Elektrichestvo, 2021, No.12, pp. 15–27 *DOI:10.24160/0013-5380-2021-12-15-27*

Optimal Location and Size of Multiple Renewable Distributed Generation Units in Power Systems Using an Improved Version of Particle Swarm Optimization

AHMED M.K., OSMAN M.H.
Al-Azhar University, Cairo, Egypt

KOROVKIN N.V.
SPbPU, Saint-Petersburg, Russia

The penetration of renewable distributed generations (RDGs) such as wind and solar energy into conventional power systems provides many technical and environmental benefits. These benefits include enhancing power system reliability, providing a clean solution to rapidly increasing load demands, reducing power losses, and improving the voltage profile. However, installing these distributed generation (DG) units can cause negative effects if their size and location are not properly determined. Therefore, the optimal location and size of these distributed generations may be obtained to avoid these negative effects. Several conventional and artificial algorithms have been used to find the location and size of RDGs in power systems. Particle swarm optimization (PSO) is one of the most important and widely used techniques. In this paper, a new variant of particle swarm algorithm with nonlinear time varying acceleration coefficients (PSO-NTVAC) is proposed to determine the optimal location and size of multiple DG units for meshed and radial networks. The main objective is to minimize the total active power losses of the system, while satisfying several operating constraints. The proposed methodology was tested using IEEE 14-bus, 30-bus, 57-bus, 33-bus, and 69- bus systems with the change in the number of DG units from 1 to 4 DG units. The result proves that the proposed PSO-NTVAC is more efficient to solve the optimal multiple DGs allocation with minimum power loss and a high convergence rate.

K e y w o r d s: *power loss reduction, improved PSO-NTVAC, meshed and radial networks, optimal size, optimal location*

Globally, the penetration of renewable distributed generations (RDGs) into electric power systems has increased in recent years due to the significant development of distributed generations (DGs) technologies, limitations imposed on conventional power generation, and the rapid increase in electricity consumption [1–3]. DGs make extensive use of renewable energy sources (RES) like wind energy, solar power, biomass, and photovoltaic systems [4].

DGs play an important role in the modern power system to meet the requirements and satisfaction of the end-users while transmitting and distributing the power from one point to another. The system efficiency decreases due to line losses and variation of voltage level which makes consumers suffer from poor power quality, higher cost, variation in voltage and insufficient power [3]. The installation of DGs units in the electrical power systems solves these problems because it has many benefits such as improved voltage stability, real power loss reduction, reliability, grid strengthening and reduction of Sulfur dioxide (SO_2), carbon dioxide (CO_2) gas emissions. Although DG has lots of advantages, the key problem in DG placement is the selection of optimal location and size of DG units [5, 6]. If DG units are improperly allocated and sized, the reverse power flow from larger DG units can lead to higher system losses, voltage fluctuations, and an increase in costs. Hence, to minimize losses, it is important to find the best location and size of DG units [7, 8].

In terms of size, the DGs with ratings between 1 and 5 kW are known as micro DGs, the DGs with ratings between 5 kW and 5 MW are known as small DGs, the DGs with ratings between 5–50 MW are known as medium DGs, and the DGs ratings in 50–300 MW are large DGs [9]. Furthermore, various types of DGs can be classified as follows [10, 11]:

Type 1: DG units capable of injecting active power only;

Type 2: DG units capable of injecting reactive power only;

Type 3: DG units capable of injecting both active and reactive power;

Type 4: DG units which injects active power but consumes reactive power.

There are many techniques that have been carried out to obtain the optimal location and size of DGs in power systems, such as Conventional techniques and heuristic methods including dynamic programming, linear programming, non-linear programming and other analytical methods [2, 12, 13]. These methods need a proper initial point to start the algorithm where the convergences of these algorithms are completely related to their initial point. Some kinds of these algorithms such as linear programming are fast but they need some approximation in the power system model. Besides, some constraints cannot be modeled in these algorithms like reactive power flow of transmission lines [14].

Recently, many modern meta-heuristic techniques have been applied to overcome these disadvantages, for example, Particle Swarm Optimization (PSO) [15, 16], Genetic Algorithms (GA) [17], Artificial Bee Colony (ABC) [18], Modified Moth Flame Optimization [19], Whale Optimization Algorithm (WOA) [10, 20], Stud Krill Herd Algorithm (SKHA) [7], Bacterial Foraging Optimization Algorithm (BFOA) [21], Ant Colony Optimization (ACO) [22], Differential Evolution (DE) [23], Intelligent Water Drops (IWD) [3], Ant Lion Optimization (ALO) algorithm [24].

This paper analyzes the impact of the DGs installation on the performance of the power systems and their parameters such as voltage, active and reactive power losses. To find optimal placement and size of multiple DGs units, an improved version of particle swarm optimization (PSO) called nonlinear time varying acceleration coefficients PSO (PSO-NTVAC) is used. PSO-NTVAC resolves the premature convergence problem of original PSO in problems with multiple local optimums. The main goal is to reduce power losses of radial and meshed networks.

Problem formulation.

Objective function. The main objective of determining the optimal placement and sizing of DGs is to minimize the system power loss subjected to various equality and inequality constraints of a distribution network [4]:

$$\text{objective Function} = \min(P_{loss}), \tag{1}$$

where the active power loss P_{loss} in each branch can be calculated as:

$$P_{loss} = \sum_{k=1}^{m} R_k I_k^2 , \tag{2}$$

where R_k is the resistance of branch k. The parameter I_k represents the current flow through the branch k. Also, m is the number of branches in the network.

Equality and Inequality Constraints. There are two types of constraints as following:

Equality Constraints. The power balance equation with considering RDGs units in the system can be defined as follows:

$$\sum_{i=1}^{N_B} Q_{Gi} + \sum_{j=1}^{N_{DG}} Q_{DG,j} = \sum_{i=1}^{N_B} Q_{Di} + Q_{loss} , \tag{3}$$

$$\sum_{i=1}^{N_B} Q_{Gi} + \sum_{j=1}^{N_{DG}} Q_{DG,j} = \sum_{i=1}^{N_B} Q_{Di} + Q_{loss} , \tag{4}$$

where P_{Gi} and Q_{Gi} are active and reactive power generated on the bus i from the thermal generators; P_{Di} and Q_{Di} are active and reactive power demand at the bus i, respectively; $P_{DG,j}$ and $Q_{DG,j}$ are the active and reactive power generation from the DGs units, respectively; N_{DG} is the total available number of DG units; N_B is the number of power system buses.

Inequality Constraints

a) Voltage Limit Constraints

The voltage at each bus of the distribution system is limited as following:

(5)

where V_{Li} is voltage at load bus i; $V_{Li}^{\min}$ and $V_{Li}^{\max}$ are the minimum and maximum a magnitude of voltage at load bus i.

b) DG sizing limits

$$\sum_{i=1}^{N_{DG}} P_{DGi} \le \sum_{j=1}^{N_B} P_{Dj} + P_{loss} ; \tag{6}$$

$$\sum_{i=1}^{N_{DG}} Q_{DGi} \le \sum_{j=1}^{N_B} Q_{Dj} + Q_{loss} ; \tag{7}$$

$$P_{DG,i}^{\min} \le P_{DG,i} \le P_{DG,i}^{\max} . \tag{8}$$

Particle Swarm Optimization algorithm. The Particle Swarm Optimization (PSO) algorithm, originally introduced by Kennedy and Eberhart in 1995, is a population-based evolutionary computation technique. It is motivated by the behavior of organisms such as fishing schooling and bird flock. In a PSO system, each particle corresponding to the individual of the organism is a candidate solution to the problem at hand. The particles of the population fly around in a multi-dimensional search space, to find out an optimal or sub-optimal solution by competition as well as by cooperation among them [25].

PSO is one of the modern heuristic algorithms and has a great potential to solve complex optimization problems. PSO has several key advantages over other existing optimization techniques [26]:

it is simple and has convergence speed simplicity;

it is a derivative-free algorithm unlike many conventional techniques;

PSO is easy to implement in computer simulations using basic mathematical and logic operations;

it has the flexibility to be integrated with other optimization techniques to form hybrid tools;

it is less sensitive to the nature of the objective function, i.e., convexity or continuity;

it has less parameters to adjust unlike many other competing evolutionary techniques;

it has the ability to escape local minima;

it can handle objective functions with stochastic nature;

it does not require a good initial solution to start its iteration process.

PSO facilitates a better convergence performance than some other optimization procedures like genetic algorithms, which have computationally expensive evolutionary operations such as crossover and mutation.

Original PSO algorithm. PSO is an optimization algorithm based on the population. It is initialized with a random population, called a swarm, and each individual is called a particle. The position of each particle corresponds to a candidate solution to the optimization problem at hand and is treated as a point in a D-dimensional search space. Each particle has a random velocity and flies through the solution space to find the optimal global solution. For given particle i, its position and velocity are denoted as $x_i = (x_{i,1}, x_{i,2}, ..., x_{i,D})$ and $v_i = (v_{i,1}, v_{i,2}, ..., v_{i,D})$ respectively. During the flight, the best position for each particle is stored in its memory and called the personal best (*Pbest*); $Pbest_i^k = (x_{i,1}^{Pbest}, x_{i,2}^{Pbest}, ..., x_{i,D}^{Pbest})$. The lowest value of all the Pbest, determines the global best (*Gbest* is the best particle position) of the swarm; $Gbest^k = (x_1^{Gbest}, x_2^{Gbest}, ..., x_D^{Gbest})$. For the next iteration, the modified velocity and position of each particle can be calculated as follows [27]:

$$v_i^{k+1} = v_i^k + c_1 R_1 (Pbest_i^k - x_i^k) + c_2 R_2 (Gbest^k - x_i^k); \quad (9)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1}, \quad (10)$$

where k is the index of iterations; v_i^k is the velocity of particle i at current iteration k; x_i^k is the position of particle i at current iteration k; R_1 & R_2 are uniform random value in the range between [0, 1]; $Pbest_i^k$ best position of particle i until current iteration k; $Gbest^k$ the lowest value of all the *Pbest* until current iteration k; c_1 and c_2 are acceleration coefficients, which are set to 2.0 commonly.

c_1 is called the **cognitive** component and it encourages the particles to move toward their own best positions found so far. c_2 is called the **social** component and it represents the collaborative effect of the particles in finding the global optimal solution. The social component always pulls the particles toward the global best particle found so far.

Time varying inertia weight. Significant improvement in the performance of the algorithm was obtained while a factor called inertia weight was included into the fundamental PSO equation. This inertia weight decreases linearly with respect to time. Generally, for the initial stages of the search process large inertia weight to enhance the global exploration (searching new area) is recommended while for the last stages the inertia weight is reduced for local exploration (fine tuning the current search area) [28]. The PSO equation incorporating (w) is given as follows:

$$v_i^{k+1} = w\, v_i^k + c_1 R_1 (Pbest_i^k - x_i^k) + c_2 R_2 (Gbest^k - x_i^k); \quad (11)$$

$$w = (w_{\max} - w_{\min}) \left(\frac{k_{\max} - k}{k_{\max}} \right) + w_{\min}, \quad (12)$$

where w_{max} and w_{min} are the initial and final values of the inertia weight. The typical values of w varies from 0,9 to 0,4. k_{max} and k are the maximum number of iteration and the current iteration number.

In this paper nonlinear time varying inertia weight (NTVIW) has been used so that a decrement in the initial stages is very slow and with iterations it decrements at a faster rate; this makes exploit more search space initially and later to follow the leader particles which are selected based on the dominance-based sorting technique in the objective space [29]. The NTVIW can be expressed as follows:

$$w = (w_{\min} - w_{\max}) \left(\frac{k}{k_{\max}} \right)^2 + w_{\max}. \quad (13)$$

Nonlinear Time varying accelerating coefficients (NTVAC). The acceleration coefficients (the cognitive component c_1 and the social component c_2) are fixed values in classic PSO. Studies normally keep each of the acceleration coefficients at 2. The proper control of these two components is very important to find the optimum solution accurately and efficiently [27]. However, a relatively high value of the cognitive component, compared with the social component, will result in excessive wandering of individuals through the search space. In contrast, a relatively high value of the social component may lead particles to rush prematurely toward a local optimum [27].

In population-based optimization methods, the policy is to encourage the individuals to roam through the entire search space during the initial part of the search without clustering around local optima. During the latter stages, however, convergence towards the global optima should be encouraged to find the optimum solution efficiently [27, 30]. In Time varying accelerating coefficients (TVAC), it is achieved by changing the acceleration coefficients and with time in such a manner that the cognitive component is reduced while the social component is increased as the search proceeds. A large cognitive component and small social component at the beginning allow particles to move around the search space instead of moving towards the population best prematurely. During the latter stage in optimization a small cognitive component and a large social component allow the particles to converge to the global optima [30]. The acceleration coefficients are updated using the following equations:

$$c_1 = (c_{1,f} - c_{1,i}) \frac{k}{k_{\max}} + c_{1,i}; \quad (14)$$

$$c_2 = (c_{2,f} - c_{2,i}) \frac{k}{k_{\max}} + c_{2,i}, \quad (15)$$

where $c_{1,i}$, $c_{1,f}$, $c_{2,i}$, and $c_{2,f}$ are initial and final values of cognitive and social acceleration factors, respectively.

In this paper, a new variant called nonlinear time varying acceleration coefficients (NTVAC) are added in the PSO method as a parameter update mechanism that has powerful capability of tuning the cognitive component c_1 and social component c_2. The NTVAC can be expressed as follows [31]:

$$c_1 = -(c_{1,f} - c_{1,i})\left(\frac{k}{k_{\max}}\right)^2 + c_{1,f}; \tag{16}$$

$$c_2 = c_{1,i}\left(1 - \frac{k}{k_{\max}}\right)^2 + c_{1,f}\left(\frac{k}{k_{\max}}\right). \tag{17}$$

Simulation and results. The proposed PSO-NTVAC method was created in the MATLAB environment (R2018a version), and the simulations were performed on Intel® Core™ i7-2670QM CPU @ 2.20GHz, with an 8.00 GB RAM setup and a 64-bit operating system.

Test System Cases. IEEE 14-bus, IEEE 30-bus, IEEE 57-bus, IEEE 33-bus and IEEE 69-node systems were selected to evaluate the location and size of distributed generation using PSO-NTVAC. General information about these systems is presented in Table 1. The system line and bus data as well as the system constraints are found in reference [1, 7, 32].

The results of IEEE 14-Bus system. Fig. 1 shows the IEEE 14-bus system used to evaluate location and size of DGs and reduce power losses in meshed network. The total load demand of this system is 259 MW and 73,5 Mvar, with the active and reactive power loss as 13,393 MW and 54,54 Mvar respectively.

The minimization of system losses is considered an objective function and is achieved by introducing DGs in the system. The optimal location and size of the DGs were found by the PSO-NTVAC and the corresponding results are listed in Table 2. The DG units can deliver active power and reactive power where the DG units are represented as PQ model at power factor 0,95. The number of DG's is varied from one unit to four units. The P_{loss} is reduced by 72,19 % with one DGs and by 77,15% with four DG units added to the system. Also, the Q_{loss} is reduced from 73,5 Mvar to 19,94 Mvar with one DG unit while with 4 DG units the Q_{loss} is reduced to 14,30 Mvar. Fig. 2 shows the effect of the number of DG units on P_{loss} minimization. The convergence characteristics of the PSO-NTVAC algorithm for DGs integration in system are presented in Fig. 3.

The results of IEEE 30-Bus system. The single line diagram of 30-bus system is shown in Fig. 4. This system's total load demand is 283,4 MW and 126,2 Mvar, respectively, with active and reactive power losses of 5,786 MW and 29,76 Mvar, respectively. Where the initial value of voltage deviation (VD) is 1,1484 pu. This system is a part of the American Electric Power Service Corporation network. The DG units can deliver active power and reactive power where the DG units are represented as PQ model at power

Table 1

Information of IEEE test system cases

Specifications	IEEE 14 meshed	IEEE 30 meshed	IEEE 57 meshed	IEEE 33 Radial	IEEE 69 Radial
Number of buses	14	30	57	33	69
Lines or branches	20	41	80	37	68
Generators/Feeders	5	6	7	1	1
Transformers	3	4	17	0	0
Loads bus (PQ)	9	24	50	32	68
Shunt capacitors	1	2	3	0	0
Slack bus	1	1	1	1	1
PV buses	4	5	6	0	0

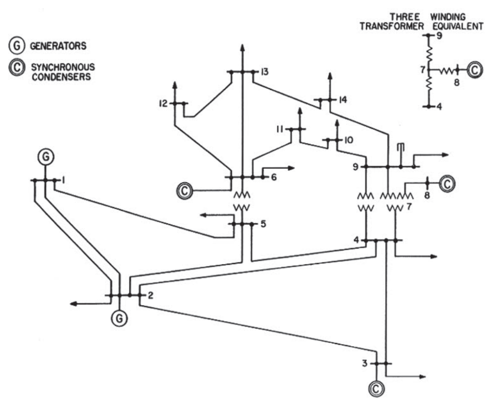

Fig. 1. Single line diagram of IEEE 14-bus

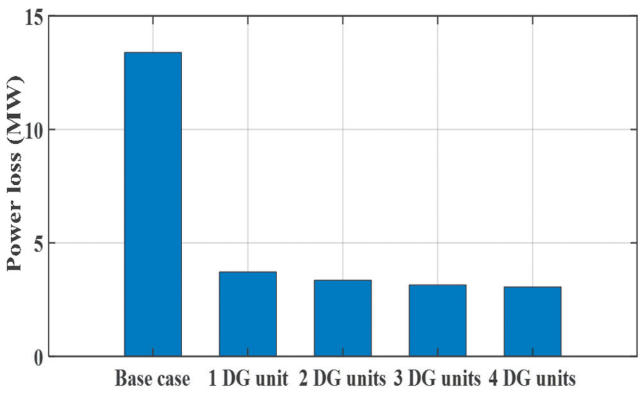

Fig. 2. Comparison of P_{loss} with DGs for 14 bus system

factor 0,95. The number of DG's is varied from one unit to four units. Table 3 shows the optimal location, size, and the real, reactive power losses and voltage deviation after the placement of many DGs in the network. From this table, it can be observed that the P_{loss} decreased from the P_{loss} without any DG unit to 45,97%, 56,52%, 64,88%, and 71,5% by integrating 1 DG, 2 DG, 3 DG, and 4 DG, respectively. In addition, when one DG unit was added to the system, the VD was reduced from 1,1484 pu to 1,0669 pu, while when 4 DG units were added, the VD was reduced to 0,589 pu. Fig. 5 shows the minimization in P_{loss} with a change in the number of DG units added to the grid. Fig. 6 illustrates the convergence characteristics of the PSO-NTVAC for DGs integration in the grid. Fig. 7 illustrates the voltage profile enhancement in relation to the number of DG units.

The results of IEEE 57-Bus system. This system has an overall load demand of 1250,8 MW and 336,4 Mvar respectively, with the active and reactive power loss as 27,864 MW and 121,67 Mvar, respectively. While the initial VD is 1,2336 pu. The single line diagram of this system is shown in Fig. 8. The effect of the number of DG

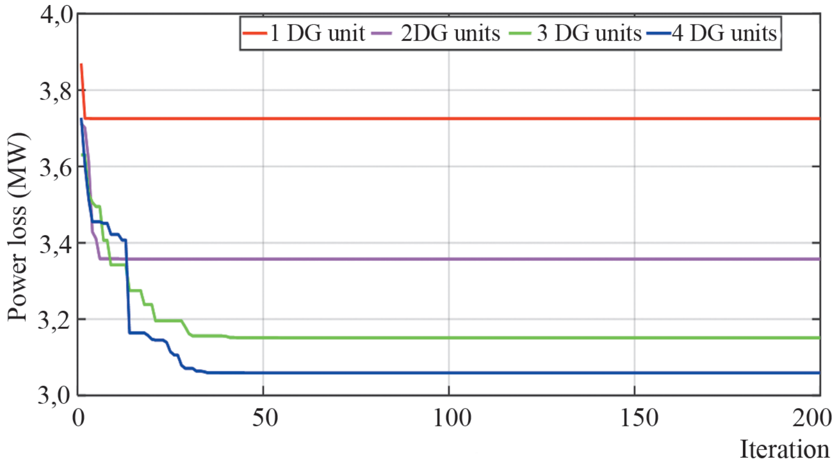

Fig. 3. Convergence characteristics of PSO-NTVAC for DGs integration in IEEE 14 bus

Table 2

The results after applying multiple DGs for IEEE 14 bus

Item	1 DG	2 DG		3 DG			4 DG			
DG location	4	4	14	4	5	14	4	5	13	14
DG size, MW	181,3	161,42	21,18	125,25	49,82	19,13	123,61	41,03	13,74	15,88
Q_{loss}, Mvar	19,94	15,85		15,81			14,30			
P_{loss}, MW	3,725	3,357		3,151			3,06			
P_{loss} reduction, %	72,19	74,94		76,47			77,15			
Q_{loss} reduction, %	63,44	70,94		71,01			73,78			

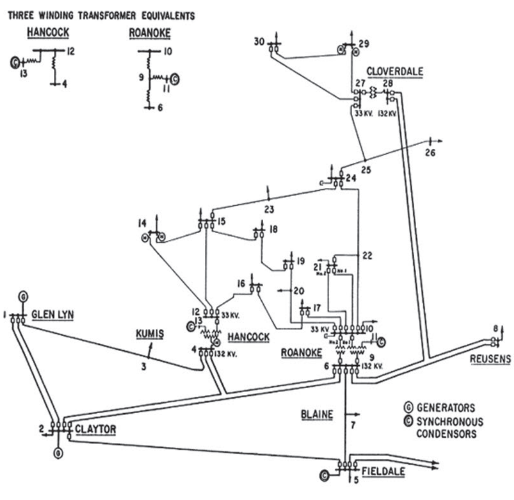

Fig. 4. Single line diagram of IEEE 30-bus

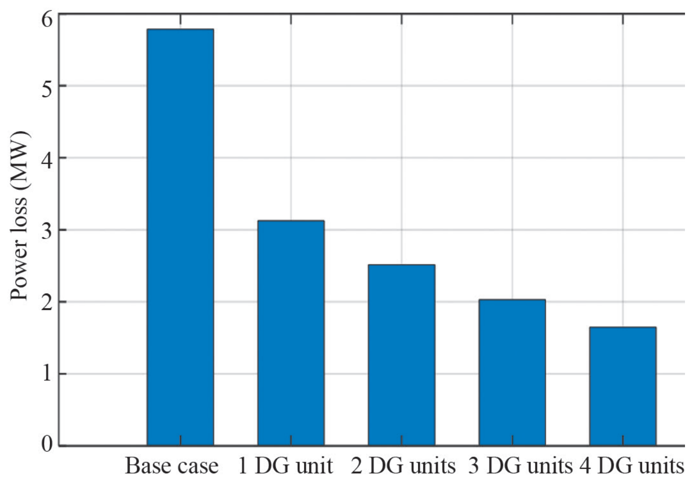

Fig. 5. Comparison of P_{loss} with DGs for IEEE 30 bus

units in P_{loss} minimization is shown in Fig. 9. The optimal locations, sizes, and active power losses are given in Table 4. This table shows that by integrating 1 DG, 2 DG, 3 DG, and 4 DG, the P_{loss} decreased by 42,92%, 50,37%, 55%, and 57,91%, respectively, from the Ploss without any DG unit. Also, the percentage reduction in Q_{loss} is 39,85%, 49,2%, 52,98%, 54,4%, respectively, from the Q_{loss} without any DG unit.

The results of IEEE 33-Bus system. The single line diagram of this system is shown in Fig. 10. This system has total load of 3715 kW and 2300 kvar, the total generation 3917,677 kW and 2435,14 kvar, with the active and reactive power loss as 202,677 kW and 135,141 kvar, respectively. While the initial VD is 1,7009 pu.

Case 1: *DGs is capable of injecting active power only*

In this case, the DG units are only capable of supplying the network with active power only, i.e., operating at the unity power factor. Table 5 shows a comparison of the results of incorporating multiple DGs into this network. Optimally placing a single DG in the network contributes 48,701% reduction in P_{loss} and reduces the VD from 1,7009 pu to 0,8296 pu. When Placing 2 DG at the same time reduces P_{loss} by 57,61% and reduces the VD to 0,6471 pu, while placing 3 DGs at the same time reduces

Table 3

The results of applying multiple DGs to IEEE 30 bus

Item	1 DG	2 DG		3 DG			4 DG			
DG location	6	7	24	7	21	30	7	19	24	30
DG size, MW	94	58,89	27,09	46,79	34,01	13,22	44,92	18,89	20,49	12,06
Q_{loss}, Mvar	19,89	14,604		11,954			10,8117			
P_{loss}, MW	3,126	2,516		2,032			1,649			
P_{loss} reduction, %	45,97	56,52		64,88			71,5			
Q_{loss} reduction, %	33,17	50,94		59,85			63,67			
VD, pu	1,0669	0,8701		0,7045			0,5890			

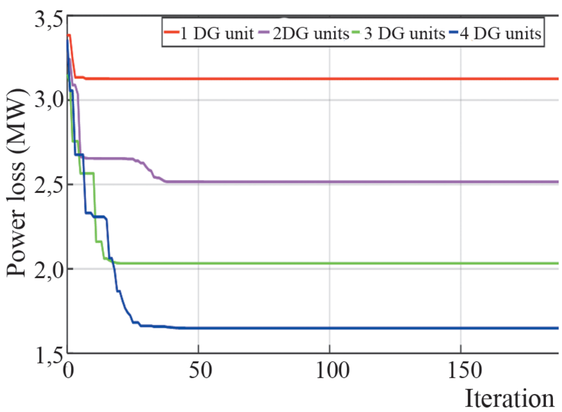

Fig. 6. Convergence characteristics of PSO-NTVAC for DGs integration in IEEE 30 bus

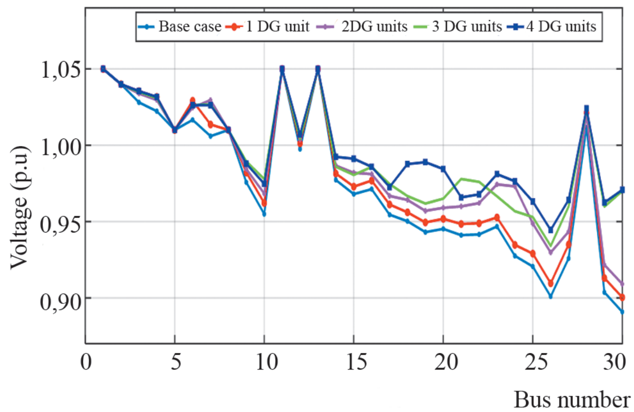

Fig. 7. Voltage profile with DGs for IEEE 30 bus

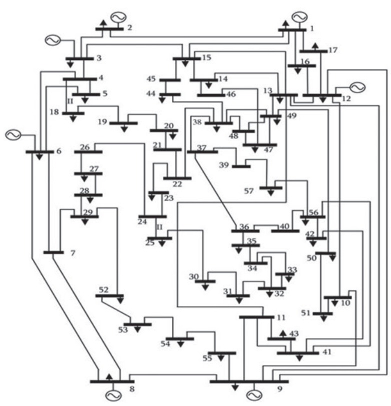

Fig. 8. Single line diagram of IEEE 57-bus

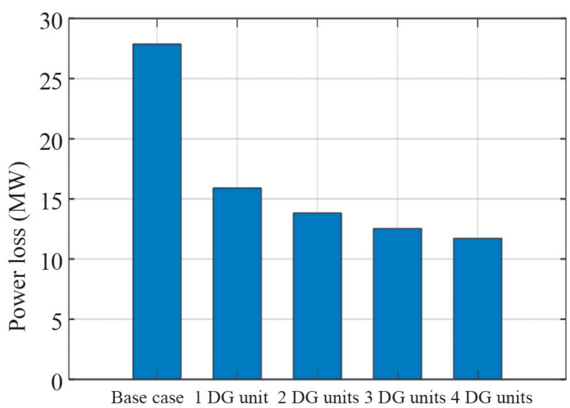

Fig. 9. Comparison of P_{loss} with DGs for IEEE 57-bus

Table 4

The results of integrating multiple DGs to the IEEE 57-bus

Item	1 DG	2 DG		3 DG			4 DG			
DG location	13	13	38	13	16	38	13	16	38	53
DG size, MW	261,08	190,08	88,07	146,52	86,24	87,67	131,13	83,79	86,39	22,04
Q_{loss}, Mvar	73,18	61,82		57,2			55,49			
P_{loss}, MW	15,905	13,83		12,54			11,73			
P_{loss} reduction, %	42,92	50,37		55			57,91			
Q_{loss} reduction, %	39,85	49,2		52,98			54,4			
VD, pu	1,1493	1,1207		1,12			1,0975			

Table 5

Comparison of results for incorporating multiple DGs units into an IEEE 33-bus for Case 1

Item	1 DG	2 DG		3 DG			4 DG			
DG location	6	13	30	14	24	30	7	14	24	31
DG size, kW	2575,3	846,4	1158,7	754	1099,4	1071,4	916,2	585,3	980,9	708,5
DG size, kvar	74,79	58,55		49,39			45,39			
P_{loss}, kW	103,97	85,91		71,46			65,94			
P_{loss} reduction, %	48,7	57,61		64,74			67,47			
Q_{loss} reduction, %	23,1	56,6		63,4			66,4			
VD, pu	0,8296	0,6471		0,5873			0,5356			

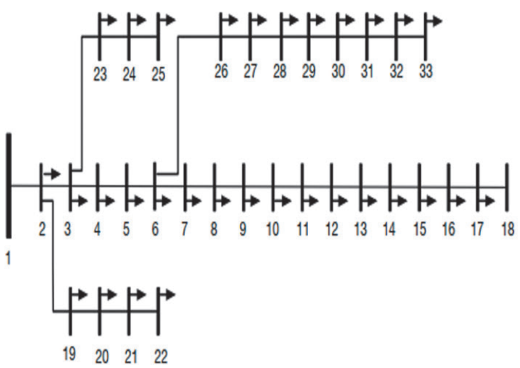

Fig. 10. Single line diagram of IEEE 33-bus

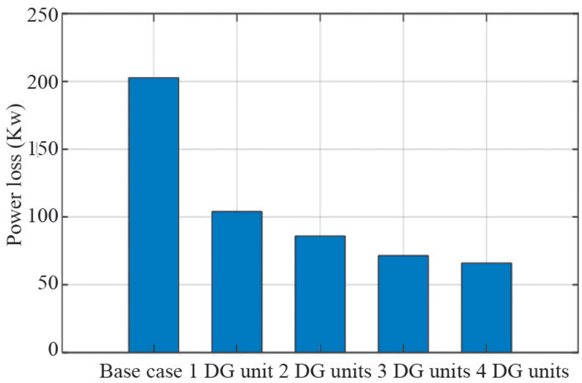

Fig. 11. Comparison of decreased Ploss with an increased number of DG units for case 1

power loss by 64,74% and reduces the VD to 0,5873 pu and Placing 4 DG at the same time reduces P_{loss} by 67,47% and reduces the VD to 0,5356 pu. Fig. 11 describes the reduction in P_{loss} as the number of DG units added to the network is increased. Fig. 12 shows the convergence characteristics of PSO-NTVAC with the integration of DG into the network. Fig. 13 shows the improvement in the voltage profile compared to the number of DG units. From these figures, it is clear that the voltage profiles are improved after the integration of DG units.

Case 2: *DGs is capable of injecting active and reactive power.*

In this case the DG units can provide both active and reactive power to the network. Fig. 14 describes the reduction in P_{loss} as the number of DG units added to the network is increased. Fig. 15 shows the improvement in the voltage profile compared to the number of DG units. The optimal location of DGs, DGs size, P_{loss}, and VD are shown in Tables 6. From this table, it can be observed that the P_{loss} decreased to 69,72%, 85,94%, 94,26%, and 96,83% by integrating 1 DG, 2 DG, 3 DG and 4 DG, respectively. In addition, when one DG unit was added to the system, the VD was reduced from 1.7009 pu to 0,4777 pu, while when 4 DG units were added, the VD was reduced to 0,0579 pu.

The results of IEEE 69-Bus system. This is a large-scale radial distribution system with 69 buses and 68 branches. The single line diagram of this system is shown in Fig.16. The total load of 3802,1 kW and 2694,7 kvar and the total generation 4027,1 kW and 2796,865 kvar, with the active and reactive power loss as 225 kW and 102,1648 kvar, respectively. The VD without the integration of the DGs in the network is 1,8369 pu.

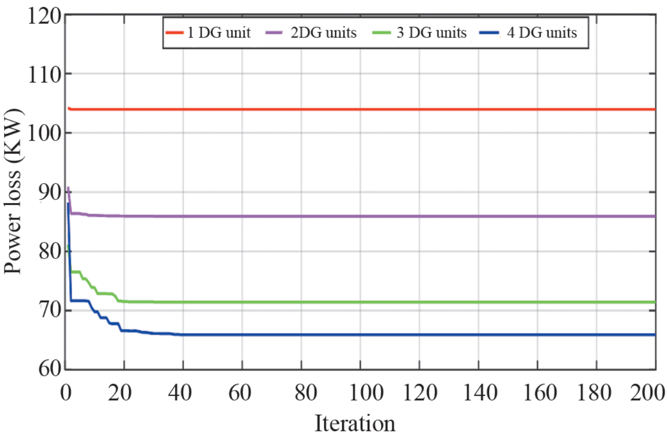

Fig. 12. Convergence characteristics of PSO-NTVAC for DGs integration in IEEE 33-bus for case 1

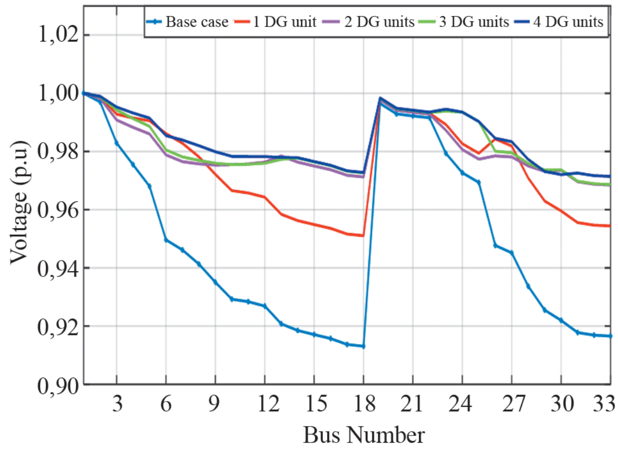

Fig. 13. Voltage profile with DGs for IEEE 33-bus for case 1

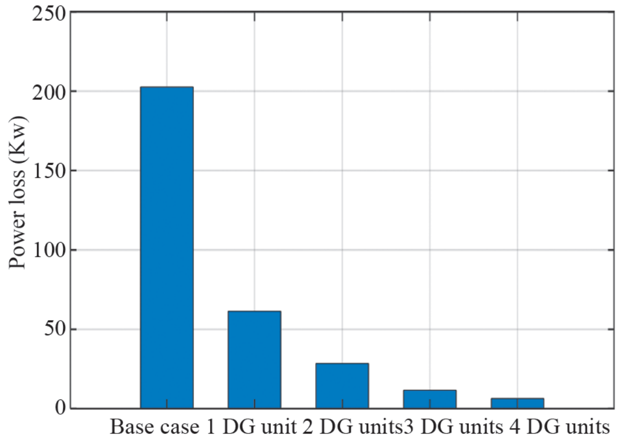

Fig. 14. Comparison of P_{loss} with DGs for 33-bus system for case 2

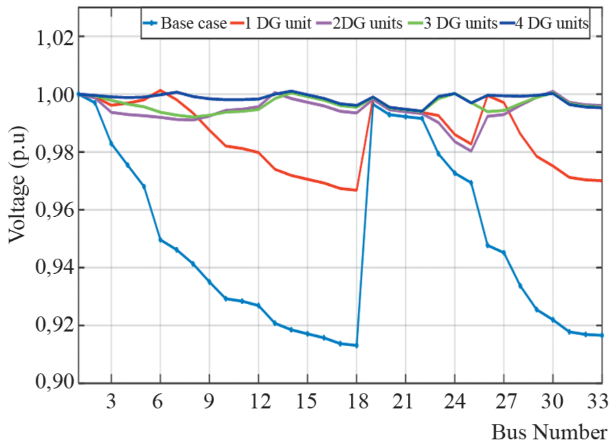

Fig. 15. Voltage profile with DGs for IEEE 33-bus for case 2

Table 6

Comparison of results for incorporating multiple dgs units into an IEEE 33 bus for case 2

Item	1 DG	2 DG		3 DG			4 DG			
DG location	6	13	30	14	24	30	7	14	24	30
DG size, kW	2544,7	839,4	1140,4	747,5	1078,3	1048,6	795,1	582,6	966,1	787,2
DG size, kvar	1750,2	395,6	1065,7	350,1	521,3	1021,0	380,4	271,0	469,5	893,9
Q_{loss}, kvar	48,3671	20,401		9,692			5,770			
P_{loss}, kW	61,3634	28,4918		11,6299			6,4282			
P_{loss} reduction, %	69,72	85,94		94,26			96,83			
Q_{loss} reduction, %	64,2	84,9		92,83			95,73			
VD, pu	0,4777	0,1886		0,1205			0,0579			

Case 3: *DGs is capable of injecting active power only*

In this case, the DGs units can only provide active power to the network, i.e., operating at the unity power factor. Table 7 shows a comparison of the results of incorporating multiple DGs into this network. Optimally placing a 1 DG in the network contributes 63,01% reduction in P_{loss} and reduces the VD from 1,8369 pu to 0,8724 pu. When Placing 2 DG at the same time reduces P_{loss} by 68,14% and reduces the VD to 0,4997 pu, while placing 3 DGs at the same time reduces P_{loss} by 69,14 % and reduces the VD to 0,4493 pu and Placing 4 DGs at the same time reduces P_{loss} by 69681% and reduces the VD to 0,4448 pu. Fig. 17 describes the reduction in P_{loss} as the number of DG units added to the network is increased. Fig. 18 shows the improvement in the voltage profile compared to the number of DG units. From this figure, it is clear that the voltage profiles are improved after the integration of DG units.

Case 4: *DG is capable of injecting active and reactive power to 69 bus system.*

Table 7

Comparison of results for incorporating multiple DGs units into an IEEE 69 bus for case 3

Item	1 DG	2 DG		3 DG			4 DG			
DG location	61	17	61	11	18	61	11	18	50	61
DG size, kW	1872,7	531,5	1781,5	526,8	380,4	1719,0	526,0	380,4	718,5	1718,8
Q_{loss}, kvar	40,53	35,94		34,96			31,27			
P_{loss}, kW	83,22	71,68		69,43			67,92			
P_{loss} reduction, %	63,01	68,14		69,14			69,81			
Q_{loss} reduction, %	60,32	64,82		65,78			69,39			
VD, pu	0,8724	0,4997		0,4493			0,4448			

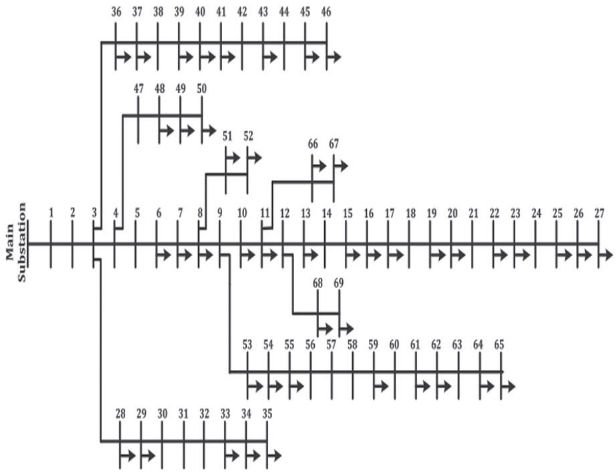

Fig. 16. Single line diagram of IEEE 69-bus

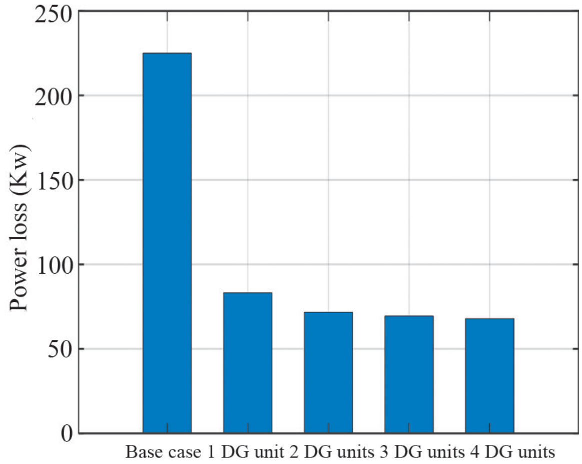

Fig. 17. Comparison of P_{loss} with DGs for IEEE 69 bus for case 3

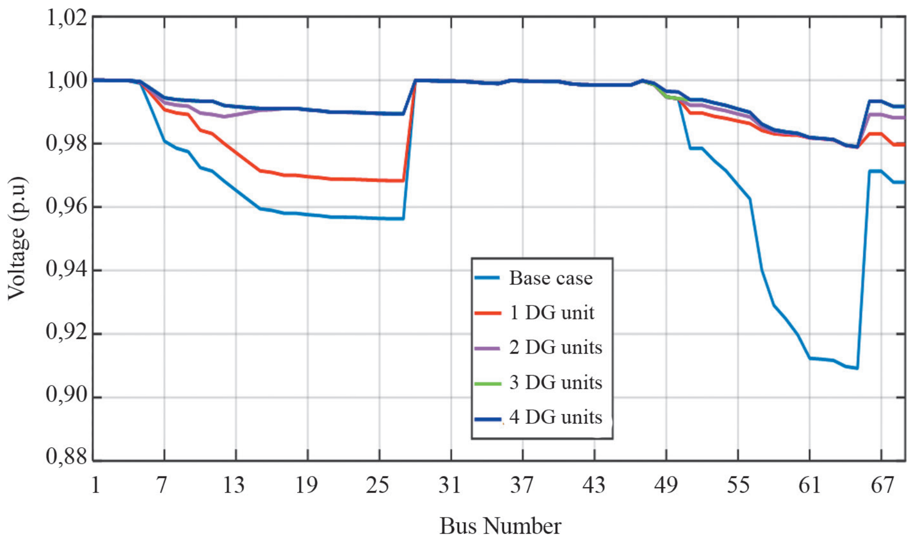

Fig. 18. Voltage profile with DGs for IEEE 69-bus for case 3

In this case, the DG units can provide both active and reactive power to the network. Fig. 19 depicts the reduction in P_{loss} as the number of DG units added to the network is increased. Fig. 20 shows the improvement in the voltage profile compared to the number of DG units. The optimal location of DGs, DGs size, P_{loss}, Q_{loss}, and VD are shown in Table 8. From this table, it can be observed that the P_{loss} decreased to 89,7%, 96,79%, 98,1%, and 99,1% by integrating 1 DG, 2 DG, 3 DG, and 4 DG, respectively. In addition, when 1 DG unit was added to the system, the VD was reduced from 1,8369 pu to 0,5868 pu, while when 4 DG units were added, the VD was reduced to 0,0518 pu.

Conclusion. In this paper an improved version of particle swarm optimization (PSO) known as nonlinear time-varying acceleration coefficients PSO (PSO-NTVAC) is used to find the optimal placement and size of single

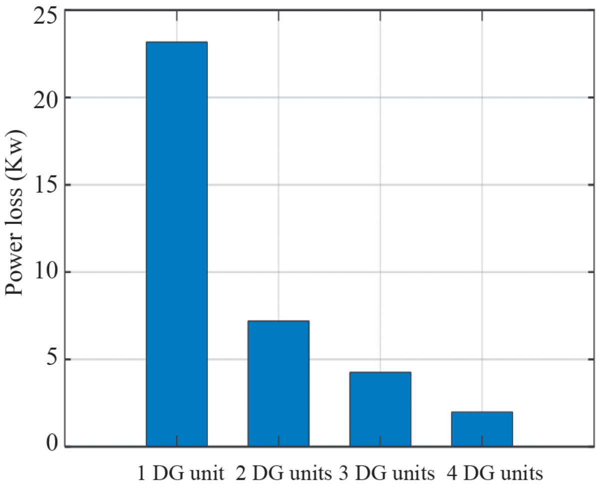

Fig. 19. Comparison of P_{loss} with DGs for IEEE 69-bus for case 4

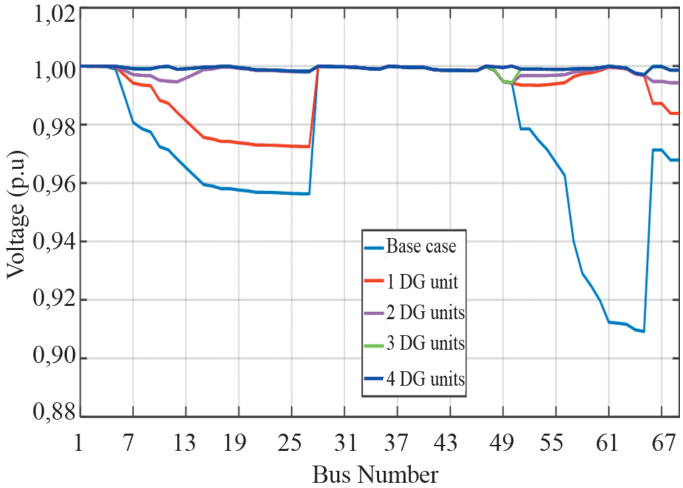

Fig. 20. Voltage profile with DGs for IEEE 69-bus for case 4

Table 8

Comparison of results for incorporating multiple DGs units into an IEEE 69 bus for case 4

Item	1 DG	2 DG		3 DG			4 DG			
DG location	61	17	61	11	18	61	11	18	50	61
DG size, kW	1828,5	522,3	1734,7	494,5	379,1	1674,3	493,6	379,1	718,1	1674,1
DG size, kvar	1300,6	353,4	1238,5	353,8	251,5	1195,5	353,3	251,5	512,7	1195,3
Q_{loss}, kvar	14,379	8,045		6,759			1,199			
P_{loss}, kW	23,1704	7,2039		4,2676			1,9951			
P_{loss} reduction, %	89,7	96,79		98,1			99,1			
Q_{loss} reduction, %	85,93	92,13		93,38			98,82			
VD, pu	0,5868	0,1299		0,0645			0,0518			

and multiple DG units based on renewable energy source in power systems. Also, the impact of DGs installation on power system performance and parameters such as voltage, active and reactive power loss is investigated. The main objective of installing DG units is to reduce the power losses of the radial and meshed networks. The proposed technique is implemented on five different IEEE standard bus systems which are IEEE 14 bus, 30 bus, 57 bus, 33 bus, and 69 bus. The results show the applicability of this technique in various network systems. Also, the results show clearly a significant reduction in an active and reactive power loss of the system and the voltage profile improvement if the optimum bus and value of RDGs are known proving the advantages of RDGs penetration into the system.

The researcher [Mamdouh K. Ahmed] is funded by a scholarship [Ph.D.] under the Joint (Executive Program between the Arab Republic of Egypt and the Russian Federation).

REFERENCES

1. **Ahmed M.K., Osman M.H., Korovkin N.V.** Optimal reactive power dispatch in power system comprising renewable energy sources by means of a multi-objective particle swarm algorithm. – Materials Science. Power Engineering, 2021, vol. 27, No. 1, pp. 5–20, DOI: 10.18721/JEST.27101.

2. **Hung D.Q., Nadarajah M, Bansal R.** Analytical Expressions for DG Allocation in Primary Distribution Networks. – IEEE Transactions on Energy Conversion, 2010, vol. 25, No. 3, pp. 814–820, DOI: 10.1109/TEC.2010.2044414.

3. **Prabha D.R., et al.** Optimal Location and Sizing of Distributed Generation Unit Using Intelligent Water Drop Algorithm. – Sustainable Energy Technologies and Assessments, 2015, vol. 11, pp. 106–113, DOI: 10.1016/j.seta.2015.07.003.

4. **Vadhera S., Mahajan S.** Optimal Allocation of Dispersed Generation Unit in a Network System. – International Conference on Microelectronics, Computing and Communication (MicroCom), 2016, pp. 0–4, 2016, DOI: 10.1109/MicroCom.2016.7522519.

5. **Osman M.H., Refaat A., Korovkin N.V.** A Novel Method to Extract Single-Diode PV Parameters Based on Datasheet Values. – Elektrichestvo, 2021, No. 2, pp. 16–21.

6. **Refaat A., Elgamal M., Korovkin N.V.** A Novel Grid-Connected Photovoltaic Centralized Inverter Topology to Improve the Power Harvest during Partial Shading Condition. – Elektrichestvo, 2019, No. 7, pp. 59–68, DOI: 10.24160/0013-5380-2019-7-59-68.

7. **ChithraDevi S.A., Lakshminarasimman L., Balamurugan R.** Stud Krill Herd Algorithm for Multiple DG Placement and Sizing in a Radial Distribution System. – Engineering Science and Technology, an International Journal, 2017, vol. 20, No. 2, pp. 748–759, DOI: 10.1016/j.jestch.2016.11.009.

8. **Martín García J.A., Gil-Mena A.J.** Optimal Distributed Generation Location and Size Using a Modified Teaching-Learning Based Optimization Algorithm. – International Journal of Electrical Power and Energy Systems, 2013, vol. 50, No. 1, pp. 65–75, DOI: 10.1016/j.ijepes.2013.02.023.

9. **Rezaee Jordehi A.** Allocation of Distributed Generation Units in Electric Power Systems: A Review. – Renewable and Sustainable

Energy Reviews, 2016, vol. 56, pp. 893–905, DOI: 10.1016/j.rser.2015.11.086.

10. **Reddy P.D.P., Reddy V.C.V., Manohar T.G.** Whale Optimization Algorithm for Optimal Sizing of Renewable Resources for Loss Reduction in Distribution Systems. – Renewables: Wind, Water, and Solar, 2017, vol. 4, No. 1, pp. 1–13, DOI: 10.1186/s40807-017-0040-1.

11. **Refaat A., Osman M.H., Korovkin N.V.** Optimum Power Extraction from Non-Uniform Aged PV Array Using Current Collector Optimizer Topology. – Elektrichestvo, 2019, No. 10, pp. 54–60.

12. **Wang C., Nehrir M.H.** Analytical approaches for optimal placement of distributed generation sources in power systems. – IEEE Transactions on Power Systems, 2004, vol. 19, No. 4, pp. 2068–2076, DOI: 10.1109/TPWRS.2004.836189.

13. **Shehata A.A., Ahmed M.K.** State estimation accuracy enhancement for optimal power system steady state modes. – IOP Conference Series: Materials Science and Engineering, 2019, vol. 643, No. 1, DOI: 10.1088/1757-899X/643/1/012049.

14. **Babaei E., Galvani S., Nejabatkhah F.** Optimal Placement of DG Units Considering Power Losses Minimization and Voltage Stability Enhancement in Power System. – International Journal of Automation and Control Engineering, 2014, vol. 3, No. 1, DOI: 10.14355/ijace.2014.0301.01.

15. **Prakash D.B., Lakshminarayana C.** Multiple DG Placements in Distribution System for Power Loss Reduction Using PSO Algorithm. – Procedia Technology, 2016, vol. 25, No. Raerest, pp. 785–792, DOI: 10.1016/j.protcy.2016.08.173.

16. **Shehata A.A., et al.** Optimal Placement and Sizing of FACTS Devices Based on Autonomous Groups Partical Swarm Optimization Technique. – Archives of Electrical Engineering, 2020, vol. 70, No. 1, DOI: 10.24425/aee.2021.136059.

17. **Shukla T.N., et al.** Optimal Sizing of Distributed Generation Placed on Radial Distribution System. – Electric Power Components and Systems, 2010, vol. 38, No. 3, pp. 260–274, DOI: 10.1080/15325000903273403.

18. **Abu-Mouti F.S., El-Hawary M.E.** Optimal Distributed Generation Allocation and Sizing in Distribution Systems Via Artificial Bee Colony Algorithm. – IEEE Transactions on Power Delivery, 2011, vol. 26, No. 4, pp. 2090–2101, DOI: 10.1109/TPWRD.2011.2158246.

19. **Elattar E.E., et al.** Optimal Location and Sizing of Distributed Generators Based on Renewable Energy Sources Using Modified Moth Flame Optimization Technique. – IEEE Access, 2020, vol. 8, pp. 109625–109638, DOI: 10.1109/ACCESS.2020.3001758.

20. **Prakash D.B., Lakshminarayana C.** Multiple DG Placements in Radial Distribution System for Multi Objectives Using Whale Optimization Algorithm. – Alexandria Engineering Journal, 2018, vol. 57, No. 4, pp. 2797–2806, DOI: 10.1016/j.aej.2017.11.003.

21. **Mohamed I.A., Kowsalya M.** Optimal Size and Siting of Multiple Distributed Generators in Distribution System Using Bacterial Foraging Optimization. – Swarm and Evolutionary Computation, 2014, vol. 15, pp. 58–65, DOI: 10.1016/j.swevo.2013.12.001.

22. **Wang L., Singh C.** Reliability-Constrained Optimum Placement of Reclosers and Distributed Generators in Distribution Networks Using an Ant Colony System Algorithm. – IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews, 2008, vol. 38, No. 6, pp. 757–764, DOI: 10.1109/TSMCC.2008.2001573.

23. **Arya L.D., Koshti A., Choube S.C.** Distributed Generation Planning Using Differential Evolution Accounting Voltage Stability Consideration. – International Journal of Electrical Power and Energy Systems, 2012, vol. 42, No. 1, pp. 196–207, DOI: 10.1016/j.ijepes.2012.04.011.

24. **Reddy P.D.P., Reddy V., Manohar T.** Ant Lion Optimization Algorithm for Optimal Sizing of Renewable Energy Resources for Loss Reduction in Distribution Systems. – Journal of Electrical Systems and Information Technology, 2018, vol. 5, No. 3, pp. 663–680, DOI: 10.1016/j.jesit.2017.06.001.

25. **Sun J., Feng B., Xu W.** Particle Swarm Optimization with Particles Having Quantum Behavior. – Proceedings of the 2004 Congress on Evolutionary Computation, CEC2004, 2004, vol. 1, pp. 325–331, DOI: 10.1109/cec.2004.1330875.

26. **Alrashidi M.R., El-Hawary M.E.** A Survey of Particle Swarm Optimization Applications in Electric Power Systems. – IEEE Transactions on Evolutionary Computation, 2009, vol. 13, No. 4, pp. 913–918, DOI:10.1109/TEVC.2006.880326.

27. **Ratnaweera A., Halgamuge S.K., Watson H.C.** Self-Organizing Hierarchical Particle Swarm Optimizer with Time-Varying Acceleration Coefficients. – IEEE Transactions on Evolutionary Computation, 2004, vol. 8, No. 3, pp. 240–255, DOI: 10.1109/TEVC.2004.826071.

28. **Samakpong T., Ongsakul W., Manjiparambil N.M.** Optimal Power Flow Incorporating Renewable Uncertainty Related Opportunity Costs. – Computational Intelligence, 2020, DOI: 10.1111/coin.12316.

29. **Jithendranath J., Das D.** Multi-Objective Optimal Power Flow in Islanded Microgrids with Solar PV Generation by NLTV-MOPSO. – IETE Journal of Research, 2021, DOI: 10.1080/03772063.2021.1886609.

30. **Chaturvedi K.T., Pandit M., Srivastava L.** Self-Organizing Hierarchical Particle Swarm Optimization for Nonconvex Economic Dispatch. – IEEE Transactions on Power Systems, 2008, vol. 23, No. 3, pp. 1079–1087, DOI: 10.1109/TPWRS.2008.926455.

31. **Chen K., et al.** An Ameliorated Particle Swarm Optimizer for Solving Numerical Optimization Problems. – Applied Soft Computing Journal, 2018, vol. 73, pp. 482–496, DOI: 10.1016/j.asoc.2018.09.007.

32. **Mamdouh K.A., Shehata A.A., Korovkin N.V.** Multi-Objective Voltage Control and Reactive Power Optimization Based on Multi-Objective Particle Swarm Algorithm. – IOP Conference Series: Materials Science and Engineering, 2019, vol. 643, No. 1, DOI: 10.1088/1757-899X/643/1/012089.

[22.09.2021]

*The authors: **Ahmed Mamdouh Kamaleldin** (Al-Azhar University, Cairo, Egypt) – Assistant of Electrical Engineering Dept., Faculty of Engineering.*

***Osman Mohamed Hassan** (Al-Azhar University, Cairo, Egypt) – Assistant of Electrical Engineering Dept., Faculty of Engineering.*

***Korovkin Nikolay V.** (Peter the Great St. Petersburg Polytechnic University, Saint-Petersburg, Russia) – Professor of Higher School of High Voltage Energy, Dr. Sci. (Eng).*

Электричество, 2021, № 12, с. 15–27 *DOI:10.24160/0013-5380-2021-12-15-27*

Оптимизация расположения и мощности возобновляемых распределенных источников энергии с использованием модифицированного метода роя частиц

АХМЕД Мамдух Камалелдин – *ассистент кафедры электротехники, Университет Аль-Азхар, Каир, Египет.*

ОСМАН Мохамед Хассан – *ассистент кафедры электротехники, Университет Аль-Азхар, Каир, Египет.*

КОРОВКИН Николай Владимирович – *доктор техн. наук, профессор высшей школы «Высоковольтная энергетика», Санкт-Петербургский политехнический университет Петра Великого, Санкт-Петербург, Россия.*

Проникновение в энергосистемы возобновляемых распределенных источников, использующих, например, энергию ветра и(или) солнца, обещает множество технических и экологических преимуществ. К ним относятся повышение надежности энергосистемы, обеспечение растущих требований к экологичности, снижение потерь мощности и улучшение профиля напряжения. Однако установка источников распределенной генерации может привести и к негативным последствиям, если их мощность и расположение не определены должным образом. Поэтому необходимо развитие методов поиска оптимальных расположения и мощности энергоустановок распределенной генерации, минимизирующих возможные негативные последствия. Для определения местоположения и мощности источников распределенной генерации в энергосистемах используются как традиционные алгоритмы (линейное программирование, градиентный метод), так и современные эвристические. Метод роя частиц является одним из наиболее эффективных и широко используемых. Предлагается новый вариант алгоритма роя частиц с нелинейными изменяющимися во времени коэффициентами ускорения (PSO-NTVAC) для решения задачи определения оптимального местоположения и мощности нескольких энергоустановок для сетчатых и радиальных сетей. Основная цель рассматриваемой задачи оптимизации состоит в минимизации общих потерь активной мощности системы при удовлетворении всех эксплуатационных ограничений. Предложенная методология апробирована с использованием тестовых схем IEEE, содержащих 14, 30, 57, 33 и 69 шин, при количестве энергоустановок, изменяющемся от 1 до 4. Результат доказывает более высокую в сравнении с аналогами эффективность предложенной модификации PSO-NTVAC для решения задач оптимального размещения нескольких энергоустановок распределенной генерации и выбора их мощности с целью минимизации потерь мощности в энергосистеме.

Ключевые слова: *снижение потерь мощности, улучшенная PSO-NTVAC, сетчатые и радиальные сети, оптимальное размещение*

СПИСОК ЛИТЕРАТУРЫ

1. **Ахмед М.К., Осман М.Н., Коровкин Н.В.** Оптимальное распределение реактивной мощности в энергосистемах с возобновляемыми источниками энергии с использованием многоцелевого алгоритма роя частиц. – Материаловедение. Энергетика, 2021, т. 27, №. 1, с. 5–20, DOI: 10.18721/JEST.27101.

2. **Hung D.Q., Nadarajah M, Bansal R.** Analytical Expressions for DG Allocation in Primary Distribution Networks. – IEEE Transactions on Energy Conversion, 2010, vol. 25, No. 3, pp. 814–820, DOI: 10.1109/TEC.2010.2044414.

3. **Prabha D.R., et al.** Optimal Location and Sizing of Distributed Generation Unit Using Intelligent Water Drop Algorithm. – Sustainable Energy Technologies and Assessments, 2015, vol. 11, pp. 106–113, DOI: 10.1016/j.seta.2015.07.003.

4. **Vadhera S., Mahajan S.** Optimal Allocation of Dispersed Generation Unit in a Network System. – International Conference on Microelectronics, Computing and Communication (MicroCom), 2016, pp. 0–4, 2016, DOI: 10.1109/MicroCom.2016.7522519.

5. **Osman M.H., Refaat A., Korovkin N.V.** A Novel Method to Extract Single-Diode PV Parameters Based on Datasheet Values. – Электричество, 2021, №. 2, с. 16–21.

6. **Refaat A., Elgamal M., Korovkin N.V.** A Novel Grid-Connected Photovoltaic Centralized Inverter Topology to Improve the Power Harvest during Partial Shading Condition. – Электричество, 2019, №. 7, с. 59–68, DOI: 10.24160/0013-5380-2019-7-59-68.

7. **ChithraDevi S.A., Lakshminarasimman L., Balamurugan R.** Stud Krill Herd Algorithm for Multiple DG Placement and Sizing in a Radial Distribution System. – Engineering Science and Technology, an International Journal, 2017, vol. 20, No. 2, pp. 748–759, DOI: 10.1016/j.jestch.2016.11.009.

8. **Martín García J.A., Gil-Mena A.J.** Optimal Distributed Generation Location and Size Using a Modified Teaching-Learning Based Optimization Algorithm. – International Journal of Electrical Power and Energy Systems, 2013, vol. 50, No. 1, pp. 65–75, DOI: 10.1016/j.ijepes.2013.02.023.

9. **Rezaee Jordehi A.** Allocation of Distributed Generation Units in Electric Power Systems: A Review. – Renewable and Sustainable Energy Reviews, 2016, vol. 56, pp. 893–905, DOI: 10.1016/j.rser.2015.11.086.

10. **Reddy P.D.P., Reddy V.C.V., Manohar T.G.** Whale Optimization Algorithm for Optimal Sizing of Renewable Resources for Loss Reduction in Distribution Systems. – Renewables: Wind, Water, and Solar, 2017, vol. 4, No. 1, pp. 1–13, DOI: 10.1186/s40807-017-0040-1.

11. **Refaat A., Osman M.H., Korovkin N.V.** Optimum Power Extraction from Non-Uniform Aged PV Array Using Current Collector Optimizer Topology. – Электричество, 2019, №. 10, с. 54–60.

12. **Wang C., Nehrir M.H.** Analytical approaches for optimal placement of distributed generation sources in power systems. – IEEE Transactions on Power Systems, 2004, vol. 19, No. 4, pp. 2068–2076, DOI: 10.1109/TPWRS.2004.836189.

13. **Shehata A.A., Ahmed M.K.** State estimation accuracy enhancement for optimal power system steady state modes. – IOP Conference Series: Materials Science and Engineering, 2019, vol. 643, No. 1, DOI: 10.1088/1757-899X/643/1/012049.

14. **Babaei E., Galvani S., Nejabatkhah F.** Optimal Placement of DG Units Considering Power Losses Minimization and Voltage Stability Enhancement in Power System. – International Journal of Automation and Control Engineering, 2014, vol. 3, No. 1, DOI: 10.14355/ijace.2014.0301.01.

15. Prakash D.B., Lakshminarayana C. Multiple DG Placements in Distribution System for Power Loss Reduction Using PSO Algorithm. – Procedia Technology, 2016, vol. 25, No. Raerest, pp. 785–792, DOI: 10.1016/j.protcy.2016.08.173.

16. **Shehata A.A., et al.** Optimal Placement and Sizing of FACTS Devices Based on Autonomous Groups Partical Swarm Optimization Technique. – Archives of Electrical Engineering, 2020, vol. 70, No. 1, DOI: 10.24425/aee.2021.136059.

17. **Shukla T.N., et al.** Optimal Sizing of Distributed Generation Placed on Radial Distribution System. – Electric Power Components and Systems, 2010, vol. 38, No. 3, pp. 260–274, DOI: 10.1080/15325000903273403.

18. **Abu-Mouti F.S., El-Hawary M.E.** Optimal Distributed Generation Allocation and Sizing in Distribution Systems Via Artificial Bee Colony Algorithm. – IEEE Transactions on Power Delivery, 2011, vol. 26, No. 4, pp. 2090–2101, DOI: 10.1109/TPWRD.2011.2158246.

19. **Elattar E.E., et al.** Optimal Location and Sizing of Distributed Generators Based on Renewable Energy Sources Using Modified Moth Flame Optimization Technique. – IEEE Access, 2020, vol. 8, pp. 109625–109638, DOI: 10.1109/ACCESS.2020.3001758.

20. **Prakash D.B., Lakshminarayana C.** Multiple DG Placements in Radial Distribution System for Multi Objectives Using Whale Optimization Algorithm. – Alexandria Engineering Journal, 2018, vol. 57, No. 4, pp. 2797–2806, DOI: 10.1016/j.aej.2017.11.003.

21. **Mohamed I.A., Kowsalya M.** Optimal Size and Siting of Multiple Distributed Generators in Distribution System Using Bacterial Foraging Optimization. – Swarm and Evolutionary Computation, 2014, vol. 15, pp. 58–65, DOI: 10.1016/j.swevo.2013.12.001.

22. **Wang L., Singh C.** Reliability-Constrained Optimum Placement of Reclosers and Distributed Generators in Distribution Networks Using an Ant Colony System Algorithm. – IEEE Transactions on Systems, Man and Cybernetics Part C: Applications and Reviews, 2008, vol. 38, No. 6, pp. 757–764, DOI: 10.1109/TSMCC.2008.2001573.

23. **Arya L.D., Koshti A., Choube S.C.** Distributed Generation Planning Using Differential Evolution Accounting Voltage Stability Consideration. – International Journal of Electrical Power and Energy Systems, 2012, vol. 42, No. 1, pp. 196–207, DOI: 10.1016/j.ijepes.2012.04.011.

24. **Reddy P.D.P., Reddy V., Manohar T.** Ant Lion Optimization Algorithm for Optimal Sizing of Renewable Energy Resources for Loss Reduction in Distribution Systems. – Journal of Electrical Systems and Information Technology, 2018, vol. 5, No. 3, pp. 663–680, DOI: 10.1016/j.jesit.2017.06.001.

25. **Sun J., Feng B., Xu W.** Particle Swarm Optimization with Particles Having Quantum Behavior. – Proceedings of the 2004 Congress on Evolutionary Computation, CEC2004, 2004, vol. 1, pp. 325–331, DOI: 10.1109/cec.2004.1330875.

26. **Alrashidi M.R., El-Hawary M.E.** A Survey of Particle Swarm Optimization Applications in Electric Power Systems. – IEEE Transactions on Evolutionary Computation, 2009, vol. 13, No. 4, pp. 913–918, DOI:10.1109/TEVC.2006.880326.

27. **Ratnaweera A., Halgamuge S.K., Watson H.C.** Self-Organizing Hierarchical Particle Swarm Optimizer with Time-Varying Acceleration Coefficients. – IEEE Transactions on Evolutionary Computation, 2004, vol. 8, No. 3, pp. 240–255, DOI: 10.1109/TEVC.2004.826071.

28. **Samakpong T., Ongsakul W., Manjiparambil N.M.** Optimal Power Flow Incorporating Renewable Uncertainty Related Opportunity Costs. – Computational Intelligence, 2020, DOI: 10.1111/coin.12316.

29. Jithendranath J., Das D. Multi-Objective Optimal Power Flow in Islanded Microgrids with Solar PV Generation by NLTV-MOPSO. – IETE Journal of Research, 2021, DOI: 10.1080/03772063.2021.1886609.

30. **Chaturvedi K.T., Pandit M., Srivastava L.** Self-Organizing Hierarchical Particle Swarm Optimization for Nonconvex Economic Dispatch. – IEEE Transactions on Power Systems, 2008, vol. 23, No. 3, pp. 1079–1087, DOI: 10.1109/TPWRS.2008.926455.

31. **Chen K., et al.** An Ameliorated Particle Swarm Optimizer for Solving Numerical Optimization Problems. – Applied Soft Computing Journal, 2018, vol. 73, pp. 482–496, DOI: 10.1016/j.asoc.2018.09.007.

32. **Mamdouh K.A., Shehata A.A., Korovkin N.V.** Multi-Objective Voltage Control and Reactive Power Optimization Based on Multi-Objective Particle Swarm Algorithm. – IOP Conference Series: Materials Science and Engineering, 2019, vol. 643, No. 1, DOI: 10.1088/1757-899X/643/1/012089.

[22.09.2021]