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Research paper

A Novel Hybrid Fuzzy-Metaheuristic Strategy for Estimation of Optimal Size and Location of the Distributed Generators

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ABSTRACT

Optimal size and location of the distributed generators (DGs) has become a new avenue applied to achieve a proper design and to provide a better performance for the distribution system. A hybrid Fuzzy-Metaheuristic strategy has been proposed in this work to provide an optimal design for sizing and placement of different types of DGs. In the introduced strategy, the fuzzy logic based adaptive weights subroutine has been combined with a metaheuristic optimizer in conjunction with a power system model, load flow software, input/output software modules and three proposed approaches software modules suitable for various types of DGs. Minimizing active and reactive power losses as well as enhancing the voltage characteristics over the whole system using a multi objective function with dynamic adjustment of weights has been introduced in this work. Furthermore, a novel approach of variable power factor has been established and investigated as well as the previously published constant power factor and unity power factor approaches. To prove the validity of the new strategy and the novel approach, IEEE distribution systems of 33 and 66 buses have been used to test the efficiency and accuracy of the proposed strategy. A novel hybrid optimization strategy named Hybrid Fuzzy Equilibrium Optimizer (HFEO) is established to estimate the optimal size and location of three DGs inserted in the selected distribution systems. The hybrid technique is based on merging fuzzy logic to adapt the weights of the objective function dynamically with a newly developed metaheuristic Algorithm named equilibrium optimizer to achieve a better performance in the optimization process. For fair verification of the proposed technique, its results have been compared with that of five algorithms presented in literature to prove its superiority and reliability over the other state of art. For intensive comparisons, some statistical analysis has been established to show the minimum objective function, the highest speed of convergence, the least execution time and the most consistent results.
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1. Introduction

Recently, the optimal design of the energy system has been considered as a crucial issue to provide an economic operation as well as ensuring the continuity of service. One of the main parts of the energy system that is required to be designed optimally is the distribution system (Mazhari et al., 2015). It is the link between the transmission system and the consumer where almost 70% of the total losses in the whole energy system is occurred (Sulaima et al., 2014). The optimal integration between the main distribution system and distributed generators DGs has been proposed as a new avenue to account for the losses in the distribution system. Where, DGs are small generating units such as photovoltaic, wind turbines (Saidur et al., 2011), etc. They have been located near the load centers to inject active and reactive power in the system (Tyagi et al., 2013). Merging DGs in the distribution system helps to reduce dependency on long transmission and distribution lines and hence decreases the power losses in the system which in turn minimizes the costs and the difficulties of installation of such these lines (Ackermann et al., 2001). Moreover, DGs improve the reliability and the power quality of the distribution system and enhance its overall voltage profile (Brown and Freeman, 2001; Pepermans et al., 2005). However, improper choice of DGs may cause larger losses as in Griffin et al. (2000) and may lead to adverse required behavior of power system (Picciariello et al., 2015; Mer and Patel, 2016). Therefore, there is a persistent need of developing new methodologies to achieve optimal size and location of DGs in the distribution system which acquire the mentioned benefits without damaging the stability of the system. Some conventional methods have been accomplished to carry out the problem of shunt capacitors and DGs' locations and sizes. Analytical approaches have been introduced to handle this optimization problem (Acharya et al., 2006; Wang and Nehrir,

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2004; Khatod et al., 2012). This analytical expression has been improved in Hung et al. (2010). In Hedayati et al. (2008), the tested analytical method has relied on the calculations of the power flow analysis and estimation of the buses that are most vulnerable to voltage drop. This approach has proved its efficiency in ameliorating the voltage characteristics and decreasing the power losses in addition to increasing the power transfer capacity. "2/3 rule" analytical method is presented for siting of the shunt capacitors as in Willis (2000). A simple iterative technique to lower the power losses using a voltage stability index (VSI) has been proposed as in Parizad et al. (2010), Chakravorty and Das (2001), Eminoglu and Hocaoglu (2009). The placement of multiple DGs has been accomplished by using the loss sensitivity factor (LSF) method as in Hung and Mithulananthan (2011), Murthy and Kumar (2013). Index vector method has been utilized for optimal placement of DG in radial distribution system as in Murthy and Kumar (2013). Another index defined as the power stability index (PSI) has been used to specify the most critical node in the system that may cause voltage instability upon load rising above certain level (Aman et al., 2012). A new power voltage sensitivity factor (PVSF) has been used to define the size and location of DG (Sharma and Nawaz, 2020). However, all the above mentioned analytical approaches depend on ranking of the buses' indices in decreasing order to form a list of priority then selecting the highest priority bus and locate the DG at it. Meanwhile, optimal sizing of DGs has been accomplished by Changing the size of DG slightly in steps and evaluate the losses at each step using the load flow calculations then selecting the size corresponding to the minimum losses which may provide an inaccurate estimation of this sizing process. After that, the combination between analytical methods and the nature inspired algorithms has been introduced to estimate the size and location of DG optimally. Particle swarm optimizer PSO has been used to amend the characteristics of voltage and to decrease the total power losses of the system (Devi and Geethanjali, 2014). Genetic algorithm GA has been employed with a Power Loss Index (PLI) on 15& 33 IEEE bus systems for voltage regulation and stability (Banhidarah and Al-Sumaiti, 2018). The genetic algorithm has been implemented with a loss sensitivity to minimize the generation cost as in Tian et al. (2017). The optimal size and location of DG has been estimated by the Cuckoo Search Algorithm (CSA) with voltage stability index for power loss reduction (Yuvaraj et al., 2017). lately, newly developed metaheuristic algorithms have been proposed for optimal estimation of both location and size of DGs simultaneously. These novel methodologies are robust, efficient and immune to local minima (Carpinelli et al., 2001; Singh et al., 2007). Many researches have been introduced to implement these algorithms in optimal design of the distribution networks. Harmony search algorithm (HAS) has been employed to improve the voltage stability (Rao and Rao, 2012). Artificial bee colony algorithm (ABC) has been utilized to reduce the cost (Singh and Kaushik, 2016). Ant lion optimization (ALO) (Mansour et al., 2017), back-tracking search algorithm (BSA) (Fadel et al., 2017), grey wolf optimizer (GWO) (Sanjay et al., 2017) and War Optimization (WO) (Banhidarah and Al-Sumaiti, 2018) have been tested to decrease the power loss. In literature, two types of objective functions have been utilized as the single objective function that has been used as in Griffin et al. (2000) and multi objective function in Celli et al. (2005). Authors in Oda et al. (2017) have presented flower pollination algorithm (FPA) for solving the best location and size of DGs to reduce losses and enhance the voltage profile. Furthermore, Whale optimization algorithm (WOA) has been proposed to maximize the voltage stability and decrease the energy loss (Marimuthu et al., 2017). In Ramadan et al. (2022), the artificial hummingbird algorithm (AHA) has been utilized to minimize the total emissions and total cost. The Grasshopper optimization algorithm (GOA) has been presented to maximize energy transfer in Ahmadi et al. (2021). Furthermore, the multiobjective particle swarm (MOPSO) was carried out for practical case study to prove the efficiency of this research point on real world systems (Sellami et al., 2022). In addition, merging between different meta-heuristic has become a new avenue in tackling with optimal design of DGs. The hybrid techniques provide simplicity of implementation, fast convergence and improving the quality of solutions (Kim et al., 1998; Gandomkar et al., 2005). A hybrid algorithms have been proposed for DG placement and sizing optimally as in Gandomkar et al. (2005) where Genetic-Tabu Search (GA-TS) algorithm has been implemented to decrease the losses. Another hybrid algorithm named Genetic-Particle Swarm Optimization technique (GA-PSO) has been applied to ameliorate voltage regulation and decrease the power loss as in Moradi and Abedini (2012). Various objective functions including minimization of the cost and DG unit capacity have been addressed in Crossland et al. (2014) where the optimization process has been accomplished by Genetic-Simulated Annealing (GA-SA). The combined improved grey wolf with particle swarm optimization (GWO-PSO) is carried out by incorporating dimension learning hunting (Akbar et al., 2022). In Hemeida et al. (2021), the GA is combined with stain bowerbird optimization (SBO) to estimate the best location of DGs and detect most suitable DG type according its ability.

In this work, the first main contribution is introducing a novel hybrid fuzzy metaheuristic strategy named HFEO that has been proposed and tested on two IEEE standards 33& 69 bus radial distribution networks to achieve optimal sizing and siting of three DGs. This novel strategy consists of several modules working together within the main code. These modules can be defined as power system model, inputs/outputs modules, EO optimizer module, load flow module, three approaches modules and fuzzy logic based adaptive weights module. The optimization process has been accomplished based on a multi objective function with adapted dynamic weights. The objective function is of three terms defined as the active power losses, the reactive power losses and the voltage profile. This novel strategy has been established by merging the fuzzy logic with EO optimizer to optimize the weights of the objective function dynamically and to estimate sizing and sitting of DGs optimally. The second main contribution of this research is the introduction of a newly developed approach that relies on injecting active and reactive power by DGs at variable power factor rather than the previously published techniques that have been relies on unity power factor and constant power factor approaches. Efficiency and robustness of the proposed approach have been proven via investigating and comparing the results of the proposed approach with that of the other two approaches of unity and constant power factor. Furthermore, five different previously used techniques in literature named GWO, MFO, FPA, GOA, PSO have been executed and processed individually at the same conditions as HFEO and on the same selected power systems at the three approaches under test to obtain and compare the results of the state of art techniques with those of the new proposed technique in order to prove its superiority over the previous ones. Moreover, some statistical analysis has been accomplished on the results of the tested techniques to provide intensive comparisons among them in order to prove the accuracy of the proposed strategy over the previous ones. This paper is organized as follows: Section 2, the component, description and problem formulation are shown. In Section 3, the HFEO based approach is described. Results and analysis are given in Section 4. Finally, the conclusion is presented in Section 5.

Table 1
DG classification according to its capacity.

DG category	DG ratings
Micro-distributed generation	~1 W < 5 kW
Small distributed generation	5 kW < 5 MW
Medium distributed generation	5 MW < 50 MW
Large distributed generation	50 MW < 300 MW

2. Problem formulation

2.1. Distributed generators

DGs have been merged in the distribution network to fulfill many targets such as decreasing active & reactive power losses. Moreover, stability improvement and cost reduction have been carried out when DGs have been integrated with the distribution system. Furthermore, one of the most important aspects in using DGs is that the pollution reduction of the renewable energy types of DGs has been accomplished remarkably. The capacity of DGs is in range from a few KW and up to a few MW as shown in Table 1. Moreover, DGs can be categorized according to its type and operation mode such as solar photovoltaic cells that can be considered as a constant active power (CAP) sources with unity power factor while gas turbines are operated at a constant power factor (CPF) and wind turbines can be tackled as variable reactive power (VRP) sources working at variable power factor.

Despite of these merits resulting from the integration of DGs in the distribution system, non-appropriate sitting and sizing of DGs may cause unsatisfactory performance of power system and may lead to instability issue. The proposed methodology in this work has been introduced to avoid these problems by accurate estimation of the optimal size and location of DGs considering a proper multi objective function and the operating technical constraints.

2.2. The objective function

There are many factors influenced by merging DGs in the distribution networks. Three of them have been selected to be investigated simultaneously within the multi objective function (MOF) which provides a better model and compromises between all objectives to find the best solution. Estimating proper weights for the multi objective function that can be adjusted dynamically is very essential issue. In this work, this can be carried out using fuzzy logic that has been established to extract these weights dynamically as explained in next section. The multi objective function has been used to determine the optimal size and place of DGs in order to decrease active and reactive power losses optimally and to enhance the voltage characteristics of the network by reducing the voltage regulation under power balance constraints.

2.2.1. Real power loss index (ILP)

One of the most important objectives that is required to be minimized is the active power losses. To know how the proper selection of DGs location and size can be achieved, the first normalized fitness function f_1 is used which represents the ratio of the active power losses after installation of DGs with respect to the base case without any installed DGs as shown in Eq. (2.1).

$$f_1 = \frac{(P_{loss})_{with\,DG}}{(P_{loss})_{without\,DG}} \tag{2.1}$$

The total active power loss can be given as:

$$P_{loss} = \sum_{i=1}^{N_b}\sum_{j=1}^{N_b}\left[a_{ij}\left(P_iP_j + Q_iQ_j\right) + b_{ij}\left(Q_iP_j - P_iQ_j\right)\right] \tag{2.2}$$

Where $a_{ij} = \frac{R_{ij}}{V_iV_j}\cos\left(\theta_i - \theta_j\right)$, $b_{ij} = \frac{R_{ij}}{V_iV_j}\sin\left(\theta_i - \theta_j\right)$

V_i and V_j are the voltages at ith and jth buses respectively, P_i and Q_i are the active & reactive power injection at bus i, P_j and Q_j are the active & reactive power injection at bus j. N_b is the buses number while θ_i and θ_j are phase angles of the voltages at ith and jth buses respectively.

2.2.2. Voltage deviation index (IVD)

The second main term in the multi objective function (MOF) is the voltage profile improvement. This normalized function can be considered as a major issue in this application. This purpose has been achieved by finding optimal placement and capacity of DGs which have led in turn to minimization of the voltage deviation expressed in Eq. (2.3).

$$f_2 = \frac{\sum_{i=1}^{N_b}\left|V_i - V_{i,ref}\right|_{with\,DG}}{\sum_{i=1}^{N_b}\left|V_i - V_{i,ref}\right|_{without\,DG}} \tag{2.3}$$

Where N_b is the buses number, V_i and $V_{i,ref}$ are the system voltage and reference voltage at ith in per unit respectively.

2.2.3. Reactive power loss index (ILQ)

The last term needs to be minimized in MOF is the reactive power losses which has represented by the normalized function illustrated in Eq. (2.4). The total reactive loss is calculated in Eq. (2.5).

$$f_3 = \frac{(Q_{loss})_{with\,DG}}{(Q_{loss})_{without\,DG}} \tag{2.4}$$

The total reactive power loss can be given as:

$$Q_{loss} = \sum_{i=1}^{N_b}\sum_{j=1}^{N_b}\left[b_{ij}\left(P_iP_j + Q_iQ_j\right) - a_{ij}\left(Q_iP_j - P_iQ_j\right)\right] \tag{2.5}$$

2.3. Technical constraints

The multi-objective function should satisfy all Equality and Inequality given constraints.

2.3.1. Equality constraints

2.3.1.1. Power balance. The power injected in the distribution networks from substation and DGs must be equal to the total power loss and power demand as obtained in Eq. (2.6) and eq. (2.7).

$$\sum_{i=1}^{N_g} P_{Gi} + \sum_{i=1}^{N_{DG}} P_{DGi} + \sum_{i=1}^{N_b} P_{li} + \sum_{i=1}^{N_l} P_{Di} = 0 \tag{2.6}$$

$$\sum_{i=1}^{N_g} Q_{Gi} + \sum_{i=1}^{N_{DG}} Q_{DGi} + \sum_{i=1}^{N_b} Q_{li} + \sum_{i=1}^{N_l} Q_{Di} = 0 \tag{2.7}$$

Where

P_{Gi}, Q_{Gi} are the real & reactive power of the ith system generator respectively.

P_{DGi}, Q_{DGi} are the ith DG real & reactive power respectively.

P_{li}, Q_{li} are the real & reactive power loss respectively.

P_{Di}, Q_{Di} are the load real & reactive power respectively.

N_g, N_{DG}, N_b, N_l are the number of generators, distributed generators, branches and load buses respectively.

2.3.2. Inequality constraints

2.3.2.1. Bus voltage. The voltage at each bus should be allowed to be varied within predetermined limits.

$$V_i^{min} \le V_i \le V_i^{max} \tag{2.8}$$

Where V_i, V_i^{min}, V_i^{max} are the voltage, minimum voltage (0.95 p.u.) and maximum voltage (1.05 p.u.) at ith bus.

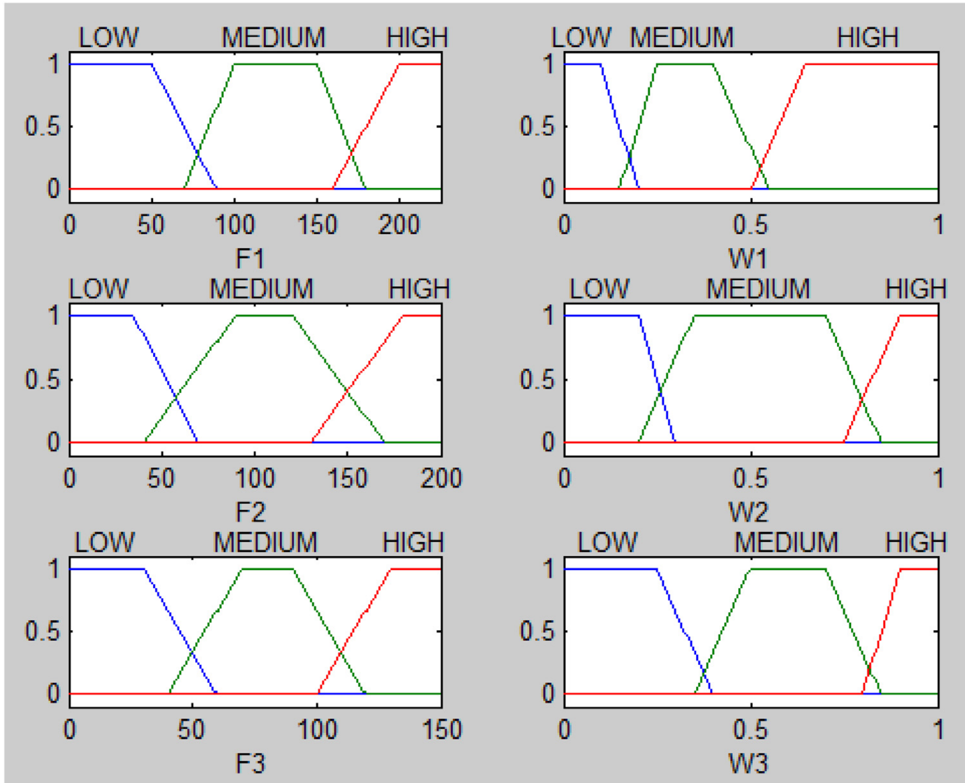

Fig. 1a. Fuzzy membership for rule based objectives' weights.

2.3.2.2. DG capacity. The real power generated must not exceed the specified limit

$$P_{DGi}^{min} \leq P_{DGi} \leq P_{DGi}^{max} \tag{2.9}$$

Where P_{DGi}, P_{DGi}^{min}, P_{DGi}^{max} are the active power, minimum real power (0.1 MW) and maximum real power (3 MW) for each DG.

2.3.2.3. Power factor. According to variable power factor approach, the power factor of DG is bounded by prescribed range.

$$0.8 \leq pf_{DGi} \leq 1 \tag{2.10}$$

2.3.2.4. Thermal constraint. The line current flow must not exceed the maximum limit.

$$I_i \leq I_i^{max} \tag{2.11}$$

Where i is the branch number.

Therefore, the overall multi-objective function can be expressed as:

$$f_{mo} = \min(\sum_{i=1}^{3} \mu_i\,(t)\, w_i f_i) \tag{2.12}$$

Where f_i is the feature and $\mu_i(t)$, w_i are the corresponding membership function characterizing and weight of the feature, respectively.

3. The hybrid fuzzy equilibrium optimizer (HFEO)

3.1. Fuzzy logic

Previously, the weights of MOF have been selected by trial and error to achieve the optimal performance of the process. However, these conventional methods have been inaccurate and time consuming. Therefore, there was a persistent need to introduce novel techniques to improve the accuracy and to reduce the time consuming. The fuzzy based fitness function has been proposed to adjust the weights dynamically and optimally. The rule based set has been utilized to evaluate the total value of the fitness function depending on the above objectives (Bingul, 2007). The fuzzy logic has been employed to determine the membership function graphs for three sets (objectives) as inputs and the corresponding weights as outputs (Nagaballi et al., 2018). Using rules based sets, it is required by EO to ameliorate the worst score with highest value of weight, the next worseness is tackled with by intermediate value and best score with low values of weights. Therefore, EO pushes up low scores and pushes down high scores by weights changes which provides the dynamics of priority change continuously during the process. The fuzzy logic system (FLS) was employed as general framework to determine the weights which made priority of objectives adjustment. Three kinds of memberships (LOW, MEDIUM and HIGH) and triangular membership functions have been used to fuzzify inputs as shown in Fig. 1a.

The descriptions of fuzzy system's rules:

1- If (F1 is LOW) then (W1 is HIGH) (W2 is MEDIUM) (W3 is LOW)
2- If (F1 is MEDIUM) then (W1 is MEDIUM)
3- If (F1 is MEDIUM) and (F2 is MEDIUM) and (F3 is MEDIUM) then (W2 is MEDIUM) (W3 is MEDIUM)
4- If (F1 is MEDIUM) and (F2 is LOW) and (F3 is HIGH) then (W2 is HIGH) (W3 is LOW)
5- If (F1 is MEDIUM) and (F2 is HIGH) and (F3 is LOW) then (W2 is LOW) (W3 is HIGH)
6- If (F1 is HIGH) then (W1 is LOW)
7- If (F1 is HIGH) and (F2 is HIGH) and (F3 is LOW) then (W2 is LOW) (W3 is HIGH)
8- If (F1 is HIGH) and (F2 is MEDIUM) and (F3 is MEDIUM) then (W2 is MEDIUM) (W3 is MEDIUM)

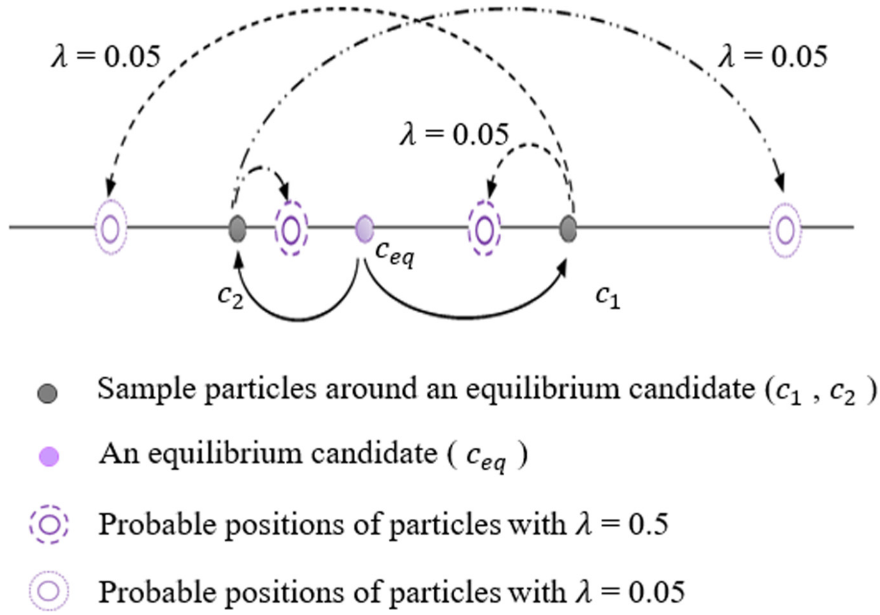

Fig. 1b. The effect of λ in exploration and exploitation.

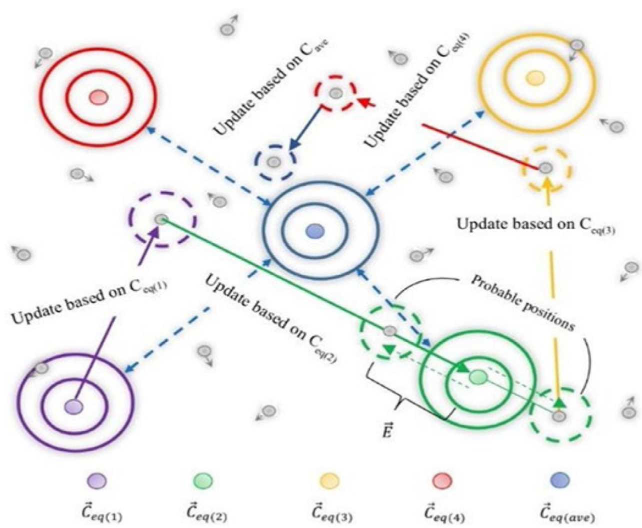

Fig. 1c. Equilibrium candidates' concentration updates.

9- If (F1 is HIGH) and (F2 is MEDIUM) and (F3 is LOW) then (W2 is MEDIUM) (W3 is HIGH)
10- If (F1 is HIGH) and (F2 is MEDIUM) and (F3 is HIGH) then (W2 is LOW) (W3 is MEDIUM)

3.2. Equilibrium optimizer technique

By the end of 2019, Afshin Faramarzi introduced one of physics-based inspiration optimization technique EO algorithm which is motivated by mass balance in a control volume (Faramarzi et al., 2020). The equation of mass balance is utilized to describe the dynamic and equilibrium states. This approach considers the particles as solutions and its concentrations as search agents. The Equilibrium Optimizer has attracted interest of researchers due to its reliability and robustness so the EO has been used to tackle several real problems such as segmentation of thresholds for set of CT images of COVID-19 (Houssein et al., 2022). In Mansoor et al. (2021), the EO is implemented to resolve the drawbacks caused by thermoelectric generation systems for controlling the maximum power point tracking. The EO is integrated to enhance the accuracy of prediction for adaptive neuro-fuzzy interface which has been used for solar parabolic dish collector parameters (Zayed et al., 2021). In Sun et al. (2021), the EO was carried out to optimize chiller loading in HVAC.

The generic mass balance equation is described as:

$$c_{new} = c_{eq} + \left(c - c_{eq}\right) * F + \frac{G}{\lambda} * (1 - F) \tag{3.1}$$

Where c and c_{new} are current and new concentration of the particle. The c_{eq} is the equilibrium state, which is chosen randomly from the $c_{eq,pool}$ vector. Equilibrium pool vector contain the concentrations of four best so far particles plus its average.

$$c_{eq,pool} = [c_{eq(1)}, c_{eq(2)}, c_{eq(3)}, c_{eq(4)}, c_{eq(avg)}] \tag{3.2}$$

λ is a turnover rate which is a random vector between 0 and 1. F is presented as follows:

$$F = \mathrm{e}^{-\lambda*(t-t_0)} \tag{3.3}$$

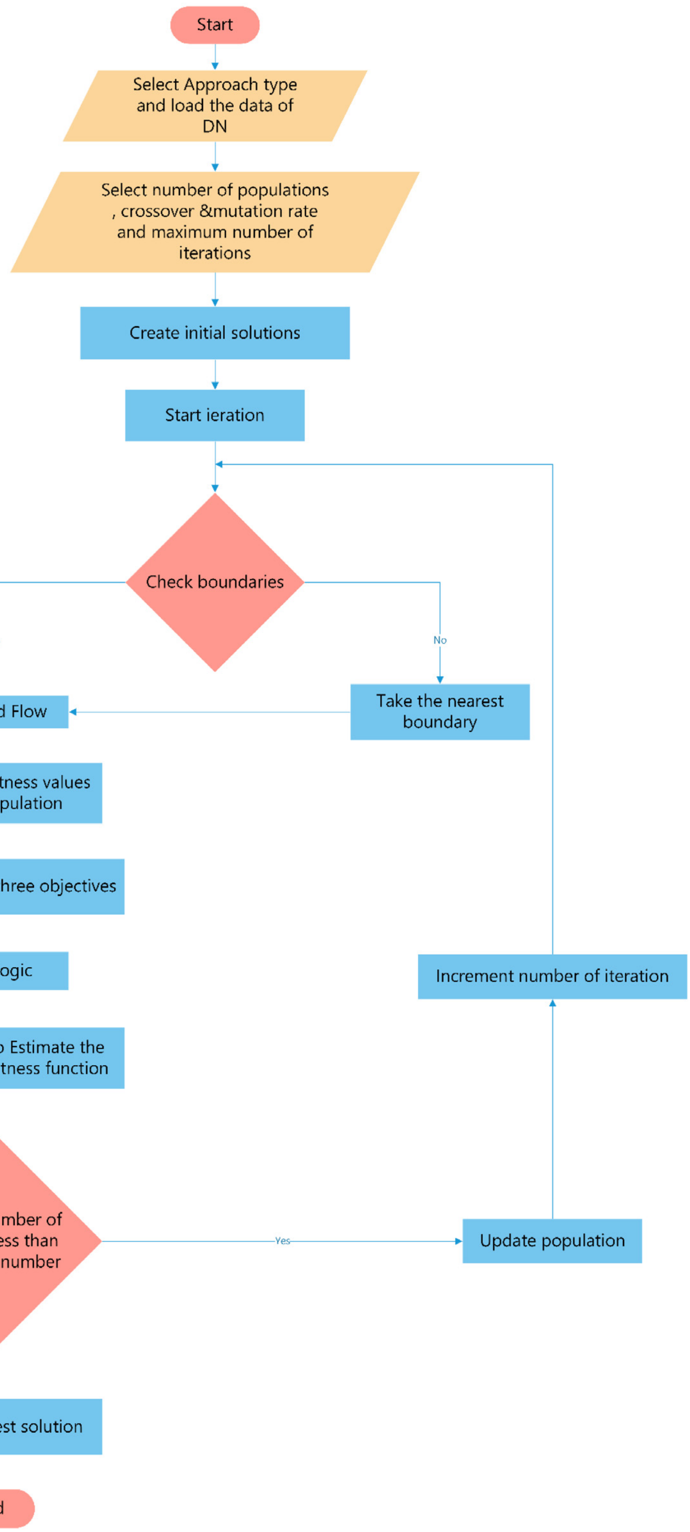

Fig. 1d. Schematic representation of HFEO algorithm.

Where t is a function of iterations as bellows:

$$t = (1 - \frac{iter}{\max\_iter})^{(a_2 * \frac{iter}{\max\_iter})} \tag{3.4}$$

$iter$ and $\max\_iter$ define the current iteration & the maximum number of iterations respectively. a_2 is a constant value that controls the intensification by moving around the optimal solution.

$$t_0 = \frac{1}{\lambda} \ln\left[-a_1 * sign\,(r - 0.5) * \left(1 - e^{-\lambda t}\right)\right] + t \tag{3.5}$$

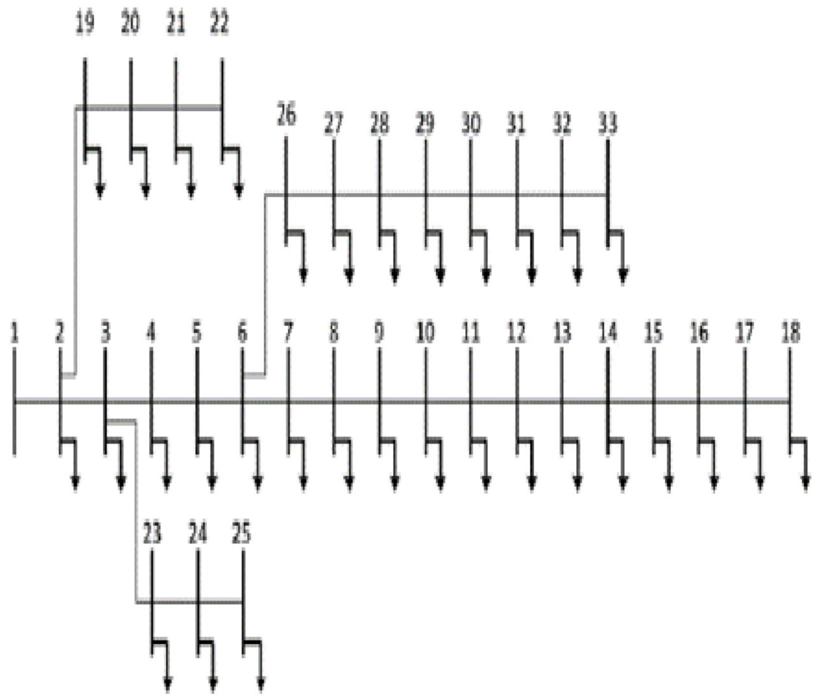

Fig. 2. Single line diagram of 33-bus Network.

r is a random vector in the interval of [0,1]. $sign\,(r - 0.5)$ is the term which controls the exploration and exploitation direction. a_1 is a constant value which magnify the capability of diversification.

The generation rate (G) is very important parameter which improves the exploitation phase in order to get the exact solution.

$$G = G_0 * e^{-\lambda(t-t_0)} = G_0 * F \tag{3.6}$$

Where:

$$G_0 = GCP * (c_{eq} - \lambda c) \tag{3.7}$$

$$GCP = \begin{cases} 0.5 * r_1 & r_2 \geq GP \\ 0 & r_2 < GP \end{cases} \tag{3.8}$$

G_0 is the initial value. GCP is the parameter of the generation rate control. r_1&r_2 are random numbers uniformly distributed between 0& 1. GP is the probability of generation that describes the number of particles utilizing the generation term for updating their concentration. balancing between diversification and exploitation is provided with GP = 0.5.

in balance Eq. (3.1), it has been noticed that the second & third term have described the concentration variations. As, the second term has been used for global searching in the space to determine the best location by a large variation of concentration. While, the third term is more responsible for achieving more accuracy in solution by a small variation in concentration. However it is not always happening, the small value of turnover λ in the third term make the variation increase, helping the exploration in the second term. The effect of turn over λ is obtained well in Fig. 1b.

Sample particles around an equilibrium candidate (c_1, c_2)

An equilibrium candidate (c_{eq})

Probable positions of particles with λ = 0.5

Probable positions of particles with λ = 0.05

Fig. 1c shows how the concentration updates itself according to the value of turnover. In the initial iteration, a large exponential term is generated which helps exploration feature. In the last iteration, this exponential term generates small random steps which refines to get the best solution.

The following steps describes the execution of EO algorithm:

1- Initialize the particles' populations.
2- Calculate the fitness of each particle.
3- Construct the equilibrium pool using (2).
4- Accomplish the memory saving.
5- Calculate t in (4) then generate λ.
6- Construct the updated F and G by (3–8).
7- Update the concentration of particle using (1).
8- Go to back to step 2 until the maximum number of iterations are done.

The stepwise procedure for the problem using adaptive EO with rule based dynamic weights is given in Fig. 1d.

4. Simulation and results

In this work, a novel hybrid fuzzy metaheuristic strategy named HFEO has been implemented on two standard radial distribution networks (RDNs) to achieve optimal sizing and placement of three DGs. the efficiency and robustness of the proposed strategy have been proven via investigating three different approaches. Furthermore, five different previously used algorithms in literature named GWO, MFO, FPA, GOA, PSO have been executed and processed at the same conditions as HFEO and on the same selected power systems for the three proposed approaches under test to obtain the results of these state of art techniques and compare them with those of the new technique. The results have been obtained at all optimization methods based on 10 independent runs, each one is of 500 iterations. The solution vector is of six dimensions, three of them have been established for the locations and the others are for the sizes of the three DGs. The population size is 100. All the stages of the proposed strategy have been designed using a main program in MATLAB code where several subroutines have been included and executed sequentially. The proposed approaches are carried out via MATLAB R2014a on Core i5 Intel processor, 2.30 GHZ, 4 RAM, 64-bit operating system. Seeking for determination of the optimal siting and sizing of DG units, the following three approaches have been investigated:

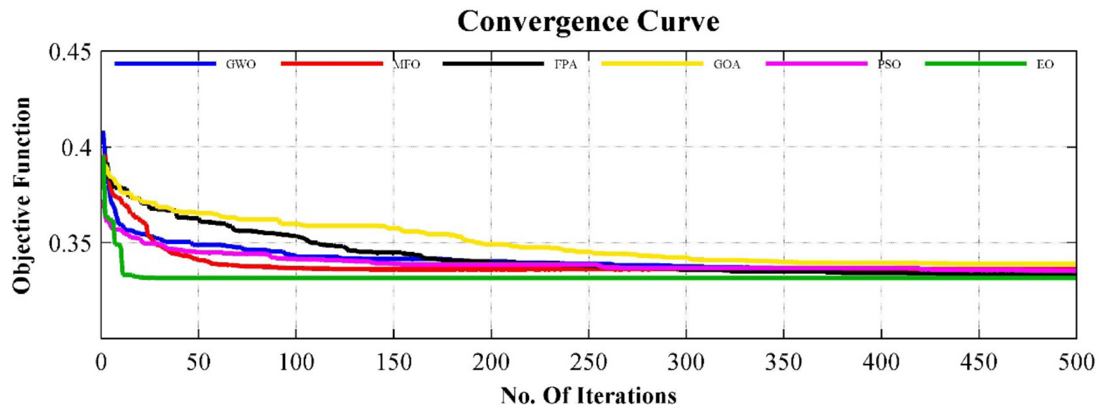

Fig. 3a. Convergence curve of Approach I.

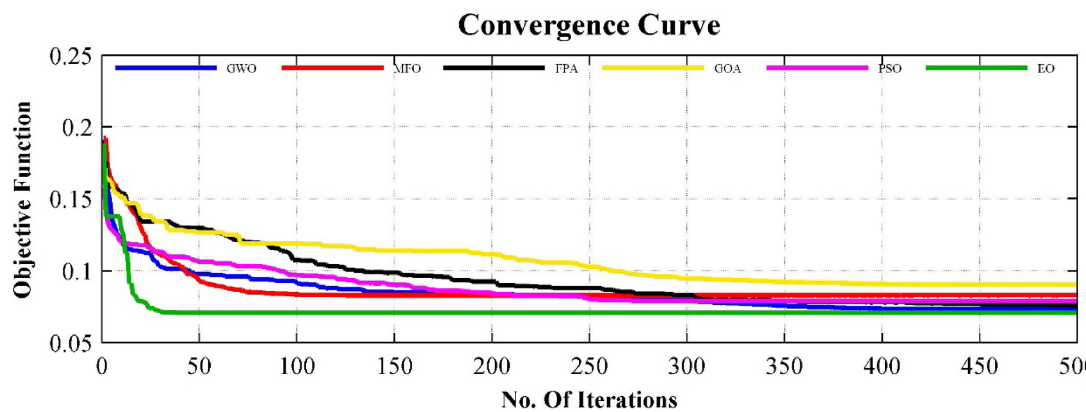

Fig. 3b. Convergence curve of Approach II.

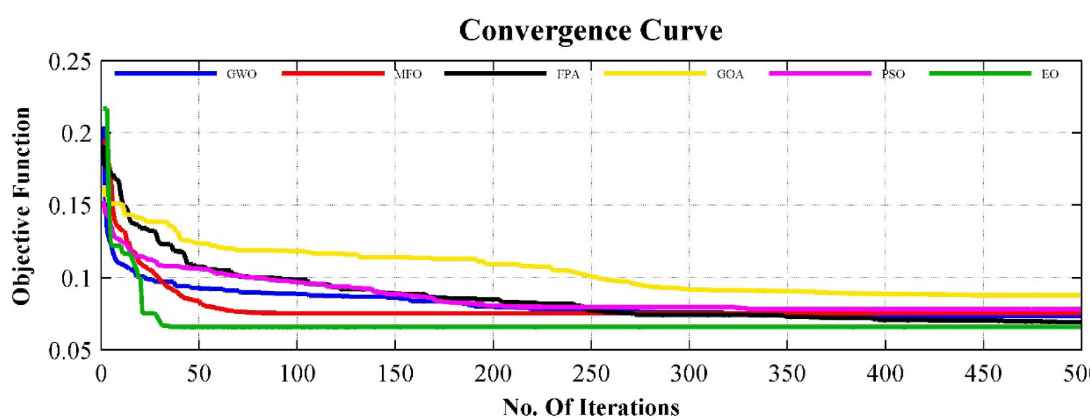

Fig. 3c. Convergence curve of Approach III.

- Approach I: Multiple DGs operating at a unity power factor (1 p.u.).
- Approach II: Multiple DGs supplying active and reactive power at constant power factor (0.866 p.u.).
- Approach III: A novel approach has been introduced in this work where multiple DGs injecting active and reactive power at variable power factor have been considered.

These Three approaches have been implemented and tested on two power networks selected from the IEEE standards using the proposed novel strategy as well as the state of art techniques.

4.1. System I: standard IEEE 33-bus

The single line diagram of 33-bus network is shown in Fig. 2. It consists of 33 nodes and 32 line branches (Baran and Wu, 1989a). The voltage of the system is 12.66 KV and the base capacity is 100 MVA. The total system load is 3715 kW real power & 2300 KVAR reactive one. Line and load data have been reported in Singh et al. (2009). Before the installation of DG units, the total

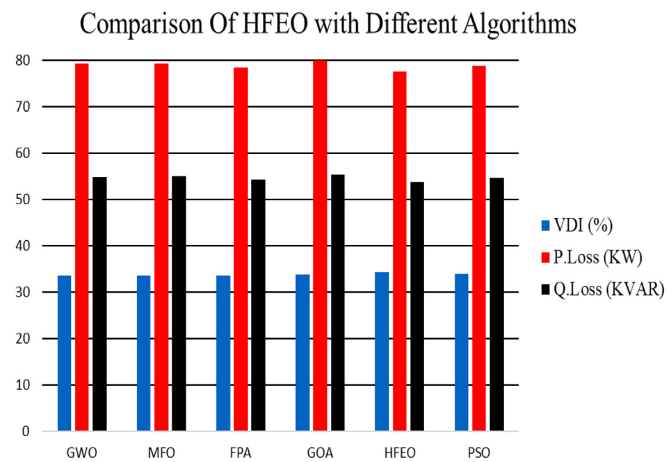

Fig. 4a. Comparison of different algorithms for Approach I.

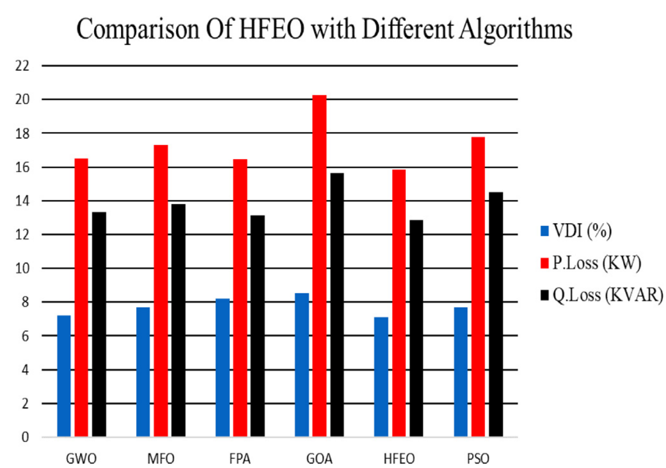

Fig. 4b. Comparison of different algorithms for Approach II.

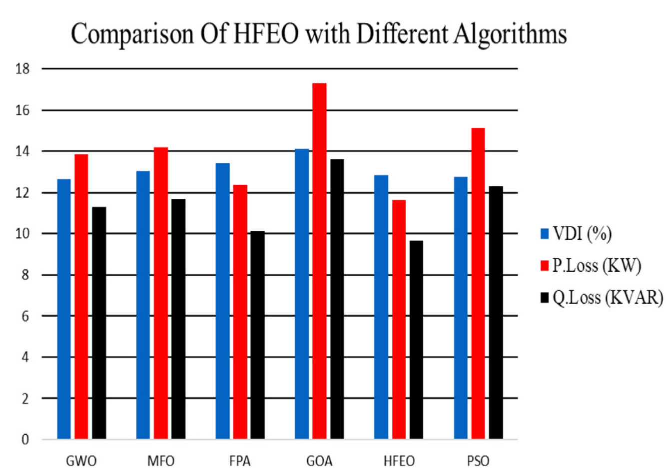

Fig. 4c. Comparison of different algorithms for Approach III.

active & reactive losses are 202.7 KW & 135.14 KVAR respectively. The load flow calculations are carried out using Newton–Raphson method that has been provided in MATLAB code.

The five codes of the tested state of art algorithms as well as that of the proposed technique have been executed at 500 iterations and 10 runs. The number of iterations versus the objective function have been plotted for the hybrid Fuzzy-EO (HFEO) proposed technique in comparison with the other previously used algorithms in literature that have been tested on the selected systems at the same conditions for the two previously published approaches and the proposed novel one. Figs. 3a, 3b and 3c show the results of the three approaches respectively. It is clearly noticed that the proposed strategy has been converged in the minimum number of iterations and to the minimum value of the

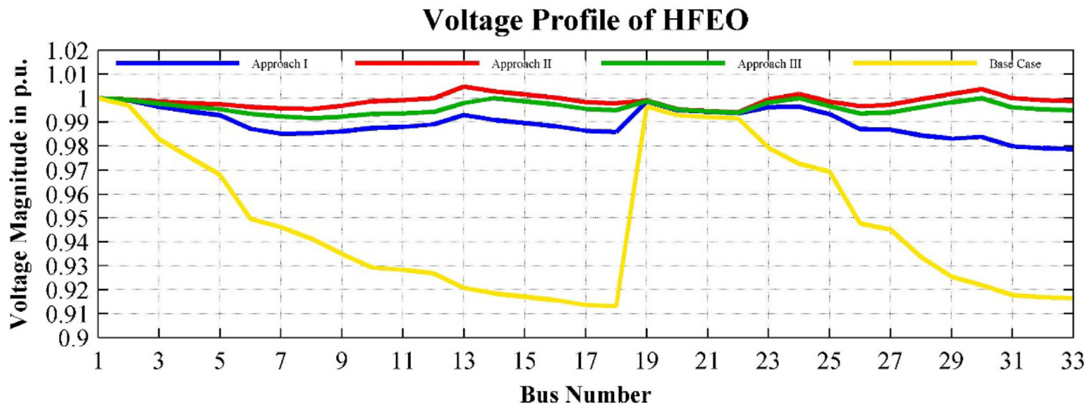

Fig. 5a. Voltage profile of the three tested Approaches using HFEO.

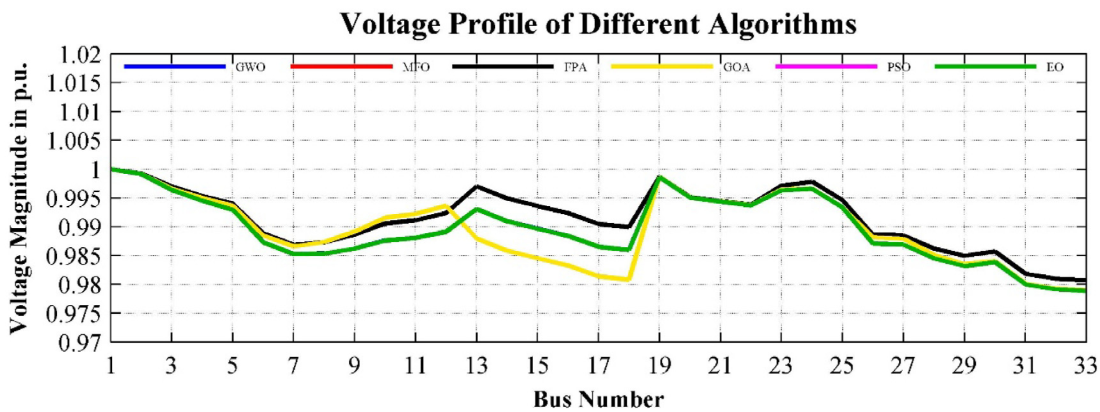

Fig. 5b. Comparison between voltage profile of different algorithms for Approach I.

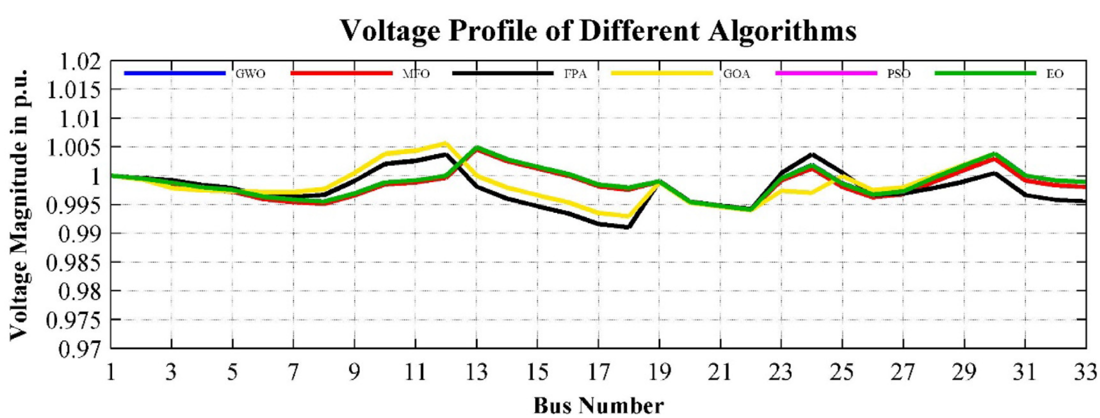

Fig. 5c. Comparison between voltage profile of different algorithms for Approach II.

objective function at all different DG types for the three tested approaches which proves its efficiency and robustness as well as the better consistency over the other state of art.

The results of the first implemented approach are shown in Fig. 4a, it can be observed that the minimum reductions of the real power loss and the reactive power loss have been accomplished by the proposed technique HFEO in comparison with the other state of art. Furthermore, the percentage of the summation of the voltage deviation from the references at all the 33 buses w.r.t the case of the original system without using DGs is of a comparative result between the proposed strategy and the previously published techniques. In case of the second approach, it is obvious that the active and reactive power losses have been reduced considerably and the minimum values have been achieved by the introduced strategy of HFEO w.r.t all other tested techniques as shown in Fig. 4b Moreover, the percentage of voltage deviation summation over 33-buses has been reduced remarkably with the least value achieved by HFEO. In case of

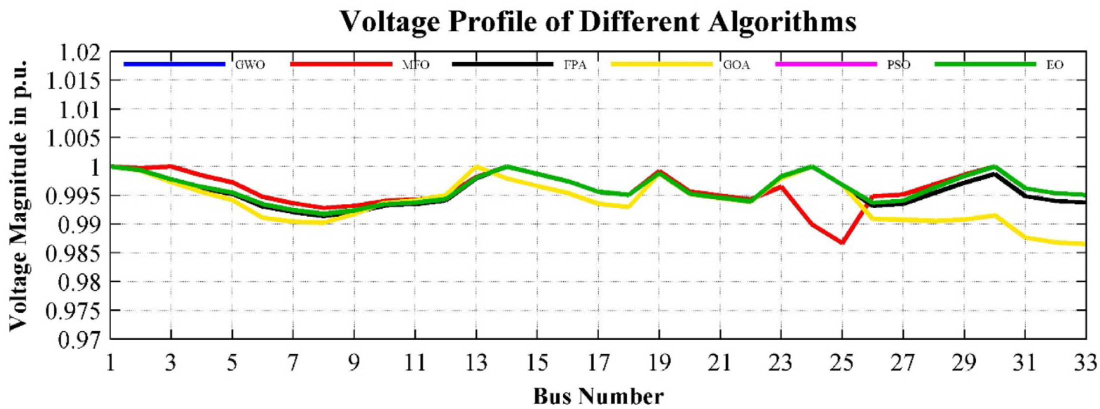

Fig. 5d. Comparison between voltage profile of different algorithms for Approach III.

Table 2a
Comparison of different algorithms for Approach I.

	GWO	MFO	FPA	GOA	HFEO	PSO	Base Case
VDI (%)	33.6766	33.5542	33.6996	33.8547	34.2419	33.9603	170.0944
P. Loss (KW)	79.2888	79.2619	78.4473	79.9849	77.6570	78.8204	202.6771
Q. Loss (KVR)	54.9134	54.9606	54.3287	55.2840	53.7182	54.6785	135.1410
Location (DG1)	24	30	13	12	24	30	
Location (DG2)	30	24	24	24	30	13	
Location (DG3)	13	13	30	30	13	24	
Size (DG1)	1.2097	1.2572	1.1223	1.1943	1.2090	1.2572	
Size (DG2)	1.2573	1.2090	1.2860	1.1835	1.2572	1.0431	
Size (DG3)	1.0431	1.0431	1.2742	1.1990	1.0431	1.2090	
Average (O.F)	0.3362684	0.3360561	0.3333677	0.3388482	0.3314711	0.3352655	
Best (O.F)	0.3314711	0.3314711	0.3315032	0.3322619	0.3314711	0.3314711	
Worst (O.F)	0.3488772	0.3467543	0.3367090	0.3533099	0.3314711	0.3525733	
Std (O.F)	0.0077458	0.0073825	0.0016079	0.0075276	6.513E−15	0.0077268	
(Bus no.) Worst Voltage	(9) 0.9862	(33) 0.9788	(33) 0.9807	(33) 0.9789	(33) 0.9788	(33) 0.9788	(18) 0.9131
Time Elapsed (Mins)	43.246	13.734	55.98	56.564	2.4	53.043	

the third approach, considerable reductions of active and reactive power losses w.r.t. the other two approaches have been detected and reported as shown in Fig. 4c Additionally, these reductions have been accompanied by a stable voltage profile with a percentage of voltage deviation summation over 33 bus around only 12% of that without optimal sitting and sizing of DGs. These results have clarified that the proposed novel approach, where a variable power factor has been used and tested, has achieved the best reduction of active and reactive power losses as well as a stable voltage profile with respect to the other approaches. Furthermore, the novel hybrid fuzzy-EO strategy has accomplished the best accuracy and the highest speed of convergence with minimum execution time as well as its superiority in consistency compared to the other state of art.

For better clarification, the results have been reported in Tables 2a, 2b, and 2c where the optimal placement and sizing of DGs for the three tested approaches have been carried out using the proposed HFEO strategy as well as five state of art algorithms and the obtained results have been compared to the results of the original case without using optimal sitting and sizing process. For more validation, statistical analysis has been established via calculation of average, best, worst and standard deviation values of the objective function. These values have proven the superiority of the introduced HFEO in comparison with the other algorithms.

Furthermore, the execution time of the proposed technique and the state of art algorithms has been tabulated at each approach in each table of the results. The results of the execution time show that the execution time of the proposed technique is much less than that of the state of art algorithms. As an example of the difference in execution time in Table 2a, the value of the minimum execution time of the previously published algorithms is 13.7 min while the introduced strategy has achieved execution time of only 2.4 min which is very remarkable reduction of the execution time and this provides very good indication about the speed of the proposed strategy.

Moreover, the voltage profile represented by the voltage deviation index VDI has been tested for the three approaches and an intensive comparisons have been accomplished between the proposed technique and the state of art algorithms well as the original case without DGs implementation. The worst voltage

Table 2b
Comparison of different algorithms for Approach II.

	GWO	MFO	FPA	GOA	HFEO	PSO	Base Case
VDI (%)	7.1948	7.7050	8.2240	8.5319	7.1267	7.6843	170.0944
P. Loss (KW)	16.4815	17.2895	16.4567	20.2278	15.8337	17.7843	202.6771
Q. Loss (KVR)	13.3433	13.8160	13.1341	15.6267	12.8557	14.4931	135.1410
Location (DG1)	13	13	12	25	30	13	
Location (DG2)	30	30	30	12	13	30	
Location (DG3)	24	24	24	30	24	24	
Size (DG1)	0.7930	0.7960	0.9100	0.7566	1.2953	0.7935	
Size (DG2)	1.2953	1.2776	1.1563	0.9512	0.7936	1.2952	
Size (DG3)	1.0796	1.0479	1.1963	1.2641	1.0754	1.0765	
Average (O.F)	0.0730964	0.0828337	0.0756199	0.0905031	0.0706587	0.0788752	
Best (O.F)	0.0706591	0.0758489	0.0720973	0.0707165	0.0706587	0.0706587	
Worst (O.F)	0.0950200	0.1141191	0.0790626	0.1105727	0.0706587	0.1117410	
Std (O.F)	0.0077032	0.013963	0.0025555	0.012909	1.7330E−09	0.017322	
(Bus no.) Worst Voltage	(22) 0.9940	(22) 0.9941	(18) 0.9910	(18) 0.9929	(22) 0.9941	(22) 0.9941	(18) 0.9131
Time Elapsed (Mins)	52.227	16.494	62.674	47.634	3.421	31.52	

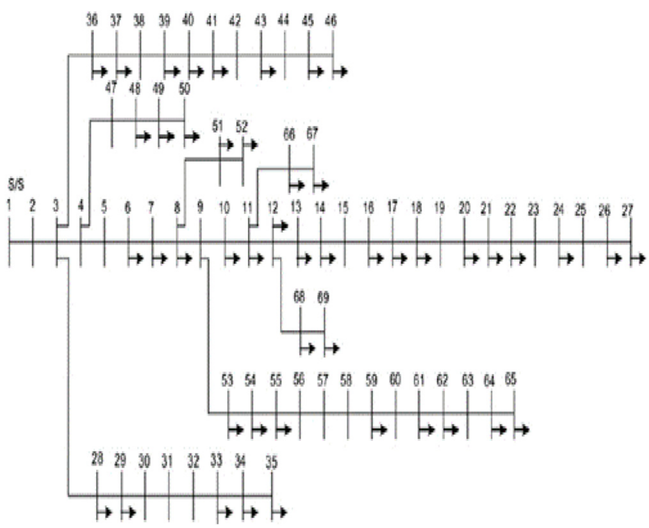

Fig. 6. Single line diagram of 69-bus Network.

value in the original case is 0.9131 p.u. at bus 33 while upon using the proposed strategy HFEO, it is 0.9788 for the first approach. These results have demonstrated that there is not only a considerable reduction in the power losses but also a remarkable improvement in the voltage stability of the whole system. The voltage profile of the proposed strategy HFEO is shown in Fig. 5a for the three approaches as well as the original case. Comparisons of the voltage profiles of the proposed technique with respect to the other state of art techniques have been performed for the three approaches as presented in Figs. 5b, 5c and 5d.

These intensive comparisons have proven the superiority of the introduced technique in tackling with the proposed novel approach besides the other approaches. In addition to its robustness and accuracy compared to the state of art techniques as well as the better efficiency of the novel approach in reducing the power losses and enhancing the voltage stability. Furthermore, the proposed strategy has achieved minimum execution time as well as the maximum speed of convergence and the best consistent results w.r.t. all state of art algorithms. Therefore, it is recommended as an efficient generalized tool in sizing and siting of DGs in the distribution system due to its efficiency, accuracy, fastness and compatibility with different types of DGs.

4.2. System II: standard IEEE 69-bus

For more verification of the novel approach and the proposed hybrid fuzzy metaheuristic strategy, more complicated IEEE 69-bus distribution system is selected to be tested as shown in Fig. 6 a main feeder and 7 sub-feeders are included in the system (68 Branches) (Baran and Wu, 1989b). The rated voltage of the system is 12.66 KV. The total peak real and reactive power demand are 3802.19 kW and 2694.6 KVAR respectively as given in Haque (1996). For 69-bus original test case without DGs, the real power losses are 225.0007 kW and reactive power losses are 102.16475 KVAR. Similarly, the same steps have been performed as in 33-bus case and the results have been plotted and reported by the same manner.

From Figs. 7a, 7b and 7c, it is observed that the accuracy and the convergence speed of the proposed technique HFEO are better than that of the other techniques for the three approaches while the execution time is the minimum one which proves the efficiency and the robustness of the proposed strategy in the more complex systems.

From the results that have been demonstrated in Figs. 8a, 8b and 8c, it is obvious that the active and reactive losses as well as the voltage deviation have been reduced remarkably after the optimal installation of DGs for the three approaches under test and The minimum values have been achieved by the proposed technique HFEO in all test cases.

The optimal values of voltage deviation, the active power loss, the reactive power loss and optimal capacities as well as the optimal locations of the distributed generator units obtained by HFEO and other algorithms for the three approaches have been reported in Tables 3a, 3b and 3c.

Fig. 9a shows the impact of the optimal location and size of DGs using the novel proposed HFEO technique on the voltage characteristics of IEEE 69-bus system. The voltage profile at each bus is improved for the three investigated approaches. It is observed that the minimum achieved bus voltages after optimal

Table 2c
Comparison of different algorithms for Approach III.

	GWO	MFO	FPA	GOA	HFEO	PSO	Base Case
VDI (%)	12.6643	13.0371	13.4194	14.1198	12.8289	12.7675	170.0944
P. Loss (KW)	13.8647	14.2032	12.3862	17.3031	11.6413	15.1437	202.6771
Q. Loss (KVR)	11.2928	11.6743	10.1222	13.6273	9.6678	12.2949	135.1410
Location (DG1)	30	30	24	30	30	14	
Location (DG2)	14	3	14	24	14	24	
Location (DG3)	24	14	30	13	24	30	
Size (DG1)	1.0408	0.9891	1.1629	0.8257	1.0406	0.7460	
Size (DG2)	0.7464	1.6357	0.7438	1.1053	0.7460	1.0678	
Size (DG3)	1.0679	0.7197	0.9911	0.8387	1.0678	1.0406	
Average (O.F)	0.0733	0.0753	0.0692	0.0878	0.0657	0.0781	
Best (O.F)	0.0656532	0.0656532	0.0664349	0.0658662	0.0656532	0.0656532	
Worst (O.F)	0.0916010	0.0897547	0.0717424	0.1042506	0.0658153	0.0916005	
Std (O.F)	0.0122470	0.0124321	0.0016357	0.0148151	2.2223E−15	0.0131091	
(Bus no.)	(8)	(25)	(8)	(33)	(8)	(8)	(18)
Worst Voltage	0.9917	0.9867	0.9914	0.9865	0.9917	0.9917	0.9131
Time Elapsed (Mins)	42.27	8.511	49.815	52.064	3.814	39.326	

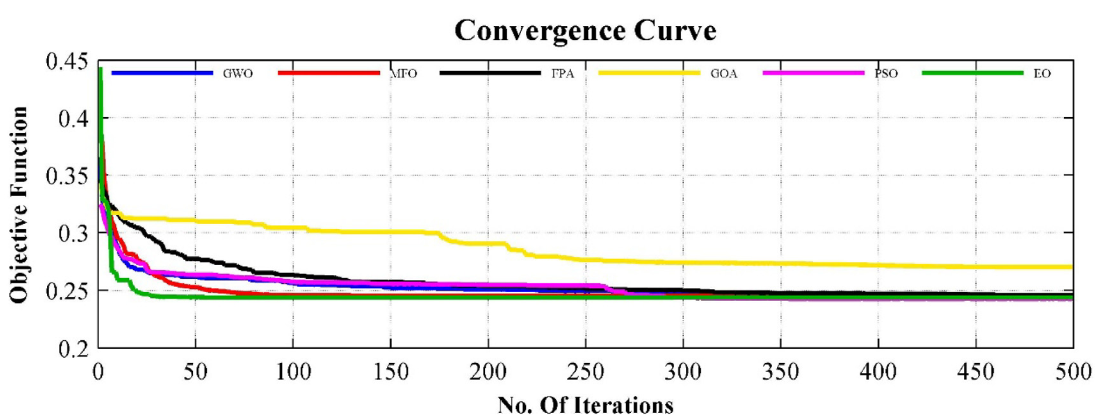

Fig. 7a. Convergence curve of Approach I.

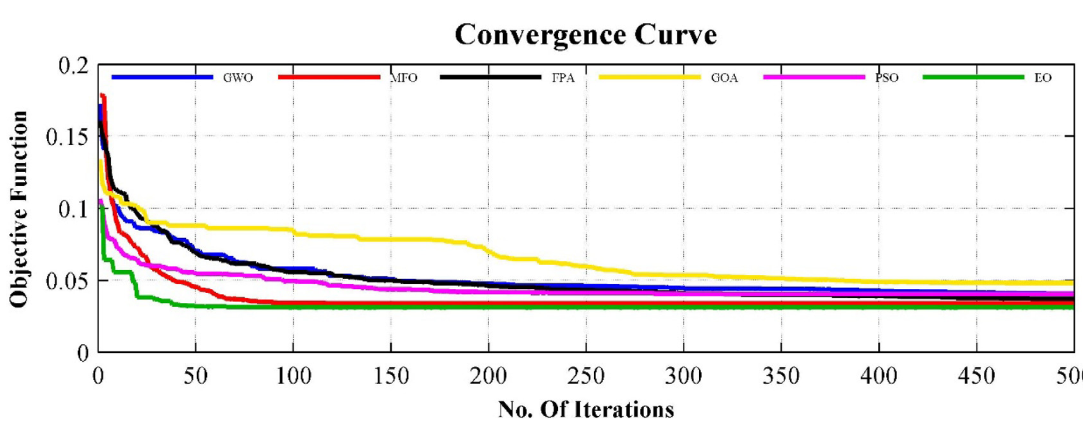

Fig. 7b. Convergence curve of Approach II.

installation of DGs at constant and variable lagging power factor approaches have shown better values compared to those obtained at unity power factor due to reactive power injection capability. At unity power factor approach the worst value of voltage is

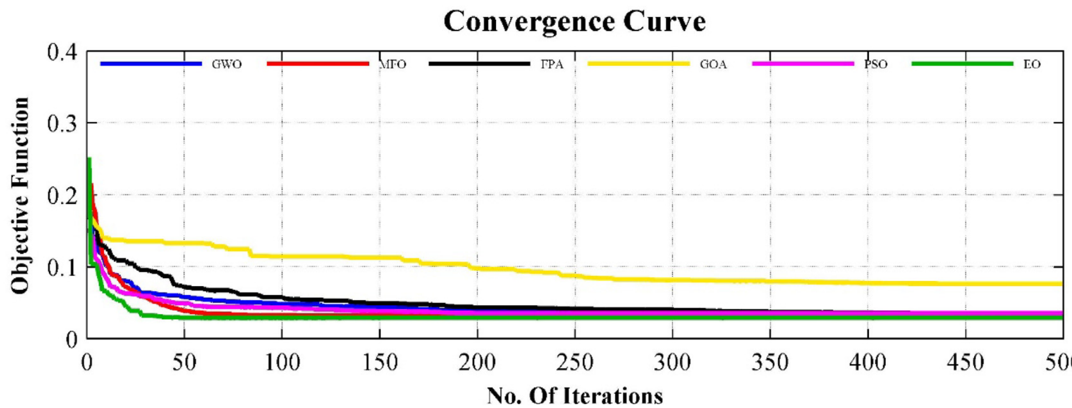

Fig. 7c. Convergence curve of Approach III.

Table 3a
Comparison of different algorithms for Approach I.

	GWO	MFO	FPA	GOA	HFEO	PSO	Base Case
VDI (%)	2.9368	3.4004	3.1733	6.5883	2.8735	2.6244	183.6904
P. Loss (KW)	72.9543	73.0154	73.2369	77.5360	72.9450	72.8384	225.0007
Q. Loss (KVR)	36.2120	35.9065	36.3217	37.2787	36.1789	36.1821	102.1648
Location (DG1)	61	19	66	61	66	11	
Location (DG2)	19	61	22	16	19	19	
Location (DG3)	11	69	61	53	61	61	
Size (DG1)	1.7345	0.5295	0.8413	1.4602	0.7702	0.8784	
Size (DG2)	0.5004	1.7867	0.4752	0.7168	0.5305	0.5009	
Size (DG3)	0.8803	0.5526	1.8690	1.0275	1.7483	1.7344	
Average (O.F)	0.2441458	0.2454413	0.2458855	0.2702621	0.2438204	0.2426454	
Best (O.F)	0.2416095	0.2416095	0.2436011	0.2514970	0.2438204	0.2416095	
Worst (O.F)	0.2581142	0.2487507	0.2486583	0.3191150	0.2438204	0.2475472	
Std (O.F)	0.0050298	0.0027871	0.0014725	0.0263062	2.5373E−10	0.0019522	
(Bus no.) Worst Voltage	(65) 0.9823	(65) 0.9823	(65) 0.9865	(65) 0.9760	(65) 0.9823	(65) 0.9823	(65) 0.9092
Time Elapsed (Mins)	66.289	14.924	67.342	69.375	6.417	52.646	

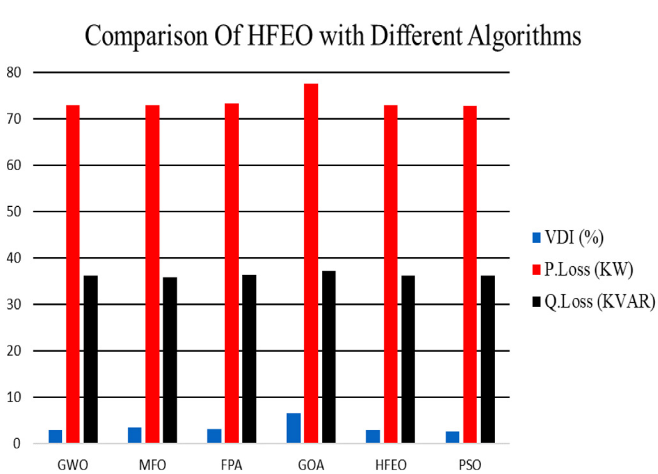

Fig. 8a. Comparison of different algorithms for Approach I.

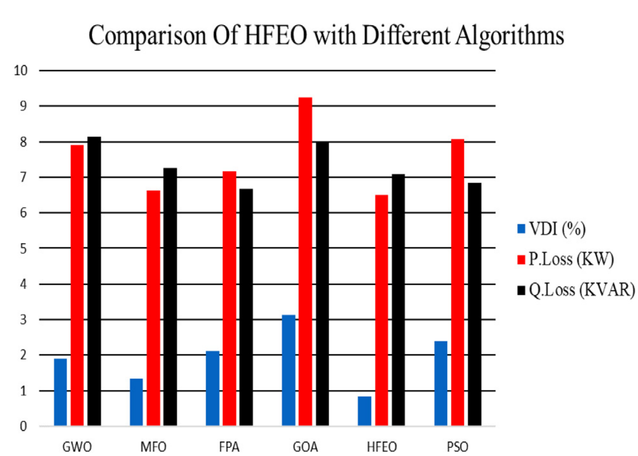

Fig. 8b. Comparison of different algorithms for Approach II.

Table 3b
Comparison of different algorithms for Approach II.

	GWO	MFO	FPA	GOA	HFEO	PSO	Base Case
VDI (%)	1.8873	1.3292	2.1186	3.1376	0.8423	2.3956	183.6904
P. Loss (KW)	7.9113	6.6310	7.1779	9.2391	6.4955	8.0853	225.0007
Q. Loss (KVR)	8.1389	7.2580	6.6804	7.9656	7.0791	6.8347	102.1648
Location (DG1)	66	11	49	49	20	20	
Location (DG2)	61	61	18	61	66	61	
Location (DG3)	20	20	61	13	61	69	
Size (DG1)	0.5881	0.6293	0.8937	1.3049	0.3641	0.3477	
Size (DG2)	1.8034	1.7944	0.5727	1.8277	0.5865	1.8437	
Size (DG3)	0.3636	0.3522	1.8341	0.9355	1.8038	0.4591	
Average (O.F)	0.0406702	0.0339840	0.0370622	0.0480226	0.0310394	0.0404312	
Best (O.F)	0.0310402	0.0310394	0.0339784	0.0347604	0.0310294	0.0310394	
Worst (O.F)	0.0929519	0.0498990	0.0411417	0.0846187	0.0310497	0.0775092	
Std (O.F)	0.0191829	0.0058025	0.0021478	0.0147727	4.2998E−10	0.0139565	
(Bus no.)	(50)	(50)	(69)	(13)	(50)	(50)	(65)
Worst Voltage	0.9943	0.9943	0.9950	1.0069	0.9943	0.9943	0.9092
Time Elapsed (Mins)	73.205	14.891	70.321	68.291	12.093	42.257	

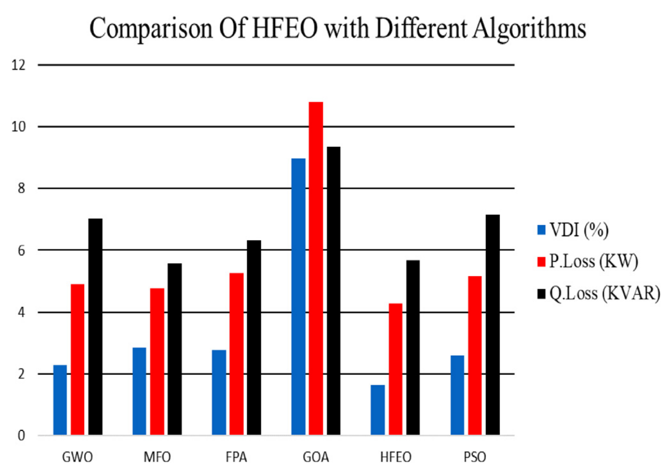

Fig. 8c. Comparison of different algorithms for Approach III.

0.98226 p.u. at bus 65. While, at constant and variable power factor approaches, the minimum voltage is around 0.99426 at bus 50. The voltage profile of all tested algorithms for the three different cases are shown in Figs. 9b, 9c and 9d respectively. These results prove the suitability of the introduced strategy for different configurations of power distribution systems.

5. Conclusion

Lately, optimal sitting and sizing of DGs have played an essential role in the optimal design of the distribution system. As the most accurate estimation of sizing and allocation of DGS is not only providing the best performance in minimization of active and reactive power losses as well as the best voltage characteristics but also achieving the least generating power of DGs which reduces in turn the required capacity of the selected DGs.

This paper introduces a novel strategy based on consolidation between a newly developed hybrid Fuzzy-metaheuristic technique named HFEO exerting on a dynamic weighted multi objective function and a novel approach considering a new concept named variable power factor approach. This novel strategy is able to achieve the optimal size and place of DGs in the distribution system based on minimizing of real active and reactive power losses as well as voltage profile improvement over the whole distribution system. Furthermore, two commonly used approaches in literature at unity and constant power factors have been tested at the same conditions and the results have been compared with that of the proposed approach. For more validation, comprehensive comparisons have been carried out among the results of the introduced hybrid technique HFEO and the results of other five state of art techniques tested at the two previously published approaches and the newly developed one to prove the powerfulness of the introduced strategy. The novel technique has shown an overall better performance regarding to the accuracy, conversion speed, execution time and consistency at the three applied approaches. To reinforce this outcome, some statistical analysis has been performed among the results. Therefore, the novel strategy is recommended to be the most efficient and superior generalized technique in locating and sizing of DGs in the distribution system.

CRediT authorship contribution statement

Mohamed Yehia: Designed the case under study, Performed the simulations, Obtained the results, Analyzed the obtained results, Wrote the paper. **Dalia Allam:** Supervised the work, Edited the paper. **Ahmed F. Zobaa:** Supervised the work, Edited the paper.

Data availability

No data was used for the research described in the article.

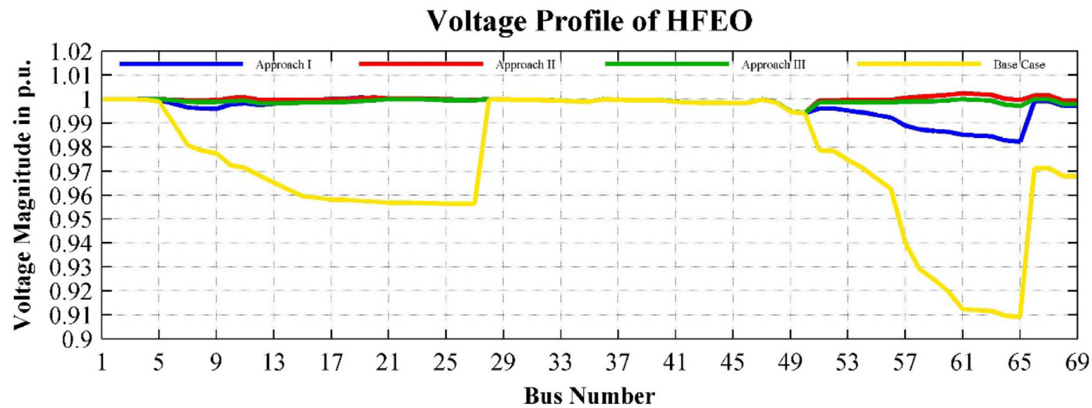

Fig. 9a. Voltage profile of the three tested Approaches using HFEO.

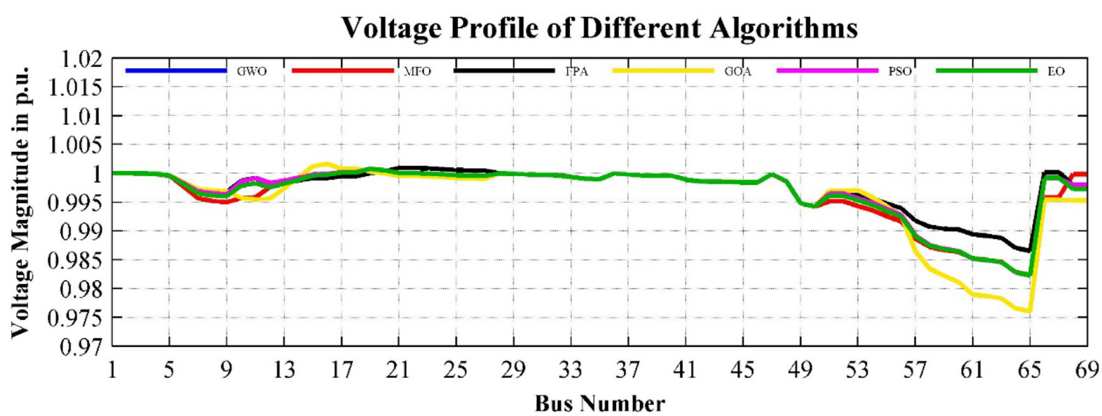

Fig. 9b. Comparison between voltage profile of different algorithms for Approach I.

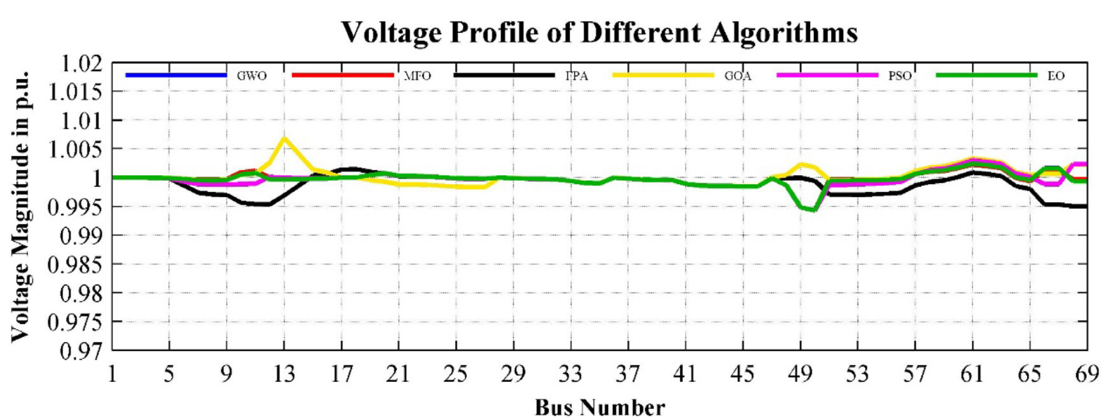

Fig. 9c. Comparison between voltage profile of different algorithms for Approach II.

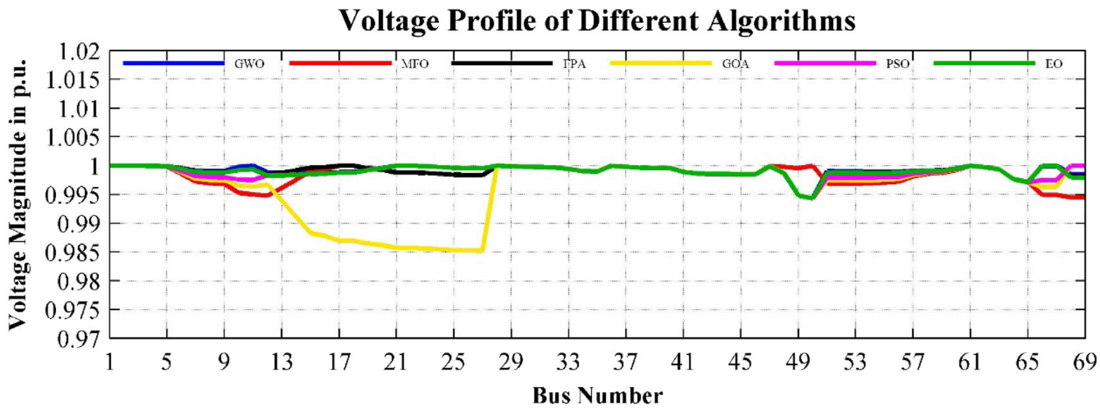

Fig. 9d. Comparison between voltage profile of different algorithms for Approach III.

Table 3c
Comparison of different algorithms for Approach III.

	GWO	MFO	FPA	GOA	HFEO	PSO	Base Case
VDI (%)	2.2716	2.8485	2.7570	8.9642	1.6330	2.5851	183.6904
P. Loss (KW)	4.8950	4.7592	5.2507	10.8029	4.2759	5.1643	225.0007
Q. Loss (KVR)	7.0104	5.5770	6.3326	9.3652	5.6806	7.1459	102.1648
Location (DG1)	21	50	67	69	66	61	
Location (DG2)	11	61	17	4	61	21	
Location (DG3)	61	18	61	61	21	69	
Size (DG1)	0.3449	0.7196	0.4107	0.6490	0.4675	1.7042	
Size (DG2)	0.5314	1.7352	0.3858	2.5947	1.681999	0.3585	
Size (DG3)	1.6737	0.5240	1.6806	1.7147	0.3613	0.3438	
Average (O.F)	0.0332155	0.0322950	0.0345195	0.0763323	0.0289222	0.0352678	
Best (O.F)	0.0289222	0.0289222	0.0327659	0.0429526	0.0289222	0.0289222	
Worst (O.F)	0.0491215	0.0356447	0.0376687	0.1271954	0.0289222	0.0492709	
Std (O.F)	0.0083654	0.0017459	0.0016464	0.0358799	6.9317E−13	0.0056788	
(Bus no.)	(50)	(69)	(50)	(27)	(50)	(50)	(65)
Worst Voltage	0.9943	0.9945	0.9943	0.9852	0.9943	0.9943	0.9092
Time Elapsed (Mins)	64.722	12.775	71.047	90.849	7.381	29.876	

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