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Enhancing energy efficiency for optimal multiple photovoltaic distributed generators integration using inertia weight control strategies in PSO algorithms

Abstract: Recently, interest in incorporating distributed generators (DGs) into electrical distribution networks has significantly increased throughout the globe due to the technological advancements that have led to lowering the cost of electricity, reducing power losses, enhancing power system reliability, and improving the voltage profile. These benefits can be maximized if the optimal allocation and sizing of DGs into a radial distribution system (RDS) are properly designed and developed. Getting the optimal location and size of DG units to be installed into an existing RDS depends on the various constraints, which are sometimes overlapping or contradicting. In the last decade,

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meta-heuristic search and optimization algorithms have been frequently developed to handle the constraints and obtain the optimal DG location and size. This paper proposes an efficient optimization technique to optimally allocate multiple DG units into a RDS. The proposed optimization method considers the integration of solar photovoltaic (PV) based DG units in power distribution networks. It is based on multi-objective function (MOF) that aims to maximize the net saving level (NSL), voltage deviation level (VDL), active power loss level (APLL), environmental pollution reduction level (EPRL), and short circuit level (SCL). The proposed algorithms using various strategies of inertia weight particle swarm optimization (PSO) are applied on the standard IEEE 69-bus system and a real 205-bus Algerian distribution system. The proposed approach and design of such a complicated multi-objective functions are ultimately to make considerable improvements in the technical, economic, and environmental aspects of power distribution networks. It was found that EIW-PSO is the best applied algorithm as it achieves the maximum targets on various quantities; it gives 75.8359%, 28.9642%, and 64.2829% for the APLL, EPRL, and VDL, respectively, with DG units' installation in the IEEE 69-bus test system. For the same number of DG units, EIW-PSO gives remarkable improved performance with the Adrar City 205-bus test system; numerically, it shows 72.3080%, 22.2027%, and 63.6963% for the APLL, EPRL, and VDL, respectively. The simulation results of this study prove that the proposed algorithms exhibit higher capability and efficiency in fixing the optimum DG settings.

Keywords: renewable-based distributed generation, maximization of energy efficiency, techno-economic -environmental levels, particle swarm optimization (PSO), inertia weight strategies, radial distribution system

Nomenclature

P_{Loss}, Q_{Loss}	Total active and reactive power losses
P_{ij}, Q_i	Active and reactive power between branch i, j
P_i, Q_i	Active and reactive power at bus i
N_{bus}	Number of buses in the network
R_{ij}, X_{ij}	Reactance and resistance of the line ij
Z_{ij}	Impedance of the distribution line ij
S_{ij}	Apparent power between branch
$S_{\max}$	Maximum limits of apparent power
V_i, δ_i	Voltage magnitude and angle at bus i
P_G, Q_G	Powers injected by substation
P_D, Q_D	Powers of load demand
P_{DG}	Active power delivered by PV-DG unit
$V_{\min}$, $V_{\max}$	Allowable limits of voltages
$\Delta V_{\max}$	Upper limits of voltage drop at each branch

$n_{PV\text{-}DG,\,i}$	Location of PV-DG units at bus i
$N_{PV\text{-}DG.\max}$	Maximum number of PV-DG units
$N_{PV\text{-}DG}$	Number of PV-DG units
$PV\text{-}DG_{Position}$	Position of PV-DG unit
T	Equal to 8760 hours per year
K_p	Incremental cost of P_{Loss}, equal to 0.06 ($/kW)
EG_g	Emission quantity of a generator pollutant
AE_g	Emission quantity of substation
c_1, c_2	Acceleration coefficient factors
$w_{\max}$, $w_{\min}$	Maximum and minimum values of the w
k, $k_{\max}$	Current and maximum number of iterations
r_1, r_2	Random values between 0 and 1

Introduction

The optimal DG incorporation into electrical distribution networks provides many technical and economic benefits, such as: reduction in power loss, reduction in energy purchase from the grid, improved bus voltage, and enhanced system stability and reliability (Bayod-Rújula 2009; El-Khattam et al. 2004).

Identifying the optimum DG location is, in general, a complex non-linear optimization problem. The literature in this research area can be divided into several categories based on the considered constraints, objectives, and solution algorithms (Mahmoud Pesaran et al. 2017).

There are numerous objective functions formulated to determine the optimal locations and sizes of DG units. Some of these significant objective functions include the minimization of the following factors: loss sensitive factor for finding the weak buses, in addition to the main objective of reducing the active power losses (Yang et al. 2018). Other methods incorporated an applied moth-flame optimization (MFO) algorithm, which is based on the minimization of active power loss (Settoul et al. 2019a). Minimization of active and reactive power losses in RDS using an analytic method was also performed (Naik et al. 2015). A single objective based on the minimization of power and energy losses by using a genetic algorithm have been presented (Hassan et al. 2017). An implanted MFO algorithm to reduce active power loss and Voltage Stability Index (VSI) considering various renewable energy-based DG units have been addressed (Settoul et al. 2019b). An applied teaching-learning-based optimization technique to minimize voltage deviation, active power loss, and the maximization of VSI has been published (Quadr et al. 2019). The authors in (Hassan et al. 2019) proposed a multi-verse optimizer algorithm to minimize three indices, which are the annual losses cost, total voltage variation, and apparent power loss.

A mixed-integer linear programming model was proposed to find the optimal short-term plan of RDS considering siting of DG sources and voltage regulators allocation to minimize the energy cost supplied (Dominguez et al. 2019).

A multi-objective PSO based on the minimization of he total operational cost and risk factor has been presented (Ganguly et al. 2013). An optimal power factor of DG has been used for minimization power losses, total cost and carbon emissions (Hung et al. 2014). A sine-cosine algorithm based was deployed for minimizing the total power losses, total voltage deviation, and VSI considering four typical days of the four seasons in the year (Selim et al. 2020). The minimization of active power loss, total harmonic distortion (THD), and the total cost of DG units by considering different types of loads was presented (Fard et al. 2018).

Practically, most of these operational objectives are inherently inconsistent and conflict with each other. Hence, the problem of allocating DGs in RDS becomes a complex multi-objective function (MOF) problem since it is quite hard to simultaneously optimize multiple conflicting objectives. Finding the best compromise among all the objectives is also difficult since the optimization algorithms are typically designed to fulfill a single objective (Saha et al. 2019).

This paper addresses the optimal incorporation of multiple PV-based DG units in RDS using various inertia weight PSO Algorithms. This paper aims to solve the optimal allocation of DG problem in a RDS using a new optimization algorithm to reduce various technical and economic parameters.

In this study, the optimal deployment of renewable-based DGs was applied and tested on a standard IEEE 69-bus, and practical (205-bus) RDS of Adrar city, which is a system in the Algerian RDS. The optimal integration is designed to maximize the following levels: NSL, VDL, APLL, EPRL, and SCL.

This paper comprises five sections followed by a references list, which is organized as follows: Section 2 demonstrates the problem formulation; Section 3 presented the overview of various inertia weight control strategies in PSO algorithms; Section 4 contains the results of the simulation, discussions; Section 5 presents the results of the comparisons with published papers in the literature; finally, the conclusions and future perspectives are addressed in Section 6.

1. Problem formulation

1.1. Multi-objective function

The multi-objective level considered in this paper to solve the problem of finding the optimal size and location of PV-DG, planning by giving a specified weight for each level can be formulated as follows:

$$MOF = Max\sum_{i=1}^{N_{Bus}}\sum_{j=2}^{N_{Bus}}\left(\alpha_1.APLL_{i,j} + \alpha_2.SCL_{i,j} + \alpha_3.VDL_j + \alpha_4.NSL_{i,j} + \alpha_5.EPRL_G\right) \tag{1}$$

where:

α_1, α_2, α_3, α_4 and α_5 – the weighting factors. The choice of the weighting factors are depending on the importance of each objective function, in several research and practical factors.

In this paper, due to the importance of the reduction of power loss for the reliability of the system and for its direct influence on minimizing the cost, so due to these two advantages α_1 is taken as 0.30, in addition, for the technical reason α_2, α_3 and α_4 are taken as 0.20, and finally, α_5 is taken as 0.10. The proposed levels can be given as:

The first level is the active power loss (APLL), which can be represented as follows (Lasmari et al. 2020a):

$$APLL = \frac{P_{Loss}^{Before\ DG}}{P_{Loss}^{Before\ DG} + P_{Loss}^{After\ DG}} \times 100 \tag{2}$$

where:

P_{Loss}, can be given as (Belbachir et al. 2021):

$$P_{Loss} = R_{ij}\frac{\left(P_{ij}^2 + Q_{ij}^2\right)}{V_i^2} \tag{3}$$

The second level is the voltage deviation (VDL), which can be expressed as follows (Ameli et al. 2014):

$$VDL = \frac{VD_{Before\ DG}}{VD_{Before\ DG} + VD_{After\ DG}} \times 100 \tag{4}$$

where

$$VD = \left|1 - V_j\right| \tag{5}$$

The expression of the short circuit level (SCL) can be calculated as per the equation below (Parizad et al. 2018):

$$SCL = \frac{SC_{After\ DG} - SC_{Before\ DG}}{SC_{Before\ DG}} \times 100 \tag{6}$$

where

$$SC = \frac{V_j}{Z_{ij}} \tag{7}$$

The fourth level is the net saving level (NSL) which can be express as follows:

$$NSL = \frac{ALC_{Before\ DG} - ALC_{After\ DG}}{ALC_{Before\ DG}} \times 100 \tag{8}$$

The annual losses cost (ALC), can be calculated as (Hassan et al. 2019):

$$ALC = P_{Loss} \times K_P \times T \tag{9}$$

Finally, the environmental pollution reduction level (EPRL) can be expressed as:

$$EPRL = \frac{PE_{After\ DG}}{PE_{Before\ DG} + PE_{After\ DG}} \times 100 \tag{10}$$

where:

PE – Pollution of Emissions, which can be expressed as (Chiradeja et la. 2004):

$$PE = EG_g . AE_g \tag{11}$$

1.2. Power Balance Constraint

The power balance equations can be formulated as below (Hung et al. 2014):

$$P_G + P_{DG} = P_D + P_{Loss} \tag{12}$$

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

1.3. Distribution Line Constraints

The inequality constraint of the line can be expressed as follows:

$$\left|S_{ij}\right| \le \left|S_{\max}\right| \tag{14}$$

$$V_{\min} \le \left|V_i\right| \le V_{\max} \tag{15}$$

$$\left|V_1 - V_j\right| \le \Delta V_{\max} \tag{16}$$

1.4. The constraints related to PV-based DGs

The inequality constraint of PV-DG can be expressed as follows (Zellagui et al. 2021):

$$P_{DG}^{\min} \le P_{DG} \le P_{DG}^{\max} \tag{17}$$

$$2 \le DG_{Position} \le N_{Bus} \tag{18}$$

$$N_{DG} \le N_{DG.\max} \tag{19}$$

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

2. An overview of IW control strategies in PSO algorithms

The basic PSO algorithm was first proposed in 1995 as a population-based stochastic optimization algorithm, which can be seen as a global search technique. The population of individuals (P) or swarm evolves through successive iterations. At each iteration k, each particle is moved according to the equations (Kennedy et al. 1995):

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

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

Inertia weight w is an important parameter in the PSO algorithm, which was originally proposed (Parizad et al. 2018) which has a critical role for the guaranteed efficiency of PSO. Since the introduction of this parameter, there has been a number of proposals of different strategies to determine the value of w during a course of run (varied for each iteration and execution).

To suggest an appropriate strategy for a user of PSO involving w, comprehensive studies have been performed in this paper using nine different w-related strategies, namely adaptive inertia weight (AIW-PSO), inertia weight with Butterworth (B-PSO), chaotic decreasing inertia weight (CDIW-PSO), decreasing inertia weight with non-linear coefficient (DW), exponential inertia weight (EIW-PSO), nonlinear inertia weight variation for dynamic adaptation (NLDA), nonlinear improved inertia weight (NLI), oscillating inertia weight (OIW), and random inertia weight (RIW) are shown in Table 1.

Table 1. Various inertia weight strategies of PSO algorithms

Tabela 1. Różne warianty wag bezwładności algorytmów PSO

No.	Algorithm	Reference	Formula of Inertia Weight	Value
1	2	3	4	5
1	AIW-PSO	(Nickabadi et al. 2011)	$w = w_{\min} + (w_{\max} - w_{\min}) \cdot p_s(k)$	$w_{\min} = 0.4$ $w_{\max} = 0.9$
2	B-PSO	(Zhu et al. 2018)	$w = w_{\max} \cdot \left(\dfrac{1}{1 + \left(\dfrac{k}{p_1} \right)^{p_2}} \right) \cdot w_{\min}$	$P_1 = k_{\max}/3$ $P_2 = 10$
3	CDIW-PSO	(Feng et al. 2017)	$w = z_k \cdot w_{\min} + (w_{\max} - w_{\min})^{\frac{k_{\max} - k}{k_{\max}}}$	$w_{\min} = 0.4$ $w_{\max} = 0.9$
4	DW-PSO	(Fan et al. 2007)	$w = \left(\dfrac{2}{k} \right)^{\alpha}$	$\alpha = 0.3$
5	EIW-PSO	(Ting et al. 2012)	$w = w_0 e^{-\alpha x \left(\frac{k}{k_{\max}} \right)^{\beta}}$	$\alpha = 2$ $\beta = 2$ $w_0 = 0.9$
6	NLDA-PSO	(Chatterjee et al. 2006)	$w = \left(\dfrac{k_{\max} - k^n}{k_{\max}^n} \right) \cdot (w_{\min} - w_{\max}) + w_{\max}$	$n = 0.6$
7	NLI-PSO	(Liao et al. 2011)	$w = w_{\max} \cdot (1.0002)^{-k}$	$w_{\max} = 0.9$

1.	2	3	4	5
8	OIW-PSO	(Kentzoglanakis et al. 2009)	$w=\begin{cases}\frac{w_{\min}+\varpi_k}{2}+\frac{\varpi_k+w_{\min}}{2}\cos\left(\frac{2\pi k(4k+6)}{T}\right) & \text{if } k<\gamma \\ w_{\min} & \text{otherwise}\end{cases}$	$T = 2\times\gamma/17$ $\gamma = 3\times k_{\max}/4$
9	RIW-PSO	(Eberhart et al. 2001)	$w=0.5+\frac{\alpha}{2}$	$\alpha =$ *random* [0 1]

Different time-varying updating strategies for the inertia weight parameter in various PSO algorithms are traced in Figure 1. As shown in Figure 1, there is a variation of inertia weight with iterations. In general, this variation spans between 0.4 and 0.9.

The inertia weight of the DW-PSO algorithm decreases quickly compared to other algorithms, which signifies a rapid convergence. Nevertheless, the efficiency and accuracy indices of these algorithms for the optimal DG location and size will be verified in the next section.

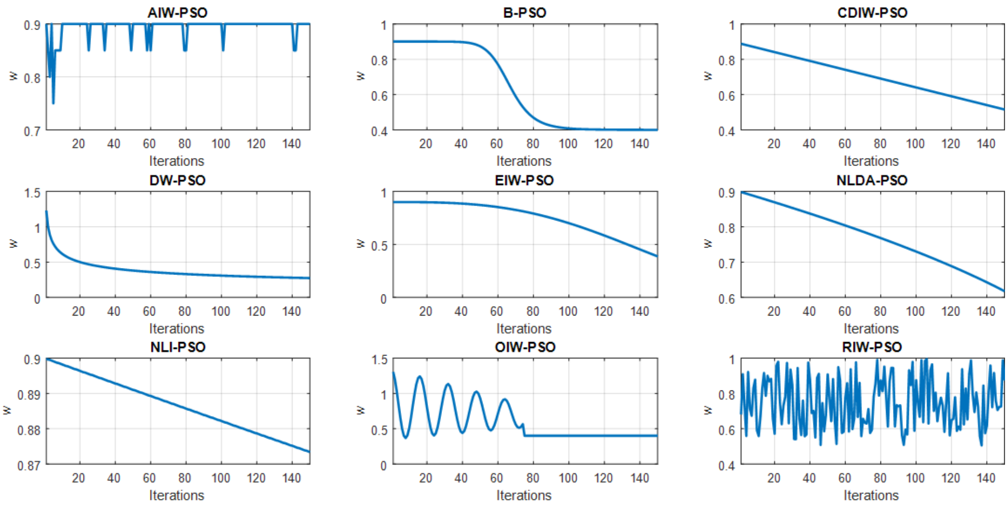


Fig. 1. Inertia weight variation for different PSO algorithms

Rys. 1. Zmienność masy bezwładności dla różnych algorytmów PSO

The flowchart of the PSO algorithm is shown in Figure 2.

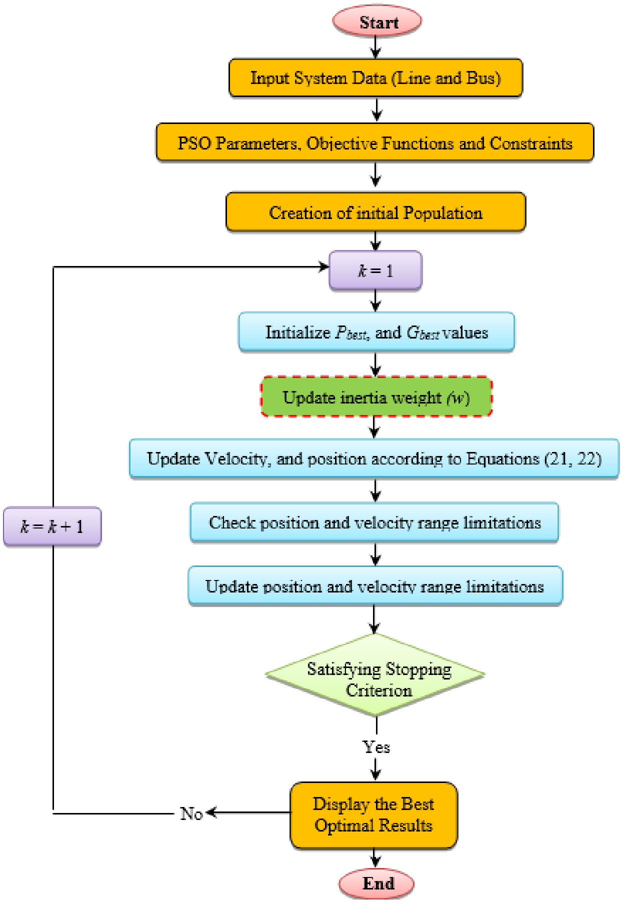


Fig. 2. Flowchart of IW-PSO algorithms

Rys. 2. Schemat blokowy algorytmów IW-PSO

3. Testing systems, results and discussions

To evaluate the efficiency and the accuracy of the proposed IW-PSO algorithms, the IEEE-69 bus and the practical Adrar city (Algeria) RDS are considered for testing. The first test system consists of 69 buses with total active and reactive load of 3,791.9 kW and 2,694.1 kVar, respectively as shown in Figure 3 (Naik et al. 2015).

The second test system is the practical Algerian RDS which compose of 205-bus, also this system has four principal deviations, with total active and reactive load of 7,839.7 kW and 5,594.0 kVar, respectively, as represented in Figure 4 (Lasmari et al. 2020b).

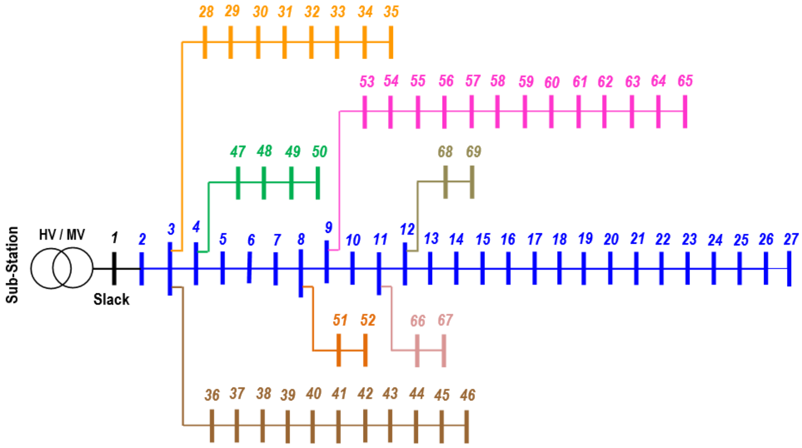


Fig. 3. Single line diagram of the IEEE 69-bus RDS

Rys. 3. Schemat pojedynczej linii IEEE 69-bus w promieniowym systemie dystrybucji

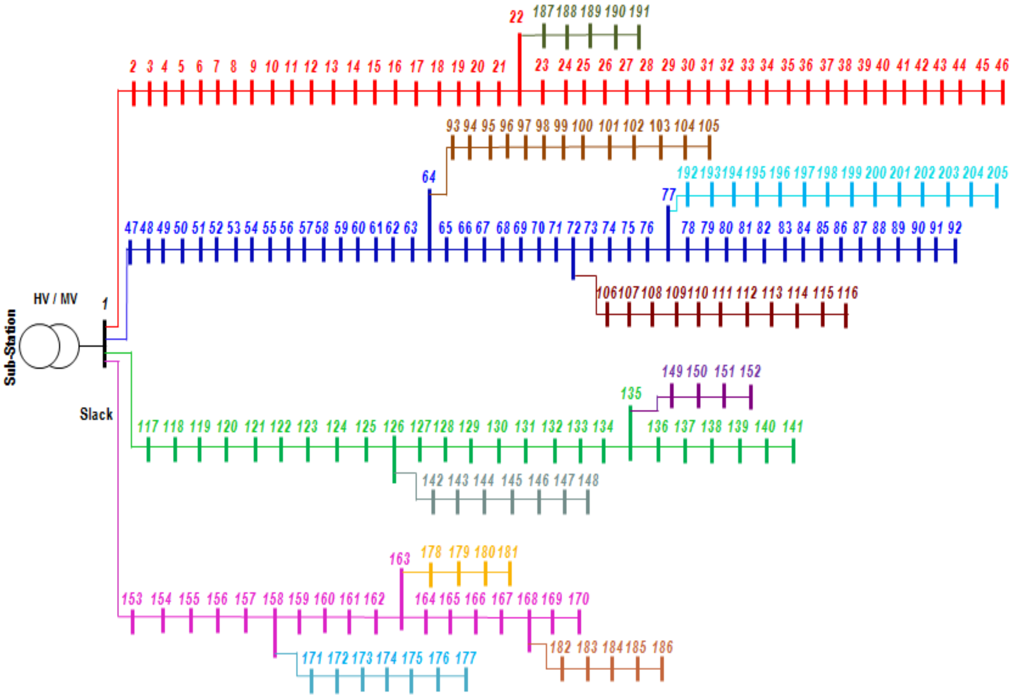
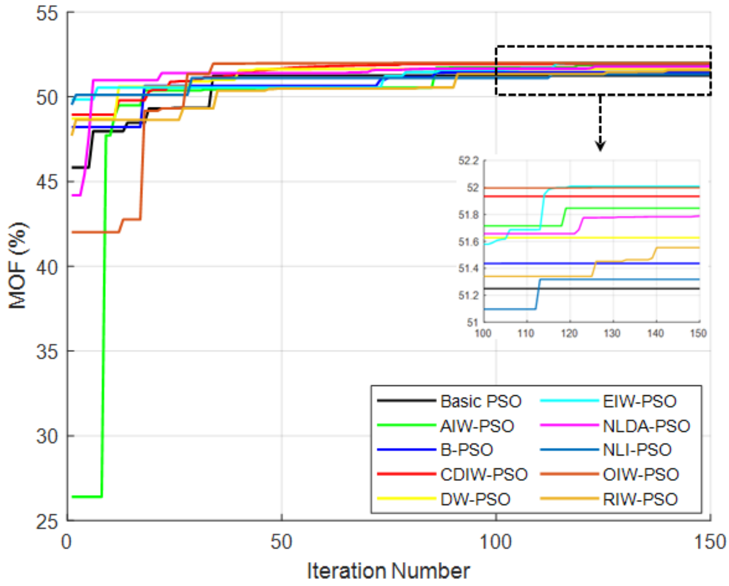


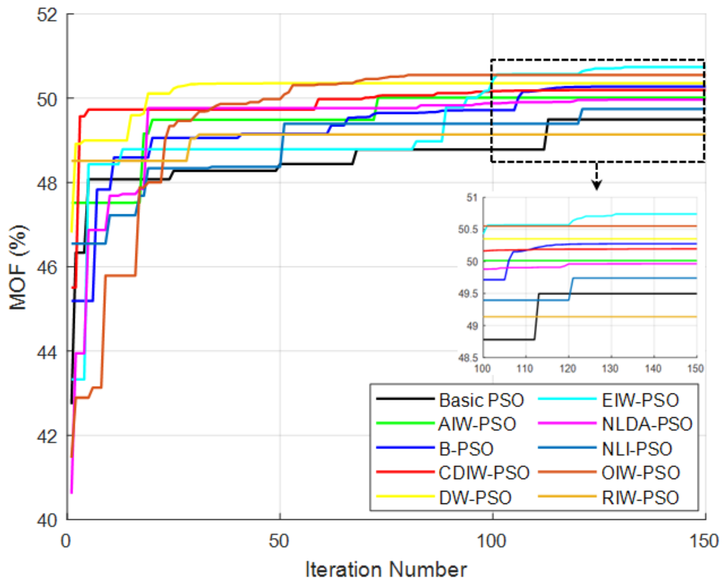
Fig. 4. Single line diagram of practical RDS in Adrar City 205-bus

Rys. 4. Schemat pojedynczej linii rzeczywistego promieniowego systemu dystrybucji dla autobusu 205
w mieście Adrar

The convergence characteristics of the proposed PSO algorithms for the optimal integration of multiple PV-based DG units in the two RDS test systems is illustrated in Figure 5.



(a)



(b)

Fig. 5. Convergence characteristics of IW-PSO algorithms: a) IEEE 69-bus, b) Adrar City 205-bus

Rys. 5. Charakterystyki zbieżności algorytmów IW-PSO: a) Magistrala IEEE 69, b) Miasto Adrar autobus 205

Figure 5 shows the results obtained when applying the proposed IW-PSO algorithms to both testing systems. It is clear that each algorithm has a different number of iterations to reach the optimal solution, where the OIW-PSO, CDIW-PSO DW-PSO converge rapidly with less than 80 iterations. In fact, the DW-PSO algorithm converges the quickest compared to other algorithms, taking less than fifty iterations, and having the least value of MOF. On the other hand, other algorithms take more than eighty iterations to converge.

In the other extreme, EIW-PSO recorded the maximum value of MOF, which are 52.0079%, and 50.7391%, respectively, for the first and the second test systems, and it takes more than 110 iterations to attain the optimal solution.

Also, it can be observed that some algorithms such as AIW-PSO converge rapidly in the two test systems considered in this paper. In addition, the results of 20 runs of each algorithm prove the superiority of EIW-PSO results that are closer to each other compared to other algorithms.

The optimization results of multiple PV-DGs using different PSO algorithms for the two test systems are tabulated in Table 2.

Table 2. Comparison of optimization results for all test systems

Tabela 2. Porównanie wyników optymalizacji dla wszystkich systemów testowych

(a) IEEE 69-bus

Methods	Size [MW] (location)	P_{Loss} [kW]	Q_{Loss} [kVar]	$V_{\min}$ [p.u.]	*APLL* [%]	*EPRL* [%]	*SCL* [%]	*NSL* [%]	*VDL* [%]	*MOF* [%]
1	2	3	4	5	6	7	8	9	10	11
Basic PSO	0.7448 (14) 0.0100 (22) 1.7852 (62)	74.2008	36.8281	0.9814	75.1960	24.8270	1.2175	67.0142	64.5688	51.2487
AIW-PSO	0.6220 (15) 0.0100 (44) 1.7142 (61)	72.0575	36.0130	0.9771	75.7387	27.4309	1.1625	67.9670	64.5359	51.8462
B-PSO	0.4293 (27) 0.0100 (59) 1.6926 (62)	75.4966	37.6329	0.9765	74.8717	30.1786	1.0336	66.4382	64.1006	51.4363
CDIW-PSO	0.3649 (22) 0.1056 (24) 1.7164 (61)	72.3221	36.2927	0.9763	75.6713	29.4651	1.0653	67.8494	64.2804	51.9340
DW-PSO	0.3640 (23) 0.1056 (60) 1.1782 (61)	83.2038	41.3421	0.9601	72.9991	35.6788	0.8209	63.0120	62.2618	51.6269
EIW-PSO	0.3539 (18) 0.1179 (24) 1.7546 (61)	71.6766	36.0317	0.9777	75.8359	28.9642	1.0617	68.1364	64.2829	52.0079
NLDA- -PSO	0.3437 (21) 0.0100 (27) 1.7565 (61)	73.0965	36.6685	0.9770	75.4746	30.4122	0.9484	67.5052	63.7757	51.7880

1	2	3	4	5	6	7	8	9	10	11
NLI-PSO	0.4748 (18) 0.5053 (54) 1.5795 (63)	73.2179	36.7348	0.9781	75.4439	24.5360	1.1339	67.4512	64.3341	51.3175
OIW-PSO	0.4687 (18) 0.0390 (27) 1.7077 (61)	71.7828	36.0669	0.9763	75.8088	29.0270	1.0889	68.0891	64.3463	51.9982
RIW-PSO	0.2948 (24) 1.0660 (61) 0.7260 (63)	74.1418	37.0898	0.9790	75.2109	30.7058	0.8957	67.0405	63.4440	51.5535

(b) Adrar City 205-bus

Methods	Size [MW] (location)	P_{Loss} [kW]	Q_{Loss} [kVar]	$V_{\min}$ [p.u.]	*APLL* [%]	*EPRL* [%]	*SCL* [%]	*NSL* [%]	*VDL* [%]	*MOF* [%]
Basic PSO	2.1674 (33) 1.8016 (73) 0.0100 (111)	232.6199	164.6921	0.9546	69.8836	32.8278	6.7016	56.9050	62.1553	49.4962
AIW-PSO	2.2809 (31) 2.0913 (76) 0.3471 (166)	223.8668	154.9193	0.9538	70.6846	28.5343	7.7411	58.5265	62.8593	50.0137
B-PSO	1.7151 (37) 2.1740 (72) 0.3575 (168)	221.4880	153.1897	0.9512	70.9055	31.2916	7.1811	58.9672	62.6644	50.2743
CDIW-PSO	2.0219 (33) 1.1910 (64) 1.2215 (77)	221.5178	157.5614	0.9512	70.9027	30.2171	7.4423	58.9617	62.5166	50.1961
DW-PSO	1.9976 (34) 2.0605 (75) 0.3759 (168)	219.9361	151.9497	0.9530	71.0504	30.2098	7.3810	59.2547	62.8565	50.3520
EIW-PSO	2.1439 (33) 2.3029 (72) 1.2091 (182)	206.7219	138.9249	0.9550	72.3080	22.2027	8.0329	61.7028	63.6963	50.7391
NLDA-PSO	2.1202 (33) 1.1435 (77) 0.9816 (107)	226.8493	160.8734	0.9542	70.4096	31.3295	7.4659	57.9740	62.4923	49.9625
NLI-PSO	1.9929 (35) 1.7575 (72) 0.2523 (116)	229.6264	162.3535	0.9543	70.1555	32.6837	6.8784	57.4595	62.2802	49.7399
OIW-PSO	1.9775 (35) 1.7744 (74) 0.7181 (182)	214.1975	145.8112	0.9538	71.5911	29.9660	6.7969	60.3179	62.7793	50.5517
RIW-PSO	1.3349 (40) 2.1153 (72) 2.1632 (159)	226.0159	156.4488	0.9456	70.4863	22.6450	7.1540	58.1284	62.8033	49.1375

For both test systems, the results of optimization in Table 2 show that the incorporation of PV-DGs has a clear effect on all of the study levels, and this observation is valid for all the algorithms used in this study.

A quick glance shows that the performances of all algorithms are quite close to each other. For the 69-bus IEEE system, it is observed that the EIW exhibit the best results of MOF.

Great improvements in all indices were attained when buses 18, 24 and 61 were selected for DGs emplacement with sizes of 0.3539, 0.1179, and 1.7546 MW respectively.

This DG setup reduces the active power losses with up to 68.1363%. In another angle, APLL, NSL, VDL, and SCL are maximized to 75.8359, 68.1364, 64.2829, and 1.0617%, respectively.

By taking a deep look into the results of Adrar city, it turns out that the EIW-PSO algorithm offers the best results of MOF and chooses buses 33, 72, and 182 as the optimal placements for PV-DGs integration with a total size of 5.6559 MW.

It is observed that the EIW-PSO showed the best results of all indices, except for the EPRL, and this is due to the minimization of P_{Loss} to 206.7219 kW. Concerning the APLL and NSL, they are maximized to 72.3080% and 61.7028%, respectively.

It is also noticed that SCL and VDL were maximized to 8.0329% and 63.6963% respectively. The maximum EPRL, obtained by the basic PSO, is 32.8278%. Furthermore, the voltage profile is improved, and the lowest bus voltage has been pulled up from 0.8825 to 0.9550 p.u.

Figure 6 shows the voltage profiles, before and after the integration of three DG units into the IEEE 69-bus and Adrar City test systems.

The merit of integrating three PV-DGs, demonstrated in enhancing the voltage profiles of all buses, is shown in Figure 6, where different voltage profiles are traced according to the algorithm in use.

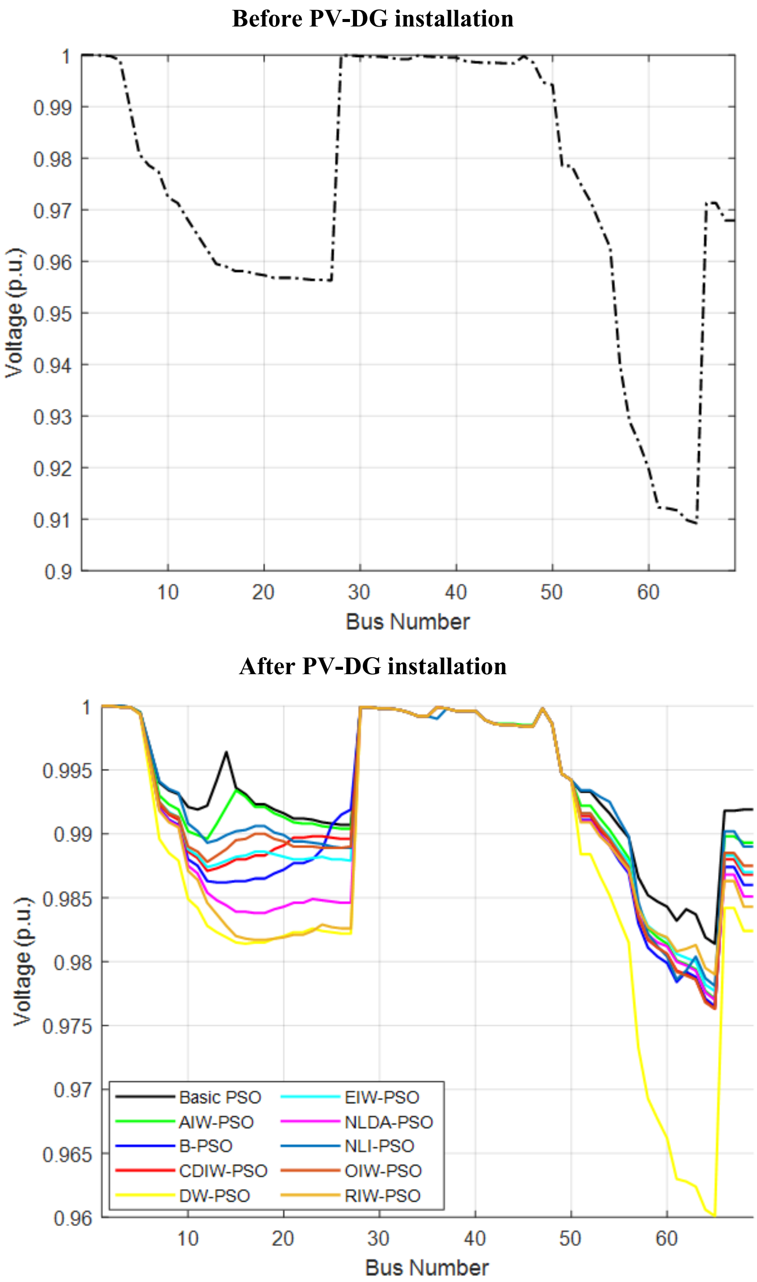
In fact, the obtained results reflect the impact of PV-DGs in improving the voltage profiles in large RDS. For the IEEE69-bus RDS, the voltage profiles of bus groups 1–7 & 28–50 are quite similar for all algorithms. On the other hand, for the rest of buses, there is noticeable variations in the voltage profiles.

Among the studied algorithms, the basic PSO recorded the maximum voltage, which recommends the optimal location and the largest total size of the PV-DGs (2.54 MW). The worst voltage profiles are obtained by the DW-PSO in all buses as it recommends the lowest size of PV-DGs. The minimum bus voltage is 0.9601 p.u., marked on bus 65.

Following this PV-DG integration, the lowest voltage, which equals 0.9456 p.u., is obtained in the case of applying the RIW-PSO algorithm, while other algorithms have improved bus voltage values to be greater than 0.95 p.u. The maximum voltage is recorded when applying EIW-PSO as it is pulled up to 0.9550 p.u., as mentioned above.

This improvement is a result of the optimal location and capacity obtained for the three used PV-based DGs. In general, AIW-PSO and EIW-PSO algorithms gave better results compared to other algorithms in improving the whole voltage profile. This does not prevent saying that other algorithms have also shown a good improvement in some buses.

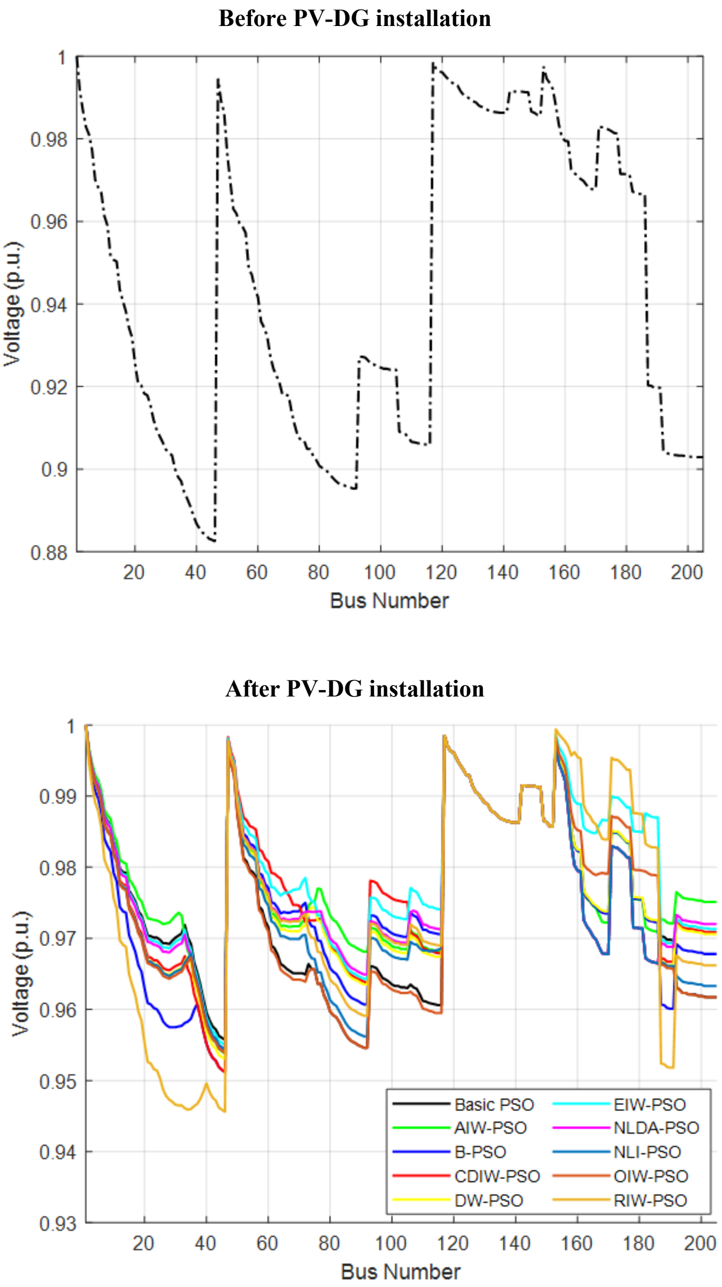
For example, the CDIW-PSO algorithm enforced the maximum voltages on buses 95 to 105. It is also observed that the RIW-PSO algorithm gives reduced voltages on the first 60 buses,



(a)

Fig. 6. Bus voltages of standard and practical RDS: a) IEEE 69-bus

Rys. 6. Napięcia magistrali standardowego i faktycznego promieniowego systemu dystrybucji: a) Magistrala IEEE 69,



(b)

Fig. 6 cont. Bus voltages of standard and practical RDS: b) Adrar City 205-bus

Rys. 6 cd. Napięcia magistrali standardowego i faktycznego promieniowego systemu dystrybucji:
b) Autobus 205 z miasta Adrar

where an observable difference between this algorithm and other algorithms can be detected in this range of buses.

This is due to the minimum size of PV-DG connected to bus number 40, which is only 1.3349 MW. This value could be seen as low compared to other algorithms which inject high power near to bus 40.

Figure 7 shows the P_{Loss} of each branch while using various PSO algorithms, before and after the incorporation of PV-DGs into the two test systems. From Figure 7 (a), it can be noted that there is a minimization in the power losses in all branches while using various PSO algorithms. Also there is a similarity in the branches between 27 to 52 which have the minimum P_{Loss}, it is noted that these branches are less affected by the integration of PV-DGs.

However, the P_{Loss} reduction in other system branches is quite significant (but it is not the same for all algorithms) for example, in branch 6, the NLI-PSO and the DW-PSO have resulted in a minimum and maximum P_{Loss} of 8.8 kW and 11.5 kW, respectively.

In addition, the peak P_{Loss} is slightly minimized by DW-PSO compared to the other algorithms which have a better reduction part.

Further analysis of Figure 7 (b) shows that there are numerous branches which have a high P_{Loss}, mostly the branches between 1 to 20, and 40 to 67. These have more than 10 kW of P_{Loss}. The maximum P_{Loss} is about 27 kW, which is associated with the first branch.

The integration of PV-DGs contributes to minimizing the losses in the first branch to less than 13 kW and if we take a look at the best value for this branch, it is minimized to about 8 kW, which is the minimum value obtained in the case of using several PSO algorithms.

The losses in other branches have been minimized and each algorithm has a different effect on these branches according to the locations of buses and the injected power. For example, the CDIW-PSO algorithm gives the minimum P_{Loss} in some branches, which are numbers 18, 68 and 74.

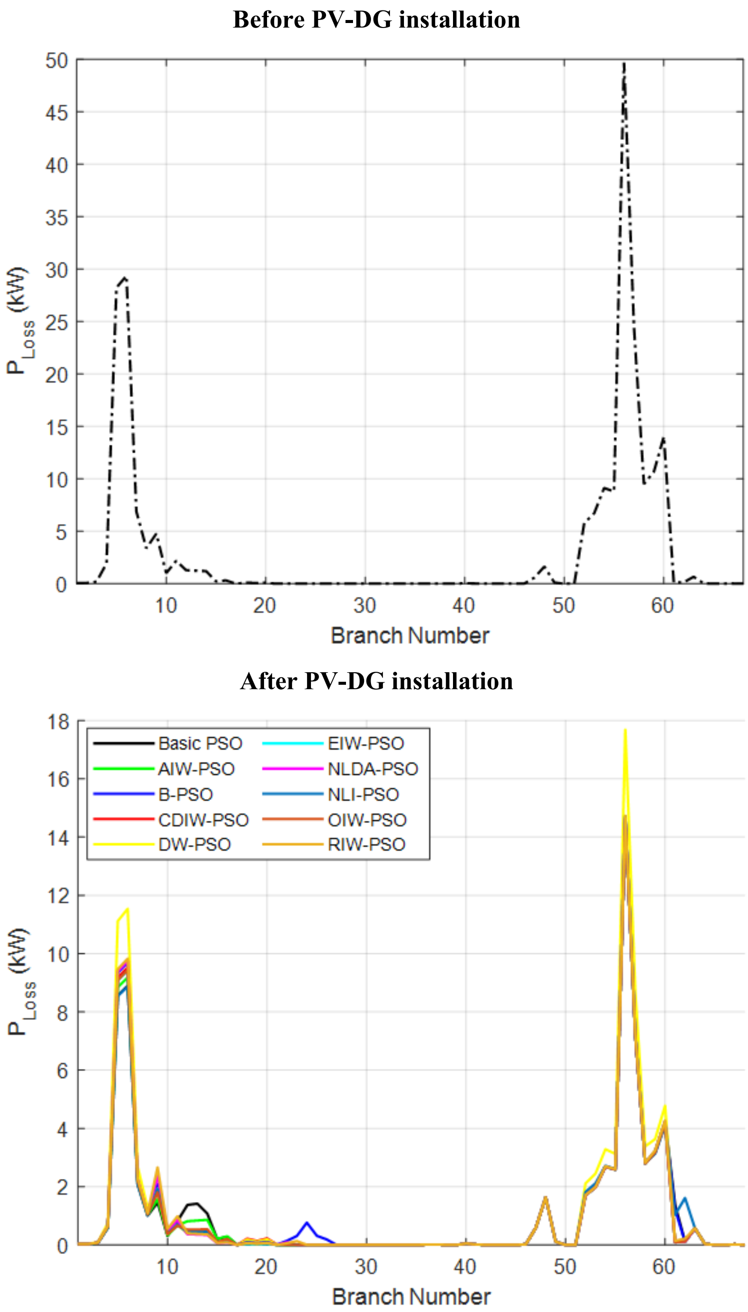
Figure 8 shows the boxplot of MOF while using different PSO algorithms for the IEEE 69-bus, and the practical RDS of Adrar City. As shown in Figure 8, for the same parameters (number of iterations and population size), the outcomes of various IW-PSO after 20 iterations show that the performances obtained by most of the algorithms are close to each other, except for AIW-PSO and DW-PSO. EIW-PSO gives the best results of MOF in this case study.

Figure 9 represents the five levels of MOF (VDL, EPRL, NSL and SCL) values using various PSO algorithms applied in this paper.

For the IEEE 69-bus RDS, Basic PSO gives the maximum results of VDL and SCL, which are 64.5688%, and 1.2175% respectively, but it enforces the worst EPRL value. Nevertheless, the DW-PSO recorded the maximum EPRL with 35.6788%, it also has the lowest VDL and SCL compared to other algorithms.

Moreover, the EIW-PSO record the maximum value of APLL with 75.8359% whereas the worst value is obtained by DW-PSO, similarly for the NSL level, where the EIW-PSO recorded the best results.

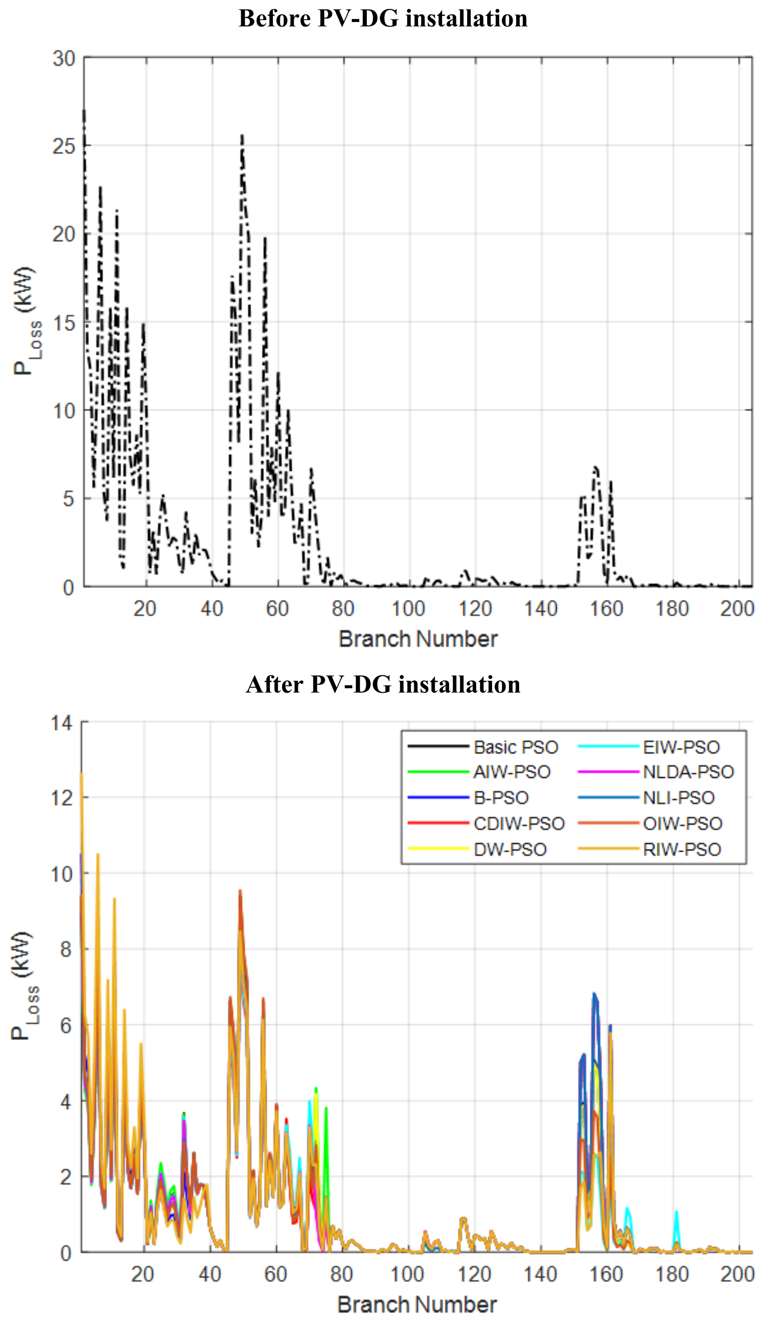
For the practical Adrar city, the results of VDL are closer to each other with a difference of 1.5410%; however, the maximum VDL value has been obtained by the EIW-PSO algorithm.



(a)

Fig. 7. Active power loss of RDSs: a) IEEE 69-bus

Rys. 7. Straty mocy czynnej promieniowego systemu dystrybucji a) Magistrala IEEE 69



(b)

Fig. 7 cont. Active power loss of RDSs: b) Adrar City 205-bus

Rys. 7 cd. Straty mocy czynnej promieniowego systemu dystrybucji: b) Autobus 205 z miasta Adrar

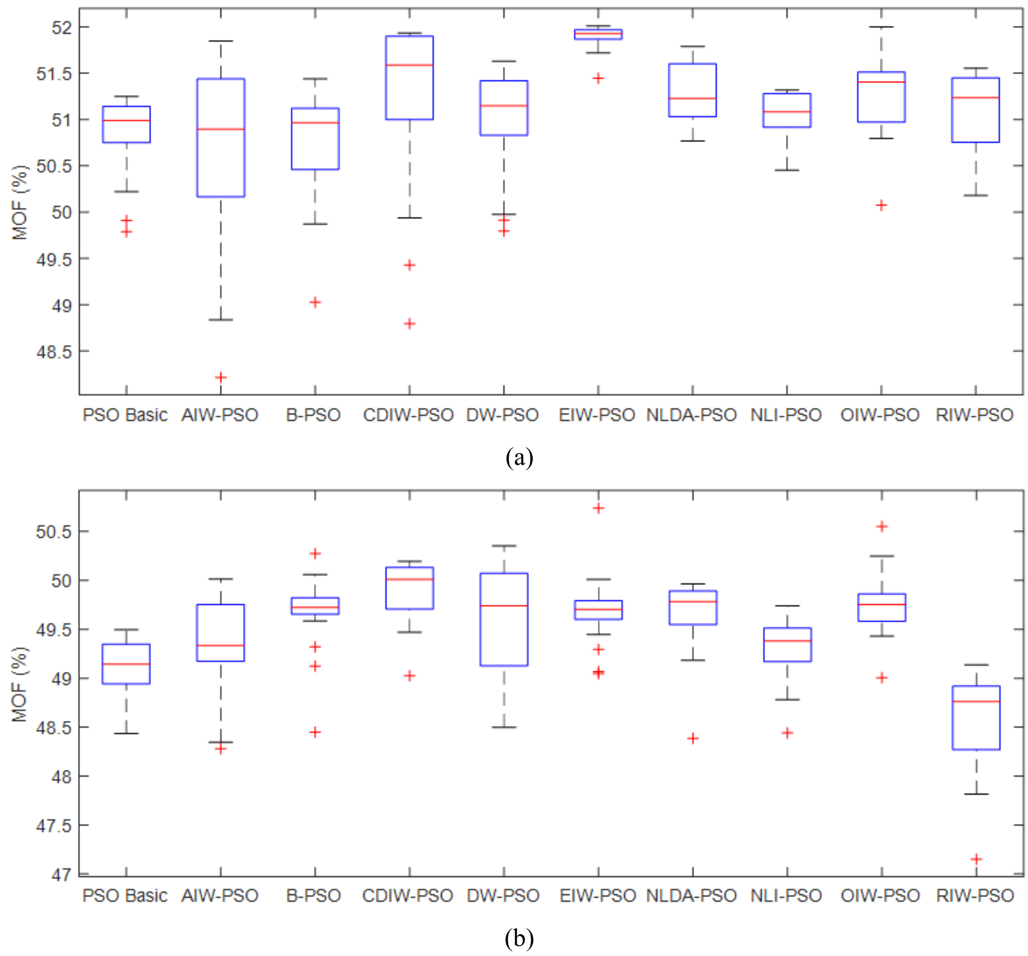
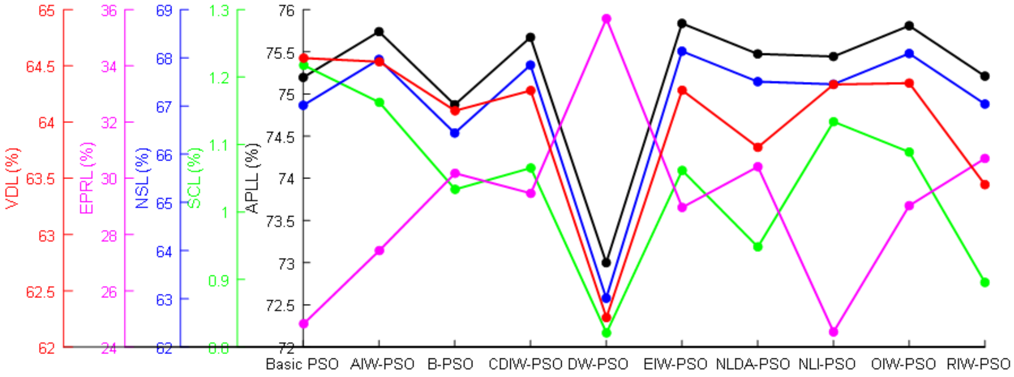


Fig. 8. Boxplot of MOF using various PSO algorithms: a) IEEE 69-bus, b) Adrar City 205-bus

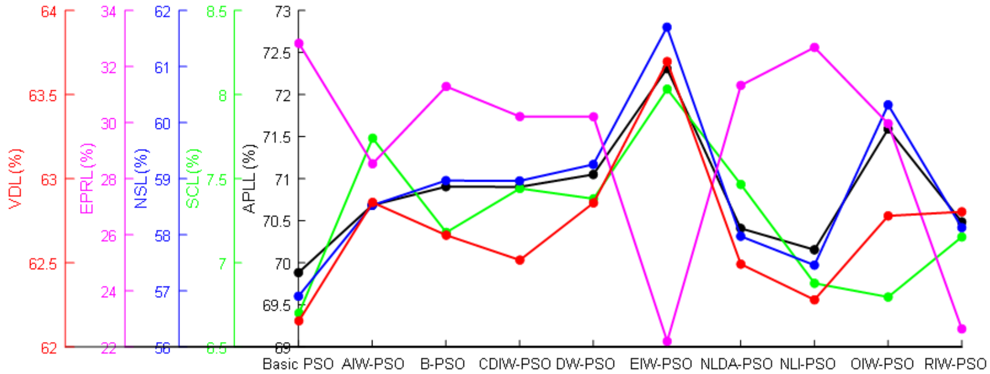
Rys. 8. Wykres pudełkowy funkcji wielokryterialnej w różnych algorytmach PSO: a) Magistrala IEEE 69, b) Autobus 205 z miasta Adrar

Meanwhile, this algorithm encounters the maximum SCL value compared to the rest of the algorithms applied.

The maximum amount of EPRL has been obtained by the Basic PSO, in addition, the EIW -PSO record the best results of APLL and NSL. It is noted that not a single algorithm has given the best results for all level values.



(a)



(b)

Fig. 9. Comparison among various PSO algorithms: a) IEEE 69-bus, b) Adrar City 205-bus

Rys. 9. Porównanie różnych algorytmów PSO: a) Magistrala IEEE 69, b) Autobus 205 z miasta Adrar

4. Benchmarking and comparison

Table 3 and Figure 10 present a comparison between the proposed EIW-PSO algorithm and other optimization algorithms in terms of achieving minimum active power losses.

These algorithms are artificial bee colony (ABC), PSO, improved sine-cosine algorithm (ISCA), invasive weed optimization (IWO), intelligent water drop (IWD), teaching learning based optimization (TLBO), and quasi-oppositional differential evolution Lévy flights algorithm (QODELFA) for standard IEEE 69-bus system.

As depicted from Table 3, there is a clear superiority of the EIW-PSO algorithm compared to other algorithms whose results are available in literature, due to obtaining the optimal sizing and placement of multiple DGs.

TABLE 3. Comparison of results for various optimization algorithms

TABELA 3. Porównanie wyników dla różnych algorytmów optymalizacji

Applied Technique	DG [MW] (Location)	Total DG Size [MW]	P_{Loss} [kW]	ΔP_{Loss} [%]
ABC (Dogan et al. 2019)	1.6530 (63) 0.1210 (64) 0.0580 (65)	1.8320	86.61	61.4977
PSO (Moradi et al. 2012)	0.9925 (17) 1.1998 (61) 0.7956 (63)	2.9879	83.20	63.0136
ISCA (Raut et al. 2020)	0.7604 (12) 0.7604 (63) 0.7604 (63)	2.2812	77.40	65.5920
IWO (Prabha et al. 2016)	0.2381(27) 1.3266(61) 0.4334(65)	1.9981	74.59	66.8412
IWD (Prabha et al. 2015)	2.9990 (17) 1.3200 (60) 0.4388 (63)	4.7578	73.55	67.3035
TLBO (Sultana et al. 2014)	0.5919 (15) 0.8188 (61) 0.9003 (63)	2.3110	72.40	67.8147
QODELFA (Jamil Mahfoud et al. 2019)	0.6294 (11) 0.4386 (20) 1.9537 (61)	3.0217	72.29	67.8636
Proposed EIW-PSO	0.3539 (18) 0.1179 (24) 1.7546 (61)	2.2264	71.67	68.1393

This has reduced P_{Loss} to 71.67 kW, which represents the lowest power loss value compared to other algorithms, which gave 86.61, 83.20, 77.40, 74.59, 73.55, 72.40, and 72.29 kW for the ABC, PSO, ISCA, IWO, IWD, TLBO, QODELFA algorithms, respectively.

From Figure 10, it is noticed that the EIW-PSO also achieved the best ΔP_{Loss} compared to other algorithms, especially the ABC algorithm which has shown a significant difference in the amount of ΔP_{Loss}, which is 6.6416%.

On the other hand, the comparison of the proposed EIW-PSO with TLBO, and QODELFA algorithms, indicate that they are very close to each other in terms of achieving the maximum ΔP_{Loss}, with minor differences of 0.3246%, and 0.2757%, respectively.

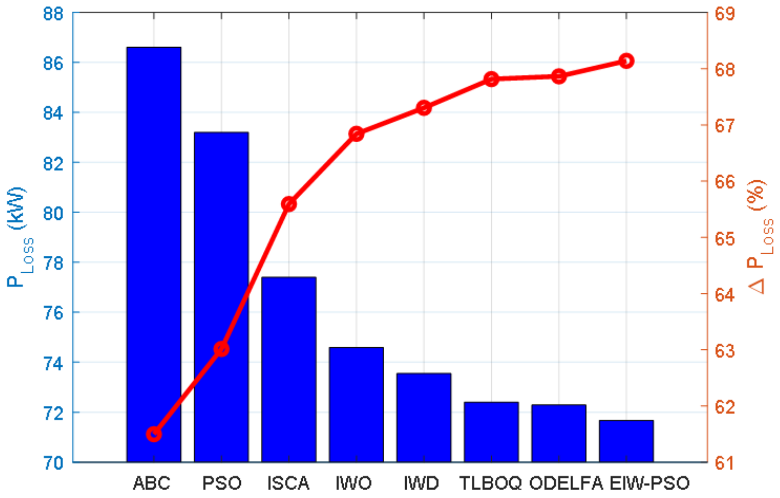


Fig. 10. Graphical comparison among various optimization algorithms

Rys. 10. Graficzne porównanie różnych algorytmów optymalizacji

Conclusions

In this paper, a comparison among a set of PSO-based algorithms with different inertia weights (constant, random, time-varying and adaptive inertia weights) has been investigated to identify the optimal location and capacity of three PV-based DG units, connected to the IEEE 69-bus RDS, and the practical 205-bus RDS, in Adrar City, Algeria.

The incorporation of multiple units reduces the total active power losses, where the P_{Loss} are minimized from 210.9875 kW to 71.6766 kW, and form 539.7834 kW to 206.7219 kW, respectively, for the standard IEEE 69-bus, and the practical Algerian 205-bus. This incorporation also contributes to improving the voltage profiles, such that all the voltages of buses have become within limits.

The proposed PSO-based algorithms with different inertia weights are used to maximize the NSL, VDL, APLL, EPRL, and SCL. In addition, the inertia weight has a direct influence on the rapidity of the convergence, where lower values of inertia weight lead to faster responses; as given by DW-PSO algorithm.

Nevertheless, this does not imply that accurate results come with lower inertia weight. On the contrary, more accurate results have come with slow convergence, as in case of using EIW-PSO algorithm.

Given results prove the efficiency of EIW-PSO by reducing the power losses, and improving the voltage profiles; furthermore, results prove the accuracy and the superiority of the EIW-PSO algorithm to determine the optimal allocation of DG by comparing with other algorithms in the literature, also we can deduce that EIW-PSO can simply be applied to practical and large-scale RDS.

The renewable-based DG might be used on a stand-alone basis or as part of a microgrid to power residential, commercial, or industrial structures. The integration of DG units with the electric utility's medium-voltage distribution networks may assist and support the delivery of clean, dependable power to more consumers while also reducing losses.

Additional advantages linked to climate resiliency and carbon emission mitigation may be realized when significant DG capacity is derived from renewable resources. Furthermore, private clients or institutions can directly use DG capacity for the energy grid, allowing them to have roles for controlling carbon emissions and system resiliency.

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Zwiększenie efektywności energetycznej dla optymalnej integracji wielu fotowoltaicznych generatorów rozproszonych przy użyciu strategii kontroli masy bezwładności w algorytmach PSO

Streszczenie

Ostatnio zainteresowanie włączeniem generatorów rozproszonych do sieci dystrybucji energii elektrycznej znacznie wzrosło na całym świecie ze względu na postęp technologiczny, który doprowadził do obniżenia kosztów energii elektrycznej, zmniejszenia strat mocy, zwiększenia niezawodności systemu elektroenergetycznego i poprawy profilu napięcia. Korzyści te można zmaksymalizować, jeśli opracuje się i zaprojektuje optymalną alokację i wielkość generatorów rozproszonych w promieniowym systemie dystrybucji. Uzyskanie optymalnej lokalizacji i wielkości jednostek generatorów rozproszonych, które mają być zainstalowane w istniejącym promieniowym systemie dystrybucji, zależy od różnych ograniczeń, które czasami nakładają się lub są sprzeczne. Aby poradzić sobie z ograniczeniami i uzyskać optymalną lokalizację i rozmiar generatora rozproszonego, w ostatniej dekadzie często opracowywano metaheurystyczne algorytmy wyszukiwania i optymalizacji. W niniejszym artykule zaproponowano skuteczną technikę optymalizacji, aby przydzielić wiele jednostek generatorów rozproszonych do promieniowego systemu dystrybucji. Zaproponowana metoda optymalizacji uwzględnia integrację jednostek generatorów rozproszonych opartych na ogniwach fotowoltaicznych w sieciach dystrybucji energii. Opiera się na funkcji wielokryterialnej, która ma na celu maksymalizację poziomu oszczędności netto, poziomu odchylenia napięcia, poziomu utraty mocy czynnej, poziomu redukcji zanieczyszczenia środowiska i poziomu zwarcia. Zaproponowane algorytmy wykorzystujące różne strategie optymalizacji roju cząstek o masie bezwładności (PSO) są stosowane w standardowym systemie IEEE 69-autobus oraz w rzeczywistym algierskim systemie dystrybucji autobusu 205. Proponowane podejście i projekt tak skomplikowanych, wielozadaniowych funkcji ma ostatecznie doprowadzić do znacznej poprawy technicznych, ekonomicznych i środowiskowych aspektów sieci dystrybucyjnych. Stwierdzono, że algorytm EIW-PSO jest najlepszy do zastosowania w systemie testowym IEEE 69-bus, ponieważ osiąga maksymalne cele dla różnych wielkości: 75,8359%, 28,9642% i 64,2829% odpowiednio dla utraty mocy czynnej, poziomu redukcji zanieczyszczenia środowiska i poziomu odchylenia napięcia w procesie instalacji jednostek rozproszonych. Dla tej samej liczby generatorów rozproszonych, EIW-PSO zapewnia znacznie lepszą wydajność w testach autobusów 205 w mieście Adrar; liczbowo: 72,3080%, 22,2027% i 63,6963% odpowiednio dla utraty mocy czynnej, poziomu redukcji zanieczyszczenia środowiska i poziomu odchylenia napięcia. Wyniki symulacji tego badania dowodzą, że zaproponowane algorytmy wykazują większą zdolność i skuteczność w ustalaniu optymalnych ustawień generatorów rozproszonych.

Słowa kluczowe: generacja rozproszona oparta na OZE, maksymalizacja efektywności energetycznej, poziomy techniczno-ekonomiczno-środowiskowe, optymalizacja roju cząstek (PSO), strategie masy bezwładności, promieniowy system dystrybucji