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Reinforcement of Power System Performance Through Optimal Allotment of Distributed Generators Using Metaheuristic Optimization Algorithms

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Abstract

Owing to the acute shortage of electric power in the majority of countries, short-term measures such as installation of Distributed Generators (DGs) have attracted much attention in recent decades. Employment of DGs can provide numerous advantages for the power systems through reduction of losses, escalation of the voltage profile, as well as mitigation of pollutant emissions. However, in case they are not optimally allotted, they may even lead to aggravation of the network operation from different aspects. The aim of this paper is to explore the optimal size and location of DGs using metaheuristic optimization algorithms so that the network performance is enhanced. The salient feature of the proposed strategy compared to the previous works is that it contemplates optimal allotment of DGs under various objectives, i.e. minimization of total network active and reactive power losses, and Cumulative Voltage Deviation (CVD), with different weight values. Furthermore, the impact of enhancement in the number of DGs on different aspects of power system performance is investigated. Finally, to increase the accuracy of the results, three different nature-inspired optimization algorithms, i.e. Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and Particle Swarm Optimization (PSO) are deployed, and their speed in approaching the global optimum is compared with each other. The simulation results on IEEE 14-bus system indicate that the proposed strategy not only can reinforce the overall network performance through reduction of active and reactive power losses, and voltage deviation but also lead to the improvement of network voltage profile.

Keywords: Distributed Generator (DG), Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), Particle Swarm Optimization (PSO), power loss minimization.

1. Introduction

The strong stimulus against global warming amalgamated with the necessity to address the rising energy demand of customers has led power companies to focus keenly on harnessing renewable energy resources so as to fulfill the global electricity demand while keeping ecological hazards like drastic climate change at the bay. Throughout the world, natural resources are unevenly distributed. Therefore, the load centers and generation sites are mostly far from each other, resulting in enormous transmission losses. On the other hand, if dispersed resources are harvested properly,

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such power losses can be remarkably reduced. Therefore, the deployment of Distributed Generators (DGs) is becoming increasingly popular, since they are often on-site or in the vicinity of consumers. The DGs facilitate reliable supply of electricity to the remote areas while making optimum use of the locally abundant resources [1]. They can also improve the power factor and mitigate the voltage drops in the distribution networks [1, 2].

In a deregulated energy market, stakeholders try to take maximum benefits from the cheapest resources. Since polluting energy sources like coal and oil still appear financially lucrative to the energy companies, the promulgation of renewable energy sources is not possible unless their power losses and operating costs are reduced. The studies have revealed that more than ten percent of the generated power is wasted in the existing radial distribution systems [3]. As each unit of energy has a production cost, such a large amount of power losses imply huge economic losses to the power companies. Taking these facts into the consideration, numerous researches have been conducted for optimal allocation of DGs using various optimization techniques. Ref. [4] proposes a strategy for optimal allocation of DGs and shunt capacitors using Differential Evolutionary Algorithm (DEA). Even though the proposed strategy is effective for minimization of both active and reactive power losses, the deviation of bus voltage magnitudes from their rated values is not considered. Moreover, the optimization problem is not solved for different weight values of objectives. In [5], another approach based on the Genetic Algorithm (GA) is proposed to optimally allocate the distributed generators. However, it does not quantify the changes in active and reactive power losses when different numbers of DGs are employed. In addition, the obtained results are not compared with other metaheuristic optimization algorithms. In [6], an optimal voltage control and coordination strategy with distributed generation units is presented using GA. Nevertheless, this study merely focuses on the voltage control, and it does not consider the reduction in active and reactive power losses for different numbers of DGs. Ref. [7] presents an optimization methodology for identifying the proper location and size of DG units in local distribution systems using Particle Swarm Optimization (PSO) algorithm. However, the optimization objective in this study is only limited to the voltage profile enhancement, and other objectives such as power losses and deviation of the bus voltage magnitudes from their rated values are not considered. Ref. [8] also discusses the scheduling of DG resources using the PSO technique so as to reduce the total network operating costs. However, alleviation of reactive power losses and voltage deviations are not contemplated. In [9], another nature-inspired optimization algorithm, i.e. Artificial Bee Colony (ABC), is adopted for optimal allocation of DGs. Nonetheless, in this research, only minimization of total network real power loss is contemplated. Moreover, the optimization problem is not solved for different numbers of DGs within the network.

Increasing the number of DGs in an electric network can potentially ameliorate the power system performance through the reduction of power losses and voltage deviations. However, if they are not properly allocated, their incorporation in the power system might further deteriorate the network losses and exacerbate the voltage profile [10]. In this paper, an optimal DG allocation strategy for improvement of the power system performance is proposed, in which the active and reactive power losses, as well as the cumulative voltage deviation are mitigated. Moreover, to enhance the precision of the results, three different nature-inspired optimization algorithms, i.e. Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and Particle Swarm Optimization (PSO) are employed, and their speed in approaching the global optimum is compared with each other. In addition to that, the impact of the increase in the number of DGs is analyzed.

The remainder of this paper is organized as follows: Section 2 briefly describes the mechanism of the metaheuristic

optimization algorithms used in this paper; Section 3 formulates the optimization problem for reinforcement of power system performance through optimal allocation of DGs; in Section 4, the test network and the obtained simulation results are presented; and finally, Section 5 portrays the conclusion.

2. Metaheuristic Optimization Algorithms

The majority of real-world optimization problems are highly nonlinear and multimodal, under various complex constraints. In such problems, finding the optimal solution or even sub-optimal solutions is not an easy task. In recent decades, metaheuristic optimization algorithms have been extensively utilized in various scientific fields due to their excellent features compared to the mathematical optimization algorithms [8]. The first feature of the metaheuristic algorithms is that they are non-complex. The simplicity of these algorithms facilitates simulating natural concepts, developing novel metaheuristics, and amalgamating different metaheuristics. Flexibility is another attribute of these algorithms which enables them to solve disparate problems without any special change in the configuration of algorithm. The third feature of metaheuristic algorithms is that they have a derivation-free mechanism, contrary to the mathematical approaches which are gradient-based. In other words, the process of metaheuristic algorithms begins with random solutions and they do not require calculating the derivative of search spaces to find the global optimum. This feature makes these algorithms appropriate for dealing with complex problems, in which derivative information is unknown. The last but not the least feature of metaheuristic algorithms is that they have a lower chance of getting trapped in the local optima, compared to conventional optimization techniques. This is pertaining to the stochastic nature of these algorithms, which allows them to avoid stagnation in the local solutions. As a result, metaheuristic algorithms are well-suited for solving real-world complex problems which often include a large number of local optima. There are various types of metaheuristic optimization algorithms with different inspiration sources. However, in this paper, Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and Particle Swarm Optimization (PSO) are adopted which are briefly explained in the following subsections:

2.1. Genetic Algorithm (GA)

Genetic Algorithm (GA) can be considered as the most well-known evolutionary algorithm which has a diverse range of applications [11, 12]. The GA, introduced by John Holland and his collaborators in the 1960s and 1970s, represents a model of biological evolution based on Charles Darwin's theory of natural selection [13]. The main components of this algorithm encompass selection, crossover, and mutation. The mechanism of GA involves the encoding of solutions as arrays of character strings (known as chromosomes), the manipulation of these strings by genetic operators, and a selection based on their fitness to find the global optimum in an optimization problem. This algorithm is implemented through the following steps: (i) defining an encoding scheme; (ii) defining a fitness function or selection criterion; (iii) creating a population of chromosomes; (iv) evaluating the fitness of every chromosome in the population; (v) creating a new population by performing fitness-proportionate selection, crossover and mutation; and (vi) replacing the old population with the new one. Steps (iv), (v), and (vi) are constantly repeated until the algorithm reaches a pre-specified number of iterations (generations). Finally, the chromosome with the best fitness value is selected as the global optimum [14, 15, 16].

Performing the selection is one of the most important stages which remarkably affects the performance of this algorithm. In this paper, the Boltzmann method is deployed for this stage which provides a higher chance of selection for the individuals with better fitness values. According to the Boltzmann method, the selection probability of the i-th individual, P_i, is calculated as:

$$P_i = \frac{e^{-\beta \frac{Z_i}{Z_{worst}}}}{\sum_{n=1}^{N_{pop}} P_n} \tag{1}$$

where P_i has a value between 0 and 1, and the sum of the probabilities of all individuals is equal to 1; P_n represents the selection probability of the n-th individual; β denotes the pressure constant; Z_i is the fitness value of the i-th individual; Z_{worst} is the worst fitness value in each iteration; and N_{pop} is the total number of individuals in the population.

In this paper, the uniform crossover is deployed for partial exchange of information between the selected individuals [17, 18]. In this type of crossover, each gene in the children's chromosome has an equal chance of being chosen from either of the parents. To simplify this, a crossover mask α can be generated randomly. This crossover mask is an array with the same length of parents chromosomes which determines the parent that contributes each gene and its elements can only take values of 0 or 1. Generally, for the i-th gene of the first child, $\alpha_i = 1$ means that the gene is taken from the first parent, while $\alpha_i = 0$ implies that the gene is taken from the second parent. The exact opposite is applied to the second child. This can be formulated as:

$$y_{1i} = \alpha_i x_{1i} + (1 - \alpha_i) x_{2i} \tag{2}$$
$$y_{2i} = \alpha_i x_{2i} + (1 - \alpha_i) x_{1i}$$

where x_{1i} and x_{2i} represent the i-th gene of the first and second parent, respectively; similarly, y_{1i} and y_{2i} represent the i-th gene of the first and second child, respectively; and α_i is the i-th element of the crossover mask.

The mutation is a random change in the gene(s) of a chromosome within a prescribed limit. It increases the diversity in a population and provides completely new solutions which may not be produced via the crossover process. Therefore, it enhances the exploration feature of the GA and it has been proved to be essential during convergence. In this paper, random resetting mutation is applied, in which a random permissible value is assigned to the chosen gene.

It should be noted that selecting appropriate values for crossover and mutation percentages is of great importance. The crossover probability P_c is usually considered very high, typically in the range [0.7, 1]. On the contrary, a small value is selected for the mutation probability P_m (typically, in the interval [0.001, 0.05]). The reason is that if P_c is too small, then crossover is applied sparsely, which is not desirable; also, in case the mutation probability is too high, the algorithm can still jump around even if the algorithm is very close to the optimal solution.

2.2. Particle Swarm Optimization (PSO) Algorithm

Particle Swarm Optimization (PSO) is another metaheuristic algorithm that was developed by Kennedy and Eberhart in 1995. This algorithm which is based on swarm behavior observed in nature has been widely used in almost

every area in optimization, computational intelligence, and design applications. In this algorithm, the space of an objective function is explored by adjusting the trajectories of individual agents, termed as particles. The movement of each particle around the search space is guided by the position of the current global best g^* and its own best-known location x_i^*.

During the optimization process, when a particle finds a position that is better than any previously discovered positions, its position is updated with its current one. In fact, there is a current best position for all particles at any time t in each iteration. Finally, a global best position is found among all current best positions after a pre-specified number of iterations which is considered as the global optimum. In this algorithm, the new velocity and position of the i-th particle, v_i^{t+1} and x_i^{t+1}, are respectively determined as follows:

$$
\begin{aligned}
v_i^{t+1} &= v_i^t + \alpha \epsilon_1 \left(g^* - x_i^t \right) + \beta \epsilon_2 \left(x_i^* - x_i^t \right) \\
x_i^{t+1} &= x_i^t + v_i^{t+1}
\end{aligned}
\tag{3}
$$

where ϵ_1 and ϵ_2 are two random vectors, either of them takes a value between 0 and 1, and parameters α and β are learning parameters.

2.3. Grey Wolf Optimizer (GWO) Algorithm

The Grey Wolf Optimizer (GWO) algorithm mimics the leadership hierarchy and hunting mechanism of grey wolves in nature. The grey wolves are highly social animals who have a complex social hierarchy. Such a hierarchical system, where they are ranked based on their strength and power is termed as dominance hierarchy.

The dominance hierarchy consists of alpha, beta, delta, and omega wolves. The alpha male and females are at the top of the hierarchy, and they lead the pack. The second level in the hierarchy of grey wolves is beta. The betas are subordinate wolves that help the alphas in decision-making or other pack activities. The delta wolves are below the beta wolves in rank. They are often strong, but lack of leadership skills or confidence makes them unable to take on leadership responsibilities. The lowest ranking grey wolves are omegas. The omega wolves are not important individuals in the pack, but the whole pack faces internal fighting and problems in case of losing the omegas. In addition to the dominance hierarchy, grey wolves have an interesting method of hunting with a unique strategy that includes three stages, i.e. chasing, encircling, and hunting the prey. The encircling behavior of the wolves can be mathematically expressed as:

$$
\begin{aligned}
\vec{D} &= |\vec{C}.\vec{X}_P(t) - \vec{X}_t| \\
\vec{X}(t+1) &= \vec{X}_P(t) - \vec{A}.\vec{D}
\end{aligned}
\tag{4}
$$

where t indicates the current iteration; $\vec{X}_P$ is the position vector of the prey; and $\vec{X}$ denotes the position vector of grey wolf; $\vec{A}$ and $\vec{C}$ are coefficient vectors which are determined by:

$$\vec{A} = 2\vec{a}\vec{r}_1 - \vec{a} \tag{5}$$

$$\vec{C} = 2\vec{r}_2$$

where components of $\vec{a}$ are linearly decreased from 2 to 0 throughout the iterations, and r_1 and r_2 are random vectors in $[0, 1]$.

For mathematical expression of the hunting behavior of grey wolves, it is supposed that the three best wolves, i.e. α, β, and γ, have better knowledge about the potential location of prey. Therefore, the first three best solutions are saved and the other search wolves (including omegas) are obliged to update their positions according to the position of the best wolf. The following formulas are used for updating the position of the best wolf:

$$\vec{D}_\alpha = |\vec{C}_1 . \vec{X}_\alpha - \vec{X}| \tag{6}$$

$$\vec{D}_\beta = |\vec{C}_2 . \vec{X}_\beta - \vec{X}|$$

$$\vec{D}_\delta = |\vec{C}_3 . \vec{X}_\delta - \vec{X}|$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 . \vec{D}_\alpha$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2 . \vec{D}_\beta$$

$$\vec{X}_3 = \vec{X}_\delta - \vec{A}_3 . \vec{D}_\delta$$

$$\vec{X}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$$

3. Reinforcement of Power System Performance Using Metaheuristic Optimization Algorithms

In recent decades, DGs have been widely utilized around the world as an effective tool for the reduction of environmental impacts in energy production. In spite of numerous advantages provided by DGs, their improper allotment may lead to aggravation of power system performance [19]. To remedy this challenge, this paper proposes a strategy to explore the optimal size and location of DGs so that the network performance is improved in terms of total active and reactive power losses, and Cumulative Voltage Deviation (CVD).

In a typical power system, in which each branch may include either a line or a transformer, the current flowing from bus k to bus n and from bus n to bus k in branch kn can be respectively calculated by:

$$\vec{I}_{kn} = \left(\frac{y}{a^2} + j\frac{b}{2} \right) \vec{V}_k + \left(\frac{-y}{a} \right) \vec{V}_n \tag{7}$$

$$\vec{I}_{nk} = \left(\frac{-y}{a} \right) \vec{V}_k + \left(y + j\frac{b}{2} \right) \vec{V}_n$$

where y denotes the total series admittance of line or transformer kn; b represents the half branch charging susceptance; a is the tap setting value of transformer kn which is equal to 1 in case the branch includes a line; and $\vec{V}_k$ and $\vec{V}_n$ are

respectively the voltage phasors of buses k and n which are calculated by the power flow algorithm. The complex power loss in branch kn can be determined as:

$$\vec{S}_{loss,kn} = \vec{S}_{k,kn} + \vec{S}_{n,nk} = \vec{V}_k \vec{I}_{kn}^* + \vec{V}_n \vec{I}_{nk}^* \tag{8}$$

where $\vec{S}_{k,kn}$ and $\vec{S}_{n,nk}$ are respectively the transferred complex power from bus k to bus n, and from bus n to bus k. Therefore, the total active and reactive power losses in a network comprising N buses are respectively computed as:

$$P_{loss,tot} = \mathrm{Re}(\vec{S}_{loss,tot}) = \mathrm{Re}(\sum_{\substack{k=1}}^{N}\sum_{\substack{n=1\\n\neq k}}^{N} \vec{V}_k \vec{I}_{kn}^* + \vec{V}_n \vec{I}_{nk}^*) \tag{9}$$

$$Q_{loss,tot} = \mathrm{Im}(\vec{S}_{loss,tot}) = \mathrm{Im}(\sum_{\substack{k=1}}^{N}\sum_{\substack{n=1\\n\neq k}}^{N} \vec{V}_k \vec{I}_{kn}^* + \vec{V}_n \vec{I}_{nk}^*)$$

In this paper, in addition to mitigation of total active and reactive power losses, the reduction of network CVD is also considered as an optimization objective which is defined as:

$$CVD = \sum_{n=1}^{N} |\frac{|V_n| - |V_{rated}|}{N}| \tag{10}$$

where $|V_n|$ is the voltage magnitude of bus n, and $|V_{rated}|$ is the rated network bus voltage magnitude which is equal to 1 p.u.. According to (9) and (10), the optimization problem includes three objectives. However, such a multi-objective optimization problem can be converted to a single-objective problem using Weighted Sum Method (WSM) as:

$$Z = \frac{P_{loss,tot}}{|P_{loss,tot,org}|}W_1 + \frac{Q_{loss,tot}}{|Q_{loss,tot,org}|}W_2 + \frac{CVD}{CVD_{org}}W_3 \tag{11}$$

where Z is the fitness function; $P_{loss,tot,org}$, $Q_{loss,tot,org}$, and CVD_{org} are respectively the original values of total network active power losses, reactive power losses, and CVD before adding new DGs; and W_1, W_2, and W_3 respectively denote the weight values for active power losses, reactive power losses, and CVD which sum of them equals 1.

In order to implement the optimization problem, first, the type, number, and range of genes (decision variables) must be determined. To improve the power system performance through adding m DGs, $2m$ genes are required for each chromosome. The first m genes represent the decision variables for the placement of each DG. Since new DGs are only connected to PQ buses, these genes can only take positive integers and their maximum value is the number of PQ buses in the power system, i.e. N_{PQ}. The second m genes denote the decision variables for the contribution percentage of each DG which take real numbers between 0 and 100 percent, defined as:

7

$$\%C_{DG} = \frac{P_{DG}}{\sum_{n=1}^{N} P_{Ln}} \times 100 \tag{12}$$

where P_{DG} represents the generated active power by the DG, and P_{Ln} denotes the active power demand by bus n. As a result, the optimization problem is formulated as:

$$
\begin{cases}
\text{Minimize } Z(x) \\
\text{where} \\
x = [x_{int,1}, x_{int,2}, x_{int,3}, \ldots, x_{int,m}, x_{real,1}, x_{real,2}, x_{real,3}, \ldots, x_{real,m}] \\
\text{subject to :} \\
1 \leq x_{int,i} \leq N_{PQ}; \ i = 1, 2, 3, \ldots, m \\
0 \leq x_{real,i} \leq 100; \ i = 1, 2, 3, \ldots, m
\end{cases} \tag{13}
$$

where x is the vector of decision variables, and $Z(x)$ is the fitness function. Fig. 1 depicts the flowchart of the proposed strategy. As can be seen from the figure, first, the desired weight values for W_1, W_2, and W_3 are set. Subsequently, the optimization algorithm parameters and stop criterion are set and a random population is created. In the next stage, a random solution is sent to the Newton-Raphson power flow program. The power flow program interprets the information of the solution, and then reconfigure the network structure accordingly. Finally, the fitness value for the received solution is computed by the power flow program and sent back to the main algorithm. In the main algorithm, all of the evaluated solutions are sorted in ascending order based on their fitness values. This procedure continues until the optimization algorithm stop criterion is met. Finally, after the execution of last iteration, the best solution and its corresponding fitness value are recorded.

4. Test Network and Simulation Results

In order to verify the effectiveness of the proposed strategy, several simulations have been conducted on the IEEE 14-bus system, as test network. The bus data and branch data of this test network considering S_{base}= 100 MVA are listed in Tables 1 and 2, respectively.

Tables 3 to 5 depict the simulation results for optimal allocation of one DG under various objectives, i.e. minimization of total network active and reactive power losses, and cumulative voltage deviation using GA, GWO, and PSO, respectively. In each table, seven different sets of weight values, namely $[1/3, 1/3, 1/3]$, $[1, 0, 0]$, $[0, 1, 0]$, $[0, 0, 1]$, $[2/5, 2/5, 1/5]$, $[2/5, 1/5, 2/5]$, and $[1/5, 2/5, 2/5]$ are simulated. From these tables, it can be seen that the proper allotment of DGs can remarkably reduce the total network active power losses, total network reactive power losses, and cumulative voltage deviation from their original values, i.e. $P_{loss,tot,org} = 13.5929$ MW, $Q_{loss,tot,org} = 31.0093$ MVAR, and $CVD_{org} = 0.0404$ p.u.. For example, in Table 3, among the optimization results under different weight values, the total network active power losses, total network reactive power losses and cumulative voltage deviation are reduced
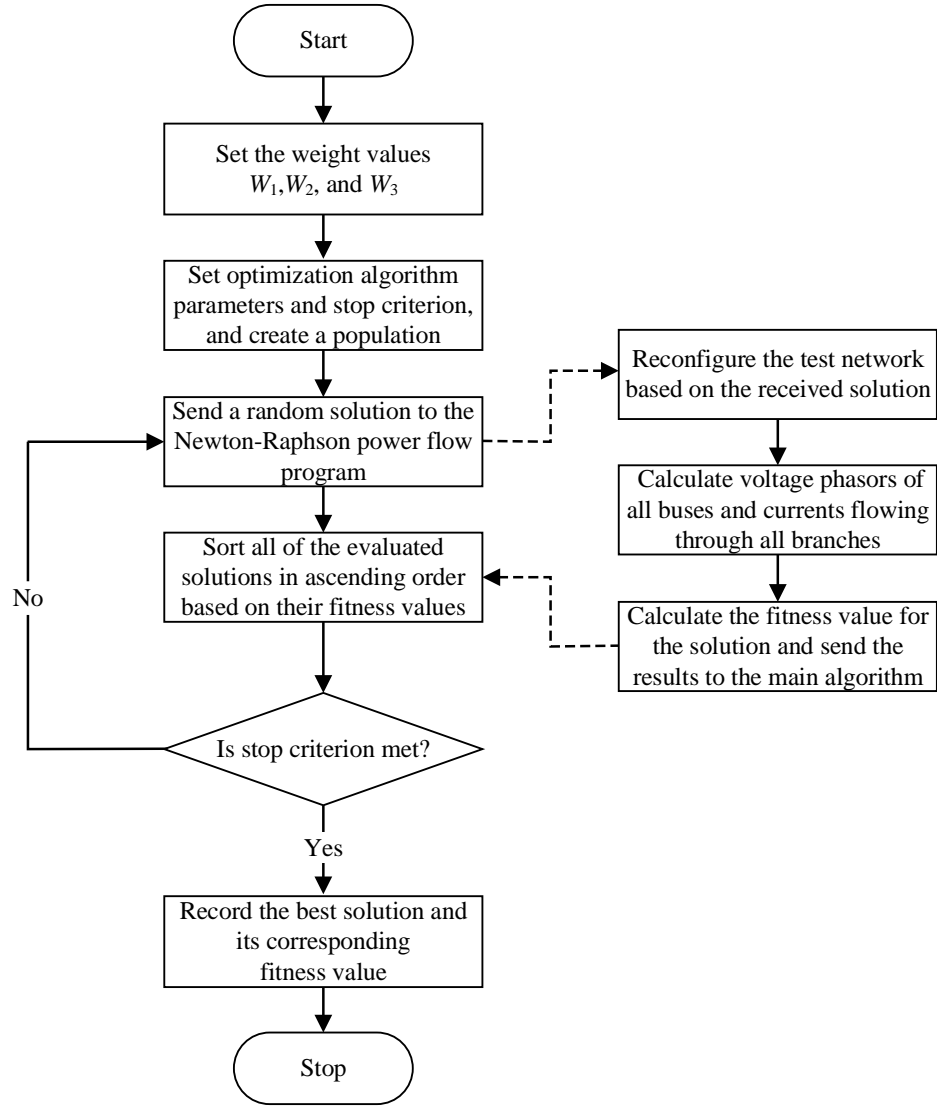
8

Fig. 1. Flowchart of the proposed strategy.

Table 1. Bus data of the IEEE 14-bus system.

Bus number	Bus type	Bus voltage		Generation		Load		Reactive power limits	
		Magnitude [p.u.]	Phase angle [deg.]	Active power [MW]	Reactive power [MVAR]	Active power [MW]	Reactive power [MVAR]	Qmin [MVAR]	Qmax [MVAR]
1	Slack	1.06	0	0	0	0	0	0	0
2	PV	1.045	0	40	0	21.7	12.7	-40	50
3	PV	1.01	0	0	0	94.2	19	0	40
4	PQ	1	0	0	0	47.8	-3.9	0	0
5	PQ	1	0	0	0	7.6	1.6	0	0
6	PV	1.07	0	0	0	11.2	7.5	-6	24
7	PQ	1	0	0	0	0	0	0	0
8	PV	1.09	0	0	0	0	0	-6	24
9	PQ	1	0	0	0	29.5	16.6	0	0
10	PQ	1	0	0	0	9	5.8	0	0
11	PQ	1	0	0	0	3.5	1.8	0	0
12	PQ	1	0	0	0	6.1	1.6	0	0
13	PQ	1	0	0	0	13.5	5.8	0	0
14	PQ	1	0	0	0	14.9	5	0	0

Table 2. Branch data of the IEEE 14-bus system.

From bus	To bus	Total series impedance		Half branch charging susceptance [p.u.]	Tap setting
		Resistance [p.u.]	Reactance [p.u.]		
1	2	0.01938	0.05917	0.0264	1
1	5	0.05403	0.22304	0.0246	1
2	3	0.04699	0.19797	0.0219	1
2	4	0.05811	0.17632	0.017	1
2	5	0.05695	0.17388	0.0173	1
3	4	0.06701	0.17103	0.0064	1
4	5	0.01335	0.04211	0	1
4	7	0	0.20912	0	0.978
4	9	0	0.55618	0	0.969
5	6	0	0.25202	0	0.932
6	11	0.09498	0.19890	0	1
6	12	0.12291	0.25581	0	1
6	13	0.06615	0.13027	0	1
7	8	0	0.17615	0	1
7	9	0	0.11001	0	1
9	10	0.03181	0.0845	0	1
9	14	0.12711	0.27038	0	1
10	11	0.08205	0.19207	0	1
12	13	0.22092	0.19988	0	1
13	14	0.17093	0.34802	0	1

to 5.0559 MW, 0.6327 MVAR, and 0.0198 p.u.. It can be also concluded that the optimal locations for installation of one DG are buses 4 and 7. Moreover, this table illustrates that the network average bus voltage magnitude can be significantly improved from its original value of 1.0113 p.u. after optimal location of the DG using GA. Since the execution time of an optimization algorithm may vary from one computer to another, the parameter Number of Function Evaluation (NFE) is often used to judge on the speed of different algorithms. Fig. 2 compares the speed of applied optimization algorithms for optimal allocation of one DG. As can be seen from the figure, the solid, dashed, and dotted lines respectively represent the procedure of optimization using GA, GWO, and PSO for 60,000 function evaluations.

Similarly, Tables 6 to 8, and Tables 9 to 11 respectively show the results for optimal allocation of DGs using two and three DGs under various optimization algorithms. Also, the speed of the applied optimization algorithms for optimal allocation of two and three DGs is compared in Figs. 3 and 4, respectively. Comparing the simulation results presented in Figs. 2, 3, and 4, it can be concluded that GA has a better performance for the case with one added DG, while GWO is more suitable for the cases with two and three added DGs.

Table 3. Simulation results for optimal allocation of one DG using GA.

Weight values			DG₁		$P_{loss,tot}$ [MW]	$Q_{loss,tot}$ [MVAR]	CVD [p.u.]	$V_{avg.}$ [p.u.]	Z [p.u.]
W_1	W_2	W_3	Bus location	C_{DG} [%]					
1/3	1/3	1/3	4	66.5666	5.0614	0.6486	0.0287	1.0287	0.3676
1	0	0	4	64.8968	5.0559	0.7008	0.0286	1.0287	0.3719
0	1	0	4	68.1285	5.0765	0.6327	0.0287	1.0287	0.0204
0	0	1	7	99.9921	8.6411	61.5906	0.0198	1.0163	0.4916
2/5	2/5	1/5	4	66.6869	5.0622	0.6463	0.0287	1.0287	0.2992
2/5	1/5	2/5	4	65.9092	5.0579	0.6648	0.0287	1.0287	0.4370
1/5	2/5	2/5	4	66.9970	5.0646	0.6411	0.0287	1.0287	0.3667

Table 4. Simulation results for optimal allocation of one DG using GWO.

Weight values			DG₁		$P_{loss,tot}$ [MW]	$Q_{loss,tot}$ [MVAR]	CVD [p.u.]	$V_{avg.}$ [p.u.]	Z [p.u.]
W_1	W_2	W_3	Bus location	C_{DG} [%]					
1/3	1/3	1/3	4	66.5666	5.0614	0.6486	0.0287	1.0287	0.3676
1	0	0	4	64.8969	5.0559	0.7008	0.0287	1.0287	0.3719
0	1	0	4	68.1284	5.0765	0.6327	0.0287	1.0287	0.0204
0	0	1	7	99.8343	8.6146	61.3113	0.0198	1.0163	0.4915
2/5	2/5	1/5	4	66.6869	5.0622	0.6463	0.0287	1.0287	0.2992
2/5	1/5	2/5	4	65.9092	5.0579	0.6648	0.0287	1.0287	0.4370
1/5	2/5	2/5	4	66.9969	5.0646	0.6411	0.0287	1.0287	0.3667

Table 5. Simulation results for optimal allocation of one DG using PSO.

| Weight values			DG₁		$P_{loss,tot}$ [MW]	$Q_{loss,tot}$ [MVAR]	CVD [p.u.]	$V_{avg.}$ [p.u.]	Z [p.u.]
W_1	W_2	W_3	Bus location	C_{DG} [%]					
1/3	1/3	1/3	4	66.5666	5.0614	0.6486	0.0287	1.0287	0.3676
1	0	0	4	64.8968	5.0559	0.7008	0.0287	1.0287	0.3719
0	1	0	4	68.1285	5.0765	0.6327	0.0287	1.0287	0.0204
0	0	1	7	36.7500	6.6726	7.5751	0.0258	1.0253	0.6378
2/5	2/5	1/5	4	66.6869	5.0622	0.6463	0.0287	1.0287	0.2992
2/5	1/5	2/5	7	48.2275	5.8152	9.3251	0.0212	1.0191	0.4407
1/5	2/5	2/5	4	75.0341	5.2576	0.9410	0.0288	1.0288	0.3739
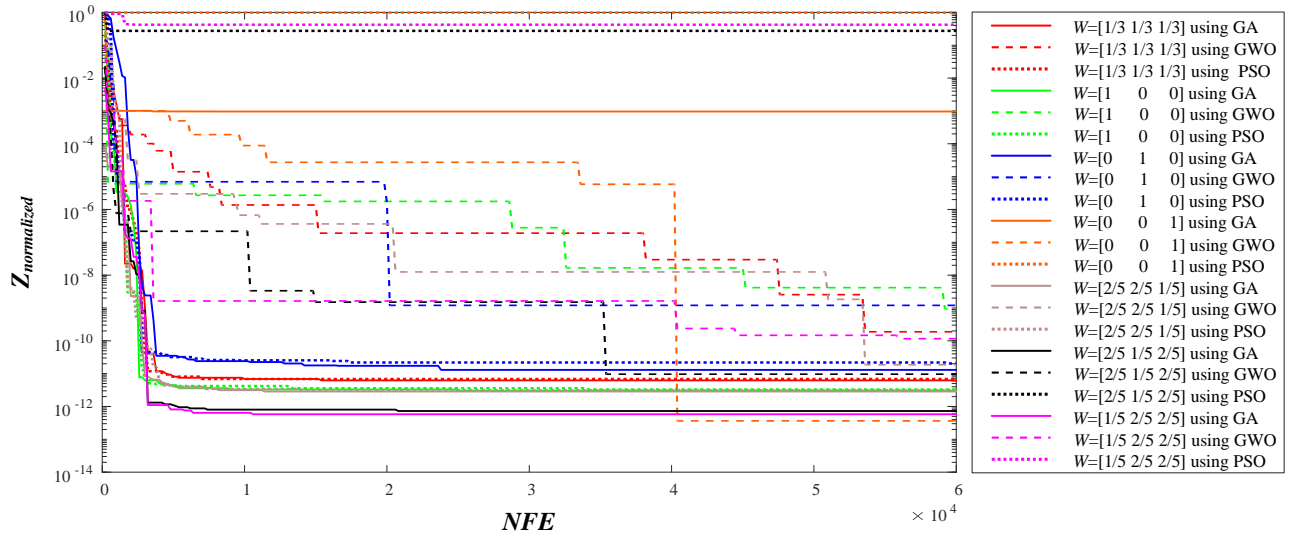
Fig. 2. Comparison between the speed of applied optimization algorithms for optimal allocation of one DG.

Table 6. Simulation results for optimal allocation of two DGs using GA.

Weight values			DG$_1$		DG$_2$		$P_{loss,tot}$ [MW]	$Q_{loss,tot}$ [MVAR]	CVD [p.u.]	$V_{avg.}$ [p.u.]	Z [p.u.]
W_1	W_2	W_3	Bus location	C_{DG} [%]	Bus location	C_{DG} [%]					
1/3	1/3	1/3	4	51.0919	13	18.8942	5.2210	-5.1347	0.0239	1.0235	0.2527
1	0	0	5	53.2285	13	13.6998	4.3881	7.7529	0.0226	1.0212	0.3228
0	1	0	4	43.7963	9	25.8337	5.0811	-5.6977	0.0237	1.0219	-0.1837
0	0	1	4	97.0849	7	90.4614	33.6244	126.3291	0.0149	1.0075	0.3695
2/5	2/5	1/5	4	42.6227	9	24.1476	5.0101	-5.6158	0.0237	1.0219	0.1922
2/5	1/5	2/5	4	49.0820	13	20.2047	5.3554	-4.4901	0.0210	1.0194	0.3370
1/5	2/5	2/5	4	50.3453	13	19.1829	5.2478	-4.5515	0.0210	1.0195	0.2270

Table 7. Simulation results for optimal allocation of two DGs using GWO.

Weight values			DG$_1$		DG$_2$		$P_{loss,tot}$ [MW]	$Q_{loss,tot}$ [MVAR]	CVD [p.u.]	$V_{avg.}$ [p.u.]	Z [p.u.]
W_1	W_2	W_3	Bus location	C_{DG} [%]	Bus location	C_{DG} [%]					
1/3	1/3	1/3	4	51.0997	13	18.8949	5.2210	-4.5691	0.0211	1.0196	0.2527
1	0	0	7	53.2265	13	13.7016	4.3881	7.7518	0.0226	1.0212	0.3228
0	1	0	4	43.9784	9	25.7868	5.0811	-5.7008	0.0237	1.0219	-0.1838
0	0	1	4	97.2333	7	90.3255	33.6244	126.1773	0.0149	1.0075	0.3695
2/5	2/5	1/5	4	43.0472	9	24.1400	5.0103	-5.6360	0.0237	1.0219	0.1919
2/5	1/5	2/5	4	50.5700	13	18.8885	5.2181	-4.5596	0.0211	1.0196	0.3327
1/5	2/5	2/5	4	51.5480	13	18.9000	5.2243	-4.5743	0.0211	1.0196	0.2265

Table 8. Simulation results for optimal allocation of two DGs using PSO.

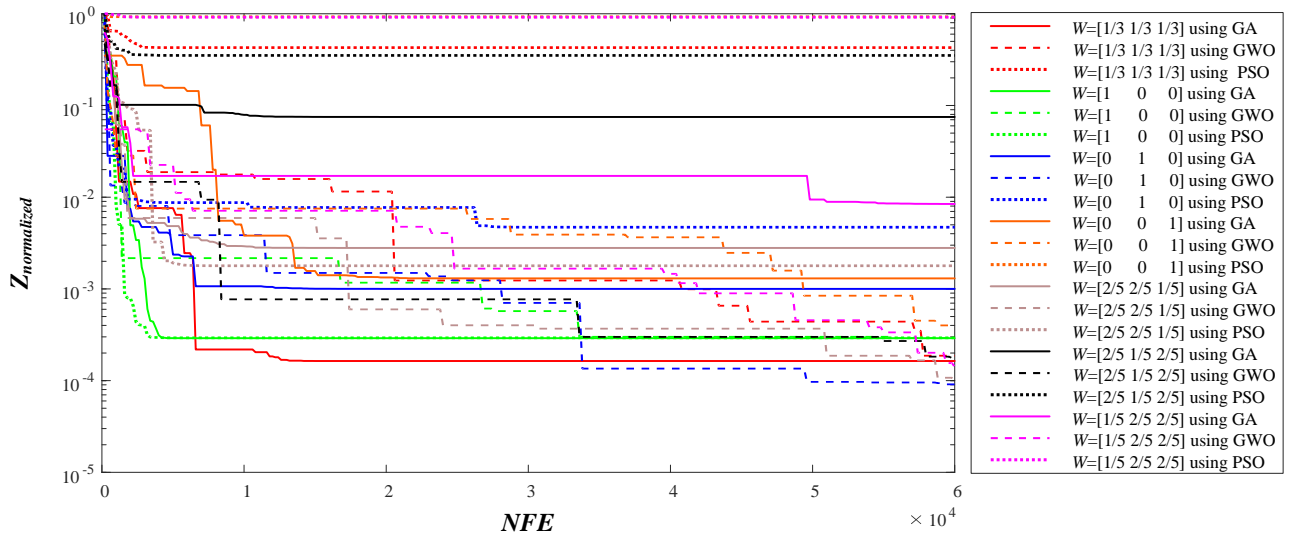| Weight values			DG$_1$		DG$_2$		$P_{loss,tot}$ [MW]	$Q_{loss,tot}$ [MVAR]	CVD [p.u.]	$V_{avg.}$ [p.u.]	Z [p.u.]
W_1	W_2	W_3	Bus location	C_{DG} [%]	Bus location	C_{DG} [%]					
1/3	1/3	1/3	4	30.3671	9	33.8759	4.8089	-1.9232	0.0215	1.0197	0.2788
1	0	0	7	53.2087	13	13.6970	4.4851	17.0417	0.0218	1.0208	0.3228
0	1	0	4	43.1680	9	25.9157	4.7743	-5.7911	0.0219	1.0202	-0.1833
0	0	1	4	79.5007	7	70.2810	20.0901	61.4180	0.0137	1.0095	0.4103
2/5	2/5	1/5	4	42.9988	9	24.4835	5.2595	-1.8897	0.0229	1.0205	0.1921
2/5	1/5	2/5	4	30.3054	9	32.9272	4.6980	-0.4748	0.0190	1.0164	0.3527
1/5	2/5	2/5	7	31.7828	13	19.3096	5.2835	-1.7684	0.0254	1.0237	0.2912

Fig. 3. Comparison between the speed of applied optimization algorithms for optimal allocation of two DGs.

Table 9. Simulation results for optimal allocation of three DGs using GA.

Weight values			DG$_1$		DG$_2$		DG$_3$		$P_{loss,tot}$ [MW]	$Q_{loss,tot}$ [MVAR]	CVD [p.u.]	$V_{avg.}$ [p.u.]	Z [p.u.]
W_1	W_2	W_3	Bus location	C_{DG} [%]	Bus location	C_{DG} [%]	Bus location	C_{DG} [%]					
1/3	1/3	1/3	4	36.8973	9	17.3548	13	16.7796	4.4106	-8.2619	0.0223	1.0206	0.2039
1	0	0	4	17.8228	7	37.6467	13	12.1182	4.4487	-1.0250	0.0218	1.0199	0.3273
0	1	0	4	40.2422	9	17.5358	13	14.2961	4.3705	-8.6612	0.0246	1.0237	-0.2793
0	0	1	5	68.2792	7	99.8129	14	13.1583	26.6891	129.0575	0.0129	1.0108	0.3205
2/5	2/5	1/5	4	36.6331	9	17.6789	13	16.8125	4.4146	-8.2531	0.0223	1.0206	0.1342
2/5	1/5	2/5	4	36.5304	7	15.9984	13	16.3595	4.3620	-7.2365	0.0214	1.0203	0.2935
1/5	2/5	2/5	4	36.1445	9	17.4418	13	16.9903	4.4223	-8.2260	0.0223	1.0206	0.1804

Table 10. Simulation results for optimal allocation of three DGs using GWO.

Weight values			DG$_1$		DG$_2$		DG$_3$		$P_{loss,tot}$ [MW]	$Q_{loss,tot}$ [MVAR]	CVD [p.u.]	$V_{avg.}$ [p.u.]	Z [p.u.]
W_1	W_2	W_3	Bus location	C_{DG} [%]	Bus location	C_{DG} [%]	Bus location	C_{DG} [%]					
1/3	1/3	1/3	4	38.9140	9	15.8240	13	16.7119	4.4041	-8.2820	0.0223	1.0206	0.2035
1	0	0	4	18.0047	7	38.1747	13	11.9166	4.0559	-1.3481	0.0228	1.0213	0.2984
0	1	0	4	40.6634	9	17.4920	13	14.0932	4.3658	-8.6623	0.0246	1.0237	-0.2793
0	0	1	4	100	9	100	14	10.6496	44.3736	177.4889	0.0125	1.0091	0.3091
2/5	2/5	1/5	4	38.7534	9	15.7917	13	16.7106	4.4027	-8.2786	0.0223	1.0206	0.1335
2/5	1/5	2/5	4	38.7392	7	14.4012	13	16.2905	4.8737	-6.1144	0.0201	1.0188	0.2935
1/5	2/5	2/5	4	39.3340	9	16.0226	13	16.7183	4.4100	-8.2905	0.0223	1.0206	0.1794

Table 11. Simulation results for optimal allocation of three DGs using PSO.

| Weight values			DG$_1$		DG$_2$		DG$_3$		$P_{loss,tot}$ [MW]	$Q_{loss,tot}$ [MVAR]	CVD [p.u.]	$V_{avg.}$ [p.u.]	Z [p.u.]
W_1	W_2	W_3	Bus location	C_{DG} [%]	Bus location	C_{DG} [%]	Bus location	C_{DG} [%]					
1/3	1/3	1/3	7	23.4684	9	14.3105	13	17.3522	4.8089	-1.9232	0.0214	1.0197	0.2740
1	0	0	7	63.6870	11	5.0939	13	11.9574	4.4851	17.0417	0.0218	1.0208	0.3300
0	1	0	4	27.4259	5	22.2755	9	24.1777	4.7743	-5.7911	0.0219	1.0202	-0.1868
0	0	1	4	60.0106	7	49.3716	9	38.6243	20.0901	61.4180	0.0137	1.0095	0.3397
2/5	2/5	1/5	7	13.3948	9	29.4255	12	10.9015	5.2595	-1.8897	0.0229	1.0205	0.2441
2/5	1/5	2/5	4	22.6070	5	17.3969	7	32.8359	4.6980	-0.4748	0.0190	1.0164	0.3235
1/5	2/5	2/5	5	29.3539	9	44.4127	12	7.0056	5.2835	-1.7684	0.0254	1.0237	0.3066
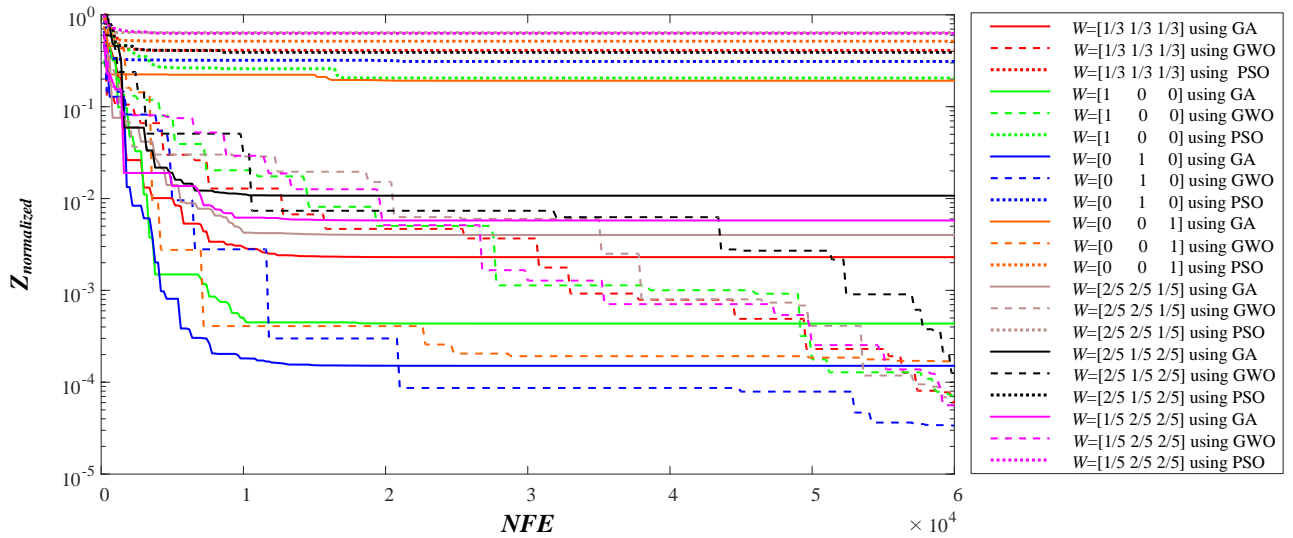
Fig. 4. Comparison between the speed of applied optimization algorithms for optimal allocation of three DGs.

5. Conclusion

The main objective of the power system operation is to meet the electricity demand at all locations within the power network as economically and reliably as possible. However, due to the gradual depletion of fossil fuels, enhanced transmission and distribution costs, deregulation trends, and heightened environmental concerns, the justification for installation of large central power plants is weakening. Deployment of DGs is one of the most effective methods to remedy such challenges. Nevertheless, improper allocation of DGs may even degrade the performance of the power system. In this paper, an attempt was made to optimally allocate the DGs such that the power system operation is improved from different aspects, i.e. of total active and reactive power losses, and cumulative voltage deviation. In addition, to enhance the precision of the simulation results, three different metaheuristic optimization algorithms, i.e. Genetic Algorithm (GA), Grey Wolf Optimizer (GWO), and Particle Swarm Optimization (PSO) were deployed. The simulation results on IEEE 14-bus system indicated that the proposed approach can be effective in mitigation of total network power losses, as well as enhancement of the network bus voltage magnitudes.

Acknowledgments

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