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AN OPTIMIZATION APPROACH FOR MINIMIZING ENERGY LOSSES OF DISTRIBUTION SYSTEMS BASED ON DISTRIBUTED GENERATION PLACEMENT

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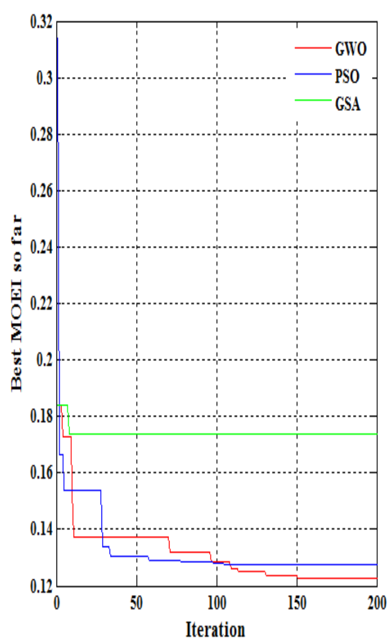
Graphical abstract



Abstract

The interest of electric utilities in distributed energy resources has increased in terms of maximising the latter's technical, economic and environmental benefits. This paper presents a Grey Wolf Optimizer (GWO) -based approach for optimal placement and sizing of multiple Distributed Generation (DG), aimed at reducing active and reactive energy losses in the distribution system. Power system constraints, such as voltage magnitude limits and current boundaries are also considered. Recently, a swarm intelligence technique, namely, GWO was introduced, which is inspired by grey wolves strategy and utilises four categories of grey wolves (alpha, beta, delta and omega) to simulate a leadership hierarchy. The GWO technique and two other popular methods Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA) – are here tested on 15- and 33-bus radial distribution systems. The numerical results obtained using these methods are compared, with the best performance recorded via the proposed GWO method in terms of not only active and reactive energy loss but also voltage profile and convergence characteristics.

Keywords: Grey Wolf Optimizer, Distributed Generation, Distribution System, Energy Losses, Voltage Profile

Abstrak

Tumpuan oleh pembekal elektrik kepada sumber tenaga teragih semakin bertambah dari segi memaksimumkan faedah teknikal, ekonomi dan alam sekitar kepada mereka. Kertas kerja ini membentangkan pendekatan berasaskan Pengoptimum Serigala Kelabu (GWO) untuk memperoleh penempatan dan pensaizan optimum Penjanaan Teragih (DG) yang bertujuan mengurangkan kehilangan kuasa aktif dan reaktif dalam sistem pengagihan. Had dalam sistem kuasa seperti had magnitud voltan dan batas arus juga diambil kira. Teknik kecerdikan kerumunan yang terkini iaitu GWO telah diperkenalkan yang diilhamkan oleh strategi serigala kelabu dengan empat kategori serigala kelabu (alpha, beta, delta dan omega) yang digunakan untuk mensimulasikan susunan kepimpinan. Teknik GWO dan dua kaedah popular lain iaitu Pengoptimuman Kerumunan Zarah (PSO) dan Algoritma Carian Graviti (GSA) juga diuji ke atas sistem agihan jejari 15 bas dan 33 bas. Hasil yang diperoleh daripada kaedah tersebut dibandingkan dengan hasil terbaik daripada kaedah GWO yang dicadangkan bukan sahaja daripada segi kehilangan tenaga aktif dan reaktif, malah juga melibatkan profil voltan dan ciri penumpuan penyelesaian.

Kata kunci: Pengoptimum Serigala Kelabu, Penjanaan Teragih, Sistem Agihan, Kehilangan Tenaga, Profil Voltan

1.0 INTRODUCTION

In recent years, power generation and transmission systems are operating under increasingly stressed conditions and are experiencing increasing power loss due to rising demand, environmental and economic constraints, as well as a competitive energy market [1]. The demand for energy is expected to rise 37% by 2040 [2]. Both electric utilities and society require environmentally friendly technology, more economic solutions, reliable operation, compensation in load demand, a reduction in losses and voltage profile improvement. Among the support methods available to the distribution grid, the strategic allocation of Distributed Generation (DG) in the grid is widely considered a viable option in comparison to network reconfiguration and capacitor placement [3].

Power can be maximised at the demand side via energy loss reduction in distribution and transmission lines. Over the last three decades, power loss minimisation based on optimal DG allocation has become one of the most attractive areas of research, including topics such as distribution system voltage stability enhancement, loadability improvement, reliability improvement and economic cost reduction. Real and imaginary power losses are generated due to the resistive and reactive elements of distribution lines, respectively. Active power loss reduces the efficiency of energy transmission, with distribution companies (DISCOs) subject to financial penalties if active power losses are higher than standard ones and obtaining a profit if the reverse is true [1]. Therefore, an extensive body of literature has been devoted to this area, with a range of different approaches adopted aimed at real power loss minimisation [4-12] and active energy loss minimisation [13-17]. Furthermore, reducing active power/energy loss and improving the voltage profile of the distribution network have been formulated as a multi-objective function [18-20].

In contrast, imaginary power loss reduction has received less attention. Many of the benefits associated with reactive power improvement, such as reducing imaginary power consumption and the suspension of network upgrades; decreasing voltage drops and enhancing system loadability;and helping active power flow through transmission lines to the client [21-25]. In terms of reactive power loss minimisation, fewer authors have considered this a single objective [24] than as part of a multi-objective study [22, 26-29].

In the literature, authors have adopted a variety of different approaches to achieve their loss minimisation objective, approaches which can be best described by their classification into analytical and optimisation techniques. Whereas one group of researchers have employed an analytical approach [4, 10, 11, 15], others have used optimisation techniques, such as Particle Swarm Optimization [6-8, 16], Mixed–Integer Nonlinear Programming [13], Evolutionary Programming [14], Modified Teaching–Learning–Based Optimization [5], and Gravitational Search Algorithm (GSA) [9, 12]. In [17], Oppositional Krill Herd Algorithm was utilised to determine DG optimal capacity and site.

In the present paper, a GWO-based optimisation approach is proposed with which to solve the multi-objective problem for optimal DG placement and sizing, with the weighted sum of active energy loss and reactive energy loss taken as a fitness function with network constraints. The same multi-objective is also achieved via the implementation of some other two techniques, such as PSO and GSA. Finally, the proposed and existing techniques are compared with the results validated using 15-bus and 33-bus radial distribution systems and discussed in detail.

The rest of the paper is structured as follows: Section 2 provides the multi-objective problem formulation, a description, and implementation of the proposed methodology. The detailed comparative study, including statistical results, the graphical representation of voltage profiles and convergence characteristics of all the analysed methods, is outlined in Section 3; while the concluding remarks are presented in Section 4.

2.0 METHODOLOGY

The multi-objective of the proposed methodology is to minimise both active and reactive energy losses in distribution networks via the optimal allocation of multiple DG units. The mathematical formulation of the multi-objective index and the imposed constraints used to ensure the safe operation of the distribution system are described as follows:

2.1 Multi-Objective Energy Index

The Multi-objective Energy Index (MOEI) is formulated as the weighted sum of the Active Energy Index (PEI) and Reactive Energy Index (QEI). These indices can be expressed by Equations(1),(2)and(3), respectively.

$$MOEI = w_{PE}PEI + w_{QE}QEI \quad (1)$$

When selecting weighting factor values from 0 to 100 percent, the relative percentages depend on the objective function considered the more important; in the present study, an equal trade-off was considered between the weighting factors of active energy loss (w_{PE}) and reactive energy loss (w_{QE}).

$$QEI = \frac{QE_{loss}^{DG}}{QE_{loss}^{w/oDG}} \quad (3)$$

where PE_{loss}^{DG} and QE_{loss}^{DG} are active energy loss and reactive energy loss with DG, respectively, and $PE_{loss}^{W/oDG}$ and $QE_{loss}^{W/oDG}$ are active energy loss and reactive energy loss without DG, respectively.

In the absence of DG, total active power loss (kW), reactive power loss (kVAr), and load values of the IEEE-RTS system presented in [30] versus time (T hours) graphs for a 15-bus system and a 33-bus system are shown in Figure 1 and Figure 2, respectively. In the planning horizon, it is assumed that the same 24-hour load profile is repeated over the whole year.

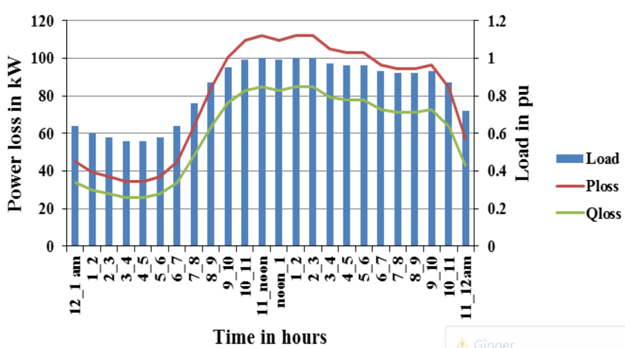


Figure 1 Active and reactive power loss and load versus time for the 15-bus distribution system

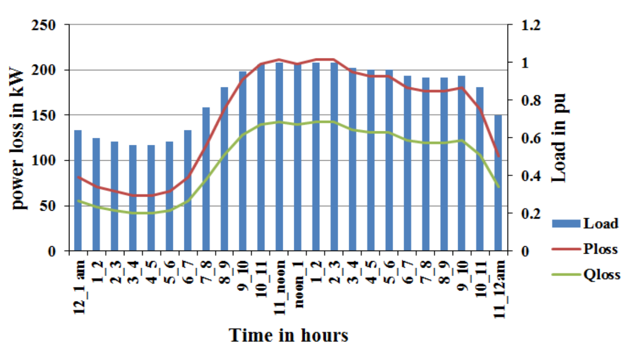


Figure 2 Active and reactive power loss and load versus time for the 33-bus distribution system

$$PE_{loss}^{W/oDG} = 365^{*} \sum_{hr=1}^{24} \sum_{K=1}^{Nbr} P_{lossk}^{w/oDG} * \Delta T_{hr} \quad (4)$$

$$PEI = \frac{PE_{loss}^{DG}}{PE_{loss}^{w/oDG}} \quad (2)$$

$$QE_{loss}^{W/oDG} = 365^{*} \sum_{hr=1}^{24} \sum_{K=1}^{Nbr} Q_{lossk}^{w/oDG} * \Delta T_{hr} \quad (5)$$

$$PE_{loss}^{DG} = 365^{*} \sum_{hr=1}^{24} \sum_{K=1}^{Nbr} P_{lossk}^{DG} * \Delta T_{hr} \quad (6)$$

$$QE_{loss}^{DG} = 365^{*} \sum_{hr=1}^{24} \sum_{K=1}^{Nbr} Q_{lossk}^{DG} * \Delta T_{hr} \quad (7)$$

where N_{br}= number of network branches; ΔT_{hr} = time period (1 hour); $P_{loss}^{w/oDG}$ and P_{loss}^{DG} = active power loss without and with considering DG, respectively; and Q_{loss}^{DG} and $Q_{loss}^{w/oDG}$ = *reactive power loss with and without considering DG, respectively.*

2.2 Power System Constraints

The constraints considered in this study for the safe operation of DG and the distribution system are listed below:

2.2.1 DG Active and Reactive Power Operating Limit

Usually, the specific range of DG active power (P^{DG}) is predefined. In the present study, a discretised size of DG is considered, which is generally readily available in the market. When the DG operating power factor (*pf*) is known, the reactive power of DG (Q^{DG}) follows its active power supply.

$$P_K^{DG,\min} \le P_K^{DG,new} \le P_K^{DG,\max} \quad (8)$$

$$Q_K^{DG,new} = P_K^{DG,new} \tan\left(\cos^{-1}(pf)\right) \quad (9)$$

where k= DG number

2.2.2 Active and Reactive Power Conservation Limits

DG allocation on the buses typically causes the voltage level to rise at some buses in the distribution system. If the total DG output exceeds total demand and losses, reverse power flow may occur in the system. Therefore, a total demand plus total system losses should be greater than the total DG supply.

$$\sum_{j=1}^{Nbus} P_j^{load} + \sum_{L=1}^{Nbr} P_L^{loss} > \sum_{K=1}^{4} P_k^{DG} \quad (10)$$

$$\sum_{j=1}^{Nbus} Q_j^{load} + \sum_{L=1}^{Nbr} Q_L^{loss} > \sum_{K=1}^{4} Q_k^{DG} \quad (11)$$

where P^{load} and Q^{load} are active and reactive demands, respectively; P^{loss} and Q^{loss} are real and imaginary distribution line losses, respectively; and N_{bus} is the total bus numbers.

2.2.3 Voltage Magnitude Limits

During operation, the voltage magnitudes (V_{bus}) at every bus in the distribution system are kept within a prescribed range from 95% to 105% of the nominal voltage value.

$$V_{bus}^{\min} \le V_{bus}^{k,new} \le V_{bus}^{\max} \tag{12}$$

where k=1,2,.....N_{bus}

2.2.4 Line Amperage Limits

The injection of DG power on the buses may increase the current in some of the branches. Therefore, line current in the presence of DG(I_{DG}) must not exceed the maximum allowable branch current limit ($I_{\max}$).

$$I_{DG}^{K} < I_{\max}^{K} \qquad k= 1, 2 \ldots N_{br} \tag{13}$$

2.2.5 Grey Wolf Optimizer

The Grey Wolf Optimizer (GWO) technique was first introduced by Syedali Mirjalili *et al*. in [31], largely inspired by grey wolf hunting strategy in the wild. As apex predators, grey wolves typically live in packs and strictly follow the dominant social leadership hierarchy. Figure 3 displays the clear hierarchy level decreases from Alphas (α) to omega (ω) search agent.

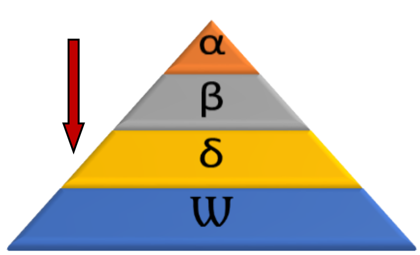


Figure 3 Hierarchy level of grey wolves from α to ω

α are the leaders of the pack and occupy the highest level in the hierarchy; α individuals can be male or female and he/she makes all decisions. Beta (β) wolves are subordinate to α and help the leader to make and implement decisions. In addition, they also act as a source for giving back information to the leader. Delta (δ) wolves report to α and β but are dominant over the ω wolves, who occupy the lowest level in the hierarchy and must follow all governing wolves.

Social Hierarchy

For the mathematical formulation of the GWO algorithm, the priority of the fittest solution is ordered according to the level of hierarchy in the pack, such as α, β, δ and ω wolves.

Encircling Prey

Grey wolves firstly encircle their prey when hunting. This encircling attitude was mathematically modelled in [31] and can be expressed as follows:

$$\vec{K} = \left|\vec{B} \bullet \vec{Z}_p(IT) - \vec{Z}(IT)\right| \tag{14}$$

$$\vec{Z}(IT+1) = \vec{Z}_p(IT) - \vec{D} \bullet \vec{K} \tag{15}$$

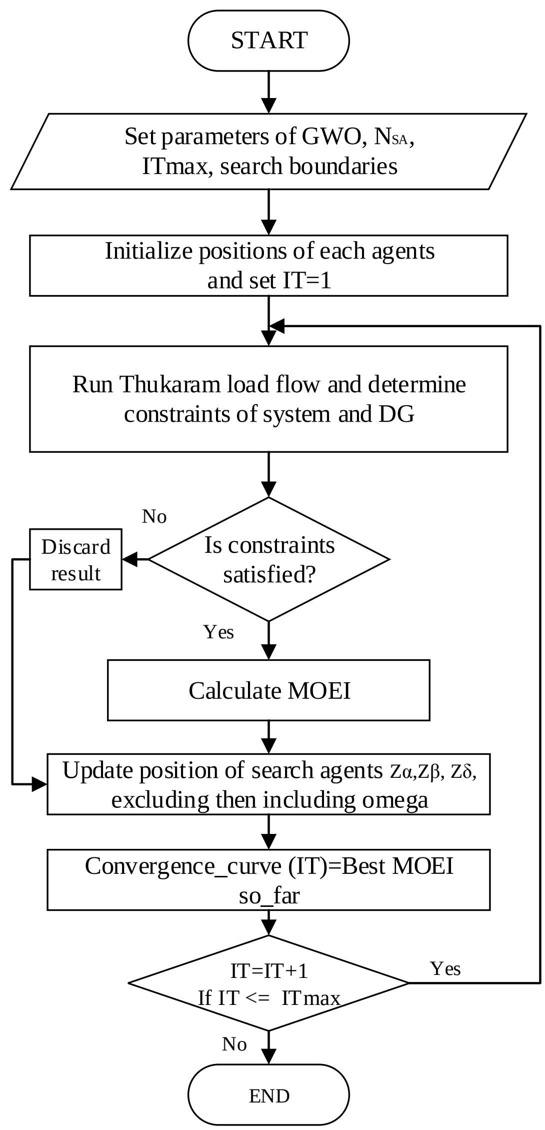


Figure 4 Flow chart of proposed methodology

where the position vectors of grey wolf and prey are denoted by $\vec{Z}$ and $\vec{Z}_p$, respectively; the algorithm's current iteration by IT; and $\vec{B}$ and $\vec{D}$ are coefficient vectors calculated as

$$\vec{B} = 2 \bullet \vec{r}2 \quad (16)$$
$$\vec{D} = 2\vec{d} \bullet r1 - \vec{d} \quad (17)$$

where r_1 and r_2 are random numbers in the range [0,1]; component d is a linear decreases from 2 to 0 over the iterations range.

Hunting Prey

When simulating the hunting attitude of grey wolves, α, β and δ individuals have a better knowledge regarding the probable location of the victim. The first three solutions $(\vec{Z}_1, \vec{Z}_2, \vec{Z}_3)$ obtained so far are stored, with the other search agents (including omegas) updating their locations according to the location of the best search agent [31]. The following mathematical equations were developed in this regard [31]:

$$\{\vec{K}_\alpha = \left|\vec{B}_1 \bullet \vec{Z}_\alpha - \vec{Z}\right|, \vec{K}_\beta = \left|\vec{B}_2 \bullet \vec{Z}_\beta - \vec{Z}\right|, \vec{K}_\delta = \left|\vec{B}_3 \bullet \vec{Z}_\delta - \vec{Z}\right|\} \quad (18)$$

$$\{\vec{Z}_1 = \vec{Z}_\alpha - \vec{D}_1 \bullet \left(\vec{K}_\alpha\right), \vec{Z}_2 = \vec{Z}_\beta - \vec{D}_2 \bullet \left(\vec{K}_\beta\right), \vec{Z}_3 = \vec{Z}_\delta - \vec{D}_3 \bullet \left(\vec{K}_\delta\right)\} \quad (19)$$

$$\vec{Z}(it+1) = \left(\vec{Z}_1 + \vec{Z}_2 + \vec{Z}_3\right)/3 \quad (20)$$

Attacking and Searching Prey (Exploitation)

exploitation and exploration abilities of grey wolves, respectively. Here 'D' is a random value that lies in the range [-d,d]. These values are used to energise the search agent to move away from the victim. When $|D| < 1$, the wolves make an effort to attack the prey, and vice versa in the case of $|D| > 1$. Vector C contains values in the range [0,2] [31].

In the present study, the DG output and address are set as position vectors and MOEI as the fitness function. The GWO algorithm follows steps to obtain optimal sites and sizes of DG units in order to reduce energy loss in the distribution system with constraints. The flow chart of the algorithm is shown in Figure 4.

3.0 RESULTS AND DISCUSSION

The proposed method (GWO) and comparative techniques (PSO and GSA) were implemented on 15- and 33-bus systems in order to determine the optimal capacity and address of four DG units. The summary of these test systems are indicated as follows:

3.1 15-bus Distribution Network

Figure 5 shows the single line diagram of the 15-bus distribution network. This system comprises 15 buses and 14 branches, with a total active load of 5.54 MW and a reactive load of 4.31 MVAr [32].

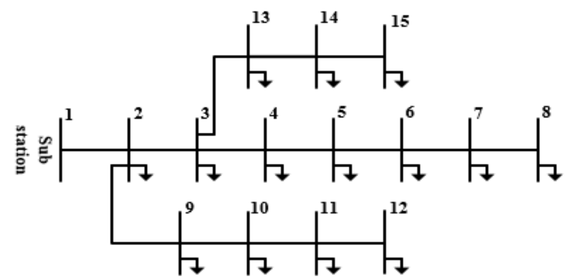


Figure 5 Single line diagram of the 15-bus distribution system

3.2 33-bus Distribution Network

A bus system comprising 33 buses and 32 branches, 3.715 MW active load and 2.3 MVAr reactive load was considered as the second test system; its single line diagram is shown in Figure 6 [33].

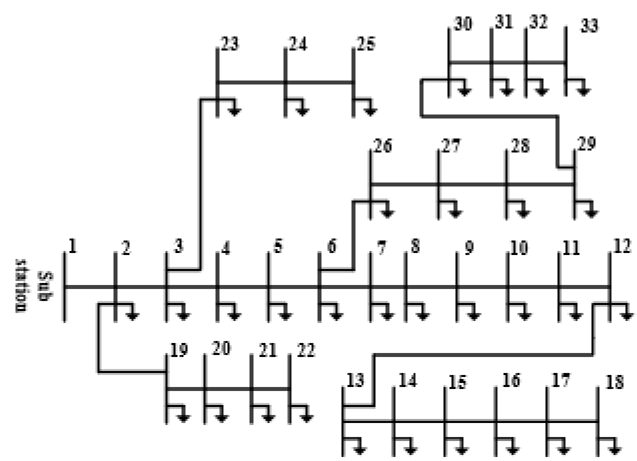


Figure 6 Single line diagram of the 33-bus distribution system

Simulations were carried out using 15-bus and 33-bus radial distribution systems in the MATLAB environment. All optimisation results were tabulated after 200 iterations for all algorithms. In order to obtain more fruitful results, it was assumed that all DG units feeding both real and imaginary power to the grid, with their operating *pf* assumed at 0.9. Thukaram load flow technique [34] was used to determine the bus voltages, branch current, as well as power and energy loss.

After simulation, the optimal sites and sizes of four different DG units in the 15-bus and 33-bus networks according to the three methods are shown in Tables 1 and 2, respectively, while Tables 3 and 4 present the pre- and post-installation results for DG units in the 15-bus and 33-bus systems, respectively, in terms of PE, QE, PEI, QEI, V_{min}, V_{max} and best MOEI. The lower the value of all of these parameters, with the exception of the voltage magnitude, the better the performance. Figures 7 and 8 present convergence characteristic curves for the 15-bus and 33-bus systems, respectively. In addition, Figures 9 and 10 show the voltage magnitude at every bus of 15-bus and 33-bus distribution system according to the three methods, respectively, before and after DG unit allocation. The following parameters of the two comparative methods (PSO proposed in [35] and GSA presented in [36]) were considered:

PSO: C1=C2=1.7, Wmax=0.9, and Wmin=0.4
GSA: alfa=20 and G0=100

Table 1 15-bus system: Optimal size and site of four DG units according to the three different methods

	DG1		**DG2**		**DG3**		**DG4**	
Method	**Size *(MVA)***	**Site *(bus no.)***	**Size *(MVA)***	**Site *(bus no.)***	**Size *(MVA)***	**Site *(bus no.)***	**Size *(MVA)***	**Site *(bus no.)***
GWO	1.7	5	1.3	8	0.8	11	0.8	15
PSO	1.5	6	1.1	8	0.9	11	0.9	15
GSA	0.8	5	1.9	8	1.1	11	0.9	14

Table 2 33-bus system: optimal size and site of four DG units according to the three different methods

Method	**DG1**		**DG2**		**DG3**		**DG4**	
	Size *(MVA)*	**Site *(bus no.)***	**Size *(MVA)***	**Site *(bus no.)***	**Size *(MVA)***	**Site *(bus no.)***	**Size *(MVA)***	**Site *(bus no.)***
GWO	0.7	7	0.6	14	0.9	24	0.9	30
PSO	0.8	7	0.5	14	0.6	25	0.9	30
GSA	0.6	13	0.8	25	1.1	26	0.8	30

Table 3 Performance analysis of the 15-bus radial distribution system without and with DG allocation

Analysis	PE *(MWh)*	QE *(MVArh)*	V_{min} (pu)	V_{max} (pu)	PEI (pu)	QEI (pu)	Best MOEI (pu)	Elapsed time (S)
Without DG	1.9091	1.4430	0.9648	1	1	1	1	--
GWO	0.2505	0.1647	0.9927	1	0.1312	0.1141	0.1227	219.683
PSO	0.2607	0.1710	0.9932	1	0.1366	0.1185	0.1276	104.178
GSA	0.3736	0.2187	0.9911	1.0005	0.1957	0.1516	0.1736	244.075

Table 4 Performance analysis of the 33-bus radial distribution system without and with DG allocation

Analysis	PE *(MWh)*	QE *(MVArh)*	V_{min} (pu)	V_{max} (pu)	PEI (pu)	QEI (pu)	Best MOEI (pu)	Elapsed time (S)
Without DG	3.5574	2.4105	0.9038	1	1	1	1	--
GWO	0.3450	0.2665	0.9804	1	0.096981	0.110558	0.10376	329.829
PSO	0.3611	0.2719	0.9760	1	0.101507	0.112798	0.10716	188.284
GSA	0.4029	0.3127	0.9816	1	0.113257	0.129724	0.12150	766.596

- It is clearly indicated in Table 1 that bus numbers 8 and 11 have the same optimal address for DG placement in all the examined methods. On the other hand, Table 2 shows that bus number 30 was the common location for single DG placement regardless of the applied algorithm.
- The statistical data displayed in Tables 3 and 4 indicate that a significantly greater amount of active and reactive energy is conserved via the GWO approach compared to the PSO algorithm and GSA methods. For both 15- and 33-bus systems, the highest MOEI, PEI, and QEI were obtained via GSA, followed by the PSO and GWO algorithms, for both systems. PSO provided a better performance than GSA.
- For both systems, it can be observed in Figures 7 and 8 that the GWO algorithm results were slowest to converge among the three techniques, followed by PSO and GSA. However, premature convergence can lead to generation of low-quality solutions.
- The elapsed time, using all three methods were tabulated in Tables 3 and 4 after 15 trials of each method seperately, with no variance obtained in MOEI value upto 15 decimal places, indicating consistency in the results for GWO, PSO and GSA.

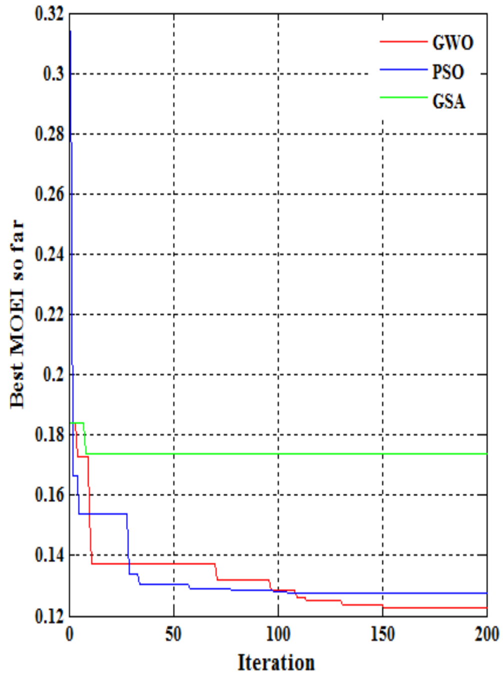


Figure 7 Convergence characteristics of the different approaches for the 15-bus system

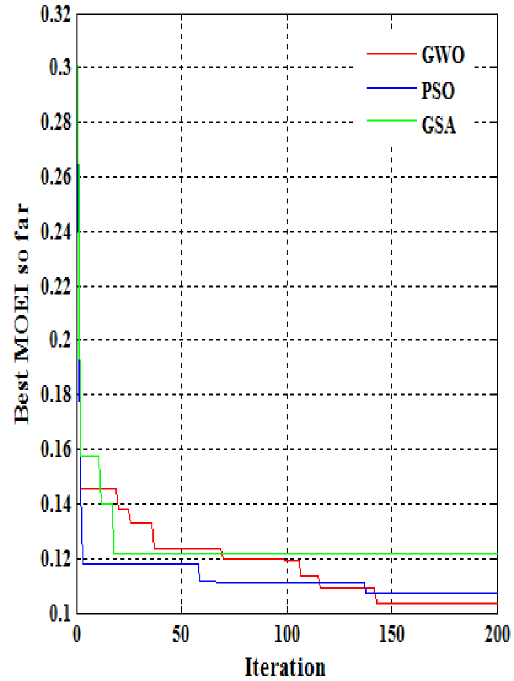


Figure 8 Convergence characteristics of the different approaches for the 33-bus system

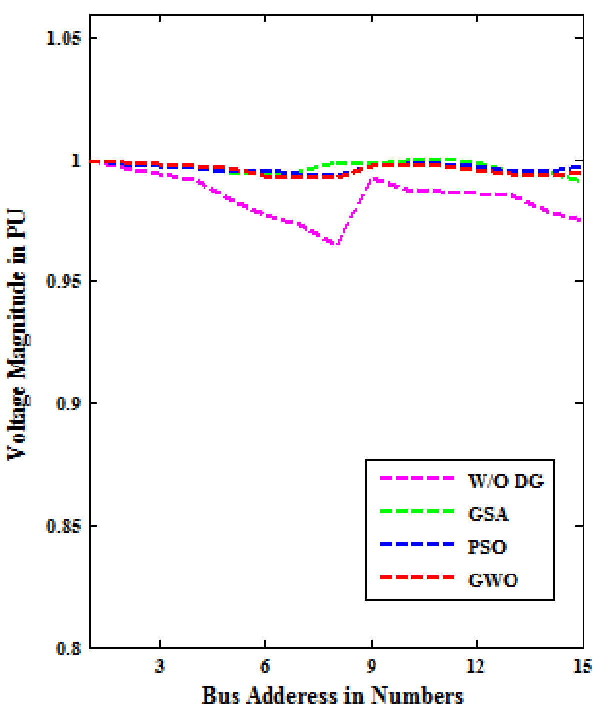


Figure 9 Voltage profile of the 15 bus distribution system with and without DG

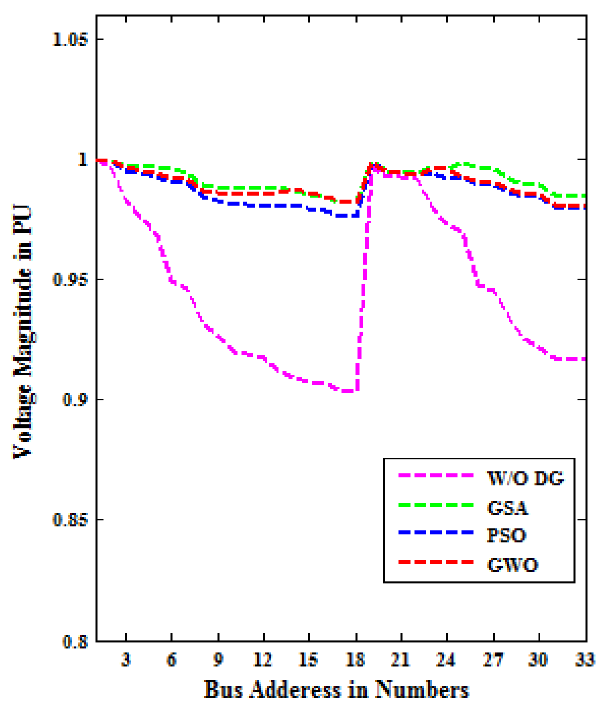


Figure 10 Voltage profile of the 33-bus distribution system with and without DG

- It can be noticed from Tables 3 and 4 that the proposed GWO method requires more computational time than the other applied technique, namely PSO. As these methods were implemented in off-line mode, time is not of great concern.
- It can clearly be observed from Figures 9 and 10 that the voltage magnitude at every bus improved after DG unit installation at its base value, with the system operating within the prescribed range of voltage (i.e. +/-5% nominal voltage).

4.0 CONCLUSION

A new approach based on GWO for DG allocation in 15- and 33-bus radial distribution systems was presented, aimed at reducing annual active energy and reactive energy losses with imposed network constraints. Two existing methodologies, PSO and GSA, were also implemented to solve the DG allocation problem. Besides the tested GWO, PSO and GSA methods all provided optimal site and size information for multiple DG units. Considerably, more active energy and reactive energy were conserved via the GWO approach, as well as an improvement in the voltage profile of both 15-bus and 33-bus distribution system. The convergence characteristic curves indicate that the presented approach is simple, reliable and competent to handle the multiple DG allocation problems in distribution systems.

The develped technique is important for energy planners to achieve optimal active and reactive energy loss reduction within the system constraints.

In addition, the application of a GWO hybrid with another algorithm may provide a more exciting area of future research.

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