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Impact of Loading Capability on Optimal Location of Renewable Energy Systems Distribution Networks

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Abstract: A distribution system's network reconfiguration is the process of altering the open/closed status of sectionalizing and tie switches to change the topological structure of distribution feeders. For the last two decades, numerous heuristic search evolutionary algorithms have been used to tackle the problem of network reconfiguration for time-varying loads, which is a very difficult and highly non-linear efficiency challenge. This research aims to offer an ideal solution for addressing network reconfiguration difficulties in terms of a system for power distribution, to decrease energy losses, and increase the voltage profile. A hybrid Genetic Archimedes optimization technique (GAAOA) has also been developed to size and allocate three types of DGs, wind turbine, fuel cell and PV considering load variation. This approach is quite useful and may be used in many situations. This technique is evaluated for loss reduction and voltage profile on a typical 33-bus radial distribution system and a 69-bus radial distribution system. The system has been simulated using MATLAB software. The findings suggest that this approach is effective and acceptable for real-time usage.

Keywords: Distribution systems; Distributed generators; Different Load Levels; hybrid; Genetic algorithm; Archimedes optimization algorithm; Power losses; Voltage stability.

1. Introduction

The network in question is an essential component of the electricity system. Radial distribution is utilized since it is simple to manage and configure protective devices, given the unidirectional flow of power. Nowadays, the distribution system is radially configured as the most effective configuration. Power system performance enhancement has been studied since the existence of power system networks. Minimizations of power system losses and voltage deviation have received a great attention to improve system performance. For many years compensating capacitors and FACTs devices have been presented as the most efficient solution [1-4]. Another solution is network reconfiguration which aims to modify the topological properties of the distribution system to accomplish incident recovery. Distribution system reconfiguration (DSR) of a distribution system (DS) is typically done to increase the DS's operating efficiency [5-8]. The configuration of the networks [9-10] leads to a significant effect on the power quality factors [11] like power loss [12-13], voltage profile [14-15], reliability [16], and networks resiliency [17-18]. The energy business has seen some isolationism in recent years [19] as costs for traditional energy sources [20-21] such as petroleum, have risen.

Distributed generators (DG) are a smaller energy producing systems. They have been widely used to support electrical networks against sudden variation related to load demand, power supplied or faults. DG could be divided into conventional and renewable energy type [22]. Due to scarcity in energy resources, world has directed towards alternative energy resources especially renewable energy types. Supplying the required electrical energy through RER has increased incredibly worldwide. Both wind and solar energies has the highest contribution compared to other types of RERs [23]. Fuel cell is a green types RER that produces electricity and water as a side product. It works based on chemical reaction between oxygen and hydrogen. It is fast start up, reliable, efficient, light weight, and low-temperature source of energy so it has a promising future [24]. RER based DG has increased recently to earn the advantages of RER. This resulted in the development of smaller energy producing systems that could be linked together to provide better performance. Different DGs have been applied to DS planning as in [25-26].

The current emphasis on green power technology [27-29] has resulted in a large rise in the adoption of sustainable energy supply oriented on DGs in the DS under consideration [5]. DG installations are typically less than 100 MW and are linked to distribution networks with voltages ranging from 230/400 V to 145 kV [30]. Sustainable [31-32] or non-renewable [33-34] distributed generating sources are available. Sustainable sources, such as solar [35], wind [36], biomass [37], Micro turbines [38], photovoltaic [39], fuel cells [40], small hydro [41], and gas turbines [42] etc. The DG's goal is to connect all generating plants in order to decrease waste, costs, and greenhouse gas emissions [43]. The major rationale for employing DG units in a power grid is for the technological advantages listed below. The following are some of the most significant benefits [44]:

- Decreased system losses
- Voltage profile enhancement
- Improvement of frequency
- Enhanced system reliability and security
- Increased overall energy efficiency

Operating engineers need to know the best location [45], characteristics, scale, and quantity of necessary distributed energy resources (DERs) for maximum power network performance. The DERs source application process is quite significant. There are many optimization techniques have been presented in the literature to locate the best location and DG sizing, and its effect on power network performance such as AC-OPF [46], PSO [47], BA [48], FA [49], IFPA [50], and whole popular one is Genetic algorithm (GA) [51]. So if a comprehensive model of the workflow is not accessible, a genetic algorithm (GA) [52-54] is an improvement [55] approach that may be applied. GA is founded on Darwin's genetic evolution hypothesis [56], and it uses genetic operators including selecting, mutations, and crossovers to solve issues. However, most applications of the standard GA suffer from the following drawbacks: the sensitivity analysis of several parameters [57] for the purpose of increasing efficacy and exude a suitable initialization of the method Aside from the most notable disadvantage, which is the vast number of analyses needed to attain a high degree of confidence throughout the optimization search. In reality, GA may take several generations to reach its optimal state. Each generation has a large number of function assessments, particularly because evaluating the objective function necessitates a finite element computation, which takes a long time and is quite costly.

Different alternatives have indeed been suggested to solve this restriction and reduce the time taken to conduct function evaluation, including approximation methods [58], simultaneous computation [59-60], improvement by addition of layers, or through their deletion, permutation, and inter laminar modification [61], artificial neural network training [62], and finally hybrid approaches [62]. By employing hybrid approaches, a novel metaheuristic algorithm named Archimedes optimization algorithm (AOA) [63-66] is applied to eliminate GA shortcomings. AOA is based on Archimedes' Principle [67], a fascinating physics law. It stimulates the buoyant process; the upward buoyant force effect on an item partly or completely submerged in a fluid produces a displaced fluid with weight proportional to this buoyant force.

This paper provides a new algorithm for radial distribution network reconfiguration using different load level. This algorithm hybrid between Genetic Algorithm and Archimedes optimization algorithm (GAAOA), most studies don't consider the load variations. The loading of the system fluctuates based on the exact usage. In most cases, a set size and location of DG is not able to establish ideal network objectives. As a result, assuming a changing load intensity considering reduction in total power losses, increasing voltage stability and reducing fuel cost would vary the optimal sizes and placements of DGs in the grid. The proposed GAAOA algorithm is compared with GA, AOA, GASBO, SBO, and EO to evaluate performance.

2. Modeling of Distributed Generation

DG units usually operate in a constant power mode. Their connected node is considered a negative PQ load [68]. Optimal location and size of DG has a big effect in improving DN performance. Optimal location improves system efficiency, load-ability, reliability and overall system stability. It increases voltage stability margin, capacity release from sub-stations thermal loading in feeders and loss minimizations. The power supplied by DGs would reduce the total net load [69]. DGs are categorized into four types as follows:

- DGs Type 1 produces only active power. Micro turbines, fuel cells, and Photovoltaic could represent this type.
- DGs Type 2 produces reactive power. Synchronous compensator gas turbines could represent this type.
- DGs Type 3 produces active and reactive power. Synchronous machines could represent this type.
- DGs Type 4 produces real energy and consumes reactive energy. Induction Generators driven by wind turbines could represent this type.

This research uses three types of DG units: a wind turbine with a rated capacity of 3MW, a fuel cell with a rated capacity of 2MW, and a photovoltaic with a rated capacity of 1MW.

3. Problem Identification

The objective function (F) could be mathematically represented by equations (1) subject to equality constraints in eq. (2) and inequality constraints in eq. (3):

$$\text{Min. } F(x, y) \tag{1}$$

$$h(x, y) = 0 \tag{2}$$

$$g(x, y) \geq 0 \tag{3}$$

Where, x is a vector that includes system's state parameters, y is a vector that includes control parameters.

Power flow problem optimization aims to minimize objective function according to load flow equations while satisfying inequality constraints without violation [70]. The power system's state could be represented by a set of variables as follows:

$$x = \left[P_{G_1}, V_{L_1}, \ldots, V_{L_{NL}}, Q_{G_1}, \ldots, Q_{G_{NG}}, S_{l_1}, \ldots, S_{l_{nl}}\right] \tag{4}$$

The former parameters are explained as follows: P_{G1} represents real energy supplied at the slack bus. Q_G represents output reactive power. V_L represents voltage magnitude appears at load bus. S_l represents apparent power. NL represents the number of load buses. NG represents the number of generator buses. Nl represents the number of transmission lines.

3.1. Constraints

The system needs to achieve both equality and inequality constraint requirements. Power balance restrictions are considered as equality constraints while inequality constraints include the power system's operational limits.

3.1.1. Equality Constraints

These restrictions represent the power system's mechanics and the intended voltage set positions across the network. The power flow equations control the mechanics of the power system. That requires the net active and reactive powers at each bus equal zero [71].

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nb} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \quad \forall\, i\, \varepsilon\, nb \tag{5}$$

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{nb} V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] = 0 \quad \forall\, i\, \varepsilon\, nb \tag{6}$$

Where the former parameters are explained as follows: Q_G represents supplied reactive power. Nb represents the number of buses. Q_D represents reactive power demand. P_D represents active power demand. G_{ij} represents the transfer conductance between bus i and bus j. B_{ij}represents the transfer susceptance between bus i and bus j.

3.1.2. Inequality Constraints

Parameters that define the operational limitations of the power system, are detailed as under Limitations on generation: The real and reactive power produced by the generator, and voltage at each bus are limited in the stable operation by the high and low limits according to equations (7-9). Security constraints should be kept in the range according to bus voltage and line loadings based on equations (10) and (11). The shunt VAR compensators limits restrict VAR compensator constraints according to equation (12). Transformer constraints are restricted by transformers' tap settings' higher and lower limits according to equation (13). Technical constraints of DG determine its capacity, which is restricted by energy resources between the higher and lower levels [72].

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \qquad \forall\, i\, \varepsilon\, N \tag{7}$$

$$GP_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max} \quad \forall\ i\ \varepsilon\ NG \tag{8}$$

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max} \quad \forall\ i\ \varepsilon\ NG \tag{9}$$

$$V_{Bi}^{min} \le V_{Bi} \le V_{Bi}^{max} \quad \forall\ i\ \varepsilon\ NL \tag{10}$$

$$S_{Li} \le S_{Li}^{max} \quad \forall\ i\ \varepsilon\ nl \tag{11}$$

$$Q_{ci}^{min} \le Q_{ci} \le Q_{ci}^{max} \quad \forall\ i\ \varepsilon\ NC \tag{12}$$

$$T_{i}^{min} \le T_{i} \le T_{i}^{max} \quad \forall\ i\ \varepsilon\ NT \tag{13}$$

$$P_{gni}^{min} \le P_{gni} \le P_{gni}^{max} \tag{14}$$

4. Objective Functions

This work proposes two objective functions, including power losses and voltage deviations. Both objective function could be mathematically presented as follows:

4.1.Energy Losses

Minimizing total energy losses is a basic objective for network reconfiguration optimization and many other power system optimization problems. It could be mathematically expressed by equation (15).

$$\min f_1(\overline{X}) = P_L = \sum_{i=1}^{N_1} g_k \left[V_i^2 + V_j^2 - 2V_iV_j\cos(\delta_i - \delta_j)\right] \ [73] \tag{15}$$

4.2. Voltage Deviation

Minimization of voltage deviation is one of the most common objectives related to network reconfiguration. It could be mathematically expressed by equation (16).

$$\min f_2(\overline{X}) = \Delta V_D = \max\left(\frac{V_1 - V_k}{V_1}\right)\ \forall\ k = 1,2,\ldots.., \quad [74] \tag{16}$$

5. Proposed Algorithm

5.1. Genetic Algorithm (GA)

It is a search strategy deployed in computers to identify real or approximate answers to optimization and search issues. Global search heuristics are what genetic algorithms are classified as. Genetic algorithms are one of the evolutionary algorithms that use processes like heredity, mutations, selecting, and crossover inspired by evolutionary biology (AKA recombination). The Genetic Algorithm approach is shown in Figure 1.

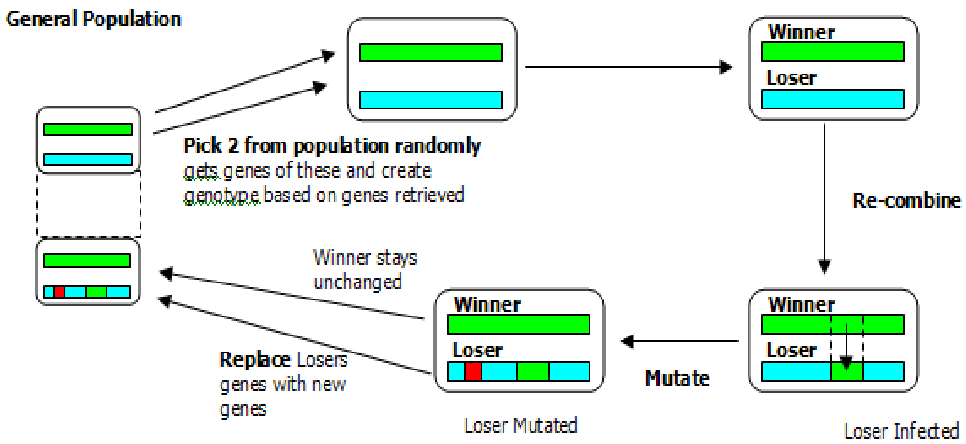


Figure 1. Genetic algorithm technique.

Genetic techniques are tested as a simulation where a population of abstract models of possible solutions (labelled phenotypes, creatures, or people) for an optimization problem develops approaching superior solutions (called chromosomes, genotypes, or genomes). Solutions are usually expressed as strings of 0s and 1s in binary, although different encodings are also feasible. Evolution begins mostly with a group of randomly initialized people and proceeds in generations. Every generation, the fitness for every item in the group is calculated. Several individuals are randomly selected from the current population (depending on their fitness value) and changed (recombined and maybe mutated) to generate a new population. The new population is subsequently utilized in the algorithm's following iteration [75-77]. Figure 2 shows the Genetic algorithm step-by-step flow chart.

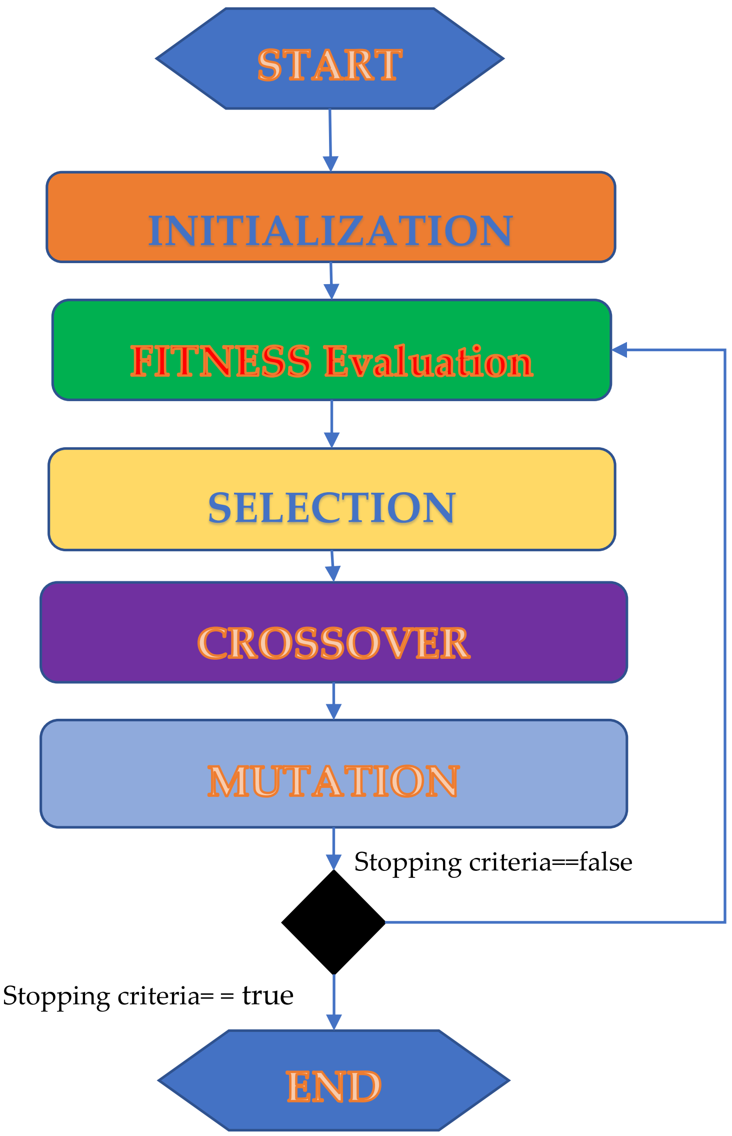


Figure 2. Genetic algorithm step-by-step flow chart.

5.1.1. Applying GA

GA could be applied effectively according to a set of rules which includes different steps that could be implemented as follows:

Step 1: - (Initialization): Initialize the constants and input parameters. Set the time counter as t=0.

Step 2: - Randomly generate a population of n solutions/chromosomes.

Step 3: - (Evaluation): Calculate the fitness function for all chromosomes included in the population. Each chromosome in the primary population is checked to select the suitable one. The best chromosome of all is that produces the best objective function and represented by X_{best}.

Step 4: - (Keep up with the time): The time counter gradually increases (t= t+1).

"Step 5: - (Adding of the new population): a new population is created according to the following guidelines.

Selection: Select some solutions based on their fitness to provide better solutions for the next generation.

Crossover: The parents are crossed to generate new offspring.

Mutation: the new chromosomes may be changed according to the capability for mutation.

Acceptance: the new offspring are transferred to the new population.

Step 5 (replacement): Replace the newly generated solutions with randomly selected solutions.

Step 6: when met a terminating condition stop; if not, return to step 2.

5.2. Archimedes Optimization Algorithm (AOA)

AOA is distinguished by its ease of use, requiring less regulating parameters (size of population and ending criteria) [78]. This optimizer takes its inspiration from Archimedes' principle statements. It defines how an object behaves when it is partially or entirely submerged in a fluid and the fluid produces an upward push on the item proportional to the displacement caused, with regards to the fluid, by the item. When an item is submerged in a fluid, it is subjected to an upward force known as buoyant force, which is equal to the displaced fluids' weight (see Figure 3) [79].

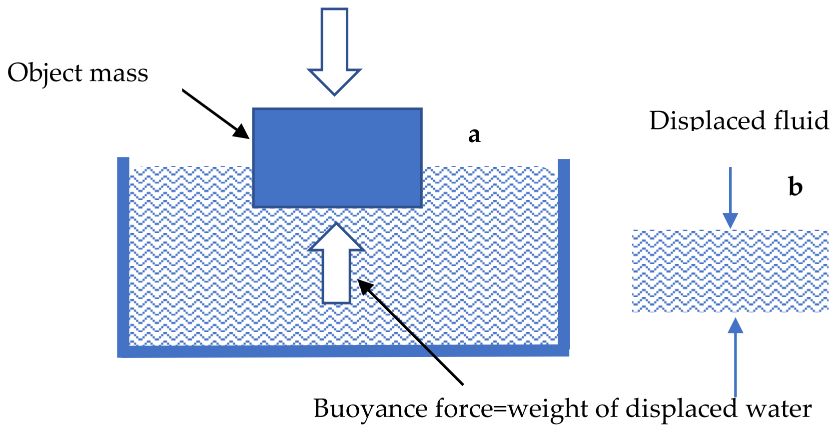


Figure 3. (a) immersed object in a fluid, and (b) The fluid displaced volume.

The Optimization Algorithm (AOA) has been used successfully to welded beam layout, speed reducer design issues and pressure vessel design [64]. It can handle difficult optimization problems providing better global optimization ability accurately and fast with. However, there is a paucity of research on AOA [80] handling DG setup and network restoration challenges. AOA is a population-based metaheuristic algorithm. It randomly starts the search using a population of objects (candidate solutions) with different volumes, accelerations and densities. At this point, each item is randomly located in the fluid. The optimization process goes on until the termination condition is met or at the end of iterations. The density and volume of each object are changed every iteration. The ability of object to collide with other near objects would define whether the acceleration would change or not. The new location of an item will be updated according to new density, volume, and acceleration. The complete mathematical formulation of AOA stages is given below.

5.2.1. AOA Solution Steps

I. Initialization

Set algorithm parameter C_1,C_2,C_3,C_4,u and I, where C_1,C_2,C_3,C_4 are a constant equal to 2,6,2 and 0.5, respectively. The highest and lowest range of normalization (u and I) are adjusted to be 0.9 and 0.1, respectively. Creating initial population with random volumes, densities, and accelerations according to equation (17).

$$X_i = lb_i + rand\ x\ (ub_i - lb_i); i = 1,2, \dots, N \quad (17)$$

Where, x represents the object, i is the number of objects and N is the maximum number of objects. lb_i and ub_i are the lower and higher limits of the search space respectively. Initialize density (den), acceleration (acc) and volume (vol) for each ith

$$den_i = rand \quad (18)$$

$$acc_i = lb_i + rand\ x\ (ub_i - lb_i) \quad (19)$$

$$vol_i = rand \quad (20)$$

Where, rand is a vector that includes numbers generated randomly between [0, 1].

II. Calculate Fitness Value

$$Y_i = fobj\ (X_i) \quad (21)$$

"Where fobj is a function that calculates initial population value to choose the best object with the best fitness value. Assign X_{best}, den_{best} , acc_{best} ,$and\ vol_{best}$, where den_{best} ,acc_{best} ,and vol_{best} The density, acceleration ,and volume are associated with the best object found so far."

III. Transfer Operator and Density Factor

TF is a transfer operator that helps the objects reach the state of balance. After the collision between them. This changes search into exploitation from exploration, while the value of TF is calculated using Equation. (22)

$$\text{TF}=\exp(\frac{t-t_{max}}{t_{max}}) \quad (22)$$

Where, t represents the iteration number and t_{max} represents maximum iterations. TF is gradually increased with time and its maximum value is 1. Density factor d helps the algorithm on global to local search. The density factor is gradually reduced with time according to Equation (23)."

$$d^{t+1} = \exp(\frac{t-t_{max}}{t_{max}}) - (\frac{t}{t_{max}}) \quad (23)$$

The ability to converge in the promising region is achieved through a gradual decrease d^{t+1} with time. The balance between exploration and exploitation could be achieved by properly handling of this variable."

IV. Update Density and Volume

The density and volume for any object *i* is updated for any iteration *t + 1* according to equation (24-25).

$$den_i^{t+1} = den_i^t + rand\ x\ (den_{best} - den_i^t). \quad (24)$$

$$vol_i^{t+1} = vol_i^t + rand\ x\ (vol_{best} - vol_i^t). \quad (25)$$

V. Exploration Phase (collision)

The collision between objects occurs if TF $\leq$ 0.5. Select an object of random material (mr) and update its acceleration for iteration t + 1 using equation (26)."

$$acc_i^{t+1}\frac{den_{mr}+vol_{mr}\ x\ acc_{mr}}{den_i^{t+1}\ x\ vol_i^{t+1}} \quad (26)$$

"Where $den_{mr}, vol_{mr}\ and\ acc_{mr}$ are density ,volume and acceleration of random material .It is important to mention that TF ≤ 0.5 ensures exploration during one-third of iterations."

VI. Exploitation phase (no collision)

If TF $>$ 0.5 there is no collision between objects; update object's acceleration for iteration t + 1 using Eq. (27)"

$$acc_i^{t+1} = \frac{den_{best} + vol_{best}\ x\ acc_{best}}{den_i^{t+1} x\ vol_i^{t+1}} \quad (27)$$

VII. Normalize acceleration

The percentage of change is calculated according to equation (28)

$$acc_{i,norm}^{t+1} = u\ x\ \frac{acc_i^{t+1} - \min(acc)}{\max(acc) - \min(acc)} + I \quad (28)$$

The step for each agent will change according to the percentage of ($acc_{i,norm}^{t+1}$). Acceleration value for objects outside optimum global region is high means. The search transforms from exploration to exploitation in the same manner.

VIII. Update position

If TF $\le$ 0.5 (Exploration phase) the i^{th} object's position for the next iteration t + 1 using Eq. (29)

$$X_i^{t+1} = X_i^t + C_1\ x\ rand\ x\ acc_{i,norm}^{t+1}\ x\ d\ x(X_{rand} - X_i^t) \quad (29)$$

Otherwise, if TF > 0.5(exploitation phase), the objects update their positions using Eq. (30)

$$X_i^{t+1} = X_{best}^t + F\ x\ C_2\ x\ rand\ x\ acc_{i,norm}^{t+1}\ x\ d\ x(TX_{best} - X_i^t) \quad (30)$$

Where T= $C_3 x\ TF$ (31)

and F is the flag to change the direction of motion.

$$F = \begin{cases} +1\ if\ \ P \le 0.5 \\ -1\ \ if\ P\ > 0.5 \end{cases} \quad (32)$$

Where P= 2 x rand - C_4 (33)

IX. Evaluation

"Evaluate each object according to objective function (f) and keep the best solution found so far. Determine the values of the following parameters $X_{best}, den_{best}\ , vol_{best}\ and\ acc_{best}$. Figure 4 shows the flowchart of AOA algorithm.

5.3.Hybrid Genetic Algorithm Archimedes Optimization Algorithm (GAAOA)

As previously stated, GA has several limitations, such as the fact that it may take several generations to reach the optimum. As a result, it takes a long time to compute in addition to being exceedingly costly.To get around this constraint and shorten the time it takes to evaluate a function, then the overall performance and solution quality can be enhanced A hybrid method has been proposed. A hybrid algorithm mixes two or more different algorithms to address the very same issue, and is commonly deployed when using programming languages such as C++, picking one (based on the input) or changing between them throughout the procedure. This is usually done to integrate each component's desirable qualities such that the entire method outperforms the separate components.

This research proposes a new hybrid algorithm, combining Genetic Algorithm and Archimedes Optimization Algorithm. This algorithm is called Hybrid Genetic Algorithm Archimedes Optimization Algorithm (GAAOA). The suggested method has various distinguishing characteristics. To begin, AOA is utilised to escape from the local minimum solution since it has the ability to be faster and deliver a better solution than GA. As a result, AOA has a significant impact on the search process because it has the ability to rapidly identify the ideal DG size and location. Secondly, by splitting the optimization population, the algorithm's performance is increased. The first half of the initialized population is passed through the GA algorithm. And this half population is gradually enhanced through the GA operators at each stage make a new population. The second population applies AOA. then these two populations are added together to find the best solutions. Lastly, it finds the ability to tackle GA adversities.

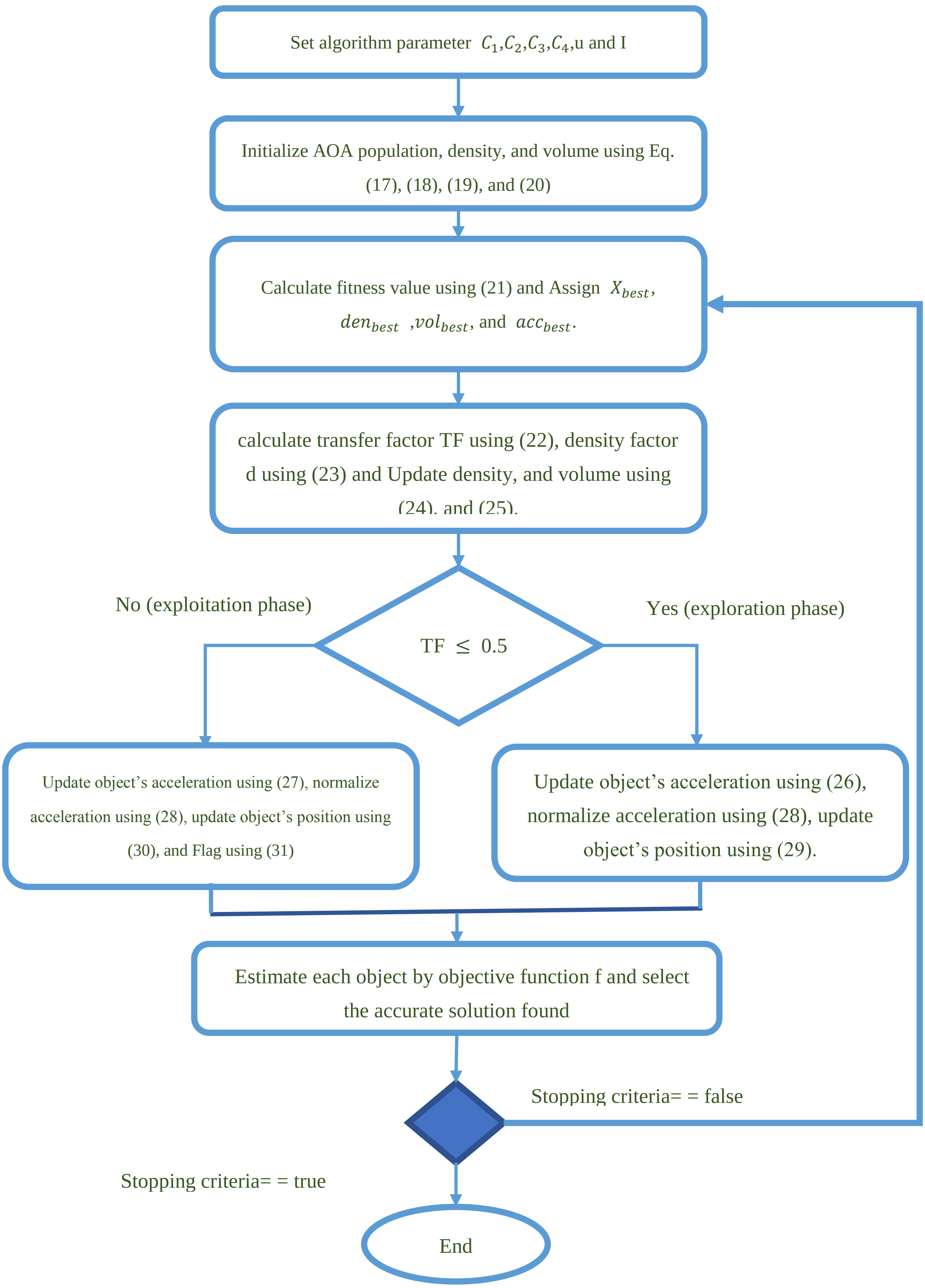


Figure 4. AOA Flowchart

5.3.1. GAAOA Step Solution

The flow chart of the proposed (GAAOA) optimization algorithm is illustrated in figure (5). It could explained properly according to the following steps:

I. Initialization: - read power system data and Initialize the constants and input parameters C_1,C_2,C_3,C_4,u and I. and Generate random population of n Materials with random volumes, densities, and accelerations using Eqs. (17-20).

II. Evaluation: - evaluate initial population value using Eq. (21). Sorting the initial population and select the object with the best fitness value. Assign X_{best}, den_{best} , acc_{best} ,$and\ vol_{best}$. Set The time counter as t=0

Main loop

III. if $t < Max\_iter$ contain,els stop.

IV. Create GA population and it should be an odd population. The first half population survives GA (selection =0.5), and AOA takes the return population. This would simplify the complexity of the suggested technique.

Apply GA: -

V. the GA algorithm performs pairing and mating using single point crossover, then Mutate the population.

VI. GA algorithm evaluates the position and cost function for each chromosome in the population.

Pop.Cost=fobj(Pop). (34)

Pop. Position=Pop. (35)

Where Pop is GA population, Pop. Cost and Pop. Positions are cost function and position for each chromosome in the population.

Apply AOA: -

VII. calculate transfer factor TF using Eqs. (22), density factor d using Eqs. (23) and Update density and volume using Eqs. (24), and (25).

VIII. Update object's acceleration: - "If TF $\leq$ 0.5 update object's acceleration for iteration t + 1 using ing Eq. (26), else If TF $>$ 0.5 using Eq. (27).

IX. calculate normalize acceleration to determine the percentage of change using Eq. (28)

X. Update position If TF $\leq$ 0.5 update object's position for iteration t + 1 using Eq. (29), also If TF $>$ 0.5 using Eqs. (30-33).

XI. AOA algorithm evaluates the position and cost function for each material in the population.

Newpop. Cost=fobj(Newpop). (36)

Newpop. Position=Newpop. (37)

Where Newpop is AOA population, Newpop.Cost and Newpop. Positions are cost function and position for each material in the population.

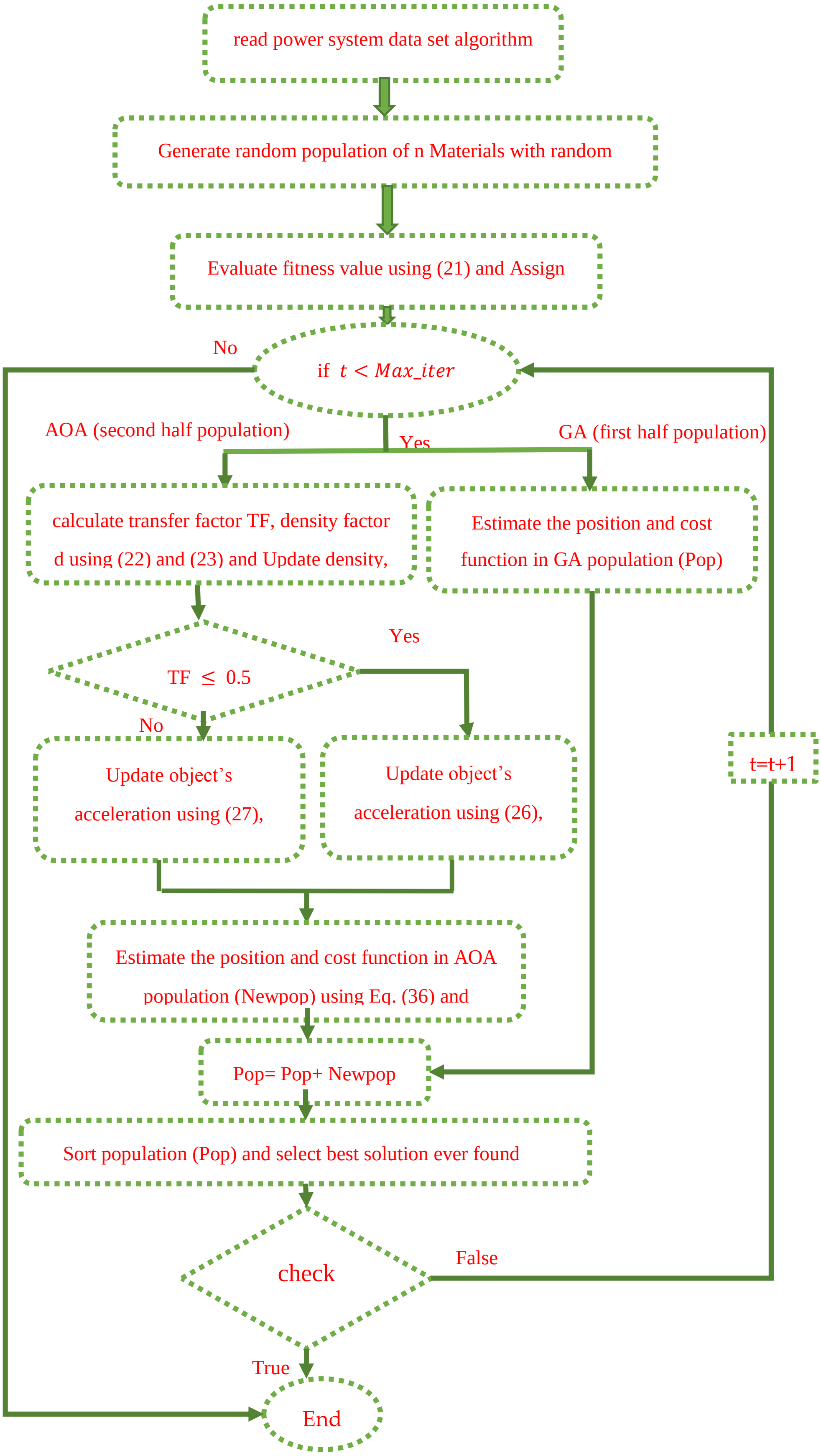


Figure 5. Flow chart of GAAOA .

XII. Adding GA population and AOA population all together.

Pop= Pop+ Newpop. (38)

XIII. Sort the population and select best solution ever found.

XIV. Set The time counter as t=t+1.

End of Main Loop

XV. check termination conditions.

6. Test System

The hybrid algorithm GAAOA is utilized in this research to increase DS performance utilizing various load levels and by adding particular types of DG (photovoltaic cell, fuel cell, and wind turbines). The major purpose is to discover the appropriate position and size of DGs to attain the greatest outcome for given objective functions. For the IEEE 33-bus power structure and the IEEE 69-bus based on power losses minimization and voltage stability improvement. The following section of the study concentrates on evaluating the hybrid, which is accomplished by simulating and projecting these two methods. This gives a testing environment and the convenience of not starting the systems.

6.1 .IEEE 33-bus system

The first proposed system is the IEEE 33-Bus radial distribution system. This system is illustrated as a single line diagram presented by Figure (6). the system parameters are listed in appendix Table A1[81-83].

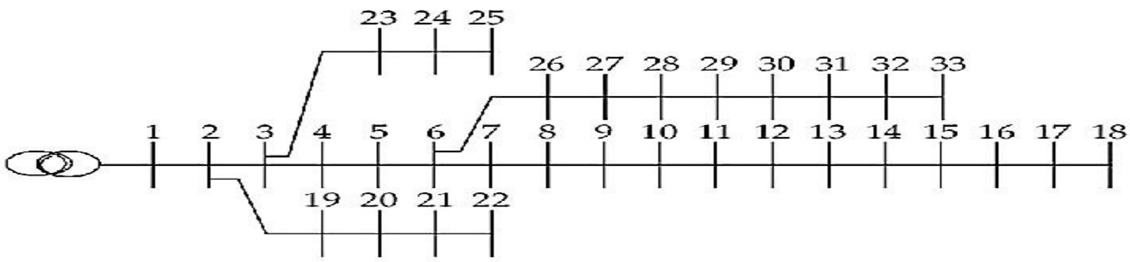


Figure 6. IEEE 33 bus system

6.2 IEEE 69-bus system

The second proposed system is IEEE 69-Bus radial distribution system. This system is illustrated as a single line diagram presented by Figure (7). The system parameters are listed in appendix Table A2 [81-83].

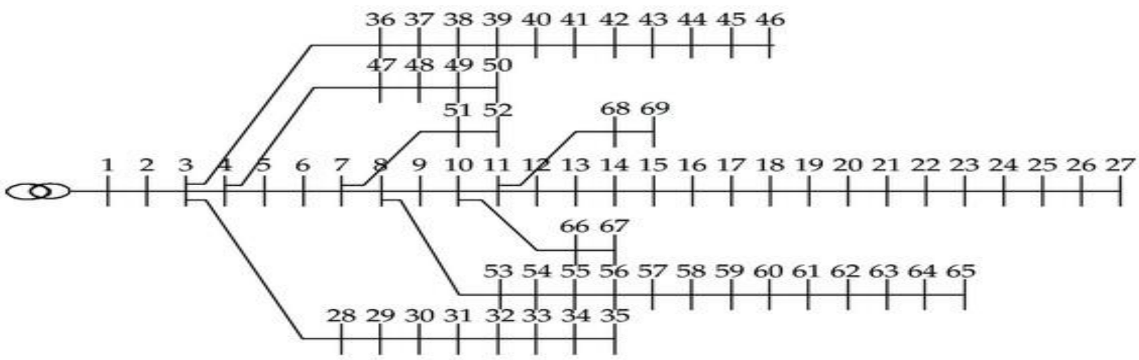


Figure 7. IEEE-69-bus system.

6.3 DG Specification

In our study, we used three types of DG. The first one is photovoltage, the second is fuel cell, and the third is a wind turbine. Table 1 shows the number of units and their specification of them [84].

Table 1. DG specification (84)

Type	Unit No.	Rated capacity (kw)	Lifetime (years)
PV	2	1000	20
FC	2	2000	10
WT	2	3000	20

7. Test Results

To test our study, new algorithm GAAOA is tested using Matlab R2014a. to prove the effectivity of GAAOA, we compared its results with GA and AOA algorithms. There are six Cases. Every case has two scenarios one without penetration of DG, and the other with penetration of DG units. To prove the strongest and evidence of our new hybrid algorithm IEEE 118-bus system is used for three load level and compared with GA, AOA, WMA[85], SBO[86], NSGA-III [87], EO[88], and GASBO[89].

Table 2. Test system cases

CASE	LOAD LEVEL	TEST SYSTEM
CASE 1	(50 %) of load	IEEE 33-bus system
CASE 2	(100 %) loading condition	
CASE 3	(160 %) of load	
CASE 4	(50 %) half load	IEEE 69-bus system
CASE 5	(100 %) full load	
CASE 6	(160 %) of load	
CASE 7	(50 %) of load	IEEE 118-bus system
	(100 %) full load	
	(160 of load	

7.1 IEEE 33-bus system

- *Case 1: Light loading condition.*

In this case, the system is operating at 50% of the base load condition.

- Scenario one without DGs penetration.

Scenario one GA, AOA and GAAOA algorithms are employed to minimize power losses and improve voltage profile without penetration of any DGs units. We can see the effect of hybrid method in our system. Both energy losses and voltage variation earned by GAAOA are smaller than those obtained by GA and AOA. The proposed algorithm minimizes the objective functions. The power losses is minimized to be 26.28 kw in scenario 1, while the worst value is obtained by AOA which is 29.58 kw. Also, GAAOA finds the least optimal voltage deviation and the value 0.0273 in scenario 1. The obtained results for scenario 1, including energy losses and voltage deviation, are listed in Table (3). It also simulated over iteration, as illustrated in Fig 8 (a, c).

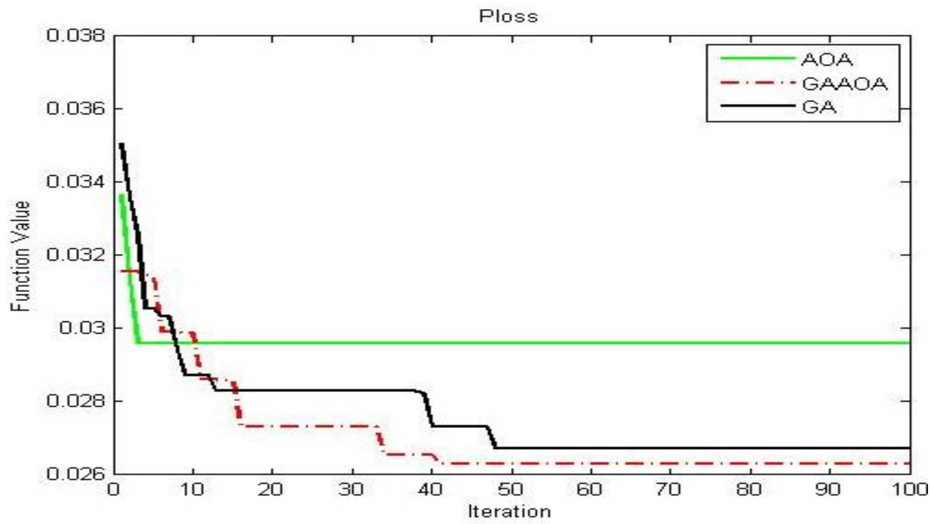
- Scenario two with DGs penetration.

As the name implies, DGs are utilized in this case to ensure even greater improvements in the system's efficiency. This helps to prevent energy loss and other possible damage. When it comes to the amount of time and steps required to reach an ideal result, GAAOA outperforms GA and AOA. Table 3 summarizes the findings. Figure 8 shows a contrast of Simulation convergence parameters for scenario two (b, d). The voltage deviation has decreased from 0.0278 without DG to 0.0042 while using DG based on GAAOA.

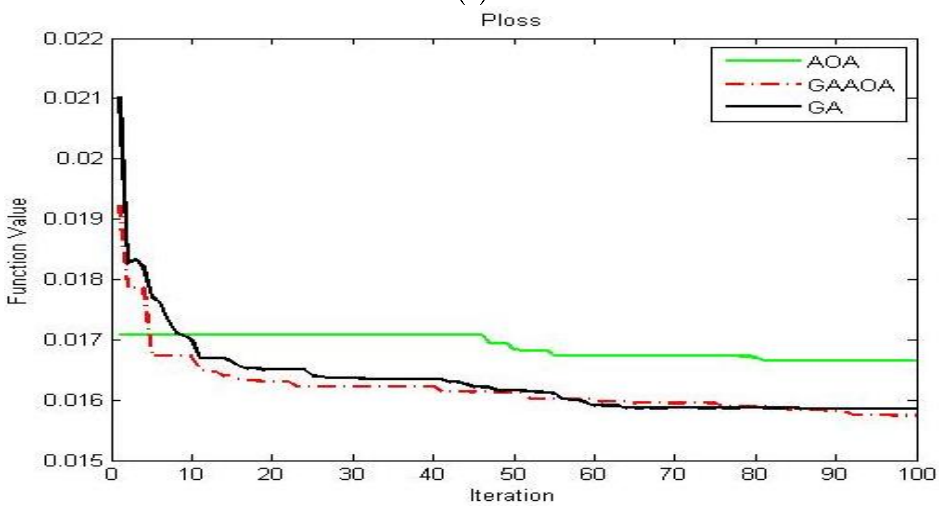
According to the obtained results from case1, it is obvious that adding DG improves the objective function greatly. The best results obtained by using GAAOA. According to figure (8), the system characteristics without DG based on GAAOA are best for both objective functions , while the system characteristics with DG based on GA and AOA are very close.

Table 3. Results found for case 1

Test Case		Method	scenario	PV Size(location)	FC Size(location)	WT Size(location)	f_x
Case 1	**Power losses (kw)**	GA	Without DG	-	-	-	26.7
			With DG	0.00476(25) ,0.06145(24)	0.14489(16) ,0.19802(10)	0.28094(31) ,0.29980(6)	15.85
		AOA	Without DG	-	-	-	29.58
			With DG	0.08464(29) , 0.04410(28)	0.13140(33) ,0.18199(22)	0.13498(17) , 0.22206(11)	16.65
		GAAOA	Without DG	-	-	-	26.28
			With DG	0.09302(8), 0.09961(7)	0.13359(28) ,0.18628(25)	0.22525(14), 0.19716(31)	15.73
	Voltage deviation (p.u.)	GA	Without DG	-	-	-	0.0278
			With DG	0.09881(32), 0.09701(30)	0.19686(31), 0.19489(18)	0.28764(10), 0.26660(25)	0.0038
		AOA	Without DG	-	-	-	0.0302
			With DG	0.01259(25) ,0.01418(33)	0.11402(14) ,0.13634(2)	0.03771(11) ,0.16670(4)	0.0104
		GAAOA	Without DG	-	-	-	0.0273
			With DG	0.05282(7), 0.09483(25)	0.19917(30), 0.18551(10)	0.29274(32), 0.27033(14)	0.0042


Ploss
AOA
GAAOA
GA
Function Value
Iteration
0.038
0.036
0.034
0.032
0.03
0.028
0.026
0
10
20
30
40
50
60
70
80
90
100

(**a**)


Ploss
AOA
GAAOA
GA
Function Value
Iteration
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0.02
0.019
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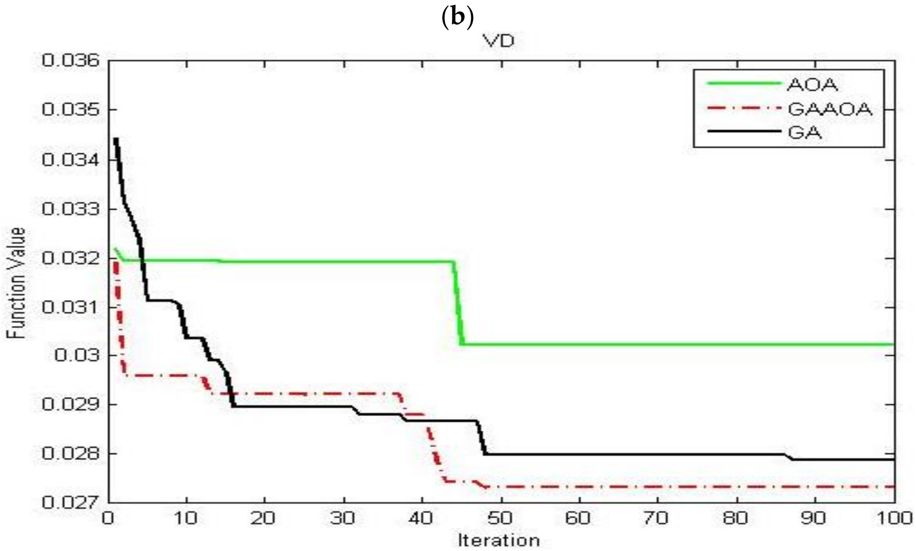
0.015
0
10
20
30
40
50
60
70
80
90
100

(**b**)


VD
AOA
GAAOA
GA
Function Value
Iteration
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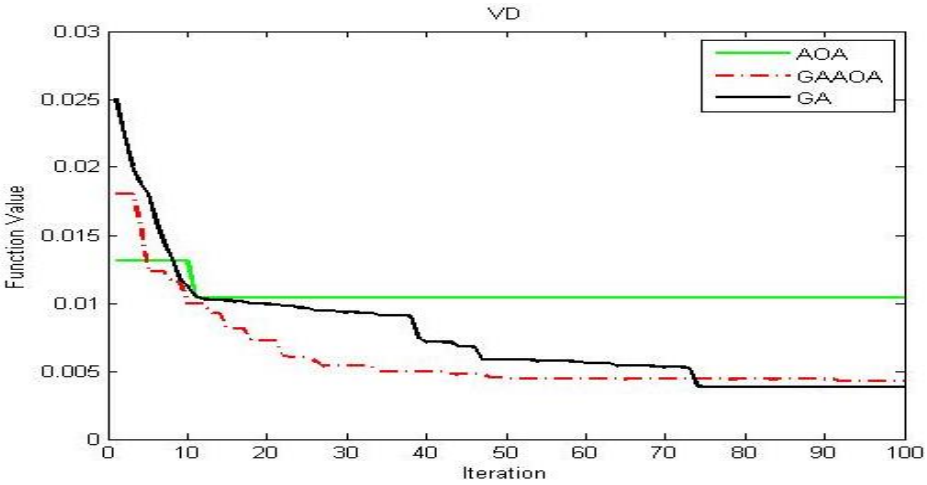
0.035
0.034
0.033
0.032
0.031
0.03
0.029
0.028
0.027
0
10
20
30
40
50
60
70
80
90
100

(**c**)



(**d**)

Figure 8. Convergence curves for 33-bus system Case 1 (a, c) scenario one, (b, d) scenario two.

Addig DG improved the system performance

- *Case 2: Normal loading condition.*

An Increase in the load level in this case increases all objective values and increases the total capacity of DGs units compared to case 1

- Scenario one without DGs penetration.

This example demonstrates how DGs may be implemented into a system to increase overall performance. When comparing GAAOA to AOA and GA for energy losses and voltage fluctuation, GAAOA comes out on top. When contrasted to AOA, which is the poorest, GA is the top performance. These evaluations emphasise the suggested algorithms' unique specialisation and superiority in the respective functions. Table 4 summarises the contrast. Figure 9 shows a comparative study of the convergence response for scenario 2 for a 33-bus system (a, c).

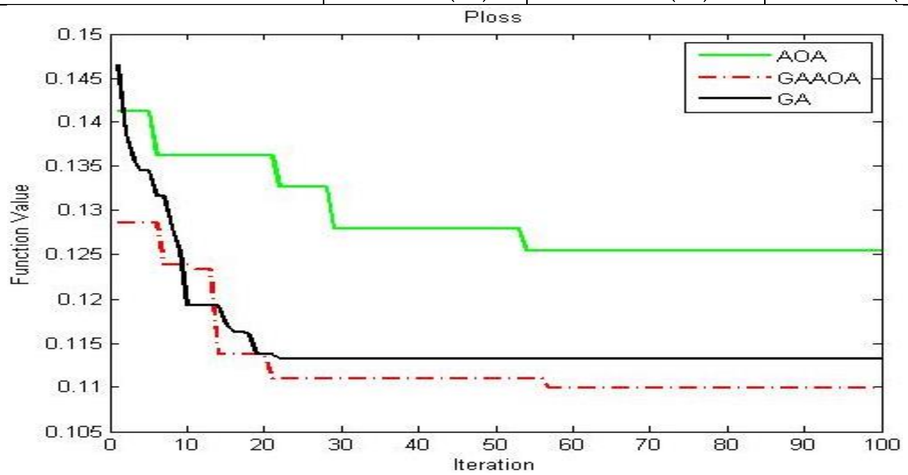
- Scenario two with DGs penetration.

As case 1, in this scenario, DGs are used. This helps reduce power losses by 37% and voltage deviation by 61%. When comparing GAAOA with AOA, GAAOA and GA found the same value for voltage deviation. But for power losses GAAOA found the best one; its value is 109.96 kw. Table 4 shows the result of scenario two. And Figure 9 (b, d) shows a comparison of convergence characteristics of simulation scenario two. The system characteristics without DG based on GAAOA are best for both objective functions , while the system characteristics with DG based on GA and AOA are very close.

Table 4. Results obtained for case 2.

Test case		**Method**	**scenario**	**PV Size(location)**	**FC Size(location)**	**WT Size(location)**	f_x
Case 2	Power losses (kw)	GA	Without DG	-	-	-	113.28
			With DG	0.09840(14), 0.08960(25)	0.18456(30), 0.19485(18)	0.29838(8), 0.29324(32)	69.75
		AOA	Without DG	-	-	-	125.48
			With DG	0.02134(2), 0.03371(26)	0.09387(28), 0.14053(32)	0.22188(4), 0.07009(24)	82.46
		GAAOA	Without DG	-		-	109.96

					-		
			With DG	0.09291(32), 0.09034(8)	0.20000(14), 0.20000(18)	0.28650(30), 0.29512(25)	69.12
	Voltage deviation (p.u.)	GA	Without DG	-	-	-	0.0578
			With DG	0.09503(32), 0.09866(30)	0.19189(18), 0.19608(14)	0.29440(8), 0.29324(31)	0.0221
		AOA	Without DG	-	-	-	0.0613
			With DG	0.06743(16), 0.08156(26)	0.09518(1), 0.15901(18)	0.22396(2), 0.13651(11)	0.039495
		GAAOA	Without DG	-	-	-	0.0561
			With DG	0.10000(14), 0.10000(30)	0.20000(18), 0.20000(32)	0.29856(31), 0.30000(16)	0.0221



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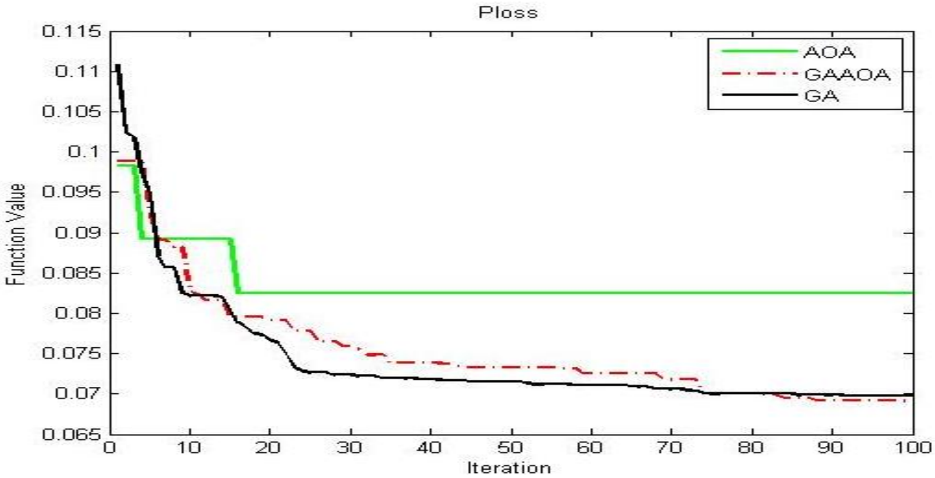
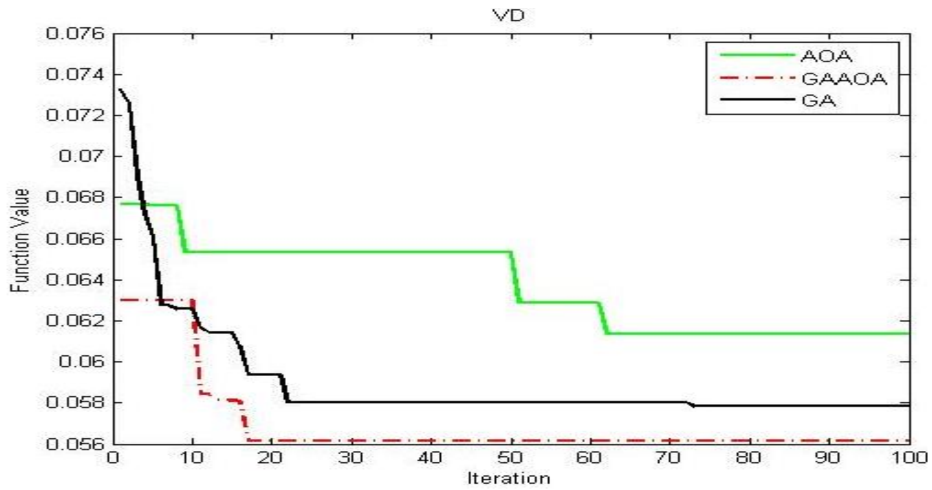


(**b**)



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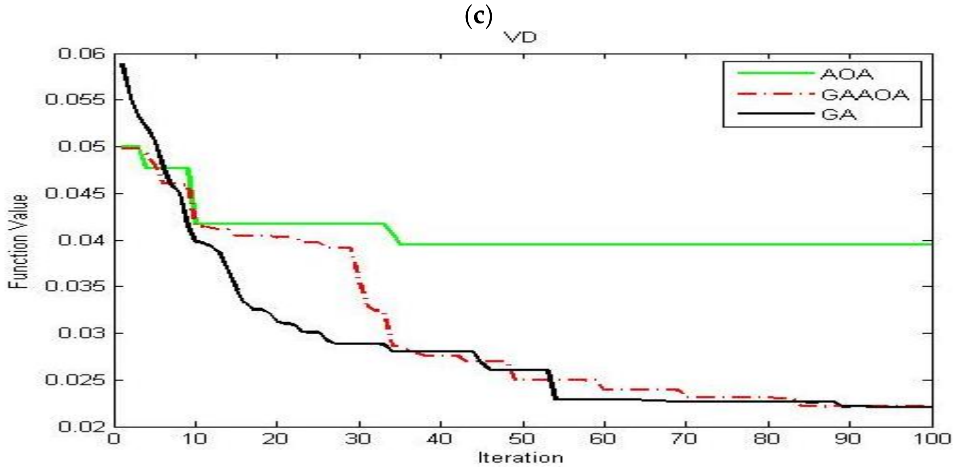


(**d**)

Figure 9. Convergence curves for 33-bus system case 2. (a, c) scenario one, (b, d) scenario two.

- *Case 3: Heavy loading condition.*

To simulate this operating condition, the system operates at heavy load (160 %) of total system load.

- Scenario 1 without DGs penetration.

The same objective functions are introduced. GAAOA provides the best possible solution for the power losses to be 302.34 kw and fo voltage deviation to be 0.093204 p.u.. And worst outcome is 447.14 kw and 0.22827 p.u. by AOA. All of these results prove the proposed algorithms' efficiency in reaching the optimal results despite there being no DGs penetration. Table 5 illustrate the obtained results for this scenario. The convergence curves represent the simulation of case 3 is illustrated by Figure 10 (a, c).

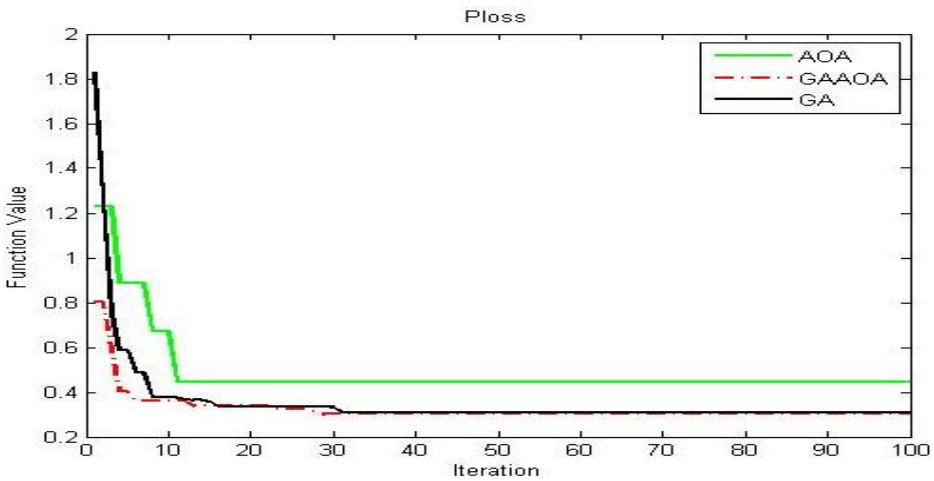
- Scenario 2 with DGs penetration.

The connected DGs size and location would optimize the proposed objective functions when optimized accurately. At this point, the energy losses and voltage variations would be minimum. In cases 1and 2, in this scenario, DGs are used. This helps reduce power losses referring to GAAOA results by 33% and voltage deviation by 44%. When comparing GAAOA with AOA, GAAOA, AOA and GA, GAAOA found the best values for energy losses and voltage variation. Table 5 shows the result of scenario 2. Figure 10 (b, d) shows a comparative study of scenario two's convergence.

According to the obtained results from case3, adding DG reduced the objective function greatly. Overloading the system has not reduced theeffeciency of the proposed algorithm. The best results obtained by using GAAOA and GA. Although the obtained results in favor of GAAOA, the convergence curves belong to GA and GAAOA are very close for both scenarios. The power losses decreased from 302.34 kw to 203.45 kw and the voltage deviation has decreased from 0.093204 pu to 0.05213 pu.

Table 5. Response earned for case 3

Test case		Method	scenario	PV Size(location)	FC Size(location)	WT Size(location)	f_x
Case 3	Power losses (kw)	GA	Without DG	-	-	-	308.51
			With DG	0.09902(14), 0.09502(32)	0.18981(18), 0.18254(25)	0.28094(30), 0.29980(8)	212.71
		AOA	Without DG	-	-	-	447.14
			With DG	0.08308(30), 0.02229(33)	0.11486(32), 0.16890(24)	0.12399(16), 0.27344(8)	242.12
		GAAOA	Without DG	-	-	-	302.34
			With DG	0.08382(25), 0.09900(30)	0.19493(18), 0.19907(32)	0.30000(8), 0.29900(14)	203.45
	Voltage deviation (p.u.)	GA	Without DG	-	-	-	0.095106
			With DG	0.09964(31), 0.09314(32)	0.19734(8), 0.19820(18)	0.29557(14), 0.28003(30)	0.052926
		AOA	Without DG	-	-	-	0.22827
			With DG	0.09033(31), 0.05114(15)	0.06755(15), 0.10220(18)	0.16756(12), 0.23393(21)	0.081158
		GAAOA	Without DG	-	-	-	0.093204
			With DG	0.09711(31), 0.09753(14)	0.20000(32), 0.19796(18)	0.30000(15), 0.29784(30)	0.05213



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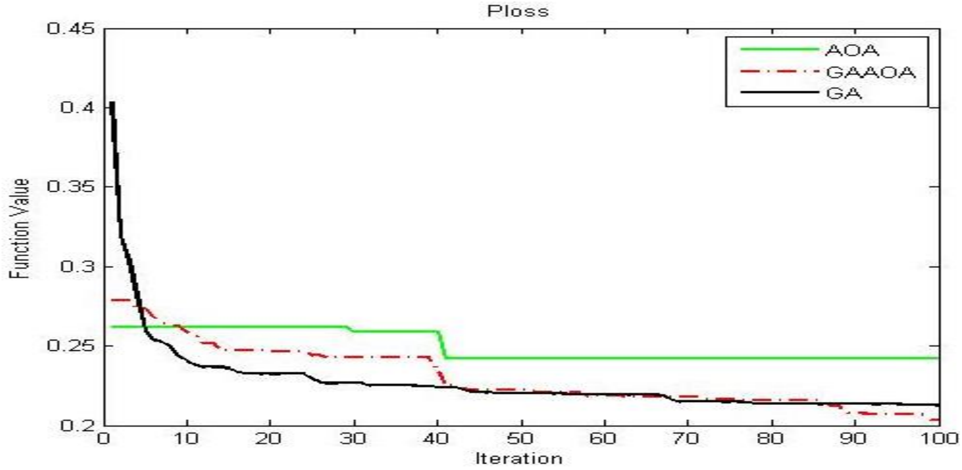

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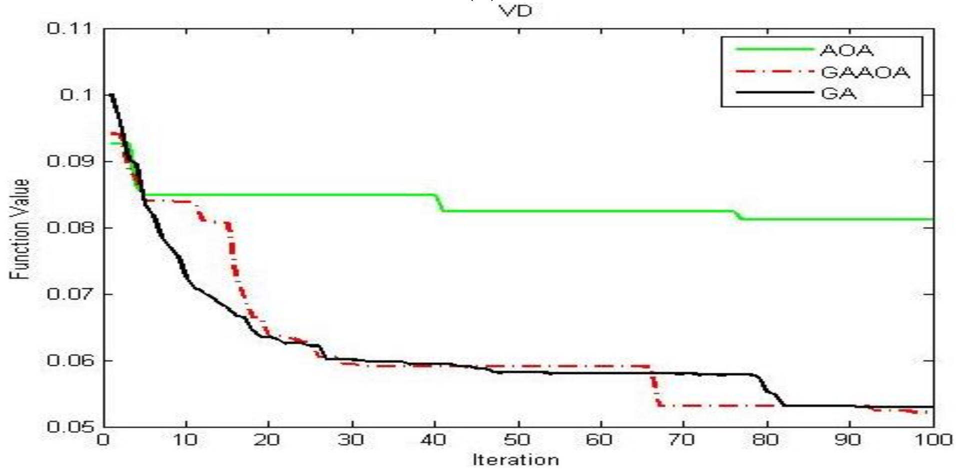

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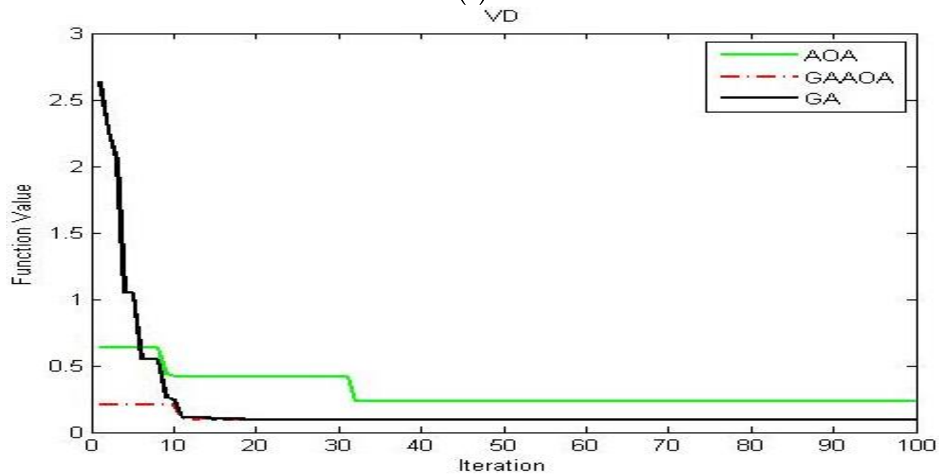


(**d**)

Figure 10. Convergence curves for 33-bus system case 3 (a, c) scenario one, (b, d) scenario two.

7.2 IEEE 69-bus system

- *Case 4: Light loading condition.*

• Scenario 1 without DGs penetration.

Same as case 1 GA, AOA and GAAOA algorithms are employed to find the best solution of energy losses and voltage deviation without penetration of any DGs units. The value of power losses and voltage deviation by GAAOA become less than the value using GA and AOA. It is observed that the GAAOA algorithm succeeded in minimizing our objective functions and leads to the most optimal execution. When discussing power losses, the best solution is done by GAAOA; the value is 18.13kw in scenario 1, and the worst value is by AOA, which is 19.73kw. Also, GAAOA finds the least optimal voltage deviation and the value 0.0125in scenario 1. Table 6 show the results obtained of scenario 1. Figure 11 (a, c) demonstrates the energy losses and voltage variation over the iterations.

- Scenario 2 with DGs penetration.

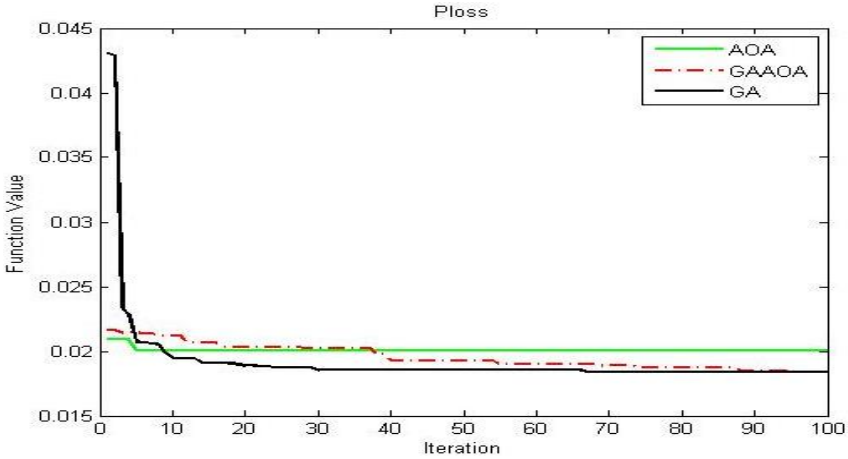
Here GAAOA is the better performer than GA and AOA for power losses and the value is 0.0125 kw. and for voltage deviation, GA finds the least optimal one and the value 0.00217. "The results are shown in Table 6. A Comparative study of scenario two convergence is given in Figure 11 (b, d).

The results obtained in case 4 show that the proposed algorithm stills has a good efficiency even with 69-bus system. The power losses decreased from 18.13 kw to 16.25 kw and the voltage deviation has decreased from 0.0125 pu to 0.0024 pu.

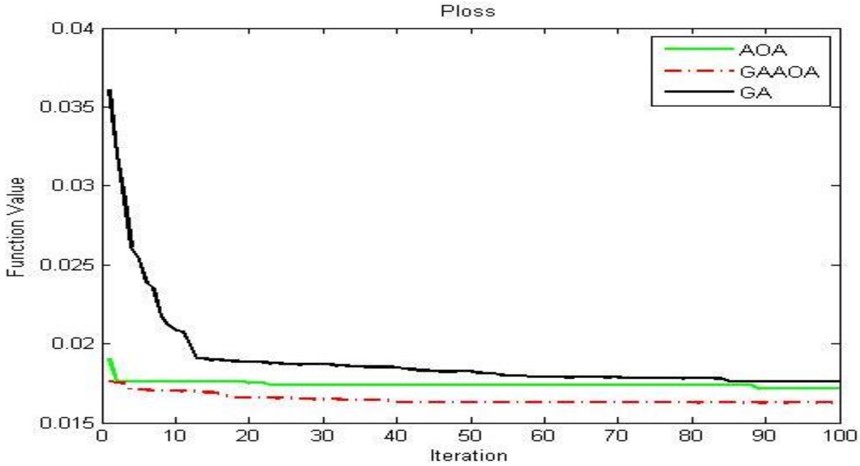
Table 6. Results obtained for IEEE 69-bus system case 4

Test case		**Method**	**scenario**	**PV Size(location)**	**FC Size(location)**	**WT Size(location)**	f_x
Case 4	Power losses (kw)	GA	Without DG	-	-	-	18.3
			With DG	0.07415(61), 0.03187(59)	0.18318(20), 0.16986(11)	0.16475(50), 0.05711(65)	16.55
		AOA	Without DG	-	-	-	19.73
			With DG	0.05188(66), 0.09651(57)	0.05226(22), 0.16084(56)	0.22301(33), 0.10122(43)	17.21
		GAAOA	Without DG	-	-	-	18.13
			With DG	0.07747(17), 0.09745(11)	0.03075(12), 0.05181(24)	0.22612(61), 0.20284(49)	16.25
	Voltage deviation (p.u.)	GA	Without DG	-	-	-	0.01305
			With DG	0.09229(59), 0.09697(68)	0.13098(61), 0.16837(49)	0.28094(16), 0.23160(63)	0.00217
		AOA	Without DG	-	-	-	0.0152
			With DG	0.03809(52), 0.06394(17)	0.05263(12), 0.05446(41)	0.12578(62), 0.27946(17)	0.0041
		GAAOA	Without DG	-	-	-	0.0125

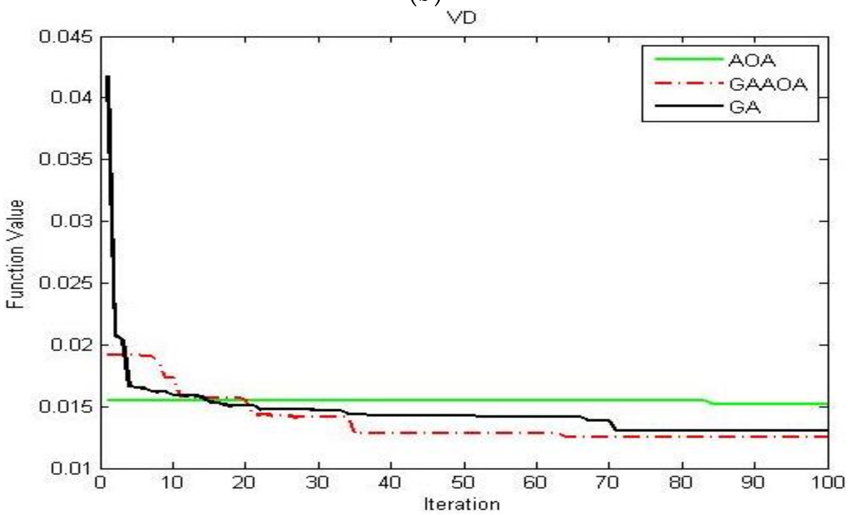
			With DG	0.09919(68), 0.05991(61)	0.10161(49), 0.10071(17)	0.15039(16), 0.29689(64)	0.0024



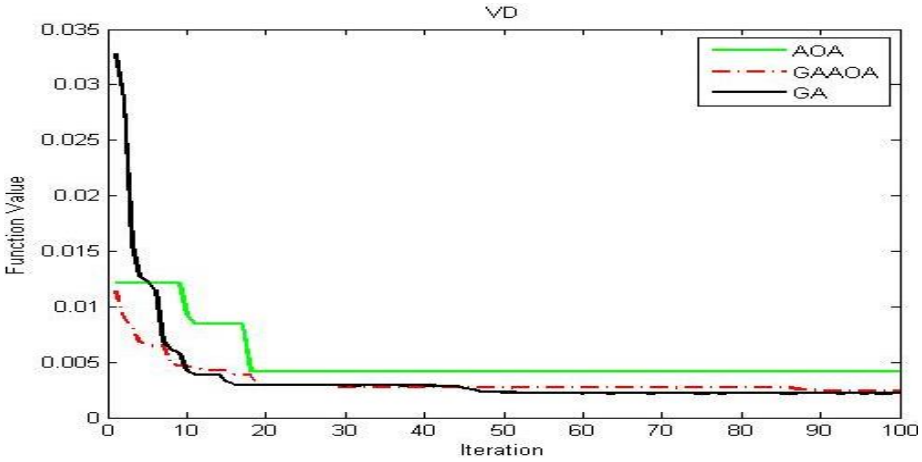
(a)



(b)



(c)



(**d**)

Figure 11. Convergence curves for 69-bus system case 4 (a, c) scenario one, (b, d) scenario two.

- *Case 5: Normal loading condition.*

- Scenario one without DGs penetration.

This case 69 bus system works with its normal load and without penetration of DGs. this scenario proves the efficiency of GAAOA method and its ability to reach the optimum value of specific objective function. "GAAOA performs the best for power losses and voltage deviation. The comparison is tabulated in table 7. A comparative study of the convergence of case 5 is given in Figure 12(a, c).

- scenario two with DGs penetration.

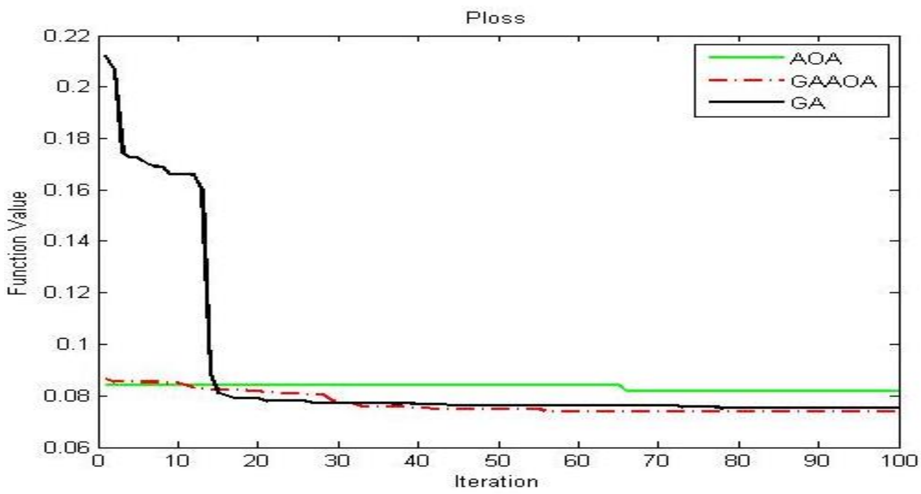
Using DGs units help in reducing energy losses by 10% and has a significant effect on voltage variation which reduced by 78%. Using the GAAOA algorithm table 7 shows the results of this scenario, and Figure 12(b, d) shows convergence characteristics of this scenario.

According to the obtained results from case5, the proposed algorithm effeciency stills very good under normal loading conditions.. Although the obtained results in favor of GAAOA, the convergence curves belong to GA and GAAOA are very close for both scenarios. The power losses decreased from 73.97 kw to 66.72 kw and the voltage deviation has decreased from 0.0255 pu to 0.0056 pu.

Table 7. Results obtained for IEEE 69-bus system case 5

Test case		Method	scenario	PV Size(location)	FC Size(location)	WT Size(location)	f_x
Case 5	Power losses (kw)	GA	Without DG	-	-	-	75.16
			With DG	0.09509(68), 0.08622(61)	0.19333(11), 0.18041(50)	0.22754(21), 0.13304(64)	67.51
		AOA	Without DG	-	-	-	77.43
			With DG	0.01278(23), 0.01349(58)	0.05740(59), 0.02309(21)	0.00216(10), 0.14043(63)	70.42
		GAAOA	Without DG	-	-	-	73.97
			With DG				66.72

			0.05820(17), 0.08969(50)	0.19718(11), 0.15387(59)	0.28026(61), 0.29683(22)	
Voltage deviation (p.u.)	GA	Without DG	-	-	-	0.0280
		With DG	0.09775(61), 0.09657(21)	0.19551(18), 0.18201(65)	0.29847(12), 0.29356(64)	0.0057
	AOA	Without DG	-	-	-	0.0322
		With DG	0.05948(54), 0.06371(64)	0.10240(6), 0.04937(45)	0.04393(7), 0.26926(22)	0.0260
	GAAOA	Without DG	-	-	-	0.0255
		With DG	0.09978(64), 0.09862(17)	0.19978(65), 0.16657(12)	0.28689(61), 0.28383(21)	0.0056



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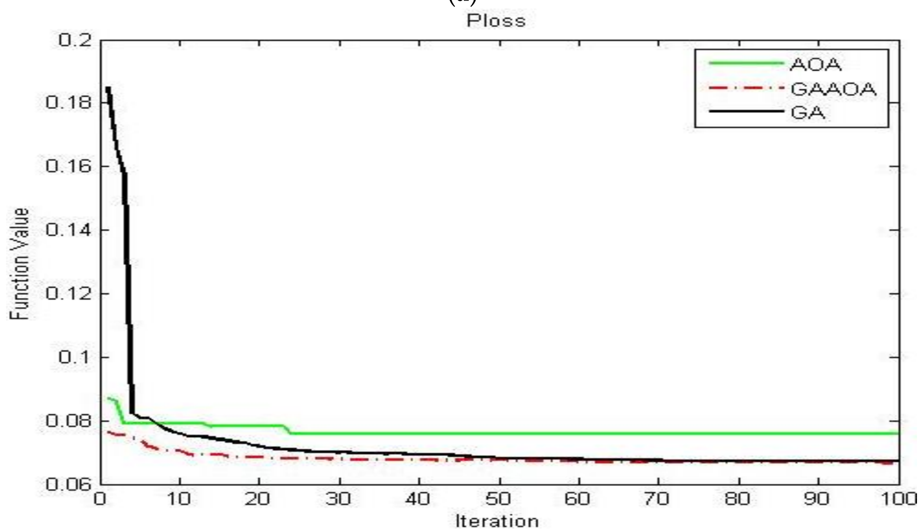

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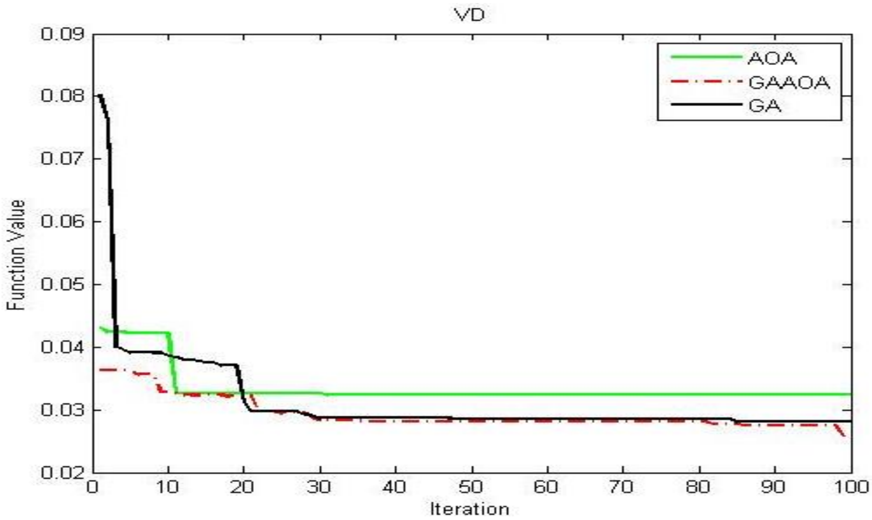

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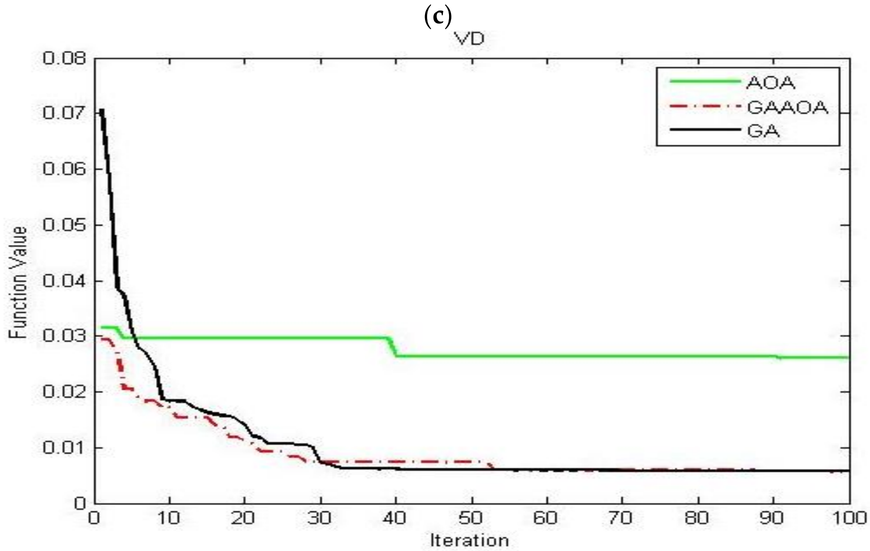


(**d**)

Figure 12. Convergence curves for 69-bus system case 5. (a, c) scenario one, (b, d) scenario two.

- *Case 6: heavy loading condition.*

- Scenario one without DGs penetration.

This scenario, GAAOA achieves the greatest for power loss and voltage deviation. Power losses value is 196.75 kw, and voltage value is 0.0441 regarding to hybrid GAAOA. A comparative study of convergence of case 6 is depicted in Figure 13(a, c). The comparison is tabulated in table 8.

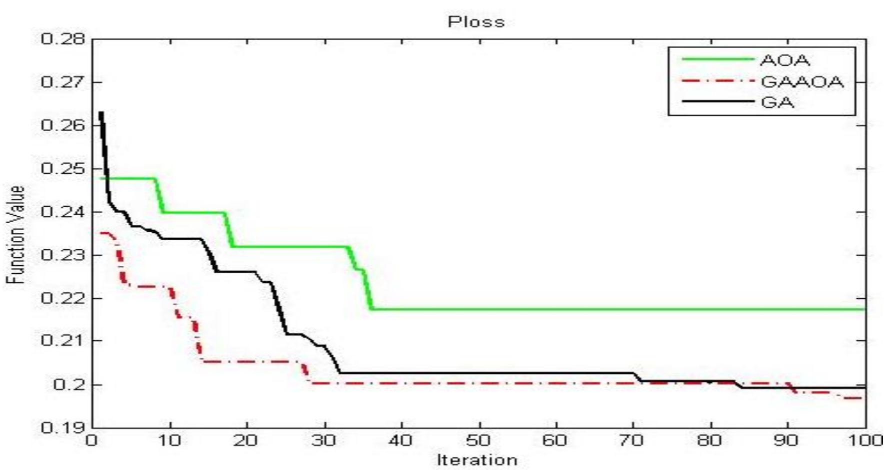
- Scenario two with DGs penetration.

In heavy load DGs size increase more than in the other cases.Power losses were reduced by 10% and significantly affected voltage deviation, which was reduced by 56%. Using GAAOA algorithm table 8 shows the results of this scenario, and Figure 13(b, d) shows the convergence characteristics of this scenario.

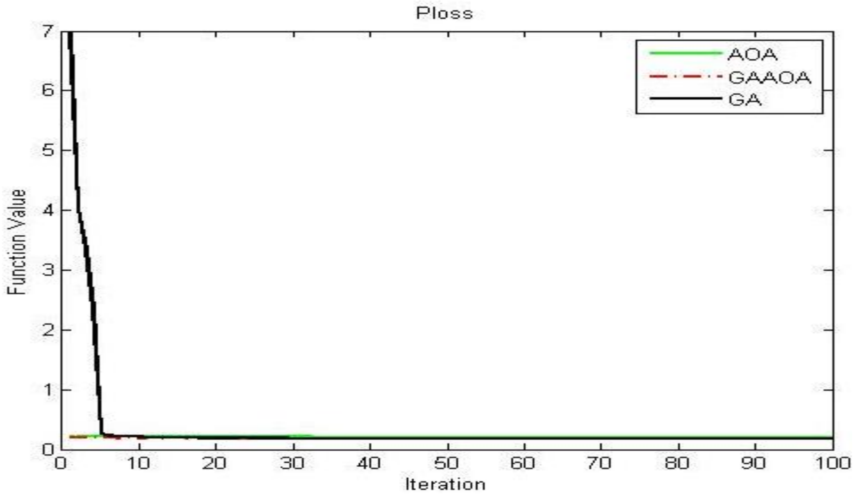
According to the obtained results from case 6, overloading the system has reduced the effeciency of the proposed algorithm to be almost the same as other algorihms GA and AOA, except for scenario 1 without DG. The convergence curves for all three algoritms are almost the same for both scenarios.

Table 8. Results obtained for IEEE 69-bus system case 6

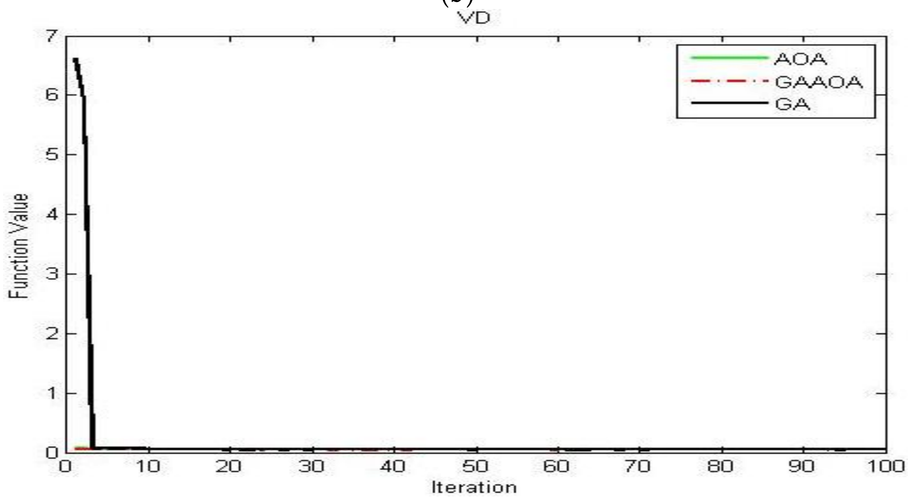
Test case		Method	sce-nario	PV Size(location)	FC Size(location)	WT Size(location)	f_x
Case 6	Power losses (kw)	GA	With-out DG	-	-	-	199.17
			With DG	0.09647(61), 0.09439(50)	0.19553(21), 0.19344(17)	0.29502(64), 0.29572(11)	178.25
		AOA	With-out DG	-	-	-	217.3
			With DG	0.06441(13), 0.03565(49)	0.16088(56), 0.14054(28)	0.13952(17), 0.09002(64)	193.19
		GAAOA	With-out DG	-	-	-	196.75
			With DG	0.10000(61), 0.09135(11)	0.20000(64), 0.20000(22)	0.30000(69), 0.29965(18)	177.86
	Voltage deviation (p.u.)	GA	Without DG	-	-	-	0.0445
			With DG	0.09841(12), 0.09203(21)	0.19531(61), 0.19497(64)	0.29380(65), 0.28867(17)	0.0198
		AOA	With-out DG	-	-	-	0.0551
			With DG	0.01681(31), 0.08503(62)	0.15220(68), 0.06845(60)	0.04318(34), 0.19421(63)	0.0461
		GAAOA	With-out DG	-	-	-	0.0441
			With DG	0.09976(21), 0.09738(18)	0.19209(64), 0.19041(24)	0.28802(59), 0.29396(61)	0.0194



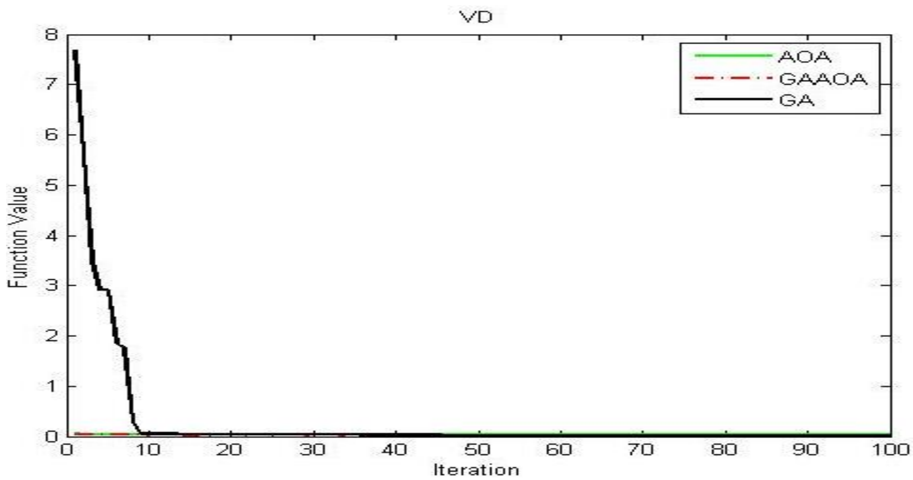
(**a**)



(**b**)



(**c**)



(**d**)

Figure 13. Convergence curves for 69-bus system case 6. (a, c) scenario one, (b, d) scenario two.

7.3 Result for IEEE 118-bus system

- *Case 7: different load level conditions.*

IEEE 118-bus system is a large-scale power system, the active power demand is 22709.72 kW and the reactive power demand is 17041.07 kVAr a [90]. Table 9.and Figure 14 obtain the comparison results for case 7.

According to the obtained results from case7 for large IEEE 18-bus system, the effeciency of the proposed algorithm is better for the proposed three scenarios. The power losses for the three scenarios are 134.47 kw, 586.23 kw and 1767.8 kw which are minimum compared to other algorithms .

Table 9. Comparison results obtained for case 7.

Method	Light load Power losses(total DGs size)	Normal load Power losses(total DGs size)	Heavy load Power losses(total DGs size)
GA	139.25 kw (5158 kw)	622.79 kw (5848kw)	1785.5 kw (5618 kw)
AOA	156.32 kw (3591 kw)	795.57 kw (3147 kw)	3206.95 kw (3387 kw)
GAAOA	134.47 kw (4245 kw)	586.23 kw (5678 kw)	1767.8 kw (5673 kw)
WMA	180.166 kw (4.134 kw)	947.74 kw (3507 kw)	3005 kw (2.893 kw)
SBO	136.38 kw (4668 kw)	671.31 kw (3948 kw)	1935.9 kw (4073 kw)
GASBO	138.76 kw (4321 kw)	608.01 kw (5217 kw)	1825.9 kw (5812 kw)
NSGA-III	218.102 kw (3.479 kw)	980.40 kw (3205 kw)	3122.8 kw (2.386 kw)
EO	147.93 kw (4.198 kw)	605.56 kw (4953 kw)	1814 kw (4279 kw)

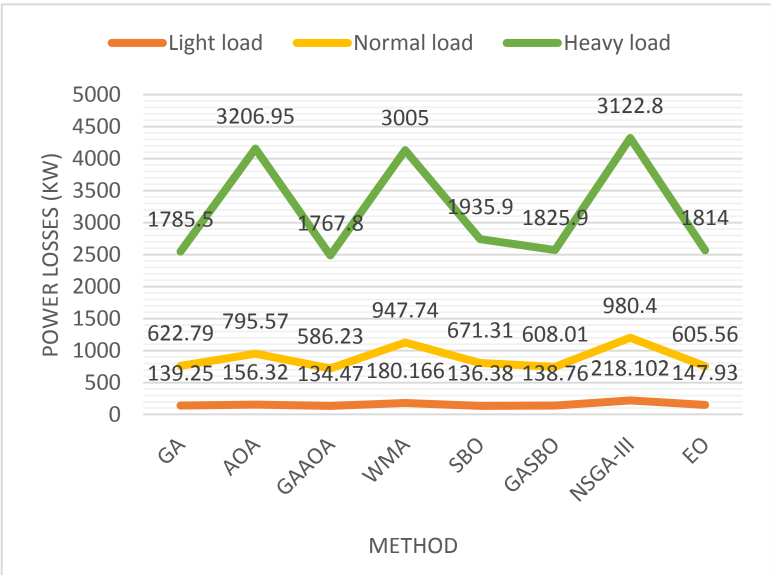


Figure 14. Comparison results for case 7.

8. Conclusions

This paper introduces new hybrid algorithm between GA algorithm and AOA algorithm, which is called GAAOA. GAAOA is used to improve power distribution system behavior, by finding the best locations and size of three DG's units including WT, FC and PV and system reconfiguration using load level technique (Light load, normal load, and heavy load). There are two types of objective functions, one is the power losses, and the other is voltage variation. IEEE 33bus system and IEEE 69 bus system are implemented as test system. GAAOA is tested in 7 cases, in all of them this novel algorithm finds the best value of specific objective function. the large scale 118 bus system is used for comparing the novel algorithm with related methods to prove the efficiency and effectivity of GAAOA algorithm. The computation results show that proposed GAAOA performance is better than other methods.

Appendix A

Table A1

How many?		How much?	P (MW)	Q (MVAr)
Buses	33	Generation (actual)	3.9	2.4
Generators	1	Load	3.7	2.3
Committed Gens	1	Fixed	3.7	2.3
Loads	32	Losses (I^2 * Z)	0.21	0.11
Fixed	32			
Branches	32			
Areas	1			

	Minimum	Maximum
Voltage Magnitude	0.911 p.u. @ bus 18	1.000 p.u. @ bus 1
Voltage Angle	-0.18 deg @ bus 18	1.00 deg @ bus 30
P Losses (I^2*R)	-	0.05 MW @ line 2-3
Q Losses (I^2*X)	-	0.03 MVAr @ line 2-3

Table A2

How many?		How much?	P (MW)	Q (MVAr)
Buses	69	Total Gen Capacity	10000.0	-1000.0 to 1000.0
Generators	1	On-line Capacity	10000.0	-1000.0 to 1000.0
Committed Gens	1	Generation (actual)	4.0	2.8
Loads	48	Load	3.8	2.7
Fixed	48	Fixed	3.8	2.7
Branches	68	Losses (I^2 * Z)	0.23	0.10
Areas	1			

	Minimum	Maximum
Voltage Magnitude	0.909 p.u. @ bus 65	1.000 p.u. @ bus 1
Voltage Angle	-0.21 deg @ bus 50	1.15 deg @ bus 65
P Losses (I^2*R)	-	0.05 MW @ line 56-57
Q Losses (I^2*X)	-	0.02 MVAr @ line 56-57

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