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Optimal integration of photovoltaic distributed generation in electrical distribution network using hybrid modified PSO algorithms

Nasreddine Belbachir[1], Mohamed Zellagui[2], Adel Lasmari[3], Claude Ziad El-Bayeh[4], Benaissa Bekkouche[5]
[1,5]Department of Electrical Engineering, University of Mostaganem, Mostaganem, Algeria
[2]Department of Electrical Engineering, École de Technologie Supérieure (ÉTS), Quebec, Canada
[2]Department of Electrical Engineering, University of Batna 2, Batna, Algeria
[3]Department of Electrotechnic, Mentouri University of Constantine 1, Constantine, Algeria
[4]Canada Excellence Research Chairs Team, Concordia University, Quebec, Canada

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ABSTRACT

The satisfaction of electricity customers and environmental constraints imposed have made the trend towards renewable energies making them more essential due to their advantages as reducing power losses and ameliorating system's voltage profiles and reliability. This article addresses the optimal location and size of multiple distributed generations (DGs) based on solar photovoltaic panels (PV) connected to electrical distribution network (EDN) using the various proposed hybrid particle swarm optimization (PSO) algorithms based on chaotic maps and adaptive acceleration coefficients. These algorithms are implemented to optimally allocate the DGs based PV (PV-DG) into EDN by minimizing the multi-objective function (MOF), which is represented as the sum of three technical parameters of the total active power loss (TAPL), total voltage deviation (TVD), and total operation time (TOT) of overcurrent relays (OCRs). The effectiveness of the proposed PSO algorithms were validated on both standards IEEE 33-bus, and 69-bus. The optimal integrating of PV-DGs into EDNs reduced the TAPL percentage by 56.94 % for the IEEE 33-bus and by 61.17 % for the IEEE 69-bus test system, enhanced the voltage profiles while minimizing the TVD by 37.35 % and by 32.27 % for two EDNs, respectively.

Corresponding Author:

Nasreddine Belbachir
Department of Electrical Engineering, Faculty of Science and Technology
University of Mostaganem
Street Hamadou Hossine, BP 188/227, Mostaganem 27000, Algeria
Email: nasreddine.belbachir.etu@univ-mosta.dz

1. INTRODUCTION

After the rapid increase in electricity demand, the balance between demand and electricity production has become an essential challenge for researchers and power producers. To deal with this, a conventional solution is widely used to generate electricity consists of creating new power stations. But this solution requires significant investments and costs as well as bad environmental effects. To mitigate these constraints, the distributed generation (DG) therefore presents a good alternative because of its advantages [1]. As the world heads toward growing its reliance on renewable energy sources, the number of DGs linked to electrical distribution network (EDN) has risen rapidly [2]. In order to cope with this high penetration of DGs into the EDN, it is critical that DGs are positioned at the optimum location with the optimum production size.

Recently, various researchers have suggested several ideas to resolve the optimum integration of PV-DG into EDN based three categories: analytical, optimization and hybrid algorithms. In this issue, the research has been implemented in various algorithms considered: applied teaching learning based optimization (TLBO) to optimize simultaneously the active power losses (APL) and voltage stability index (VSI) [3], particle swarm optimization (PSO) algorithm for two objective functions, the APL reduction and VSI improvements by active and reactive power DG [4], The invasive weed optimization (IWO) algorithm tested for different load models with the objective function to reducing APL and operating cost while enhancing the VSI [5]. Applied cuckoo search optimization (CSO) algorithm for the sizing of large-scale grid-connected photovoltaic system [6], adaptive genetic algorithm (AGA) with on-load taps changer to the objective of minimizing APL and maximum bus voltage [7], and symbiotic organism search (SOS) algorithm with loss sensitivity factor to minimize the APL of the EDN [8].

In 2018, applied binary particle swarm optimization (BPSO) to minimizing the APL for 59-bus Cairo EDN [9], novel cuckoo search (CS) algorithm with genetically replaced nests in order to minimise APL, VSI, and voltage profile [10], semidefinite optimization algorithm (SOA) with the formulate problem based on minimizing the APL and the size of DGs [11], and population-based incremental learning (PBIL) algorithm to reduce the APL and the square error in the voltage profiles of the EDN [12]. In 2019, applied spider monkey optimization (SMO) algorithm for reduced of voltage deviation problem [13], wind driven optimization (WDO) algorithm consider maximizing the VSI [14], modified crow search algorithm (MCSA) algorithm for minimizing APL and overall voltage deviation [15], moth flame optimization (MFO) algorithm, is implemented to optimal allocation of the PV-DG to minimize the APL of the distribution system [16], and also used the genetic algorithm (GA) with the aim of APL and voltage regulation [17], and application of adaptive dissipative PSO (ADPSO) algorithm with an objective of minimizing the APL [18]. In 2020, used virus colony search (VCS) algorithm for reduced the not supplied energy (NSE) [19], comprehensive learning PSO (CLPSO) algorithm with an objective of minimizing the APL [20], applied various adaptive acceleration coefficients PSO algorithms on maximizing the APL level [21], various adaptive PSO algorithms for minimizing the three technical parameters [22], and hybrid chaotic maps and adaptive acceleration coefficients PSO algorithm to multi-objective functions [23]. Recently, applied fine-tuned particle swarm optimization (FPSO) algorithm for APL with EDN reconfiguration [24], chaotic grey wolf optimizer (CGWO) to minimize a multi-objective function considering overcurrent relays indices [25], and adaptive quantum inspired evolutionary algorithm (AQiEA) to minimization of APL in addition to voltage dependent load models [26]. The authors in this paper have proposed various hybrid PSO algorithms based on chaotic maps and adaptive acceleration coefficients for the optimal location and sizing of PV-DG sources in IEEE 33-bus and 69-bus EDNs to minimize simultaniousely three technical parameters represented by the multi-objective function (MOF).

2. PROBLEM FORMULATION

2.1. Multi-objective function

The proposed MOF is considered to optimally allocate the PV-DGs by minimizing simultaneously the three parameters: total active power loss (TAPL), TVD, and TOT, as follows:

$$MOF = Minimize\sum_{i=1}^{N_{bus}}\sum_{j=2}^{N_{bus}}\sum_{i=1}^{N_R}\left[TAPL_{i,j} + TVD_j + TOT_i\right] \tag{1}$$

Firstly, the TAPL, expressed as [16], [25]:

$$TAPL_{i,j} = \sum_{i=1}^{N_{bus}}\sum_{j=2}^{N_{bus}} APL_{i,j} \tag{2}$$

$$APL_{i,j} = \alpha_{ij}\left(P_iP_j + Q_iQ_j\right) + \beta_{ij}\left(Q_iP_j + P_iQ_j\right) \tag{3}$$

$$\alpha_{ij} = \frac{R_{ij}}{V_iV_j}\cos\left(\delta_i - \delta_j\right),\ \beta_{ij} = \frac{R_{ij}}{V_iV_j}\sin\left(\delta_i + \delta_j\right) \tag{4}$$

Where, N_{bus} is the bus number, R_{ij} is the line resistance, V_i, V_j and δ_i, δ_j are the voltages and angles at the buses. P_i, P_j and Q_i, Q_j represent powers at buses. Secondly, the TVD, which is expresses by [22], [23]:

$$TVD_j = \sum_{j=2}^{N_{bus}} \left|1 - V_j\right| \tag{5}$$

Finally, the overcurrent relay's TOT, of the type based time-current-voltage tripping characteristic (NS-OCR) [27], wich is defined as follow:

$$TOT_i = \sum_{i=1}^{N_R} T_i \tag{6}$$

$$T_i = \left(\frac{1}{e^{(1-V_{FM})}}\right)^K TDS_i \left(\frac{A}{M_i^B - 1}\right) \quad , \quad M_i = \frac{I_F}{I_P} \tag{7}$$

Where, T_i is the relay's operation time, TDS_i is the time dial setting, *A, B* and *K* are constants set to 0.14, 0.02 and 1.5 respectively, V_{FM} is the fault voltage magnitude and N_R is the overcurrent relays number. M_i is the multiple of pickup current, I_F and I_P are the fault current and the pickup current, respectively.

2.2. Equality constraints

Equality constraints can be expressed by the following equations of power balance:

$$P_G + P_{PV-DG} = P_D + P_{Loss} \tag{8}$$

$$Q_G = Q_D + Q_{Loss} \tag{9}$$

2.3. Distribution line constraints

The distribution line inequality constraints can be given as:

$$V_{\min} \leq \left|V_i\right| \leq V_{\max} \tag{10}$$

$$\left|1 - V_j\right| \leq \Delta V_{\max} \tag{11}$$

$$\left|S_{ij}\right| \leq S_{\max} \tag{12}$$

2.4. PV-DG units constraints

The PV-DG unit limits inequality constraints can be expressed as:

$$P_{PV-DG}^{\min} \leq P_{PV-DG} \leq P_{PV-DG}^{\max} \tag{13}$$

$$\sum_{i=1}^{N_{PV-DG}} PV - DG(i) \leq \sum_{i=1}^{N_{bus}} P_D(i) \tag{14}$$

$$2 \leq PV - DG_{Position} \leq N_{bus} \tag{15}$$

$$N_{PV-DG} \leq N_{PV-DG.\max} \tag{16}$$

$$n_{PV-DG,i} \,/\, Location \leq 1 \tag{17}$$

3. OVERVIEW OF HYBRID PSO ALGORITHM

3.1. Basic PSO algorithm

The PSO algorithm was introduced in 1995 to develop an optimal solution to a problem, which is inspired from the social behavior of animals evolving in swarms. Each individual of its population is called a particle, that illustrates a solution, hence this particle is moving according to the following equations at each iteration *k* [28]:

$$V_i^{k+1} = \omega . V_i^k + c_1 r_1 \left[P_{best}^k - X_i^k \right] + c_2 r_2 \left[G_{best}^k - X_i^k \right] \tag{18}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{19}$$

$$\omega = \omega_{\max} - \left(\omega_{\max} - \omega_{\min} \right) \left(\frac{k}{k_{\max}} \right) \tag{20}$$

Where, ω is the inertia weight, V_i is the velocity of particle, X_i is the position of particle, G_{best} *and* P_{best} are the swarm overall best and previous personal best of the particle, respectively. k and k_{max} are iteration and maximum iterations numbers, c_1, c_2 are the acceleration coefficients, and r is a random number. Researchers have proposed many PSO algorithms by editing the parameters of (ω, c_1, c_2 and r) to reach its optimum performances and function. Therefor it is chosen in this paper an improved PSO algorithms which based on chaotic maps and adaptive acceleration coefficients.

3.2. Chaotic PSO algorithm

The chaotic maps are important functions used for solving problems in optimization methods, where generally utilized as generators of random numbers. The used ones in this paper are described by their visualization in Figure 1 and their mathematical forms as [29]:

- Chaotic logistic PSO (CL-PSO):

$$x_{k+1} = \alpha x_k \left(1 - x_k \right) \tag{21}$$

- Chaotic iterative PSO (CI-PSO):

$$x_{k+1} = \sin \left(\frac{\alpha \pi}{x_k} \right) \tag{22}$$

- Chaotic circle PSO (CC-PSO):

$$x_{k+1} = \operatorname{mod} \left(x_k + \beta - \left(\frac{\alpha}{2\pi} \right) \sin \left(\frac{2\pi}{x_k} \right), 1 \right) \tag{23}$$

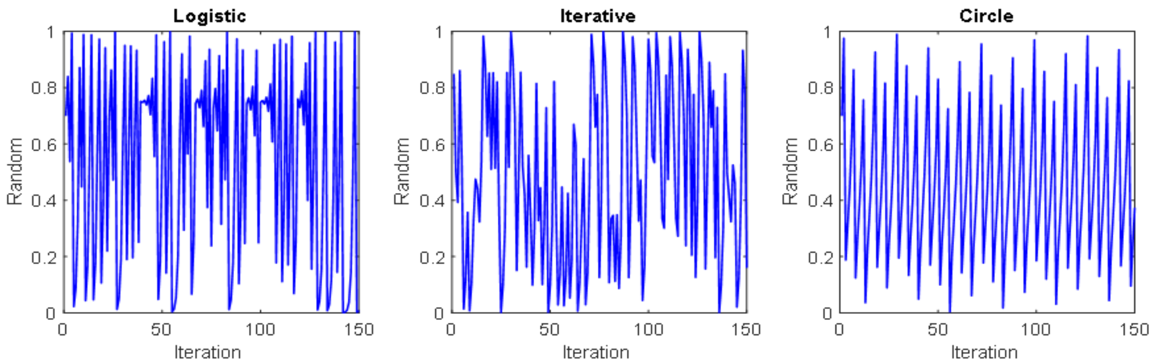


Figure 1. Visualization of chaotic maps

3.3. Adaptive acceleration coefficients

The applied PSO algorithms in this problem based on adaptive acceleration coefficients c_1, c_2 are represented in the following equations, also by the coefficients' variation in Figure 2. Sigmoid-based acceleration coefficients (SBAC-PSO) [30]:

$$c_1=\left(\frac{1}{1+e^{\left(\frac{-\lambda k}{k_{\max}}\right)}}\right)+2\left(c_{1f}-c_{1i}\right)\left(\frac{k}{k_{max}}-1\right)^2,\ c_2=\left(\frac{1}{1+e^{\left(\frac{-\lambda k}{k_{\max}}\right)}}\right)+\left(c_{1f}-c_{1i}\right)\left(\frac{k}{k_{max}}\right)^2 \tag{24}$$

Where, $\lambda = 0.0001$, $c_{1f} = 2.5$, $c_{1i} = 0.5$. Non-linear dynamic acceleration coefficients (NDAC-PSO) [31]:

$$c_1=-\left(c_{1f}-c_{1i}\right)\left(\frac{k}{k_{\max}}\right)^2+c_{1f},\ c_2=c_{1i}\left(1-\frac{k}{k_{\max}}\right)^2+c_{1f}\left(\frac{k}{k_{\max}}\right) \tag{25}$$

Where, $c_{1f} = 2.5$, $c_{1i} = 0.5$. Time-varying acceleration-PSO (TVA-PSO) [32]:

$$c_1=c_{1i}+\left(\frac{c_{1f}-c_{1i}}{k_{\max}}\right)k,\ c_2=c_{2i}+\left(\frac{c_{2f}-c_{2i}}{k_{\max}}\right)k \tag{26}$$

Where, $c_{1f} = 0.5$, $c_{1i} = 2.5$ and $c_{2f} = 2.5$, $c_{2i} = 0.5$

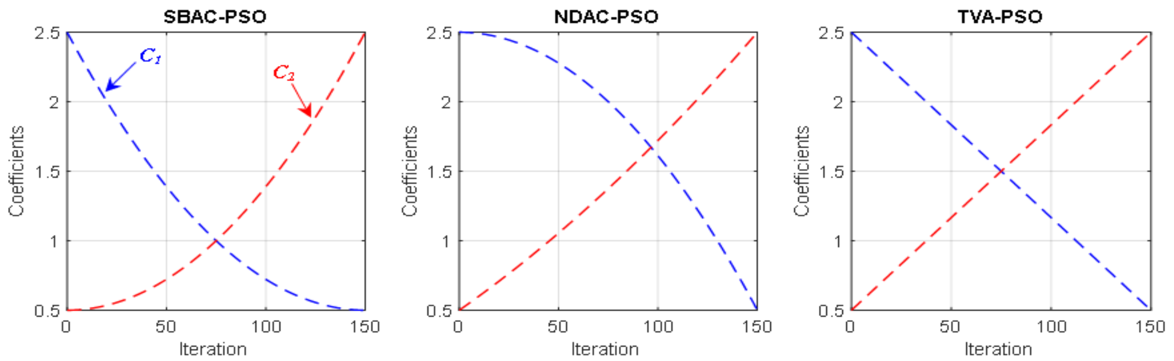


Figure 2. The variation of acceleration coefficients for various PSO algorithms

Based on hybridization of two PSO algorithms which depend on chaotic maps and adaptive acceleration coefficients as previously mentioned. This paper proposed firstly for the chaotic logistic (CL) algorithm: (CL-SBAC-PSO), (CL-NDAC-PSO) and (CL-TVA-PSO), then for the chaotic iterative (CI) algorithm: (CI-SBAC-PSO), (CI-NDAC-PSO) and (CI-TVA-PSO). Finally, for the chaotic circle (CC) algorithm: (CC-SBAC-PSO), (CC-NDAC-PSO) and (CC-TVA-PSO).

4. OPTIMAL RESULTS, DISCUSSIONS AND COMPARISON

The proposed hybrid PSO algorithms were evaluated and validated on the standards IEEE 33-bus, and 69-bus, whereas illustrated by the single line diagrams in Figures 3(a) and 3(b) respectively, under a base voltage of 12.66 kV in the two of them [22]. The proposed algorithms are implemented in MATLAB software (version 2017.b) in a PC that has a processor Intel Core i5 with 3.4 GHz and 8 GB of RAM.

The first system, the total active and reactive load are 3715.00 kW and 2300.00 kVar, while for the second system, are 3790.00 kW and 2690.00 kVar. Every bus of the two systems is protected and covered by a primary overcurrent relay (OCR), followed by its backup, and a coordination time interval (CTI) set above 0.25 second is between them. In general, it is calculated for the IEEE 33-bus, 32 OCRs with 31 CTIs, while for the IEEE 69-bus, 68 OCRs with 67 CTIs. It is chosen after the integrating of multiple PV-DGs a type of NS-OCR for all relays in the two systems, where also a descriptive summary of their main characteristics is mentioned in Table 1.

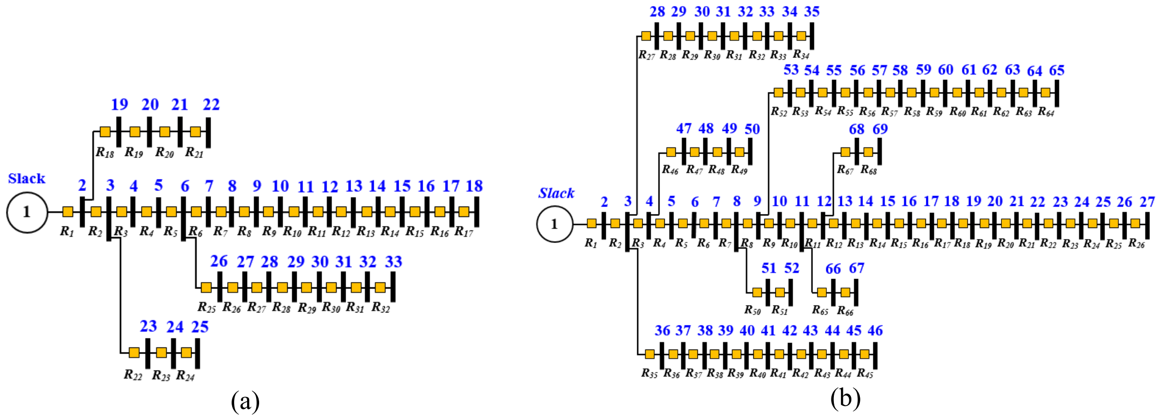


Figure 3. Single line diagram of standard test systems: (a) IEEE 33-bus and (b) IEEE 69-bus

Table 1. The main characteristics of the investigated EDN systems

Characteristics	Buses	Branches	Relays	$\sum P_D$ (kW)	$\sum Q_D$ (kVar)	$\sum P_{Loss}$ (kW)	$\sum Q_{Loss}$ (kVar)	$\sum$ VD (p.u.)	$\sum T_{Relay}$ (sec)
IEEE 33-bus	33	32	32	3715.00	2300.00	210.98	135.14	1.81	20.57
IEEE 69-bus	69	68	68	3790.00	2690.00	224.95	102.16	1.87	38.77

Figures 4(a) and 4(b) demonstrate the convergence curves of the MOF's minimization when applying the various proposed hybrid PSO algorithms on both systems. According to Figures 4(a) and 4(b), the application of various hybrid PSO algorithms on both systems with a value of k_{max}=150 iterations, population size=10, shows for the first system that CI-NDAC-PSO algorithm converged at first about 85 iterations and better than other proposed algorithms. At the same time, it may be seen that CC-TVA-PSO algorithm provided the best and minimum value of MOF among all of the applied algorithms, beside it converges late more than 140 iterations. On the other hand, it is also clear for the IEEE 69-bus, that the CC-TVA-PSO algorithm provided the best and minimum value of MOF and converging by 125 iterations. Figures 5(a) and 5(b), illustrate the boxplot of MOF results after the application of the various hybrid PSO algorithms with 20 runs in each of two systems EDNs.

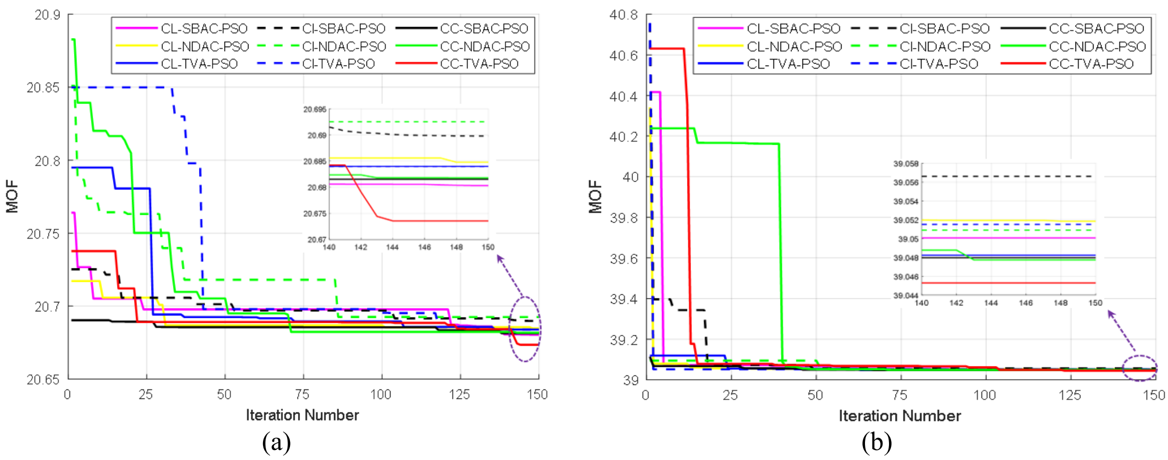


Figure 4. Convergence characteristics of PSO algorithms: (a) IEEE 33-bus and (b) IEEE 69-bus

A boxplot is presented in Figures 5(a) and 5(b), for the purpose of comparison improvement, beside to better evaluates the proposed algorithms. By considering 20 executions, it can be seen for all proposed hybrid PSO algorithms that the results are too near to their minimum and best MOF in the two systems. It is also clear that CC-TVA-PSO algorithm presents efficiency in delivering the minimum value of MOF in both systems with the lowest median for the IEEE 33-bus. While the lowest median for the IEEE 69-bus was provided by the CL-TVA-PSO algorithm.

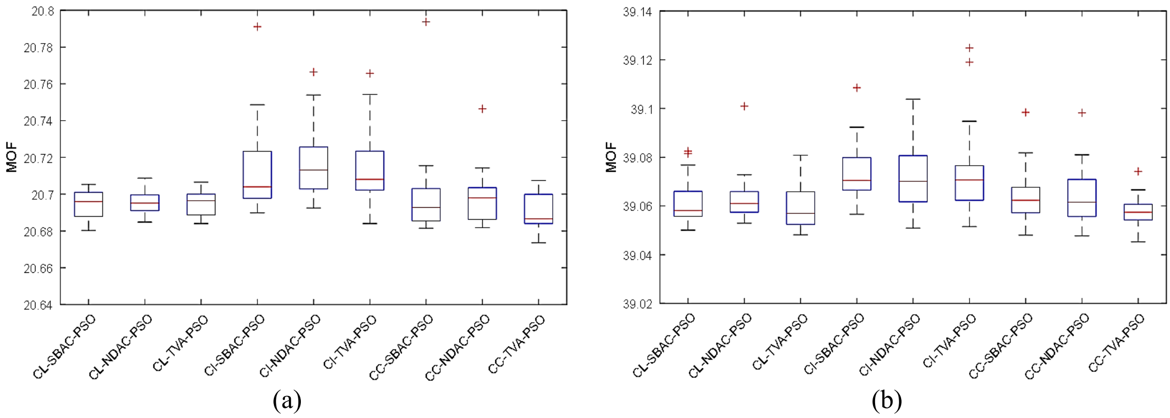


Figure 5. Boxplot of MOF for PSO algorithms applied for (a) IEEE 33-bus and (b) IEEE 69-bus

Tables 2 and 3, exhibit the results found when apply the various hybrid PSO algorithms on both test systems EDNs. Based on comparison, it can be sseen in Tables 2 and 3, that all proposed hybrid PSO algorithms have found good and close results to each other's. While the minimum MOF results were achieved by the CC-TVA-PSO algorithm for both systems, moreover, it provides the lowest TOT value of 19.4698 seconds for the IEEE 33-bus and lowest TAPL value of 87.35 kW for the IEEE 69-bus.

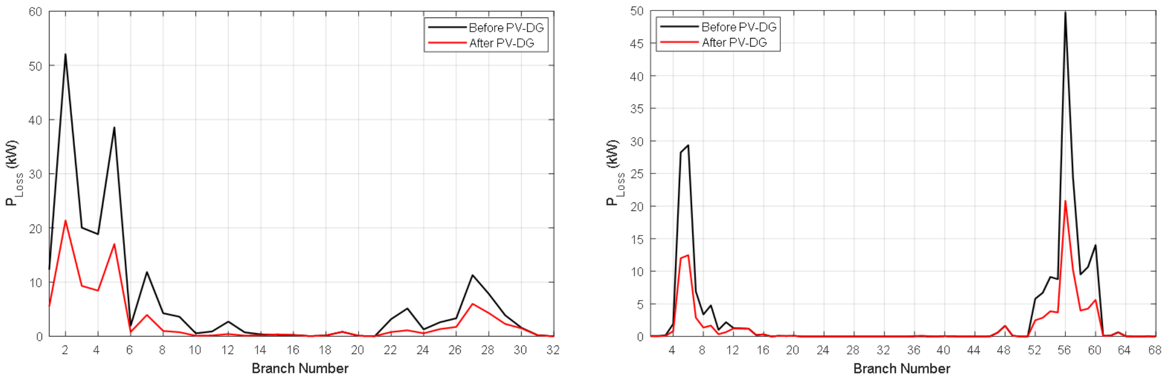
Table 2. Comparison of optimization results for IEEE 33-bus

Algorithms Applied	DG Bus Location			DG Size - P_{DG} (kW)			TAPL (kW)	TVD (p.u.)	TOT (sec)	MOF
	DG_1	DG_2	DG_3	DG_1	DG_2	DG_3				
CL-SBAC-PSO	14	24	30	462.80	896.90	895.60	82.18	1.0717	19.5301	20.6803
CL-NDAC-PSO	13	24	29	685.30	630.20	646.80	86.46	1.0737	19.5315	20.6848
CL-TVA-PSO	5	16	31	1065.20	479.90	510.30	90.77	1.0706	19.5226	20.6840
CI-SBAC-PSO	13	23	30	600.60	1046.60	802.00	82.73	1.0380	19.5691	20.6898
CI-NDAC-PSO	13	23	28	523.40	516.30	1022.60	90.25	1.0733	19.5289	20.6925
CI-TVA-PSO	15	24	30	541.00	904.30	659.80	85.63	1.0908	19.5075	20.6840
CC-SBAC-PSO	15	25	29	454.30	913.40	803.70	86.29	1.0969	19.5022	20.6815
CC-NDAC-PSO	12	25	31	746.30	811.50	489.90	86.92	1.0884	19.5102	20.6818
CC-TVA-PSO	**16**	**25**	**31**	**466.60**	**659.90**	**678.50**	**90.84**	**1.1338**	**19.4698**	**20.6735**

Table 3. Comparison of optimization results for IEEE 69-bus

Algorithms Applied	DG Bus Location			DG Size - P_{DG} (kW)			TAPL (kW)	TVD (p.u.)	TOT (sec)	MOF
	DG_1	DG_2	DG_3	DG_1	DG_2	DG_3				
CL-SBAC-PSO	13	51	62	541.00	239.50	908.20	98.27	1.2056	37.7569	39.0501
CL-NDAC-PSO	25	55	63	274.50	510.60	827.80	100.14	1.2143	37.7482	39.0518
CL-TVA-PSO	27	51	60	161.70	60.30	1119.20	104.15	1.2827	37.6717	39.0482
CI-SBAC-PSO	23	26	61	20.20	124.50	1197.20	93.05	1.2657	37.6979	39.0566
CI-NDAC-PSO	18	52	63	294.00	550.30	878.10	99.96	1.2144	37.7473	39.0509
CI-TVA-PSO	13	28	62	167.00	1076.20	1010.30	104.66	1.3483	37.6091	39.0515
CC-SBAC-PSO	24	50	62	397.70	146.30	972.40	98.29	1.1964	37.7638	39.0480
CC-NDAC-PSO	18	50	61	317.50	284.60	1030.30	95.47	1.2276	37.7247	39.0477
CC-TVA-PSO	**32**	**61**	**62**	**649.50**	**1012.80**	**616.50**	**87.35**	**1.2666**	**37.6911**	**39.0451**

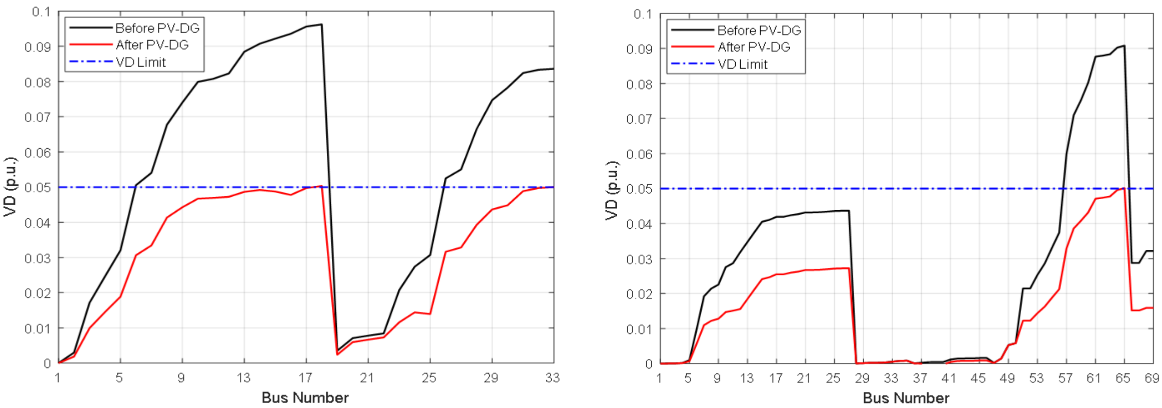
It may be noted that the rest of the hybrid PSO algorithms also show a good efficiency in delivering good results. As examples, for the first system, the CL-SBAC-PSO algorithm delivers the minimum TALP value of 82.18 kW and the CI-SBAC-PSO algorithm delivers the minimum TVD value of 1.0380 p.u. Meanwhile, for the IEEE 69-bus, it can be noted in term of TVD, the CC-SBAC-PSO algorithm gives the best and minimum value of 1.1964 p.u., where in term of TOT, the CI-TVA-PSO algorithm provides the minimum value of 37.6091 seconds. Figures 6(a) and 6(b), illustrate the comparing between the active power losses for the cases, before and after the PV-DGs presence in the two systems.



(a) (b)

Figure 6. Branch active power loss in test systems (a) IEEE 33-bus and (b) IEEE 69-bus

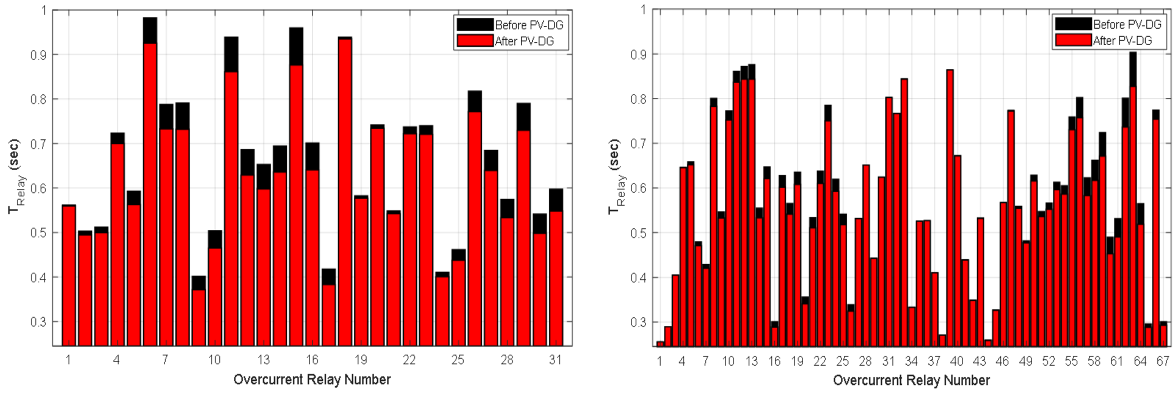
The Analyzing of Figures 6(a) and 6(b), shows that due to the best identification of location and sizing of PV-DGs in the two systems when using the CC-TVA-PSO algorithm, a significant reducing of the total active power losses is provided from 210.98 kW to 90.84 kW in the IEEE 33-bus, and from 224.95 kW to 87.35 kW in the IEEE 69-bus. Moreover, it is clear that the optimal installation of PV-DGs at buses 16, 25 and 31 of the first system, and buses 32, 61 and 62 of the second system, contributed directly to the reducing of the active power losses almost in every branch of both of them. Figures 7(a) and 7(b), represent the voltage deviation for the studied cases of the PV-DGs optimal presence of in the two EDNs.



(a) (b)

Figure 7. Voltage derivation profiles of all buses (a) IEEE 33-bus and (b) IEEE 69-bus

From Figures 7(a) and 7(b), it can be noted that the voltage deviation at the base case is out of the allowed limited range of 0.05 p.u. in almost all buses for IEEE 33-bus, and buses from 56 to 65 of the IEEE 69-bus. Moreover, it is observed after the optimal integration of PV-DGs at buses 16, 25 and 31 of the first system, and buses 32, 61 and 62 of the second system, that the voltage deviation got decreased under the allowed limited range in all buses of both systems, and as long as it represents the difference between the voltage nominal value of 1 p.u., and the actual voltage value at the base case, this minimization consequently led to the improvement of the voltage profiles in all buses for the two systems. Figures 8(a) and 8(b), represent the primary overcurrent relays' operation time in the two systems for the cases before, and after PV-DG integration.



(a) (b)

Figure 8. Operation time of overcurrent relay (a) IEEE 33-bus and (b). IEEE 69-bus

From Figures 8(a) and 8(b), and when comparing to the base case, it is obvious that the operation time in almost all of the NS-OCRs had a considerable minimization in both systems after the optimal installation of PV-DGs, at buses 16, 25 and 31 of the IEEE 33-bus, and buses 32, 61 and 62 of IEEE 69-bus, with a value of TOT from 20.57 to 19.46 seconds and from 38.77 to 37.69 seconds, respectively. This was due to the reverse relation and function between I_F and V_{FM} that measured and covered by the NS-OCR and its operation time according to (7).

Table 4 represents the comparison between the various results delivered by various algorithms published in the literature and proposed algorithm. This comparison was carried out to see the best results of TAPL minimization, when basing on the three PV-DG units' locations and sizing. As shown in Table 4, when comparing with the various algorithms, it is obvious that the optimal placement and size of multiple PV-DGs into both systems using the proposed CC-TVA-PSO algorithm provided the best results in reducing the TAPL until 90.84 kW by 56.94 %, and until 87.35 kW by 61.17 % in the IEEE 33-bus and 69-bus, respectively.

Table 4. Comparison optimal results with different algorithms

Algorithms [Ref]	IEEE 33-bus PV-DG Size in kW; (Bus)			*TAPL* (kW)	Δ*TAPL* (%)	IEEE 69-bus PV-DG Size in kW; (Bus)			*TAPL* (kW)	Δ*TAPL* (%)
GA [17]	1500.00 (11)	422.80 (29)	1071.40 (30)	106.30	49.61	929.70 (21)	1075.20 (62)	984.80 (64)	89.00	60.43
QOTLBO [3]	1199.80 (6)	1200.00 (11)	1198.30 (29)	104.88	50.29	1193.10 (22)	1196.70 (61)	1191.40 (62)	110.51	50.87
ADPSO [18]	846.00 (16)	384.00 (26)	499.00 (30)	94.02	55.44	945.00 (2)	521.00 (60)	1953.00 (62)	94.70	57.90
PMC [12]	499.30 (12)	396.60 (18)	674.40 (31)	91.63	56.57	1200.00 (63)	57.70 (68)	395.40 (69)	92.64	58.81
CC-TVA-PSO	**466.60 (16)**	**659.90 (25)**	**678.50 (31)**	**90.84**	**56.94**	**649.50 (32)**	**1012.80 (61)**	**616.50 (62)**	**87.35**	**61.17**

5. CONCLUSION

In this paper, a study of comparison was implemented between the proposed hybrid PSO algorithms which based on chaotic maps and adaptive acceleration coefficients for the purpose of identifying the optimal location and sizing of multiple PV-DGs in the two systems, to solve the MOF problem represented as reducing simultaneously the technical three parameters of TVD, TAPL and TOT. The results of simulation, showed that the proposed CC-TVA-PSO algorithm was the best choice over the rest of the proposed algorithms that solved the problem of optimization by delivering the best minimization of MOF results with a slow convergence characteristic, meanwhile fulfilling the system operational constraints. From previous discussions, it may deduce that the CC-TVA-PSO algorithm can be widely applied to EDNs and contribute to obtaining best solutions and results. Where, the next work will concentrate on studying the optimal allocation of DGs to improve the system's technical indices, considering the DGs power output and the load demand variation at different hourly.

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