE = EG_g \cdot AE_g \quad (11)$$

2.2. Power Balance and Distribution Line Constraint

The mathematical representation of the power balance line given by [27-29]:

$$P_G + P_{DG} = P_D + P_{\text{Loss}} \quad (12)$$

$$Q_G = Q_D + Q_{\text{Loss}} \tag{13}$$

The margin limits of voltage at each bus can be represented as [30, 31]:

$$V_{min} \leq |V_i| \leq V_{max} \tag{14}$$

$$|V_1 - V_j| \leq \Delta V_{max} \tag{15}$$

$$|S_{ij}| \leq |S_{max}| \tag{16}$$

2.3. PV-DG Constraints

The PV-DG constraints represented by the capacity, position, number and the location of DG given by the equations bellow:

$$P_{PV-DG}^{min} \leq P_{PV-DG} \leq P_{PV-DG}^{max} \tag{17}$$

$$2 \leq PV - DG_{Position} \leq N_{Bus} \tag{18}$$

$$N_{PV-DG} \leq N_{PV-DG \cdot max} \tag{19}$$

$$n_{DG,i} / \text{ Location } \leq 1 \tag{20}$$

3. Overview TVA-PSO Algorithm

3.1. Basic PSO algorithm

PSO is one of the most algorithm applied in the global search strategy, which is introduced in 1995 as a population-based stochastic optimization algorithm. In PSO, each member of the population represents a potential solution and it's called a particle. The population of individuals (P) or swarm is evolved through successive iterations. Each particle, has a position, and a velocity vector (X_i), and (V_i), each particular moved according to [32, 33]:

$$V_i^{k+1} = w \cdot V_i^k + c_1 r_1 \left[P_{best}^k - X_i^k\right] + c_2 r_2 \left[G_{best}^k - X_i^k\right] \tag{21}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{22}$$

Where, P_{best} represent the best position founded by the particle, and G_{best} is the best position founded among all particles, where, c_2 and c_1 are the 'social' and 'cognitive' components of the acceleration coefficients, r_2 and r_1 are random values. The weighting function (w) is defined as:

$$w = w_{max} - (w_{max} - w_{min}) \left(\frac{k}{k_{max}}\right) \tag{23}$$

3.2. Time-Varying Acceleration PSO algorithm

The acceleration coefficients are varied according to iteration or time. For visiting all the search space. At the beginning, the value of c_1 must be higher than c_2. Which allow particles to visit all the search space, whereas at the end of search, particles try to converge to the global optima, which mean that c_1 must be small than c_2. These variations can be given by [34]:

$$c_1 = c_{1i} + \left(\frac{c_{1f} - c_{1i}}{k_{max}}\right) \cdot k \tag{24}$$

$$c_2 = c_{2i} + \left(\frac{c_{2f} - c_{2i}}{k_{max}}\right) \cdot k \tag{25}$$

Where, c_{1i} and c_{1f} are initial and final values of c_1, c_{1f} and c_{2i} and are final and initial values of c_2.

4. Results, Discussion and Comparison

Two show the efficiency of TVA-PSO the proposed algorithm is implemented in MATLAB and tested in the three different tested system. These are the standard IEEE 33-, 69-, and 118-bus.

The description of these tested systems are dipected in Table 1 and their single line diagrame are shown in Figure Figure 1.

Table 1: ???

Description	IEEE 33-bus	IEEE 69-bus	IEEE 118-bus
Line Number	32	68	117
Bus number	33	69	118
Base Voltage (kV)	12.66	12.66	11.00
Q_D (MVar)	2.300	2.6941	17.0400
P_D (MW)	3.715	3.7919	22.7100

The parameters of TVA-PSO algorithm are: c_{1i} =0.5, c_{1f} 2.5, c_{2i}=2.5, c_{2f}=0.5, k_{max}=200, k_{min}=1, w_{max} =0.9, w_{min}=0.4, n_p=10.

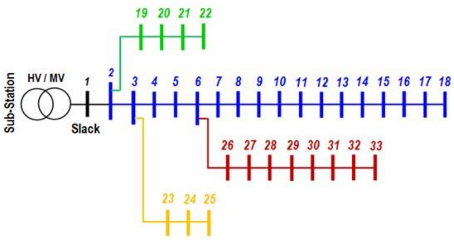
The convergence characteristics of MOF for the three tested system are presented in Figures Figure 2, the best solution is represented in red.

As seen in Figure Figure 2, for the IEEE 33 and 69 bus RDN, the comparison of the 20 runs indicates, that the result after the integration of one and three PV-DGs are closer to each other, with a more closer in the IEEE 33-bus, but they are so far for the case of two PV-DGs.

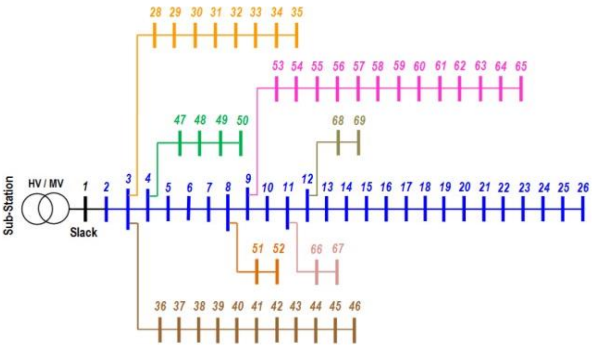
In order to reach the optimal solution, for both RDN, the algorithm converges quickly and takes less than 20 iterations after the integration of one PV-DG.

For the case of two PV-DGs, the convergence in the second test system is faster than the first system.

For the case of three PV-DGs, the TVA-PSO algorithm quickly achieved the optimal solution for the IEEE 33-bus compared to the IEEE 69-bus. For the third system (IEEE-118 bus), the results of the integration of three, four and five PV-DGs are far compared to the previous systems, in addition, it takes several iterations to reach the optimal solution, which are more than 150 iterations.



(a)



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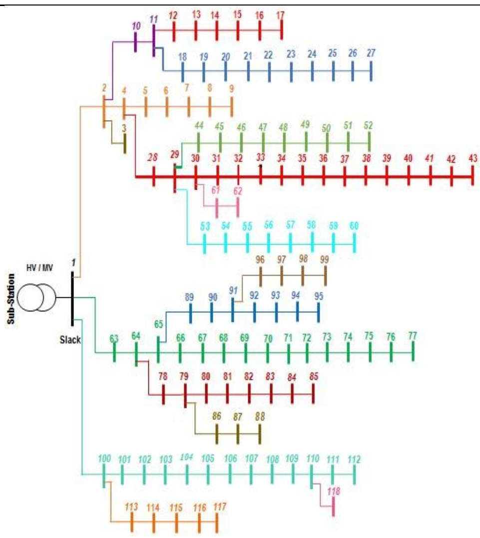
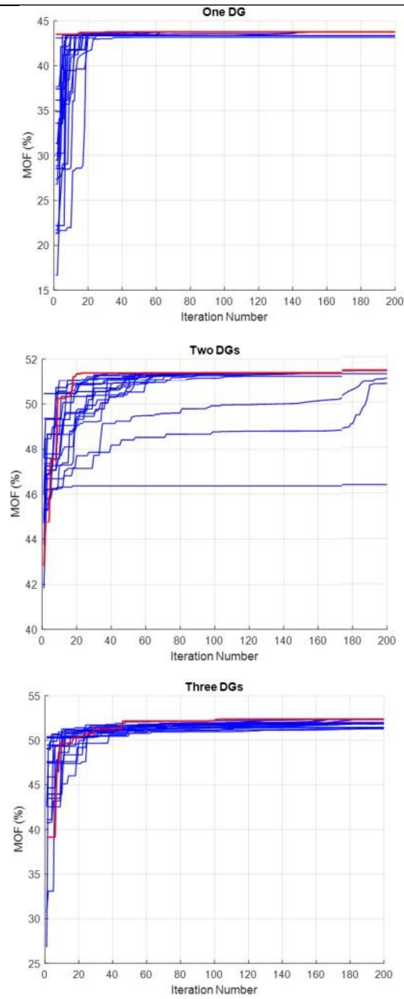


(c)

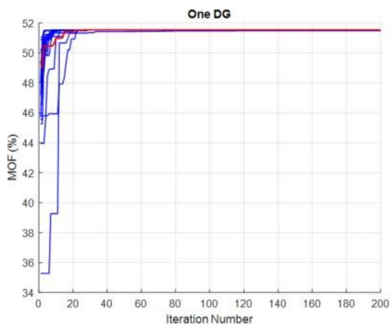
Figure 1: Single line diagram of standard distribution systems: a). IEEE 33-bus, b). IEEE 69-bus, c). IEEE 118-bus

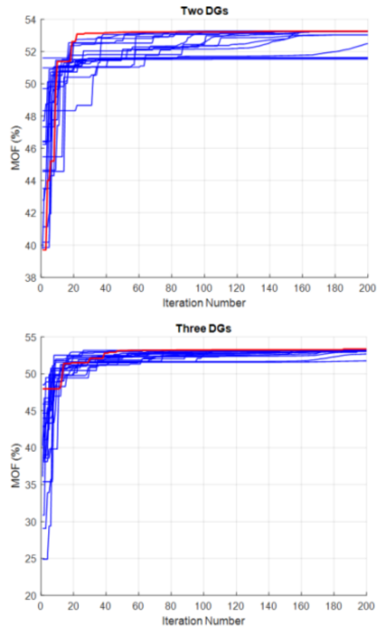
proportional relation between the number of PV-DGs and the NSL and APLL levels. In addition, the SCL and VDL increases by increasing the number of PV-DGs except for the third test system, where the maximum SCL and VDL have obtained after the integration of four PV-DGs. For the EPRL in the first test system the better results are obtained after the integration of two PV-DGs, while for IEEE 69 and 118-bus the maximum EPRL was obtained after the integration of one and three PV-DGs respectively.

Figure Figure 3 shows the benefits of the incorporation of multiple DGs in RDN. It is clear that the APLL, NSL, and VDL have an important improvement, compared to EPRL and SCL especially, in the IEEE 33-, and 69-bus RDN. For the IEEE 118-bus, the results obtained for the incorporation of five DGs are better compared to the other cases except for the EPRL. The results of the proposed algorithm were compared with the results obtained by others algorithms and techniques for the IEEE 33-, 69-, and 118-bus are dipected in tables 3, 4, and 5 respectively.

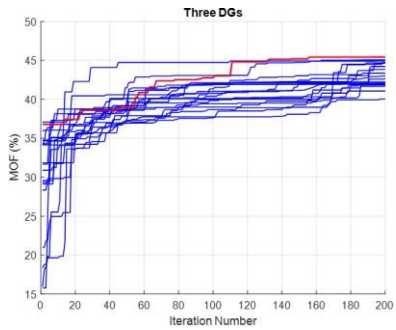

One DG
MOF (%)
Iteration Number
Two DGs
MOF (%)
Iteration Number
Three DGs
MOF (%)
Iteration Number

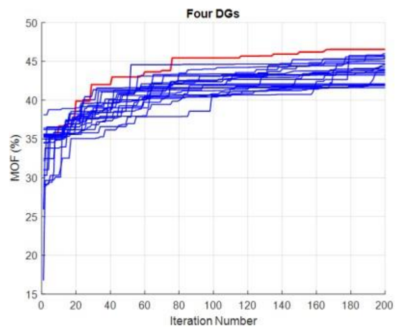
(a)

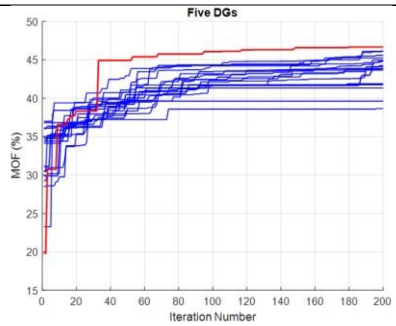

One DG
MOF (%)
Iteration Number


Two DGs
MOF (%)
Iteration Number
Three DGs
MOF (%)
Iteration Number

(b)


Three DGs
MOF (%)
Iteration Number


Four DGs
MOF (%)
Iteration Number



(c)

Figure 2: Convergence characteristic of TVA-PSO algorithm: a). IEEE 33-bus, b). IEEE 69-bus, c). IEEE 118-bus

The result tabulated in Table Table 2 represent the parameter of different level obtained by the proposed method after integration of PV-DGs for all RDNs.

Table 2: Different levels value for all test systems

Test system	Case studies	APLL (%)	NSL (%)	SCL (%)	VDL (%)	EPRL (%)	MOF (%)
IEEE 33-bus	One PV-DG	64.7796	45.6305	5.4709	62.7880	19.4496	43.7515
	Two PV-DGs	70.5995	58.3560	5.7176	64.1756	33.2026	51.3999
	Three PV-DGs	73.5391	64.0180	6.0078	64.8346	27.0867	52.3623
IEEE 69-bus	One PV-DG	72.8018	62.6408	0.5408	60.2402	34.9699	51.5300
	Two PV-DGs	75.5338	67.6090	1.0141	63.9562	30.7318	53.2565
	Three PV-DGs	75.5495	67.6364	1.0161	63.9737	30.8549	53.3525
IEEE 118-bus	One PV-DG	65.8836	48.2171	2.4429	58.7809	38.1948	45.4329
	Two PV-DGs	67.0621	50.8846	2.5712	60.0929	37.0811	46.5368
	Three PV-DGs	67.2785	51.3641	2.5258	59.8596	35.9998	46.6536

The analysis of Table Table 2, illustrates that there is a

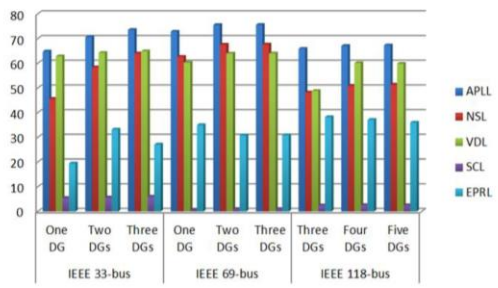


Figure 3: Comparison of Different levels for all test systems

The results of the proposed TVA-PSO for the three cases of the integration of PV-DGs are compared with results obtained by employing: Dynamic Adaptation of PSO (DA-PSO) [35]. Adaptive Dissipative PSO (ADPSO) [35], backtracking search optimization algorithm (BSOA) [36], Particle Swarm Optimization (PSO) [37], Symbiotic Organism Search (SOS) [38], flower pollination algorithm (FPA) [39], quasi-oppositional teaching learning based optimization (QOTLBO) [40], Bacterial Foraging Optimization Algorithm (BFOA) [41], intelligent water drop (IWD) [42], Simulated Annealing (SA) [43] are provided in Table Table 3: Results comparison of various algorithms for the IEEE 33-bus.

To verify the efficiency of TVA-PSO In the IEEE 69-bus, a comparison between the applied algorithm and other optimization algorithms namely: Symbiotic Organism Search (SOS) [38], Harmony Search Algorithm (HSA) [38], Hyper-Spherical Search Algorithm (HSSA) [44], Standard Genetic Algorithm (SGA) [45], harmony search algorithm with differential operator (HSDO) [46], Particle Swarm Optimization (PSO) [45], Cuckoo Search Algorithm (CSA) [45], invasive weed optimization (IWO) [42 47], Intelligent Water Drop (IWD) [43 48], Moth-Flame Optimization (MFO) [44 49], as represented in Table

To demonstrate the effectiveness of the proposed TVA-PSO in the large RDN (IEEE 118-bus), a comparative study has been done for validity the efficiency of TVA-PSO algorithm with well-known algorithms in the literature. These algorithms are: Symbiotic Organism

Search (SOS) [38], augmented Lagrangian genetic algorithm (ALGA) [50], ant-lion optimizer (ALO) [51], hybrid Harmony Search Algorithm-Particle Artificial Bee Colony Algorithm (HSA–PABC) [52], Hyper-Spherical Search Algorithm (HSSA) [44], Hybrid genetic fuzzy algorithm (GA-fuzzy) [53], Simulated Annealing (SA) [43].

Table 4.

Table 3: Results comparison of various algorithms for the IEEE 33-bus

Case	Methods	P_{DG} (MW) *(Bus)*	P_{Loss} *(kW)*	V_{min} *(p.u.)*
	Before DG	---	210.9875	0.9038
1 PV-DG	DA-PSO [35]	1.2120 (8)	0.8363 (28)	0.9349
	BSOA [36]	1.8575 (8)	118.1200	0.9441
	PSO [37]	2.0000 (7)	115.1700	0.9424
	SOS [38]	3.1322 (6)	115.0100	0.9441
	TVA-PSO	**2.8818 (7)**	**114.7128**	**0.9499**
2 PV-DGs	SOS [38]	2.2861 (6) 0.8363 (28)	107.3900	0.9500
	AD-PSO [35]	0.5500 (15) 0.6210 (30)	106.2400	0.9539
	BSOA [36]	0.8800 (13) 0.9240 (31)	89.3400	0.9665
	FPA [39]	1.0339 (12) 1.0866 (30)	89.2000	0.9675
	TVA-PSO	**0.8246 (13) 1.0273 (30)**	**87.8637**	**0.9640**
3 PV-DGs	QOTLBO [40]	1.0834 (13) 1.1876 (26) 1.1992 (30)	103.4090	0.9827
	BFOA [41]	0.6521 (14) 0.1984 (18) 1.0672 (32)	89.9046	0.9705
	IWD [42]	0.6003 (9) 0.3000 (16) 1.0112 (30)	85.7800	0.9610
	SA [43]	1.1124 (6) 0.4874 (18) 0.8679 (30)	82.0525	0.9677
	TVA-PSO	**0.7997 (13) 0.5560 (25) 0.9771 (30)**	**75.9176**	**0.9642**

To demonstrate the effectiveness of the proposed TVA-PSO in the large RDN (IEEE 118-bus), a comparative study has been done for validity the efficiency of TVA-PSO algorithm with well-known algorithms in the literature. These algorithms are: Symbiotic Organism Search (SOS) [38], augmented Lagrangian genetic algorithm (ALGA) [50], ant-lion optimizer (ALO) [51], hybrid Harmony Search Algorithm-Particle Artificial Bee Colony Algorithm (HSA–PABC) [52], Hyper-Spherical Search Algorithm (HSSA) [44], Hybrid genetic fuzzy algorithm (GA-fuzzy) [53], Simulated Annealing (SA) [43].

Table 4: Results comparison of various algorithms for the IEEE 69-bus

Case	Methods	P_{DG} (MW) *(Bus)*	P_{Loss} *(kW)*	V_{min} *(p.u.)*
	Before DG	---	224.9480	0.9092
1 PV-DG	SOS [38]	2.0870 (57)	118.6050	0.9586
	HSA [38]	1.4363(65)	112.0690	0.9656
	HSSA [44]	1.2070 (61)	99.3970	0.9554
	SGA [45]	2.3000 (61)	89.3771	0.9708
	TVA-PSO	**1.7167 (61)**	**84.0387**	**0.9674**
2 PV-DGs	SOS [38]	0.3612 (57) 1.6948 (58)	102.9200	0.9669
	HSDO [46]	1.5932 (64) 0.0544 (65)	96.5600	0.9669
	PSO [45]	0.7000 (14) 2.1000 (62)	83.9100	0.9907
	CSA [45]	0.6006 (22) 2.1000 (61)	76.4000	0.9902
	TVA-PSO	**0.4581 (18) 1.6252 (61)**	**72.8630**	**0.9731**
3 PV-DGs	PSO [40]	0.9925 (17) 1.1998 (61) 0.7956 (63)	83.2000	0.9901
	IWO [47]	0.2381 (27) 1.3266 (61) 0.4334 (65)	74.5900	0.9792
	IWD [48]	0.2999 (17) 1.3200(60) 2.4388 (63)	73.5500	0.9730
	MFO [49]	0.3000 (21) 1.4500 (61) 0.3000(65)	73.4950	0.9788
	TVA-PSO	**0.2579 (17)**	**72.8012**	**0.9729**

	0.1934 (23) 1.6216 (61)

As shown in Table Table 3, for the installation of one PV-DG the SOS algorithm have the minimum P_{Loss} (115.0100 kW) with a percentage of reduction of 45.4896 %, compared to the P_{Loss} obtained by the TVA-PSO (114.7128 kW), this comparison reveals that the TVA-PSO is better than SOS with a difference of 0.2972 kW. For the case of two PV-DGs, the FPA algorithm has the minimum P_{Loss} among other algorithms with 89.2000 kW, whereas the P_{Loss} recorded by TVA-PSO algorithm equals to 87.8637 kW which is less than P_{Loss} obtained by the FPA algorithm and the other algorithms. In the case of the installation of three PV-DGs, the TVA-PSO has the best performance in terms of minimizing P_{Loss} compared to the other algorithms.

Table 5: Results comparison of various algorithms for the IEEE 118-bus

Case	Methods	P_{DG} (MW) *(Bus)*	P_{Loss} *(kW)*	V_{min} *(p.u.)*
3 PV-DGs	Before DG	---	1297.500	0.8688
	SOS [38]	1.2591 (68) 2.3788 (70) 4.7958 (104)	875.2687	0.9095
	ALGA [50]	3.5130 (38) 2.9800 (72) 2.8750 (111)	738.6800	0.9545
	ALO [51]	2.4500 (40) 2.4500 (73) 2.5000 (110)	694.4500	0.9527
	HAS-PABC [52]	3.2500 (47) 2.9500 (71) 3.2000 (108)	677.7400	0.9127
	TVA-PSO	**2.8090 (39)** **2.9149 (70)** **2.8268 (110)**	**671.8826**	**0.9486**
4 PV-DGs	HSSA [44]	1.4355 (52) 0.8000 (79) 1.3115 (112) 1.8798 (116)	732.130	0.9355
	GA-fuzzy [53]	2.1379 (42) 1.3621 (52) 2.7410 (74) 2.4141 (110)	695.7160	0.9513
	ALGA [50]	3.3845 (38) 1.6050 (51) 2.9810 (72) 3.1264 (110)	663.7800	0.9545
	TVA-PSO	**2.4239 (40)** **2.3205 (75)** **1.7835 (97)** **2.6752 (110)**	**637.2725**	**0.9523**
4 PV-DGs	SA [43]	1.1329 (56) 4.5353 (36) 2.1318 (75) 4.9452 (103) 0.7501 (116)	858.8133	0.9190
	SOS [38]	0.9665 (68) 2.5979 (70) 0.7936 (104) 0.5095 (106) 2.4469 (108)	800.3249	0.9095
	GA-fuzzy [53]	2.6033 (41) 1.1610 (51) 2.7855 (73) 1.4538 (81) 2.4765 (111)	635.4330	0.9558
	TVA-PSO	**1.5058 (33)** **1.7098 (40)** **1.0158 (50)** **3.0000 (72)** **2.6102 (110)**	**631.0503**	**0.9511**

As shown in Table 3, for the installation of one PV-DG the SOS algorithm have the minimum P_{Loss} (115.0100 kW) with a percentage of reduction of 45.4896%, compared to the P_{Loss} obtained by the TVA-PSO (114.7128 kW), this comparison reveals that the TVA-PSO is better than SOS with a difference of 0.2972 kW. For the case of two PV-DGs, the FPA algorithm has the minimum P_{Loss} among other algorithms with 89.2000 *kW*, whereas the P_{Loss} recorded by TVA-PSO algorithm equals to 87.8637 *kW* which is less than P_{Loss} obtained by the FPA algorithm and the other algorithms. In the case of the installation of three PV-DGs, the TVA-PSO has the best performance in terms of minimizing P_{Loss} compared to the other algorithms.

The analysis of results tabulated in Table Table 4 indicates that the results of P_{Loss} obtained by TVA-PSO are better than other algorithms. By doing a numerical comparison with the other algorithms. For the integration of one PV-DG, it can be noticed that the TVA-PSO has improved the system performance by minimizing the P_{Loss}

to 84.0387 kW. In the other side, the minimum power losses obtained among the compared algorithms is recorded by SGA which is minimized to 89.3771 kW, which means that TVA-PSO is saved 5.3384 kW more than SGA which represent 2.5301 %.

Through the integration of two PV-DGs, the amount of P_{Loss} obtained by the proposed algorithm is estimated at 72.8630 kW and it is obviously the minimum results if it is compared with those obtained with the other algorithms.

In order to verify the accuracy of the TVAPSO for the integration of three PV-DGs, the numerical comparison with the other algorithms shows that TVA-PSO outperforms these algorithms by reducing total power losses to

72.8012 kW which has reduced by MFO to 73.4950 kW which is considered as the best results among compared algorithms.

To show the efficiency of TVA-PSO how to deal in the large-scale systems, the installation of three, four and five PV-DGs is introduced. Through Table 5, for the case of three PV-DGs, the P_{Loss} obtained by TVA-PSO is less than obtained by other algorithms with a comparison between TVA-PSO and HSA-PABC we found that TVA-PSO saved 5.8574 kW. For the integration of four PV-DGs, if we take ALGA as an example, we observe that the P_{Loss} of the proposed algorithm is less than obtained by ALGA with 0.0247%. For the integration of five PV-DGs, always the TVA-PSO recorded the minimum results of P_{Loss} compared to the other algorithms, in this time the minimum result of P_{Loss} obtained in the literature is 635.4330 kW which is recorded by GA-fuzzy, the comparison between the precedent algorithms (TVA-PSO and GA-fuzzy) proves that the proposed algorithm is exceeds the other algorithms.

Figure Figure 4 indicates the bus voltage profiles of different case for all tested systems.

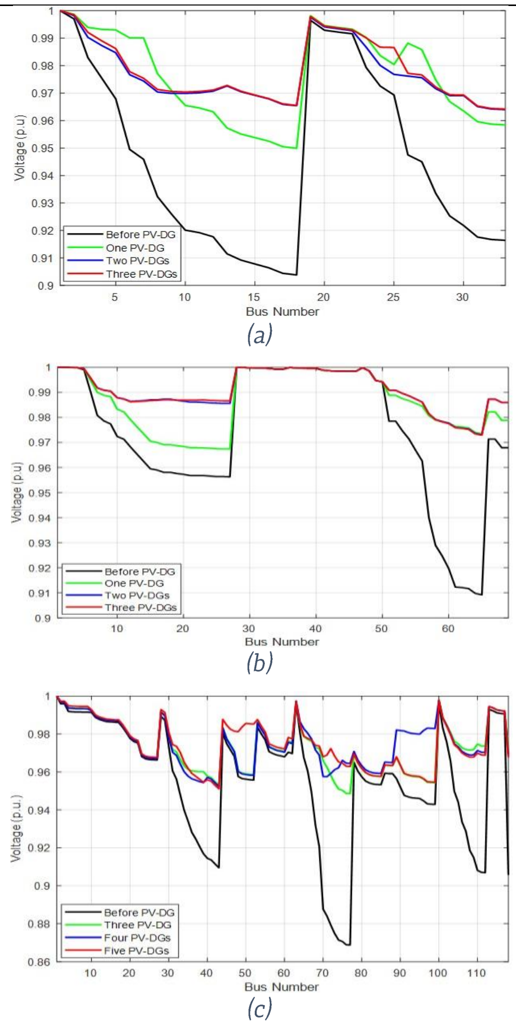


Figure 4: Bus voltages profile of standard distribution system. a). IEEE 33-bus, b). IEEE 69-bus, c). IEEE 118-bus

Through Figure Figure 4, the comparison of voltage profiles before and after PV-DGs integrations shows that in general after the integration of PV-DGs the voltage profiles have improved in all buses, with a different contribution for each number of PV-DGs, and this is valid for the three tested systems.

For the IEEE 33-bus RDS, the integration of one PV-DG gives the maximum voltages in buses from 26 to 29 as well as in the first 11 buses, which is related to the integration of PVDG in bus 7. For the other buses, the maximum voltages are obtained after the integration of two and three PV-DGs with better enhancement for the case of three PV-DGs compared to two PV-DGs installation, which is due to the total size of the three PV-DGs which is distributed on three different places, which it has more effect on the weakest busses, where the minimum voltage is reached the value 0.9499 p.u.

For the IEEE 69-bus RDS, due to the heights total size of PV-DGs the integration of two and three PV-DGs gives better improvement of voltage profiles compared to the case of one PV-DG. The voltage profiles for the cases of integration of two and three PV-DGs are identic in all the buses, moreover, for the buses from 28 to 69, the voltage profiles are slightly similar for all the cases, also the minimum voltage is improved to 0.9674, 0.9731 and 0.9729 p.u. respectively for the incorporation of one, two, and three PV-DGs.

For the IEEE 118-bus RDS, the best voltage profiles are obtained after the integration of PV-DGs, and the voltages are in the allowable limits, in the cases of installing three and four PV-DGs the voltage profiles is significantly improved, but it can be observed that it has more enhancement in the case of five PV-DGs, in other words, the number of PV-DG is the first reason of this clear improvement, in this manner, the voltages values are enhanced in almost busses, in addition, the minimum voltages are improved to 0.9486, 0.9523, 0.9511 p.u., respectively for three, four and five PVDGs. The impact of the incorporation PV-DG on active power losses for the three test systems is illustrated in Figure Figure 5.

As shown in Figure Figure 5, the P_{Loss} per branches have a clear minimization after the installation of PV-DGs for the three RDN. For the IEEE 33bus, it is clearly seen that the integration of three PV-DGs gives the minimum P_{Loss} in all branches, which is dependent on the sizes of the PV-DGs connected in different weakest busses. Branch number 2 is containing the losses which is 52.0768 kW followed by branch number 5 that it has an amount of 38.5656 kW, those branches are more affected by the incorporation of PV-DGs compared to the other branches. In general, the integration of three PV-D gives the minimum result of P_{Loss} compared to the cases of one and two PV-DGs.

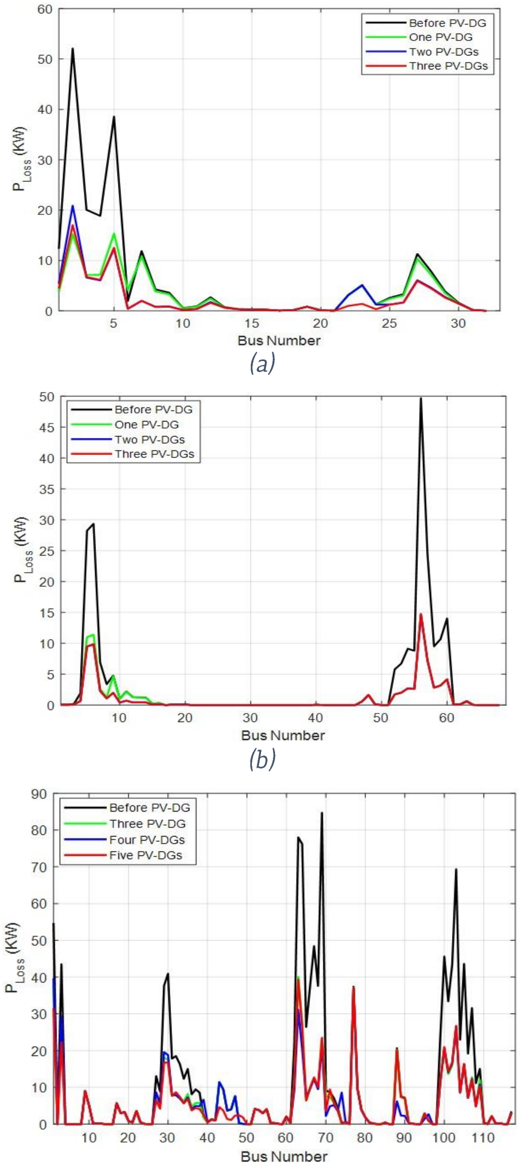


Figure 5: Active power loss of standard distribution system: a) IEEE 33-bus, b) IEEE 69-bus, c) IEEE 118-bus.

For the IEEE 69-bus, the comparison between the three cases of PV-DGs integration with the case before PV-DGs shows that the P_{Loss} is decreased in all the branches, in addition, the integration of three PV-DGs gives the best results in all the branches, moreover, the peak of P_{Loss} is decreased from 49.6845to 14.7174 kW in branch number 56.

For the large RDN (IEEE 118-bus), the integration of multi PV-DGs can affect all the branches by the minimization of P_{Loss} in each branch, which is appears through the comparison of the three cases of the integration of PV-DGs with the system before PV-DG. The integration of five PV-DGs is more efficient, which is allowed to minimize the P_{Loss} especially in branch number 69, which contains the peak of loss that is equal to 84.7016 kW and became 23.5013 kW.

5. Conclusions

In this paper, the proposed TVA-PSO algorithm have been tested on the three IEEE RDNs to determine the optimal location and size of PV-DG, considering the maximization of technical, economic and environmental levels, which are the APLL, SCL, NSL, EPRL, and VDL.

The outcomes obtained show the advantages of the incorporation of PV-DG for all the case studies by reducing the total active power losses and improvement of the voltage profiles which is becoming in the permissible limits, in addition, the better results have achieved after the integration of multi PV-DGs. In other words in the case of the integration of three PV-DG the P_{Loss} is reduced with a percentage of reduction around 64.01, 67.63, and 48.21 % respectively for the IEEE 33-, 69-, and 118-bus.

The superiority of the applied algorithm has demonstrated by compared the results obtained by TVA-PSO with those obtained by other algorithms in the literature, where it is clearly shown the superiority of TVA-PSO in term of achieving the minimum power loss.

6. Nomenclature

Nomenclature	
P_{Loss}, Q_{Loss}	Active and reactive power losses of RDN
P_{ij}, Q_{ij}	Active and reactive power in branch
Q_i, P_i	Reactive and active power at bus i
N_{bus}	Number of buses
Q_j, P_j	Reactive and active power at bus j
δ_j, V_j	Angle and voltage magnitude at bus i
X_{ij}, R_{ij}	Reactance and resistance of RDN
Q_G, P_G,	Reactive and active and power of generator
Q_D, P_D,	Reactive and active power of load
P_{DG}	Real power delivered by PV-DG unit
V_{min}, V_{max}	Margin limits of voltages
ΔV_{max}	Maximum voltage drops
S_{ij}	Apparent power in branch
S_{max}	Maximum apparent power
N_{DG}, $PVDG_{Position}$	Number and Position of PV-DG unit
$n_{DG,i}$,$N_{DG.max}$	Location and maximum number of PV-DG units
Kp	Incremental cost of PLoss, and equal to 0.06 $/kW
T	Number of hours per year
EG_g	The emission quantity of a generator pollutant
AE_g	The emission quantity of type pollutant
n_p	The population size

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