Application Hybrid Chaotic Maps and Adaptive Acceleration Coefficients PSO Algorithm for Optimal Integration Photovoltaic Distributed Generation Problem in Distribution Energy Network

Mohamed Zellagui, Nasreddine Belbachir, Adel Lasmari, Benaissa Bekkouche, and Claude Ziad El-Bayeh

Abstract Integration of Distributed Generators (DG) into Distribution Energy Network (DEN) became an important need, due to their technical advantages and economic benefits, as well as the contribution in power quality improvement and the reduction of the power losses. In this paper, is proposed a various version for hybrid Particle Swarm Optimization (PSO) algorithms based on chaotic maps and adaptive acceleration coefficients to optimally locate and size the Photovoltaic Distributed Generation (PV-DG) into DEN to minimize the Total Active Power Loss (TAPL), the Total of Voltage Deviation (TVD), and the Total Operation Time (TOT) of the overcurrent relay. The proposed algorithms were tested on the 28-bus DEN system, so that a study comparison was presented to identify the best hybrid PSO algorithm that delivers the best results in terms of achieving the best active losses reduction, enhancing the voltage profiles, and improving the overcurrent protection system.

Keywords Hybrid PSO algorithm · Chaotic maps · Adaptive acceleration coefficients · Photovoltaic DG · Optimal integration · Distribution energy network

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M. Zellagui (✉)
Department of Electrical Engineering, University of Batna 2, Batna, Algeria
e-mail: m.zellagui@ieee.org

N. Belbachir · B. Bekkouche
Department of Electrical Engineering, University of Mostaganem, Mostaganem, Algeria
e-mail: nasreddine.belbachir.etu@univ-mosta.dz

B. Bekkouche
e-mail: benaissa.bekkouche@univ-mosta.dz

A. Lasmari
Department of Electrotechnic, Mentouri University of Constantine 1, Constantine, Algeria
e-mail: adel.lasmari@umc.edu.dz

C. Z. El-Bayeh
Canada Excellence Research Chairs Team, Concordia University, Montreal, QC, Canada

J. Kumar et al. (eds.), *Control Applications in Modern Power Systems*, Lecture Notes in Electrical Engineering 870, https://doi.org/10.1007/978-981-19-0193-5_3

Notations

Symbols

CL	Chaotic logistic
CI	Chaotic iterative
CC	Chaotic circle
SBAC	Sigmoid-based acceleration coefficients
TVA	Time-varying acceleration
NDAC	Non-linear dynamic acceleration coefficients
MOF	Multi-objective functions
TAPL	Total active power loss
TVD	Total of voltage deviation
TOT	Total operation time

Parameters

P_i	Population of individuals
X_i, V_i	Position and velocity of particle
P_{best}	Best locations found by particle
G_{best}	Best locations found by all particles
c_1, c_2	Acceleration coefficients
ω	Value of the inertia weight
r	Random value, varied in the interval of [0, 1]
k	Iteration number
α, β	Constants of chaotic maps
λ, c_{1f}, c_{1i}	Constants of SBAC-PSO algorithm
c_{1f}, c_{1i}	Constants of NDAC-PSO algorithm
c_{1f}, c_{1i}, c_{2f}, c_{2i}	Constant of TVA-PSO algorithm
R	Line resistance
V, δ	Voltage and angle at buses
P, Q	Active and reactive powers at buses.
T_i	Operation time of relay
TDS	Time dial setting
M	Multiple of pickup current
V_{FM}	Fault voltage magnitude
A, B, K	Constants set to 0.14, 0.02 and1.5, respectively
N_{bus}, N_R	Number of buses and overcurrent relays
P_G, Q_G	Total powers of the generator (sub-station),
$P_{\text{PV-DG}}$	Total active power injected by PV-DG sources
P_D, Q_D	Total powers of demand load
$V_{\min}$, $V_{\max}$	Specified voltages limits

ΔV	Voltage drop of the distribution line
V_1	Voltage at the generating station is equal to 1.0 p.u.
S_{ij}	Apparent power in branch
$P_{\text{PV-DG}}{}^{\min}$, $P_{\text{PV-DG}}{}^{\max}$	Active power output limits of PV-DG sources
$\text{PV-DG}_{\text{Position}}$	Position of PV-DG units
$N_{\text{PV-DG}}$, $n_{\text{PV-DG}}$	Number, and location of PV-DG, respectively

1 Introduction

Due to urbanization and the industrial revolution, electricity demand has recently increased. In the early ages, the generation of fossil fuel-based electricity demand was predominantly met. Today, fossil fuel-based power generation poses a significant environmental threat. Renewable energy in the electric DEN is of great importance and is imported to tackle this issue.

Optimal location and size of Photovoltaic Distributed Generation (PV-DG) decreases the power losses, improves the efficiency of the voltage profile, and raises the reliability of the DEN. Therefore, the development of an optimization or heuristic technique-based methodology became a necessity to find the optimal placement of PV-DG for a given DEN system to provide various advantages [1]. The PV-DG allocation problem is a complex non-linear optimization problem [2]. Classical, analytical, metaheuristic and hybrid algorithms are the methods that have been proposed in this problem.

In the near past years, various solutions were proposed by many researchers to treat the optimal integration of PV-DG problem in DEN using multiples optimization algorithms: Ant Lion Optimization (ALO) algorithm [3], Rooted Tree Optimization (RTO) algorithm [4], and Water Cycle Algorithm (WCA) [5]. In 2019, Applied Moth-Flame Optimizer (MFO) algorithm [6], Biogeography-Based Optimization (BBO) algorithm [7], Binary PSO (BPSO) algorithm [8], Phasor PSO (PPSO) algorithm [9], Spider Monkey Optimization (SMO) algorithm [10], Novel Chaotic Stochastic Fractal Search (CSFS) method [11], and Chaotic Differential Evolution (CDE) algorithm [12]. Recently in 2020, Applied Symbiotic Organism Search (SOS) algorithm [13], Sine Cosine Algorithm (SCA) with chaos map theory [14], New Opposition-based Tuned-Chaotic Differential Evolution (OTCDE) algorithm [15], Modified particle PSO (MPSO) algorithm [16], and Modified Jaya Algorithm [17]. These advantages can only be accomplished with optimal PV-DG allocation that considers the objective function, constraints, and the necessary optimization algorithm. The objectives of these algorithms can be categorized into technical, financial, and multiples objectives [18].

In this paper, the authors proposed various versions for new hybrid chaotic maps and adaptive acceleration coefficients PSO algorithm for optimal integration of multiple PV-DG sources in DEN.

2 Proposed Hybrid PSO Algorithms

2.1 Basic PSO

PSO algorithm is an evolutionary computation technique, that aims to improve a solution when taking into consideration predefined quality measures [19]. In the PSO algorithm every individual of the swarm, so that is moving due to these equations:

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

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{2}$$

and,

$$\omega = \omega_{\max} - (\omega_{\max} - \omega_{\min}) \left(\frac{k}{k_{\max}} \right) \tag{3}$$

Many researchers have proposed various algorithms of PSO by modifying the parameters of (ω, r, c_1, and c_2) to reach the optimum function and performance. In this paper, it has been chosen improved PSO algorithms based on modified r (chaotic maps) and modified acceleration coefficients.

2.2 Chaotic Maps

The proposed chaotic maps in this paper are defined as follows [20, 21]:

Chaotic Logistic (CL):

$$x_{k+1} = \alpha x_k (1 - x_k) \tag{4}$$

Chaotic Iterative (CI):

$$x_{k+1} = \sin\left(\frac{\alpha \pi}{x_k} \right) \tag{5}$$

Chaotic Circle (CC):

$$x_{k+1} = \operatorname{mod}\left(x_k + \beta - \left(\frac{\alpha}{2\pi} \right) \sin\left(\frac{2\pi}{x_k} \right), 1 \right) \tag{6}$$

2.3 Modified PSO Algorithms-Based Acceleration Coefficients

The proposed PSO algorithms-based acceleration coefficients are defined as follows.

Sigmoid-Based Acceleration Coefficients (SBAC-PSO) [22]:

$$c_1 = \left(\frac{1}{1 + e^{\left(\frac{-\lambda k}{k_{\max}}\right)}}\right) + 2\left(c_{1f} - c_{1i}\right)\left(\frac{k}{k_{\max}} - 1\right)^2, c_2 = \left(\frac{1}{1 + e^{\left(\frac{-\lambda k}{k_{\max}}\right)}}\right) + \left(c_{1f} - c_{1i}\right)\left(\frac{k}{k_{\max}}\right)^2 \tag{7}$$

where, $\lambda = 0.0001$, $c_{1f} = 2.5$, and $c_{1i} = 0.5$.

Non-linear Dynamic Acceleration Coefficients (NDAC-PSO) [23]:

$$c_1 = -\left(c_{1f} - c_{1i}\right)\left(\frac{k}{k_{\max}}\right)^2 + c_{1f}, c_2 = c_{1i}\left(1 - \frac{k}{k_{\max}}\right)^2 + c_{1f}\left(\frac{k}{k_{\max}}\right) \tag{8}$$

where, $c_{1f} = 2.5$, and $c_{1i} = 0.5$.

Time-Varying Acceleration PSO (TVA-PSO) [24]:

$$c_1 = c_{1i} + \left(\frac{c_{1f} - c_{1i}}{k_{\max}}\right)k, c_2 = c_{2i} + \left(\frac{c_{2f} - c_{2i}}{k_{\max}}\right)k \tag{9}$$

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

This paper proposed new algorithms based on the hybridization of two modified PSO algorithms that depend on chaotic maps and acceleration coefficients.

The combining of the Chaotic Logistic (CL) with three PSO algorithms-based acceleration coefficients are CL-SBAC-PSO, CL-NDAC-PSO, and CL-TVA-PSO algorithm. The second Chaotic Iterative (CI) are CI-SBAC-PSO, CI-NDAC-PSO, and CI-TVA-PSO algorithm, and the Chaotic Circle (CC) applied are CC-SBAC-PSO, CC-NDAC-PSO, and CC-TVA-PSO algorithm.

3 Problem Formulation and Constraints

3.1 Multi-Objective Functions

The Multi-Objective Functions (*MOF*) which proposed, consists to identify the optimal location and sizing of PV-DG sources in DEN, by minimizing the three technical parameters of *TAPL*, *TVD*, and *TOT*, which are formulated as follows:

$$\text{MOF} = \text{Minimize} \sum_{i=1}^{N_{\text{bus}}} \sum_{j=2}^{N_{\text{bus}}} \sum_{i=1}^{N_R} \left[\text{TAPL}_{i,j} + \text{TVD}_j + \text{TOT}_i\right] \tag{10}$$

The first parameter *APL* of the distribution line is expressed by [25, 26]:

$$APL_{i,j} = \alpha_{ij}\left(P_i P_j + Q_i Q_j\right) + \beta_{ij}\left(Q_i P_j + P_i Q_j\right) \tag{11}$$

and,

$$\alpha_{ij} = \frac{R_{ij}}{V_i V_j}\cos\left(\delta_i - \delta_j\right) \quad \text{and} \quad \beta_{ij} = \frac{R_{ij}}{V_i V_j}\sin\left(\delta_i + \delta_j\right) \tag{12}$$

$$\text{TAPL}_{i,j} = \sum_{i=1}^{N_{\text{bus}}} \sum_{j=2}^{N_{\text{bus}}} APL_{i,j} \tag{13}$$

The second term is the *TVD*, which can be defined as [24–27]:

$$\text{TVD}_j = \sum_{j=2}^{N_{\text{bus}}} \left|1 - V_j\right| \tag{14}$$

The third parameter is *TOT* of overcurrent relay-based time–current-voltage tripping characteristic [28–30], which can be defined as below:

$$T_i = \left(\frac{1}{e^{(1-V_{\text{FM}})}}\right)^k TDS_i \left(\frac{A}{M_i^B - 1}\right) \tag{15}$$

and,

$$\text{TOT}_i = \sum_{i=1}^{N_R} T_i \tag{16}$$

3.2 Equality Constraints

Equality constraints are expressed by the balanced power's equations as below:

$$P_G + P_{PV-DG} = P_D + P_{\text{Loss}} \tag{17}$$

$$Q_G = Q_D + Q_{\text{Loss}} \tag{18}$$

3.3 Distribution Line Constraints

Inequality constraints are given for the distribution line as below:

$$V_{\min} \leq |V_i| \leq V_{\max} \tag{19}$$

$$\left|1 - V_j\right| \leq \Delta V_{\max} \tag{20}$$

$$\left|S_{ij}\right| \leq S_{\max} \tag{21}$$

3.4 PV-DG Units Constraints

Inequality constraints refer to the PV-DG units limits, which are expressed as:

$$P_{PV-DG}^{\min} \leq P_{PV-DG} \leq P_{PV-DG}^{\max} \tag{22}$$

$$\sum_{i=1}^{N_{PV-DG}} P_{PV-DG}(i) \leq \sum_{i=1}^{N_{\text{bus}}} P_D(i) \tag{23}$$

$$2 \leq PV - DG_{\text{Position}} \leq N_{\text{bus}} \tag{24}$$

$$N_{PV-DG} \leq N_{PV-DG.\max} \tag{25}$$

$$n_{PV-DG,i/\text{Location} \leq 1} \tag{26}$$

4 Test System, Optimal Results, and Comparison

The single line diagram of the 28-bus DEN test system is represented in Fig. 1 which is composed of 28 buses and 27 branches under a base voltage of 11 kV, with a total demand load of 761.04 kW and 776.42 kVar [31]. The total power losses are 68.82 kW and 46.04 kVar. All buses are protected by 27 overcurrent relays.

Figure 2 represents the curves of convergence for the minimization of *MOF* for a maximum number of iterations is 150 and a population size equal to 10. It is noticed that the CI-SBAC-PSO algorithm converges firstly at 20 iterations comparing to the rest of the algorithms but without giving the best solution. On the other hand, it is

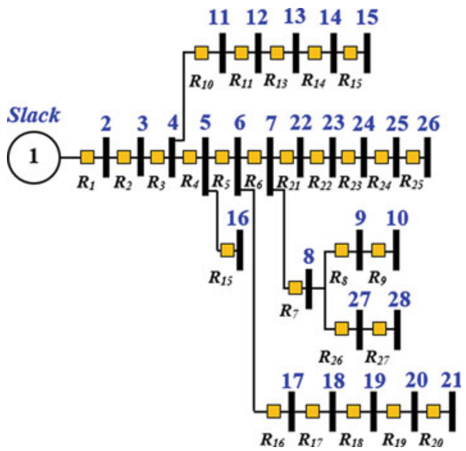

Fig. 1 Single diagram of standard 28-bus test system

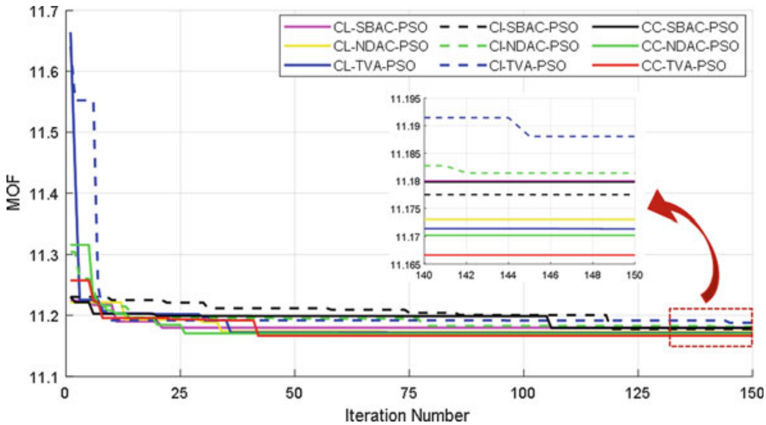

Fig. 2 Convergence characteristics of hybrid PSO algorithms

obvious that the CC-TVA-PSO algorithm delivers the best-minimized results and converges around 40 iterations.

Figure 3 represents the Boxplot of *MOF* results obtained when using the various proposed hybrid PSO algorithms for 20 executions in each of them. It can be noticed that the results for 20 executions in all proposed hybrid PSO algorithms are too close to their best and minimum *MOF*. Also, it is clear that the best *MOF* was obtained by the CC-TVA-PSO algorithm, with the lowest median comparing to the rest of the proposed hybrid PSO algorithms.

Table 1 exhibits the optimization results obtained when applying the proposed various hybrid PSO algorithms.

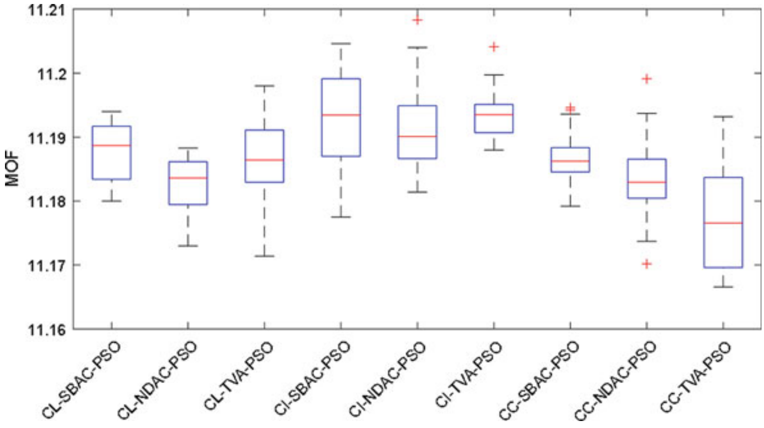

Fig. 3 Boxplot of *MOF* for applied hybrid PSO algorithms

Table 1 Comparison of the optimization results for the test system

Algorithms applied	DG Bus	P_{DG} (MW)	TAPL (kW)	TVD (p.u.)	TOT (sec)	MOF
CL-SBAC-PSO	16 22 23	0.0100 0.3757 0.0100	40.5632	1.4299	9.7325	11.1800
CL-NDAC-PSO	13 19 24	0.0100 0.1754 0.2445	38.7232	1.4015	9.7580	11.1730
CL-TVA-PSO	12 20 25	0.0860 0.0100 0.3446	39.7388	1.4029	9.7541	11.1714
CI-SBAC-PSO	8 16 24	0.2643 0.0210 0.1073	39.6009	1.4334	9.7293	11.1775
CI-NDAC-PSO	7 12 23	0.3231 0.1939 0.0100	36.2923	1.3838	9.7761	11.1814
CI-TVA-PSO	7 14 19	0.4124 0.0100 0.0100	38.7330	1.4156	9.7487	11.1880
CC-SBAC-PSO	18 20 23	0.0100 0.2733 0.1639	39.8374	1.3966	9.7685	11.1798
CC-NDAC-PSO	13 21 24	0.0582 0.1372 0.2536	38.3410	1.3912	9.7658	11.1702
CC-TVA-PSO	12 18 25	0.1645 0.1451 0.1982	36.4617	1.3801	9.7750	11.1666

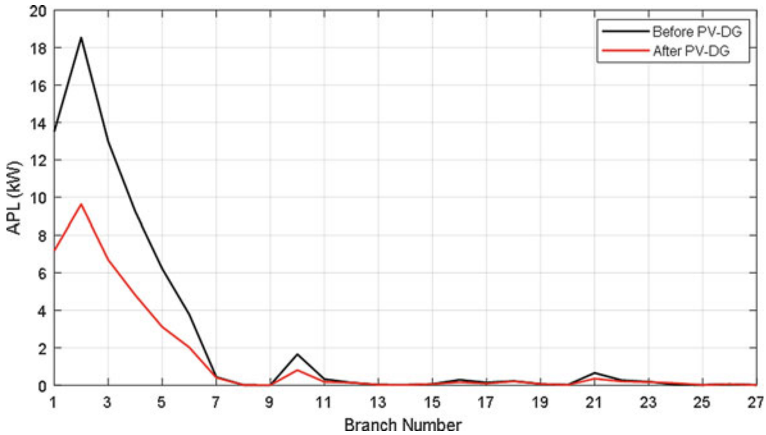

Fig. 4 Branch active power loss in test systems

Basing on the comparisons, it is observed the minimum *MOF* value of 11.1666 was obtained by the CC-TVA-PSO algorithm which delivers the *TVD*'s minimum value of 1.3801 p.u. But in terms of minimizing the *TOT* and *TAPL,* among all the proposed algorithms, the CI-SBAC-PSO algorithm and CI-NDAC-PSO algorithm show a good efficiency in delivering the minimum values of 9.7293 s and 36.2923 kW, respectively.

Figure 4 illustrates the active power losses in every branch of the 28-bus system DEN before (based case) and after PV-DG source integration based on the optimal results obtained by the CC-TVA-PSO algorithm (hybrid the chaotic circle maps with time-varying acceleration PSO). Clearly, it can be noticed after the integration of PV-DG, that the total active power losses have minimized significantly reaching a value of 36.46 kW comparing to the base case before PV-DG which was 68.82 kW.

Figure 5 represents the voltage deviation in all system buses before and after integration of PV-DG. The voltage deviation has minimized under a limit value of 0.05 p.u. in all system's buses after installation of the PV-DG at buses 12, 18, and 25, which consequently leads to the improvement of voltage profiles if the voltage deviation known as the difference between the nominal voltage of 1 p.u. and the actual voltage of the case before PV-DG.

Figure 6 illustrates the overcurrent relay operation time in the 28-bus test system for both cases before and after PV-DG integration into DEN. It is noticed that the optimized PV-DG location and size integrated into DEN causes the minimization of the operation time in all overcurrent relays installed, compared to the base case before PV-DG, and this is due to the reverse function between the fault current that passes through the overcurrent relay and its operation time as mentioned in Eq. (15).

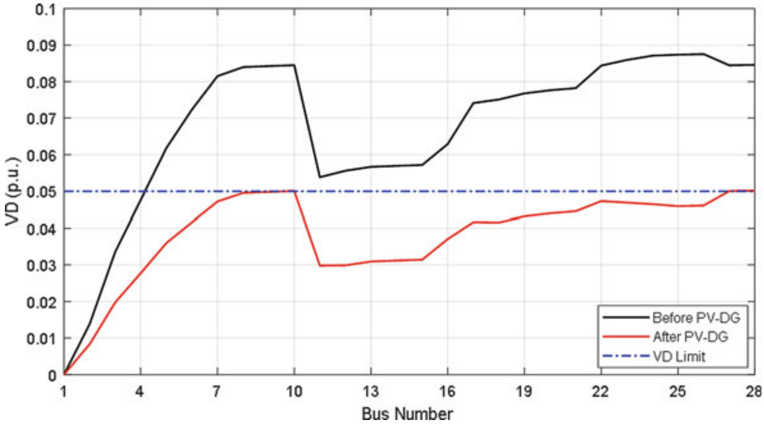

Fig. 5 Voltage derivation profiles of all buses

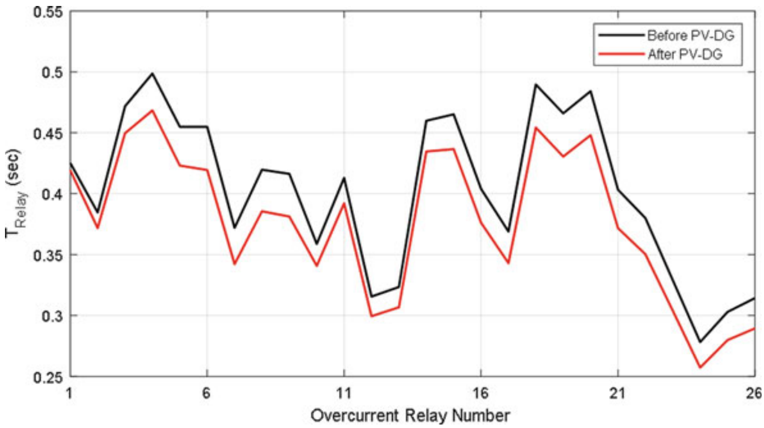

Fig. 6 Operation time of overcurrent relay

5 Conclusions

In this paper, a study of comparison between the hybrid PSO algorithms based on chaotic maps and acceleration coefficients was proposed to identify the optimal location and sizing of multiple PV-DGs into 28-bus DEN to reduce various technical parameters are *TAPL*, *TVD*, and *TOT*.

Based on the results of the simulation, it is deduced that the hybrid CC-TVA-PSO algorithm had a quick convergence characteristic, and delivers the best results comparing to the rest of the proposed hybrid PSO algorithms in terms of minimizing the multi-objective function.

From the previous discussion, it is concluded that the CC-TVA-PSO algorithm could be applied widely to DENs in terms of delivering the best optimal solutions. Depending on the obtained results, the future work will focus on the insertion of a third modified parameter which is the inertia weight to obtain better performances of the hybrid PSO algorithms.

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