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OPTIMAL DISTRIBUTED GENERATION ALLOCATION IN DISTRIBUTION SYSTEMS WITH NON-LINEAR LOADS USING A NEW HYBRID META-HEURISTIC ALGORITHM

OPTIMALNA ALOKACIJA DISTRIBUIRANE PROIZVODNJE U DISTRIBUTIVNIM SISTEMIMA S NELINEARNIM POTROŠAČIMA PRIMJENOM NOVOG HIBRIDNOG METAHEURISTIČKOG ALGORITMA

Miloš Milovanović[1], Jordan Radosavljević[1], Bojan Perović[1]

Abstract: This paper presents a new hybrid meta-heuristic algorithm based on the Phasor Particle Swarm Optimization (PPSO) and Gravitational Search Algorithm (GSA) for optimal allocation of distributed generation (DG) in distribution systems with non-linear loads. Performance of the algorithm is evaluated on the IEEE 69-bus system with the aim of reducing power losses, as well as improving voltage profile and power quality. Results, obtained using the proposed algorithm, are compared with those obtained using the original PSO, PPSO, GSA and PSOGSA algorithms. It is found that the proposed algorithm has better performance in terms of convergence speed and finding the best solutions.

Keywords: distributed generation, gravitational search algorithm, hybrid meta-heuristic algorithm, optimal allocation, phasor particle swarm optimization

Sažetak: U ovom radu je za rješavanje problema optimalne alokacije distribuiranih izvora električne energije, u distributivnim sistemima s nelinearnim potrošačima, predložen novi hibridni algoritam fazorske optimizacije rojem čestica (PPSO) i gravitacionog pretraživačkog algoritma (GSA). Performanse predloženog algoritma su procjenjene standardnim IEEE test sistemom sa 69 čvorova, s ciljem smanjenja gubitaka energije, poboljšanja naponskog profila i kvaliteta električne energije. Dobijeni rezultati su upoređeni s rezultatima dobijenim primjenom originalnih PSO, PPSO, GSA i PSOGSA algoritama. Utvrđeno je da predloženi algoritam ima bolje performanse u pogledu brzine konvergencije i pronalaženja najboljih rešenja.

Ključne riječi: distribuirana proizvodnja, gravitacioni pretraživački algoritam, hibridni metaheuristički algoritam, optimalna alokacija, fazorska optimizacija rojem čestica

INTRODUCTION

Distributed generation (DG) is the term used for small generating units connected to the medium or low voltage distribution systems. Over the past two decades, the integration of DG resources into distribution systems led to a change in the basic characteristics of the systems, providing many technical, economic and environmental benefits [1]. The impacts of DG on the system operational performance depend on many factors, including type, size and location of DG, as well as its intended mode of operation. The problem of finding the optimal location and size of DG units, namely the "DG allocation problem" is one of the major issues facing the distribution utilities. Experience has shown that the integration of DG units at non-optimal locations with non-optimal sizes can lead to higher power losses, degradation of power quality, instability of the system and increase in operational costs [2].

Depending on the type of DG, different effects on the power quality are possible. One of the most important aspects of the power quality is the presence of harmonics in the system. Harmonics are caused mainly by non-linear loads, such as adjustable speed drives (ASDs), power electronic loads, switch-mode power supplies and electronic power conversion devices. Depending on individual circumstances, the DG power plant may reduce or increase the power quality problems related to the harmonic distortion of the voltage waveform. The use of

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renewable DG sources with power electronic converters, such as wind turbine generators, solar photovoltaic cells, fuel cells and microturbines, leads to a higher harmonic distortion in the system. In addition, it should be noted that the direct connection of the generator (synchronous or induction) to the distribution system leads to a reduction in the harmonic impedance of the system and can create dangerous resonance conditions.

In the past few years, many meta-heuristic optimization techniques have been applied for optimal allocation of DG, such as Tabu Search (TS) [3], Genetic Algorithm (GA) [4], [5], Particle Swarm Optimization (PSO) [6]-[8], Gravitational Search Algorithm (GSA) [9], Evolutionary Programming (EP) [10], Cuckoo Search (CS) [11], Ant Colony Optimization (ACO) [12], Biogeography-based Optimization (BBO) [13], Artificial Bee Colony (ABC) [14], Bacterial Foraging Optimization (BFO) [15], etc. In addition to those, several hybrid algorithms, such as GA-TS [16], ACO-ABC [17], GA-PSO [18], PSO-GSA [19], EP-PSO [20], have also been suggested for finding the optimal size and location of DG units.

In the formulation of the DG allocation problem, the objective function may have a variety of forms. The most commonly used objective functions are as follows: reduction or minimization of power losses in a distribution system [3], [5], [16], [18], reduction of the economic cost of the system [6], improvement of the voltage profile [11] and voltage stability margins [14], or any combination of two or more functions, such as the simultaneous minimization of power losses and total harmonic voltage distortion (THD_V) [2], [10], simultaneous minimization of losses and maximization of the voltage deviation [4], [15], simultaneous voltage profile improvement, losses and THD_V reduction [7], [9], simultaneous minimization of DG investment cost and total operation cost of the system [12], simultaneous reduction of active and reactive power losses, reduction of purchased energy from transmission line and improvement of voltage profile [13], etc.

This paper presents a novel hybrid meta-heuristic algorithm based on the Phasor Particle Swarm Optimization (PPSO) [21] and Gravitational Search Algorithm (GSA) [22], called the hybrid PPSOGSA algorithm, for optimal allocation of DG in radial distribution systems with non-linear loads, which is the main contribution of the paper. The proposed algorithm is tested and evaluated on a standard IEEE 69-bus system with an objective of reducing power losses, as well as improving voltage profile and power quality. The calculation of the fitness function value is based on the power flow calculation at the fundamental frequency, as well as the harmonic power flow analysis. The standard backward/forward sweep power flow method and decoupled harmonic power flow (DHPF) method were integrated with the PPSOGSA algorithm in order to find the best solution of the formulated problem. The algorithm is compared to the other meta-heuristic algorithms, such as PSO, PPSO, GSA and PSOGSA by investigating the results of three various cases. These comparisons represent an additional contribution to the field of research.

1. PROBLEM FORMULATION

The problem of optimal allocation of DG is considered as a non-linear optimization planning problem with the objective of minimizing total active power losses in the system, and improving voltage profile and power quality. The control variables of the problem are locations and sizes of DG units, while the dependent variables are RMS bus voltages and THD_V levels.

1.1. Objective function

The objective function is given by the following equation:

$$\min F = \min\left\{w_1 P_{loss} + w_2 V_{dev-avr} + w_3 THD_{V-avr}\right\} \tag{1}$$

where F is the objective function that will be minimized, P_{loss} is the total active power losses in the system, $V_{dev\text{-}avr}$ is the average voltage deviation in the system, $THD_{V\text{-}avr}$ is the average voltage total harmonic distortion in the system, and w_i is the corresponding weight factor.

The total active power losses are given by

$$P_{loss} = \sum_{h=1}^{h_{max}} \left(\sum_{i=1}^{N_{bus}-1} P_{loss(i,i+1)}^{(h)} \right) \tag{2}$$

where $P_{loss(i,i+1)}^{(h)}$ is the power losses in the line section between bus i and bus $i+1$ at the h-th harmonic, N_{bus} is the total number of buses in the system and h_{max} is the maximum harmonic order under consideration.

The average voltage deviation in the system can be obtained as follows:

$${}_{dev\quad avr} \qquad \frac{\sum^{bus} \left| V_{RMS,i} \quad V_{rated} \right|}{{}_{bus}} \tag{3}$$

where $V_{RMS,i}$ is the voltage RMS magnitude at bus i, and V_{rated} is the rated operating voltage considered to be 1 p.u.

The average THD_V is defined by

$$THD_{V-avr} = \frac{\sum_{i=1}^{N_{bus}} THD_{V,i}}{N_{bus}} \tag{4}$$

where $THD_{V,i}$ denotes the total harmonic voltage distortion at bus i.

1.2. Constraints

Power balance constraint:

$$P_{grid}+\sum_{i=1}^{N_{DG}}P_{DG,i}=P_{loss}+\sum_{i=1}^{N_L}P_{L,i} \quad (5)$$

where P_{grid} is the substation active power injection, $P_{DG,i}$ is the active power generation of the i-th DG, $P_{L,i}$ is the active power of the load at bus i, while N_{DG} and N_L are the number of DG units and number of loads, respectively.

Bus voltage constraints:

$$V_{RMS}^{\min}\le\sqrt{\sum_{h=1}^{h_{\max}}\left|\underline{V}_i^{(h)}\right|^2}\le V_{RMS}^{\max} \quad (6)$$

where $\underline{V}_i^{(h)}$ is the h-th harmonic component of the voltage at bus i, while $V_{RMS}^{\min}$ = 0.95 p.u. and $V_{RMS}^{\max}$= 1.05 p.u. are the minimum and maximum RMS bus voltage limits, respectively. The harmonic voltage components are estimated using the Decoupled Harmonic Power Flow (DHPF) algorithm.

Total harmonic voltage distortion constraint:

$$THD_{V,i}(\%)\le THD_V^{max} \quad (7)$$

where THD_i^{max}=5% is the maximum acceptable level of the THD_V, according to the limit specified by the IEEE-519 standard [24].

DG capacity constraints:

$$P_{DG,i}^{\min}\le P_{DG,i}\le P_{DG,i}^{\max} \quad (8)$$

$$\sum_{i=1}^{N_{DG}}P_{DG,i}\le PL\sum_{i=1}^{N_L}P_{L,i} \quad (9)$$

where $P_{DG,i}^{min}$ and $P_{DG,i}^{max}$ are the minimum and maximum active power limits of the DG at bus i, and PL is the DG penetration level. This paper considers the maximum DG penetration level to be 100% of the total active power demand.

DG location constraints:

$$2\le L_i\le N_{bus} \quad (10)$$

where L_i presents the location of the i-th DG.

It is important to note that the control variables are self-constrained, but dependent variables (i.e. RMS bus voltages and THD_V levels) are not. The inequality constraints of dependent variables are incorporated in the objective function as quadratic penalty factors [25].

1.3. Decoupled harmonic power flow

The harmonic power flow calculation begins with the calculation of the power flow at the fundamental frequency, which is carried out by the standard backward/forward sweep power flow method. In this step, the fundamental frequency voltage magnitudes and phase angles are determined. This is followed by modeling of distribution system elements at frequencies above the fundamental one. For this purpose, distribution system is modeled as a combination of passive elements and current sources that inject harmonic currents into the system.

If the skin and proximity effects are neglected, the admittance of the linear load at bus i ($y_{l,i}^{(h)}$), shunt capacitor at bus i ($y_{c,i}^{(h)}$), generator at bus i ($y_{dg,i}^{(h)}$), and line between buses i and i+1 ($y_{i,i+1}^{(h)}$) are respectively defined by the following equations [23]:

$$y_{l,i}^{(h)}=\frac{P_{l,i}}{\left|V_i^{(1)}\right|^2}-j\frac{Q_{l,i}}{h\left|V_i^{(1)}\right|^2} \quad (11)$$

$$y_{c,i}^{(h)}=hy_{c,i}^{(1)} \quad (12)$$

$$y_{dg,i}^{(h)}=\frac{1}{\sqrt{h}R_{dg,i}+jhX_{dg,i}^{"}} \quad (13)$$

$$y_{i,i+1}^{(h)}=\frac{1}{R_{i,i+1}+jhX_{i,i+1}} \quad (14)$$

where $P_{l,i}$ and $Q_{l,i}$ are the fundamental active and reactive linear load powers at bus i, $y_{c,i}^{(1)}$ is the fundamental admittance of the shunt capacitor at bus i, $R_{dg,i}$ and $X_{dg,i}^{"}$ are the resistance and sub-transient reactance of generator i, while $R_{i,i+1}$ and $X_{i,i+1}$ are the resistance and reactance of the line between busses i and i+1, respectively.

The fundamental and h-th harmonic currents of the non-linear load at bus i with fundamental active power $P_{nl,i}$ and fundamental reactive power $Q_{nl,i}$ are [23]:

$$I_{nl,i}^{(1)}=\left|\left[\frac{P_{nl,i}+jQ_{nl.i}}{\underline{V}_i^{(1)}}\right]^*\right| \quad (15)$$

$$I_{nl,i}^{(h)}=C(h)I_{nl,i}^{(1)} \quad (16)$$

where $I_{nl,i}^{(1)}$ and $I_{nl,i}^{(h)}$ are the magnitude of fundamental and harmonic currents of the non-linear load at bus i, respectively, and $C(h)$ is the ratio of the h-th harmonic current to its fundamental value.

The phase angle of the harmonic current injected by the non-linear load at bus i ($\theta_{nl,i}^{(h)}$) can be expressed by the following formula:

$$\theta_{nl,i}^{(h)}=\theta_{nl,i}^{(h-spectrum)}+h\theta_{nl,i}^{(1)}+(h+1)\frac{\pi}{2} \quad (17)$$

where $\theta_{nl,i}^{(1)}$ is the phase angle obtained from the power flow solution for the fundamental frequency current component, and $\theta_{nl,i}^{(h-spectrum)}$ is the typical phase angle of the harmonic source current spectrum.

In order to determine the harmonic components in the system, DHPF algorithm is used in this paper. In this method, the interaction among the harmonic frequencies is assumed to be negligible and hence the admittance matrix is formulated individually for all harmonics of interest [23].

After the formation of the bus admittance matrix and calculation of the current vector, the harmonic power flow problem can be calculated directly using the following matrix equation:

$$\mathbf{V}^{(h)} = \left[\mathbf{Y}_{BUS}^{(h)}\right]^{-1} \mathbf{I}^{(h)} \tag{18}$$

where $\mathbf{Y}_{BUS}^{(h)}$ is the system bus admittance matrix at the h-th harmonic; $\mathbf{I}^{(h)}$ is the system bus injected current vector at the h-th harmonic and $\mathbf{V}^{(h)}$ is the system bus voltage vector at the h-th harmonic.

Once the harmonic voltages have been determined, the RMS bus voltages and THD_V levels can be calculated. At any bus i, the RMS value of the voltage is given by

$$V_{RMS,i} = \sqrt{\sum_{h=1}^{h_{\max}} \left|\underline{V}_i^{(h)}\right|^2} \tag{19}$$

The THD_V level at bus i is expressed by the following formula:

$$THD_{V,i} = \frac{1}{\left|\underline{V}_i^{(1)}\right|} \cdot \sqrt{\sum_{h \neq 1}^{h_{\max}} \left|\underline{V}_i^{(h)}\right|^2} \times 100(\%) \tag{20}$$

At the end of the calculation, the total power losses of the system for all harmonics are determined by Eq. (2).

2. HYBRID PPSOGSA ALGORITHM

2.1. Overview of PSO

PSO is a population-based stochastic search optimization technique developed by Kennedy and Elberhart [26]. PSO is inspired by movement of bird flocking or of fish schooling in two-dimensional search space. It conducts search using a number of particles (search agents) that constitute a swarm and fly around in the search space to find the optimal position (i.e. solution). Each particle represents a potential solution of the problem. At time (iteration) t, the i-th particle can be described by a vector in n-dimensional space to describe its position ($\mathbf{x}_i^d(t)$) and another vector to describe its velocity ($\mathbf{v}_i^d(t)$):

$$\begin{aligned} \mathbf{v}_i^d(t) &= \left[v_i^1(t), ..., v_i^d(t), \ldots, v_i^n(t)\right] \\ \mathbf{x}_i^d(t) &= \left[x_i^1(t), ..., x_i^d(t), \ldots, x_i^n(t)\right] \end{aligned} \quad \text{for } i = 1, 2, \ldots, N \tag{21}$$

where $\mathbf{x}_i^d(t)$ and $\mathbf{v}_i^d(t)$ are the position and velocity components of the i-th particle with respect to the d-th dimension, respectively, and N is the total number of agents (i.e. size of the population).

PSO begins with a randomly generated population as initial solutions of an optimization problem. During flight, each particle adjusts its position according to its own experience (its the best solution, personal best – **pbest**), and the experience of neighbouring particles (the best value of any particle, global best – **gbest**). In each of iteration, every particle calculates its velocity and position according to the following equations [25]:

$$\begin{aligned} \mathbf{v}_i^d(t+1) = w(t)\mathbf{v}_i^d(t) + c_1 r_1 \left(\mathbf{pbest}_i^d(t) - \mathbf{x}_i^d(t)\right) \\ + c_2 r_2 \left(\mathbf{gbest}^d(t) - \mathbf{x}_i^d(t)\right) \end{aligned} \tag{22}$$

$$\mathbf{x}_i^d(t+1) = \mathbf{x}_i^d(t) + \mathbf{v}_i^d(t+1) \tag{23}$$

where $\mathbf{v}_i^d(t)$ and $\mathbf{x}_i^d(t)$ are the velocity and position of the i-th particle with respect to the d-th dimension at iteration t, respectively; $w(t)$ is the inertia weight factor at iteration t that controls the dynamic of flying; c_1 and c_2 are the acceleration control coefficients that are traditionally set as the fixed values 2.0; r_1 and r_2 are the random numbers in the range [0, 1]; $\mathbf{pbest}_i^d(t)$ is the best position of the i-th particle at the d-th dimension in the t-th iteration, and $\mathbf{gbest}^d(t)$ is the best position of all particles in the group at the d-th dimension in the t-th iteration. Equation (22) contains three members: the first member provides exploration ability for PSO, while the second and third members represent private thinking and collaboration of particles, respectively.

Suitable selection of the inertia weight w provides a balance between global and local explorations. During the optimization process, w is linearly reduced from w_{max} (initial or maximum value) to w_{min} (final or minimum value) according to the equation [25]:

$$w(t) = w_{\max} - \left(w_{\max} - w_{\min}\right)\frac{t}{t_{\max}} \tag{24}$$

where t_{max} is the total number of iterations, t is the current iteration, w_{max} and w_{min} are the upper and lower limits of the inertia weight. The typical values of w_{max} and w_{min} are 0.9 and 0.4, respectively.

2.2. Overview of PPSO

In the attempt to solve the fast convergence problem of PSO algorithm and its dependency on control parameters, Ghasemi et al. have proposed a new variant of PSO, named Phasor Particle Swarm Optimization (PPSO), in which the control variables are incorporated in the phase angle (θ). By doing this, the velocity and position of the i-th particle in each of iteration are updated using the following expressions [21]:

$$\begin{aligned} \mathbf{v}_i^d(t+1) = \left|\cos(\theta_i(t))\right|^{2\sin(\theta_i(t))} \left(\mathbf{pbest}_i^d(t) - \mathbf{x}_i^d(t)\right) \\ + \left|\sin(\theta_i(t))\right|^{2\cos(\theta_i(t))} \left(\mathbf{gbest}^d(t) - \mathbf{x}_i^d(t)\right) \end{aligned} \tag{25}$$

$$\mathbf{x}_i^d(t+1) = \mathbf{x}_i^d(t) + \mathbf{v}_i^d(t+1) \tag{26}$$

where the phase angle of particle i is calculated for the next iterations through the following formula:

$$\theta_i(t+1) = \theta_i(t) + \left|\cos(\theta_i(t)) + \sin(\theta_i(t))\right| 2\pi \tag{27}$$

The values of **pbest** and **gbest** in (25) are obtained as in the original PSO algorithm. The phase angle θ converts the PSO algorithm to a self-adaptive, trigonometric, balanced, and non-parametric meta-heuristic algorithm. In almost all of the unimodal and multimodal traditional and real-parameter test functions analysed in [21], simulations are demonstrated that PPSO has the best performance in comparison to the basic PSO and other improved PSO algorithms from the literature.

2.3. Overview of GSA

GSA was introduced by Rashedi et al. in 2009 [22] and is based on the Newton's laws of gravitation and motion. The search agents in GSA are considered as objects and their performance is measured by their masses. This approach provides an iterative method that simulates mass interactions. Objects with heavier mass, which correspond to the good solutions, have higher attraction forces and move more slowly than the objects with lighter mass. The mass of each agent is calculated after computing the current population's fitness as follows [22]:

$$M_i(t) = \frac{m_i(t)}{\sum_{i=1}^{N_A} m_j(t)} \tag{28}$$

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst(t)} \tag{29}$$

where $M_i(t)$ and $fit_i(t)$ are the mass and fitness value of the i-th agent at time (iteration) t, respectively, while $worst(t)$ and $best(t)$ are the worst and the best fitness in the swarm of objects at time t.

In order to compute the acceleration of an agent, total forces applied on the object from a set of heavier objects are taken into account based on the combination of the law of gravity and Newton's second law of motion as presented in (30). Afterwards, the next velocity and the next position of an agent can be calculated by using (31) and (32), respectively.

$$\mathbf{a}_i^d(t) = \frac{\mathbf{F}_i^d(t)}{M_i(t)} = \sum_{\substack{j \in Kbest \\ j \neq i}} r_j G(t) \frac{M_j(t)}{R_{i,j}(t) + \varepsilon} \left(\mathbf{x}_j^d(t) - \mathbf{x}_i^d(t) \right) \tag{30}$$

$$\mathbf{v}_i^d(t+1) = r_i \mathbf{v}_i^d(t) + \mathbf{a}_i^d(t) \tag{31}$$

$$\mathbf{x}_i^d(t+1) = \mathbf{x}_i^d(t) + \mathbf{v}_i^d(t+1) \tag{32}$$

In (30) – (32), variables have the following meaning: $\mathbf{F}_i^d(t)$ is the total force that acts on the i-th agent in the d-th dimensional at time t; $\mathbf{a}_i^d$, $\mathbf{v}_i^d(t)$ and $\mathbf{x}_i^d(t)$ are the acceleration, the velocity and the position of the i-th agent in the d-th dimensional at time t, respectively; r_i and r_j are two uniformly distributed random numbers in the interval [0, 1]; $G(t)$ is the gravitational constant at time t; ε is a small constant; $Kbest$ is the set of the first K agents with the best fitness value and biggest mass and $R_{i,j}(t)$ is the Euclidian distance between two agents i and j, defined as $R_{i,j}(t) = \|x_i(t), x_j(t)\|_2$.

The gravitational constant in (30) is updated according to the effect of decreasing gravity as given below:

$$G(t) = G_0 e^{-\alpha(t/t_{\max})} \tag{33}$$

where G_0 is the initial value of the gravitational constant and α is a constant specified by user.

2.4. Overview of PSOGSA

The hybrid PSOGSA algorithm associates the functionality of PSO and GSA algorithms, integrating the ability for social thinking (**gbest**) in PSO with the local search capability of GSA [27]. In order to combine these algorithms, the velocity and position of agents are updated as follows [28]:

$$\mathbf{V}_i(t+1) = r_1 \mathbf{V}_i(t) + c_1 r_2 \mathbf{ac}_i(t) + c_2 r_3 \left(\mathbf{gbest}(t) - \mathbf{X}_i(t) \right) \tag{34}$$

$$\mathbf{X}_i(t+1) = \mathbf{X}_i(t) + \mathbf{V}_i(t+1) \tag{35}$$

where i = 1, 2, …, N is the agent number; $\mathbf{V}_i(t)$ and $\mathbf{X}_i(t)$ are the velocity and the position of agent i at iteration t, respectively; c_1 and c_2 are positive constants; r_1, r_2 and r_3 are random numbers between 0 and 1; $\mathbf{ac}_i(t)$ is the acceleration of agent i at iteration t and $\mathbf{gbest}(t)$ is the best solution so far at iteration t.

2.5. Hybrid PPSOGSA algorithm

The proposed PPSOGSA approach, which is similar to PSOGSA, hybridizes PPSO with GSA in order to combine their strengths and overcome their shortcomings. The control parameters of PSOGSA c_1 and c_2 are fixed during iteration process and different combination values of these parameters provide good solutions for different problems. Instead of using fixed value of c_1 and c_2, in this new hybrid PPSOGSA algorithm the periodic nature of trigonometric sine and cosine functions is utilized to represent the control parameters through phase angles θ. In addition to this, the first member of (34), that represents the particle's previous velocity, for the proposed PPSOGSA algorithm is set to zero ($r_1 \mathbf{V}_i(t) = 0$). In each iteration, the velocity and position of agents are calculated according to the following equations:

$$\mathbf{V}_i(t+1) = \left| \cos(\theta_i(t)) \right|^{2\sin(\theta_i(t))} r_1' \mathbf{ac}_i(t) + \left| \sin(\theta_i(t)) \right|^{2\cos(\theta_i(t))} r_2' \left(\mathbf{gbest}(t) - \mathbf{X}_i(t) \right) \tag{36}$$

$$\mathbf{X}_i(t+1) = \mathbf{X}_i(t) + \mathbf{V}_i(t+1) \tag{37}$$

where r_1' and r_2' are random numbers between 0 and 1.

2.6. PPSOGSA implementation

The control variables of the problem of optimal allocation of DG constitute the individual position of several agents that represent a complete solution set. In a system with N agents, the position of agent i is defined by

$$\mathbf{X}_i(t) = \left[x_i^1(t), \ldots, x_i^d(t), \ldots, x_i^n(t) \right] \text{ for } i = 1, 2, \ldots, N \tag{38}$$

where the number of control variables is: $n=2N_{DG}$.

The elements of $\mathbf{X}_i$ are locations and sizes of DG units. The different steps of the PPSOGSA algorithm for the considered optimization problem are the following:

1. Search space identification. Initialize PPSOGSA parameters: N, t_{max}, G_0 and α.
2. Initialization: Randomly generate an initial population of N agents with their own phase angle through uniform distribution $\theta_i(0) = U(0,2\pi)$, and with initial velocity within the velocity bound. The initial positions of each agent are randomly selected between the minimum and maximum values of the control variables.
3. Set the index of iteration t = 1.
4. For each particle in the population, run DHPF to obtain the power losses, bus RMS voltages and THD_V values.
5. Calculate the fitness value for each agent.
6. Update $G(t)$, $best(t)$, $worst(t)$ and $M_i(t)$ for each particle in the population.
7. Calculate total forces and accelerations for all agents.
8. Update the velocity and position of all agents by (36) and (37), respectively.
9. If the stop criteria is satisfied (i.e. the maximum number of iterations is reached), go to step 10; otherwise, set iteration index $t = t + 1$, and return to step 4.
10. Return the best solution found. Print out the optimal solution to the considered problem. Stop.

3. RESULTS AND DISCUSSION

The proposed hybrid PPSOGSA algorithm has been tested on the standard IEEE 69-bus test system with total active and reactive loads of 3791.9 kW and 2694.1 kVAr, respectively. The base voltage of this system is 12.66 kV. A single-line diagram of the system is shown in Figure 1 and the data of loads and lines can be found in [29].

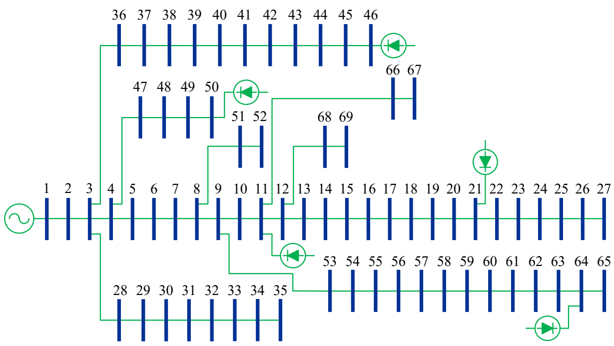

Figure 1: Single-line diagram of the IEEE 69-bus system

For the purpose of investigating the impact of non-linear loads on the power quality, it is assumed that the loads at buses 11, 21, 46, 50 and 64 are the non-linear pulse width modulation (PWM) adjustable speed drives (ASDs), while the rest ones are linear. The harmonic spectrum of the non-linear loads is presented in Table I. At the fundamental frequency, all loads are modelled as constant powers and DG units are modelled as negative loads with unity power factor.

At harmonic frequencies, the parallel RL impedance model from [30] is used to model linear loads and DG units are treated as linear elements which produce no harmonics. In addition, DG units are represented by short-circuit impedance. For this study, the impedance of a DG unit is the sub-transient reactance of 15%, while the resistance is negligible.

Table I: The harmonic spectrum of non-linear loads [31]

Harmonic order	Magnitude (%)	Phase angle (degree)
1	100	0
5	82.8	-135
7	77.5	69
11	46.3	-62
13	41.2	139
17	14.2	9
19	9.7	-155
23	1.5	-158
25	2.5	98

In order to verify the performance of PPSOGSA, the same problem was solved using PSO, PPSO, GSA and PSOGSA algorithms. Different algorithms' parameters used for the simulation are adopted as follows: for PSO, c_1 and c_2 are set to 2 and the inertia weight (w) decreases linearly from 1 to 0.1 during the iteration process; for GSA, α is set to 10 and G_0 is set to 100; for the hybrid PSOGSA, c_1 and c_2 are set to 2, α is set to 20, and G_0 is set to 200; for the hybrid PPSOGSA, the parameters α and G_0 are set up as well as for the PSOGSA. For all algorithms, the population size (N) and the maximum number of iterations (t_{max}) are set to 50 and 100, respectively. In addition to the basic case (i.e. the case without any DG), the following cases are analysed herein:

Case 1: with one DG
Case 2: with two DGs
Case 3: with three DGs

All simulations were performed using a PC with Intel Core i7 processor with 2.7 GHz speed and 8 GB of RAM. For each algorithm, 20 consecutive test runs have been performed and the best results obtained over these runs are presented in Table II. In this study, it is assumed that the weighting factors w_1, w_2 and w_3 are equal to 1, 8000 and 40, respectively. These values are carefully selected after a number of simulation experiments.

As can be seen from Table II, in the basic case, total active power losses, average voltage deviation and average harmonic distortion in the system are 236.559 kW, 0.0261 p.u. and 2.463%, respectively. In addition, the minimum RMS bus voltage and the maximum THDV level violate the allowable limits of 0.95

p.u. and 5%, respectively. In Case 1, total power losses can be reduced to 101.629 kW if one DG with the active power output of 2.4141 MW is placed at bus 61. This means, the total active power losses are reduced by 57.04%. By comparison with Case 1, it can be seen that the power losses are less in Cases 2 and 3. The reduction of power losses is pronounced with increasing the number DG units at different locations in the system. Besides that, the results from Table II show that the optimal DG allocation not only reduces the total power losses, but also improves the voltage profile and power quality in the system. In relation to the basic case, the average voltage deviation obtained by PPSOGSA algorithm for Cases 1, 2 and 3 is reduced by, respectively, 67.05%, 94.64% and 96.93%, while the average harmonic distortion level is reduced by, respectively, 16.04%, 20.06% and 20.38%. Comparisons between the corresponding voltage profiles and between the THDV levels, when the parameters of DG units are obtained by the PPSOGSA algorithm, are shown in Figures 2 and 3, respectively.

From Figures 2 and 3, it is clear that the voltage deviations and harmonic distortions are significantly reduced with optimal allocation of DG units, where the voltage magnitudes, as well as the maximum THDV levels, meet the limits defined in the IEEE-519 standard.

Table II: Optimal solutions obtained by different algorithms

Case	Algorithm	DG size (MW) and location	Total DG size (MW)	Max. V_{RMS} (p.u.)	Min. V_{RMS} (p.u.)	$V_{dev\text{-}avr}$ (p.u.)	Max. THD_V (%)	$THD_{V\text{-}avr}$ (%)	P_{loss} (kW)
Basic	-	-	-	1	0.9114	0.0261	6.945	2.463	236.559
1	PSO PPSO GSA PSOGSA PPSOGSA	2.4141 (61)	2.4141	1.0009	0.9723	0.0086	4.983	2.068	101.629
2	PSO	1.1168 (13) 2.2173 (61)	3.3341	1.0052	0.9948	0.0014	5	1.975	94.461
	PPSO	1.1813 (13) 2.2068 (61)	3.3881	1.0066	0.9948	0.0012	5	1.969	95.739
	GSA	0.6327 (22) 2.2874 (61)	2.9201	1.0011	0.993	0.0021	5	1.965	90.401
	PSOGSA	0.7709 (14) 2.2603 (61)	3.0312	1.0024	0.9948	0.0017	4.988	1.968	90.695
	PPSOGSA	0.9351 (14) 2.2389 (61)	3.174	1.0046	0.9948	0.0014	5	1.969	92.782
3	PSO	0.6182 (15) 0.9261 (54) 2.0622 (63)	3.6065	1.0026	0.9948	0.001	4.922	1.96	94.549
	PPSO	0.7721 (11) 0.4852 (18) 2.1466 (62)	3.4039	1.0013	0.9948	0.0009	4.986	1.962	89.194
	GSA	0.3244 (6) 0.6579 (19) 2.2613 (61)	3.2436	1.0012	0.9941	0.0017	5	1.967	89.712
	PSOGSA	0.6281 (16) 0.8713 (53) 2.1425 (61)	3.6418	1.0019	0.9949	0.0009	5	1.965	90.576
	PPSOGSA	0.8143 (10) 0.4858 (18) 2.1898 (61)	3.4899	1.0011	0.9948	0.0008	5	1.961	89.027

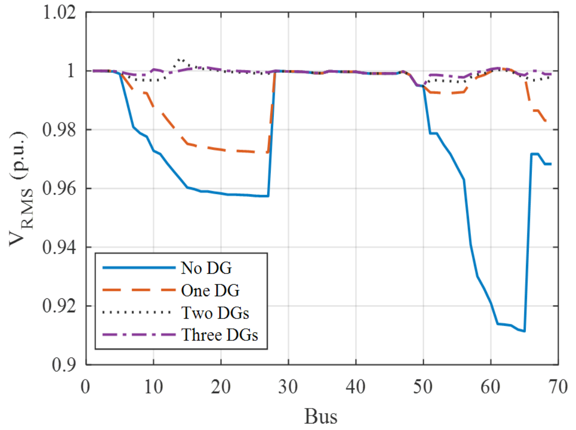

Figure 2: Comparison between voltage profiles of the IEEE 69-bus test system with and without DGs

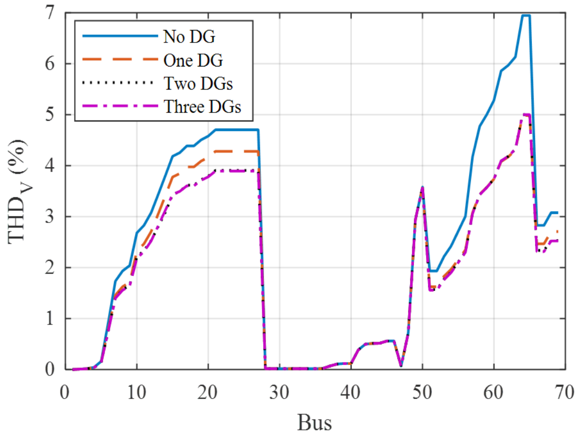

Figure 3: Comparison between THD_V levels of the IEEE 69-bus test system with and without DGs

The obtained results for 20 trial runs consisting of the minimum, maximum and mean values of the objective function F, as well as the standard deviation of the results are presented in Table III.

Table III: Comparison between different algorithms

Case	Algorithm	Min. F	Max. F	Mean F	Std. dev.
1	PSO	253.38	256.38	253.98	0.75
	PPSO	253.38	255.54	253.57	0.53
	GSA	253.38	258.41	254.19	1.16
	PSOGSA	253.38	253.38	253.38	0
	PPSOGSA	253.38	253.38	253.38	0
2	PSO	184.26	208.65	190.94	7.65
	PPSO	183.02	198.51	187.57	6.76
	GSA	185.83	211.51	197.86	8.44
	PSOGSA	182.87	189.46	183.75	2.11
	PPSOGSA	182.72	185.34	183.68	0.65
3	PSO	181.01	210.06	195.63	11.23
	PPSO	175.12	205.38	192.04	8.54
	GSA	182.16	213.57	196.42	13.74
	PSOGSA	176.26	188.49	181.39	4.03
	PPSOGSA	173.85	178.86	177.16	1.71

The results from the third column of the Table III, related to Cases 2 and 3, indicate that the proposed algorithm outperforms other algorithms because the results obtained using PPSOGSA are better than those obtained using other techniques. In Case 1, it is established that all algorithms used by the authors can find the same optimal solution. In addition, based on the results from the fourth, fifth and sixth columns of Table III, it could be observed that the proposed PPSOGSA algorithm provides more stable solutions compared to the original PSO, PPSO, GSA and PSOGSA algorithms.

The convergence profiles of one run of the algorithms for Cases 1, 2 and 3 are illustrated in Figures 4, 5 and 6, respectively. From these figures it may be observed that the proposed PPSOGSA algorithm tends to find the optimal solution faster than the other algorithms.

From the aspect of processing time, the CPU time of the proposed PPSOGSA algorithm is little longer than the CPU time of any other algorithm used for comparison. The average CPU times for the proposed algorithm in Cases 1, 2 and 3 were about 3.5 min, 4.3 min and 4.8 min, respectively.

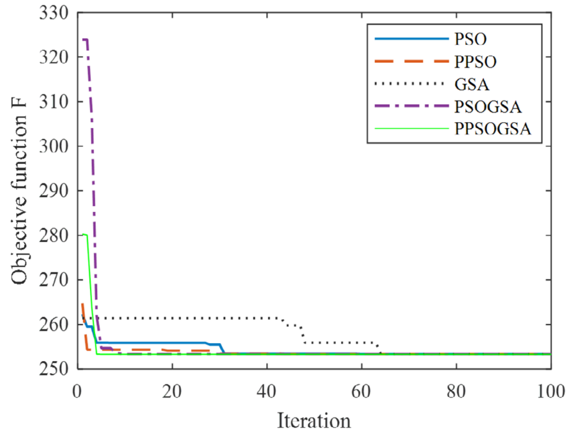

Figure 4: Convergence of algorithms for Case 1

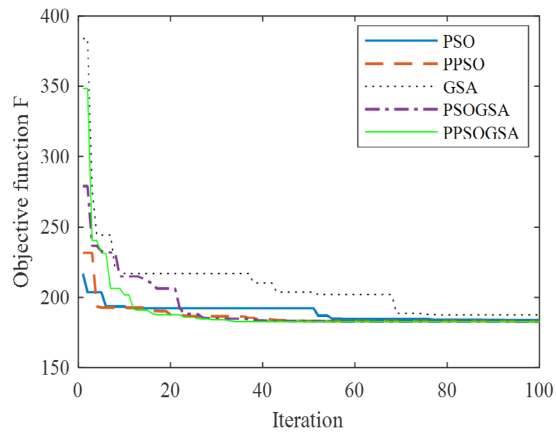

Figure 5: Convergence of algorithms for Case 2

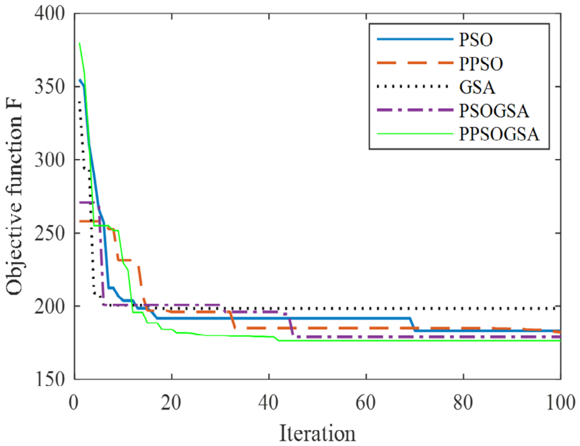

Figure 6: Convergence of algorithms for Case 3

4. CONCLUSION

In this paper a novel PPSOGSA optimization algorithm has been proposed and successfully applied to solve the optimal DG allocation problem in radial distribution systems with non-linear loads. The proposed approach has been tested and investigated on the standard IEEE 69-bus test system. Results showed that the PPSOGSA algorithm is efficient for reduction of power losses and improvement of the voltage profile and power quality. In addition to this, it is found that the proposed algorithm has better performance than the original PSO, PPSO, GSA and PSOGSA in terms of solution quality and convergence speed. For practical applications in large-scale distribution systems, there is need to improve the computational speed; this is the main disadvantage of the PPSOGSA algorithm. Other issues that are involved in the operation of the distribution systems, such as the multiphase operation with unbalanced and non-linear loads, passive power filters and capacitors, will be discussed in the future work.

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