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Original Article

Enhancing Energy Efficiency for Optimal Multiple Photovoltaic DG and DSTATCOM Integration for Techno-Economic and Environmental Analysis: A Case Study of Adrar City Distribution System

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ABSTRACT

The insertion of renewable energy resources in existing distribution systems has effectively improved its performance and operation. This paper presents the efficiency of the optimal integration of multiple Photovoltaic DG (PV-DG), and Distribution Static Compensator (DSTATCOM) simultaneously in a practical Power Distribution System (PDS), through the maximization of the Multi-objective function (MOF) based on the Real Power Loss Level (RPLL), the Short Circuit Level (SCL), the Voltage Deviation Level (VDL), the Net Saving Level (NSL), and Environmental Pollution Reduction Level (EPRL) by various Inertia Weight Particle Swarm Optimization (IW-PSO) algorithms. The proposed IW-PSO algorithms applied in the practical Adrar city 205-bus distribution system in Algeria. The obtained results prove the efficiency of the algorithms in terms of achieving the minimum power loss and improvement of the voltage profiles, the EIW-PSO exhibits the best results of MOF compared to other algorithms.

1. Introduction

Energy, especially electricity, is indisputably the foundation of a rapid social and economic development [1]. In the past, a high proportion of electricity load was provided by fossil energy. However, the rapid consumption of fossil energy has not only caused a global fossil energy crisis, but also aggravated environmental problems. In this context, it is imperative that alternative energy sources are procured on the premise of reducing carbon dioxide emissions to meet the growing energy demand [2]. The International Energy Agency defines DG as an electricity source that is connected directly to the distribution network to supply a local consumer and support the Power distribution network (PDS) usually based on renewable energy sources (RES) [3]. The RES can be obtained from nature, utilized, and recycled continuously. They are currently the most promising alternative energy source due to their rich and clean characteristics [4]. In 2017, the installed capacity of solar and wind power worldwide amounted to 903.1 GW, which represented 41.4% of the total installed capacity of RES [5]. This trend will continue to increase reaching almost 30% of global electricity demand by end of 2020, with hydropower being the primarily one [6]. In the last years, many solutions were proposed by researchers to address the optimal PV-DG problem in PDS. The solution algorithms can be broadly categorized into four categories: analytical approaches, numerical methods, metaheuristic algorithms, and hybrid techniques [7].

This paper presents the efficiency of the optimal integration of multiple Photovoltaic DG (PV-DG), and Distribution Static Compensator (DSTATCOM) simultaneously in a practical Power Distribution System

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(PDS), through the maximization of the Multi-Objective Function (MOF) based on RPLL, SCL VDL, NSL, and EPRL by various Inertia Weight Particle Swarm Optimization (IW-PSO) algorithms. These algorithms are 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-PSO), 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).

The proposed IW-PSO algorithms applied in the practical Adrar city 205-bus distribution system in Algeria to validate the accuracy and the efficiency of the proposed algorithms.

2. Problem Formulation

2.1. Multi-objective function

In this paper, the proposed new MOF aims to solve the problem of finding the optimal size and location of DG and DSTATCOM units, through the maximized various levels, which can formulate as follows:

$$MOF = Max \sum_{i=1}^{N_{Bus}} \sum_{j=2}^{N_{Bus}} \begin{pmatrix} \alpha_1.RPLL_{i,j} + \alpha_2.VDL_j \\ +\alpha_3.SCL_{i,j} + \alpha_4.NSL_{i,j} \\ +\alpha_5.EPRL_G \end{pmatrix} \tag{1}$$

In this paper, α_1 is taken as 0.30, while each of α_2, α_3 and α_4 is taken as 0.20. The value of α_5 is equal to 0.10. The technical level considered in this study are the Real Power Loss, Voltage Deviation, and Short Circuit levels are represented in the following equation:

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

Where, P_{Loss} can be represented by the equation [8, 9]:

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

Secondly, the Voltage Deviation Level (VDL) is considered as follows [10]:

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

Where,

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

The Short Circuit Level (SCL), which can be defined as follows [11]:

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

Were,

$$SC = \frac{V_j^2}{Z_{ij}} \tag{7}$$

The economic level considered in this paper is the net saving level, which can represent as follow:

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

Where, the Annual Losses Cost (ALC), can be calculated as follows [12]:

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

The environmental level is the Environmental Pollution Reduction which represents in the equations below:

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

Where the Pollution of Emissions (PE) can be calculated by the equation below [11]:

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

2.2. Power Balance Constraint

The power balance equations can be formulated as follow [13]:

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

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

2.3. Distribution Line Constraints

Inequality constraints considered in this paper can be expressed in the following equations [14, 15]:

$$V_{\min} \le \left|V_i\right| \le V_{\max} \tag{14}$$

$$\left|V_1 - V_j\right| \le \Delta V_{\max} \tag{15}$$

$$\left|S_{ij}\right| \le \left|S_{\max}\right| \tag{16}$$

2.4. DG Constraints

Inequality constraints represent the DG unit's limits which can be given as [15]:

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

$$\sum_{i=1}^{N_{DG}} P_{DG}(i) \le \sum_{i=1}^{N_{Bus}} P_D(i) \tag{18}$$

$$2 \le DG_{Position} \le N_{Bus} \tag{19}$$

$$N_{DG} \le N_{DG.\max} \tag{20}$$

$$n_{DG,i} \,/\, Location \le 1 \tag{21}$$

2.5. DSTATCOM Constraints

Inequality constraints represent the DSTATCOM unit's limits which can formulate as follows [13]:

$$Q_{DSTATCOM}^{\min} \le Q_{DSTATCOM} \le Q_{DSTATCOM}^{\max} \tag{22}$$

$$\sum_{i=1}^{N_{DST}} Q_{DSTATCOM}(i) \le \sum_{i=1}^{N_{bus}} Q_D(i) \tag{23}$$

$$2 \le DSTATCOM_{Position} \le N_{Bus} \tag{24}$$

$$N_{DSTATCOM} \le N_{DSTATCOM.\max} \tag{25}$$

$$n_{DSTATCOM,i} \,/\, Location \le 1 \tag{26}$$

3. The IW Control Strategies in PSO Algorithms

The basic PSO algorithm was first introduced 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 [16, 17].

At each iteration k, each particle is moved according to the equations [18]:

$$V_i^{k+1} = wV_i^k + c_1 r_1 \left[P_{best}^k - X_i^k \right] + c_2 r_2 \left[G_{best}^k - X_i^k \right] \tag{27}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{28}$$

In the Basic PSO algorithm, the search for optimal solution is conducted using a population of particles, guided by two stochastic acceleration coefficients.
The inertia weight (w) is one of PSO's parameters which is developed with the purpose of achieving the balance between exploration and exploitation.
Many proposals of the inertia weight PSO (constant or varying for each iteration), in this paper 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-PSO), Exponential Inertia Weight (EIW-PSO), Nonlinear Inertia Weight variation for Dynamic Adaptation (NLDA-PSO), Nonlinear Improved inertia weight (NLI-PSO), Oscillating Inertia Weight (OIW-PSO), and Random Inertia Weight (RIW-PSO) are shown in Table 1.

Table 1. Various inertia weight strategy of PSO algorithm.

No.	Algorithm	Reference	Formula of Inertia Weight	Value
1	AIW-PSO	[19]	$w = w_{\min} + (w_{\max} - w_{\min}) \times p_s(k)$	$w_{min} = 0.4$ $w_{max} = 0.9$
2	B-PSO	[20]	$w = w_{\max} \times \left(\dfrac{1}{1 + \left(\dfrac{k}{p_1} \right)^{p_2}} \right) \times w_{\min}$	$P_1 = k_{max} / 3$ $P_2 = 10$
3	CDIW-PSO	[21]	$w = z_k \times w_{\min} + (w_{\max} - w_{\min})^{\frac{k_{\max} - k}{k_{\max}}}$	$w_{min} = 0.4$ $w_{max} = 0.9$
4	DW-PSO	[22]	$w = \left(\dfrac{2}{k} \right)^{a}$	$\alpha = 0.3$
5	EIW-PSO	[23]	$w = w_0 e^{-a \times \left(\frac{k}{k_{\max}} \right)^{b}}$	$\alpha = 2$ $\beta = 2$ $w_0 = 0.9$
6	NLDA-PSO	[24]	$w = \left(\dfrac{k_{\max} - k^n}{k_{\max}^n} \right) \times (w_{\min} - w_{\max}) + w_{\max}$	$n = 0.6$

7	NLI-PSO	[25]	$w = w_{\max} \times (1.0002)^{-k}$	$w_{max} = 0.9$
8	OIW-PSO	[26]	$w = \begin{cases} \dfrac{w_{\min} + \varpi_k}{2} + \dfrac{\varpi_k + w_{\min}}{2} \cos\left(\dfrac{2\pi k(4k+6)}{T}\right) & if \ \ k < \gamma \\ w_{\min} & otherwise \end{cases}$	$T = 2\gamma / 17$ $\gamma = 3k_{\max} / 4$
9	RIW-PSO	[27]	$w = 0.5 + \dfrac{a}{2}$	$\alpha = random$ [0 1]

4. Testing System, Results and Discussions

In order to validate the efficiency of inertia weight of the proposed algorithms, the practical Adrar city (Algeria) PDS is considered as a system of test, which is composed of 205 buses, with four principal deviations, the base MVA and the base voltage in the slack bus are 100 MVA and 30 kV, respectively [28, 29].

Furthermore, the total real and reactive load are 7839.70 kW and 5594.00 kVar respectively as represented in Figure 1.

The convergence curve of various IW-PSO algorithms is represented in Figure 2.

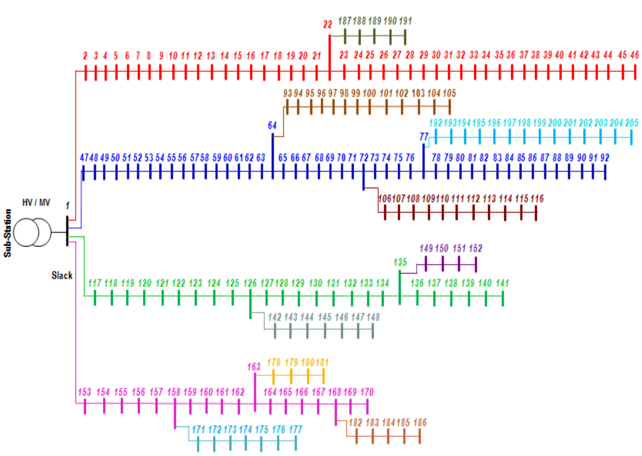

Fig 1. Single line diagram of practical Algerian PDS.

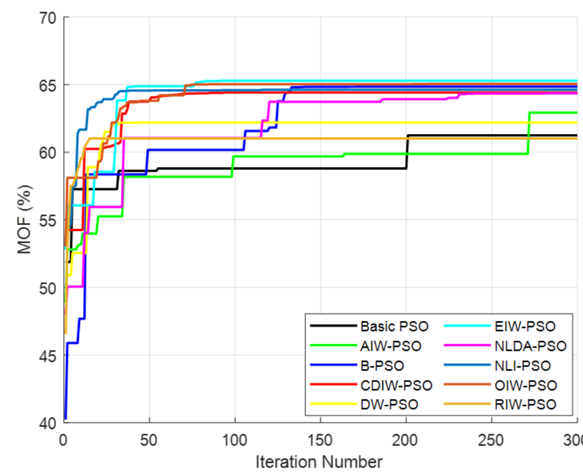

Fig 2. Convergence curve of PDS.

As shown in figure 2, each algorithm takes a specific approach to reach the optimal solution, in other words, all algorithms converge towards the optimum solution with a specified number of iterations, where the number 50 correspond to the convergence of the CDIW-PSO algorithm, and with more iterations, EIW-PSO and OIW-PSO algorithms converge as well. On the other hand, AIW-PSO needs more iterations compared to other algorithms, as it converges within 260 iterations.

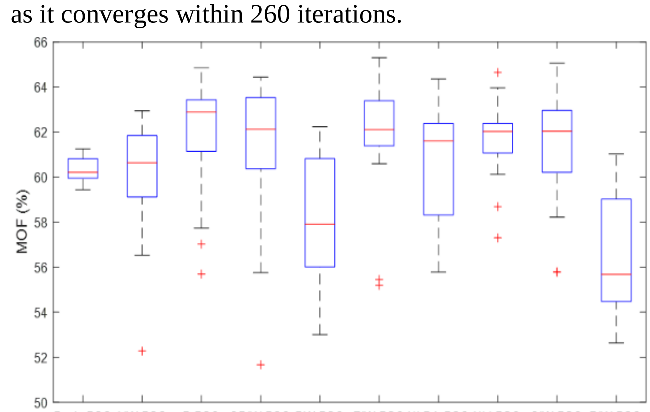

Fig 3. Boxplot of MOF using various IW-PSO algorithms.

The results of the boxplot prove the efficiency of the proposed IW-PSO algorithms in terms of achieving the best results of MOF on a large practical distribution system, where the results of B-PSO, CDIW-PSO, and EIW-PSO are very close to each other. Besides, the best result of MOF is obtained by EIW-PSO, whereas the worst results are obtained by RIW-PSO.

The results tabulated in Table 2 represent the optimization with the simultaneous integration of DG and DSTATCOM.

Table 2. Simulation results with planning simultaneous DG and DSTATCOM Units.

Applied Algorithm	Size (MW); Bus	Size (MVar); Bus	V_{min} (p.u.)	P_{Loss} (kW)	Q_{Loss} (kVar)	*RPLL* (%)	*NSL* (%)	*SCL* (%)	*VDL* (%)	*EPRL* (%)	*MOF* (%)
Basic PSO	2.0452 (45) 2.3197 (75) 0.3817 (151)	1.3103 (34) 1.1428 (85) 1.0713 (160)	0.9738	127.9713	87.8242	80.8356	76.2921	10.8259	82.6626	27.7773	61.2471
AIW-PSO	1.7272 (34) 2.1665 (77) 1.5617 (182)	1.9214 (20) 0.2479 (84) 1.4891 (97)	0.9703	101.3238	68.9200	84.1955	81.2288	12.2669	83.4335	22.8869	62.9329
B-PSO	2.0946 (34) 2.1517 (108) 0.4237 (184)	1.5770 (35) 1.9515 (70) 0.5365 (126)	0.9744	91.9172	69.0714	85.4492	82.9715	12.3099	86.7650	28.0297	64.8467
CDIW-PSO	2.0903 (34) 1.0816 (69) 0.9680 (85)	1.8118 (29) 1.4069 (63) 0.5448 (88)	0.9665	96.5066	74.0542	84.8329	82.1212	11.6172	85.5089	31.1915	64.4184
DW-PSO	1.3351 (43) 1.2132 (79) 1.2107 (93)	1.2911 (29) 1.1412 (56) 1.2362 (113)	0.9665	116.8065	88.8473	82.2101	78.3605	11.4846	81.1134	33.3869	62.1931
EIW-PSO	1.6584 (38) 2.3866 (72) 1.1965 (166)	1.4581 (36) 0.1703 (64) 1.4170 (107)	0.9808	77.8492	53.7810	87.3956	85.5777	12.2728	85.4420	24.2161	65.2986
NLDA-PSO	2.0373 (34) 2.0559 (74) 0.0100 (127)	1.4143 (45) 0.0100 (46) 1.6294 (72)	0.9665	111.2435	81.4894	82.9126	79.3911	11.6601	85.1837	31.4809	64.3511
NLI-PSO	2.4082 (31) 0.8704 (64) 1.4970 (77)	1.4770 (35) 1.4454 (77) 0.0100 (141)	0.9665	93.4480	72.2887	85.2427	82.6879	12.2058	86.6881	27.3802	64.6268
OIW-PSO	1.1792 (40) 1.9506 (76) 1.2992 (187)	1.5349 (34) 1.5113 (75) 0.0100 (133)	0.9665	88.1626	69.7812	85.9602	83.6670	11.8139	86.1154	29.4678	65.0538
RIW-PSO	1.4497 (40) 1.1266 (68) 1.4972 (97)	1.0635 (40) 0.5171 (68) 0.7619 (79)	0.9665	120.6492	89.5544	81.7318	77.6486	10.4952	78.5286	31.6994	61.0236

As depicted in Table 2 the integration of DG in buses 38, 72, and 166 with a high total size of DGs (5.2415 MW), simultaneously the integration of DSTATCOM in buses 36, 64, and 107 with a total size of 3.0454 MVar allowed to EIW-PSO to obtain the minimum results of P_{Loss} and Q_{Loss} compared to other algorithms these are minimized from 539.7834 kW to 77.8492 kW and from 369.7102 kVar to 53.7810 kVar, respectively.

Moreover, due to this minimization the RPLL, and NSL are maximized to 87.3956 %, and 85.5777 %. On the other hand, the best results of SCL, and VDL are obtained by B-PSO which are maximized to 12.3099 %, and 86.7650 % respectively. Whereas the DW-PSO algorithm records the best result of EPRL which is 33.3869 %.

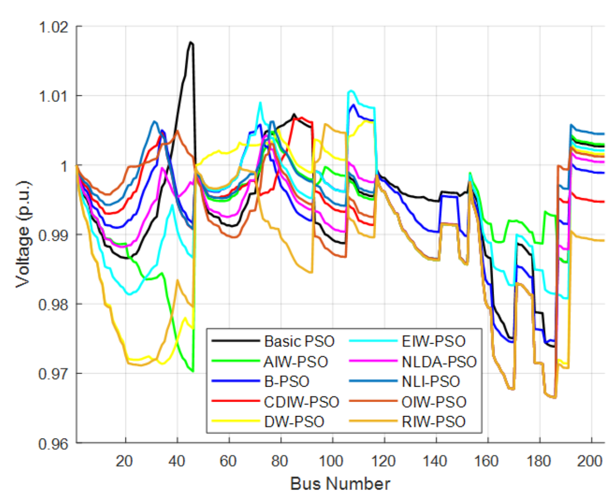

Fig 4. Bus voltages of PDS.

As shown in Figure 4, there is a significant augmentation on the voltages profile for all algorithms, where the weak voltage is enhanced from 0.8825 p.u. to more than 0.9665 p.u., in addition, it is clearly shown each algorithm affected the voltage profiles depending on their size and emplacements, where the integration of DG in bus 45 allowed to Basic PSO to obtain the best voltage profile in buses from 39 to 50 where the voltage becomes more than 1 p.u., also it has recorded the best voltage in buses 125 to 140. On the other hand, the minimum voltage is obtained by OIW-PSO which is 0.9665 p.u.

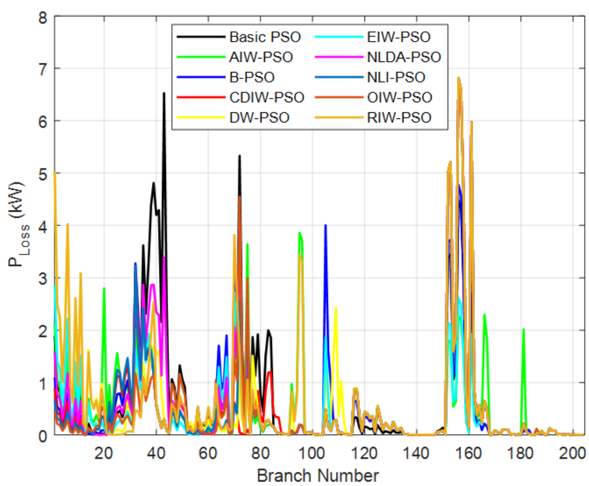

Fig 5. Real power loss of PDS.

Figure 5 shows the Contribution of the incorporation of DG and DSTATCOM Simultaneously on the minimization of P_{Loss}, where it is evident the effect of the incorporation of both devices Simultaneity on the reduction of power losses for the reason of provided the real and reactive power, other observation, the peak of P_{Loss} per branch it is occurred in the bus 158 obtained by RIW-PSO, that is close to 7 kW.

5. Conclusion

In this paper, a comparative study of various inertia weight algorithms is conducted to shows the efficiency of the integration of multiple DGs and DSTATCOM simultaneously for the aim of maximizing a multi-objective function based on RPLL, NSL, VDL, SCL, and EPRL on a practical Algerian distribution system in Adrar city.

Outcomes show the efficiency of the proposed various IW-PSO algorithms on the large practical electrical distribution system by minimizing the power losses, noted that the power loss has a significant reduction which is more than 67 %, moreover improvement on the voltage profiles which is within the permissible limits, where the minimum voltage has improved by more than 9 %.

Results show the superiority of EIW-PSO algorithm compared to other algorithms in terms to achieve the best results of MOF.

NOMENCLATURE

P_{Loss} , Q_{Loss}	Total real-reactive power losses
P_i , Q_i	Real and reactive power at bus i
P_{ij}, Q_{ij}	Real and reactive power of branch
$ALC_{Before/After}$	Annual losses cost
R_{ij} , X_{ij}	Resistance and reactance of the line
$PE_{Before\ /\ After}$	Amount of emissions
T	Number of hours per year, 8760 h
S_{ij}	Apparent power in branch
P_G , Q_G	Real and reactive power generator
P_D , Q_D	Real and reactive power of load
P_{DG}	Real power injection from DG unit
V_i , δ_i	Voltage magnitude and angle at bus
V_{min},V_{max}	Allowable limits of voltages
Z_{ij}	Impedance of the distribution line
S_{max}	Maximum apparent power
N_{DG}	Number of DG units
$n_{DG,\ i}$	Location of DG units at bus
$SC_{Before/After}$	Short circuit current before and after DG
$VD_{Before\ /After}$	Voltage deviation
N_{bus}	Number of buses of PDS
$P_{Loss}^{Before\ /After}$	Real power losses
K_p	Incremental cost of P_{Loss}, 0.06 $/kW
EG_g	Emission of a generator pollutant
AE_g	Emission quantity of substation
c_1, c_2	Cognitive and social acceleration factors
ΔV_{max}	Maximum voltage drops at each branch
w_{max} , w_{min}	Maximum and minimum values of IW
k, k_{max}	Current and maximum iterations
r_1 , r_2	Random values in the interval of [0, 1]
$DG_{Position}$	Position of DG unit

Conflict of Interest

The authors declare that they have no conflict of interest.

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