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A power loss minimization strategy based on optimal placement and sizing of distributed energy resources

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Abstract

Due to the enhanced price of electricity, the gradual depletion of fossil fuels, and the global warming concerns, power loss minimization through deployment of distributed generators (DGs) has attracted significant attention in recent decades. This paper proposes a genetic algorithm (GA) based strategy for minimization of active and reactive power losses through optimal location and size of DGs. It also quantifies and tallies the total network power losses for the cases with random as well as optimal allocation of DGs. To validate the accuracy of the obtained results from GA, another nature-inspired optimization algorithm, cuckoo search, is also deployed. The simulation results on IEEE 30 and 118 bus systems indicate that the proposed strategy not only can effectively reduce the total network active and reactive power losses but also lead to the improvement of network voltage profile.

KEYWORDS

cuckoo search algorithm, distributed generator, genetic algorithm, power loss minimization

1 | INTRODUCTION

Aspiration for the economic operation of the electric networks has invigorated numerous researches on the efficiency of power systems. As the market price of goods is substantially influenced by the energy cost, industries prefer to use cheaper sources of electricity. Due to this reason, mitigation of power loss is critical to all stakeholders for better financial gains. Regarding ecological hazards, such as climate change and the increasing concerns about pollution caused by fossil fuels, the distributed generators (DGs) based on renewable sources have attracted more engrossment in recent decades.[1,2] Pertaining to the necessity of electrification in the rural areas, governments are also eager to harness distributed energy resources. DGs also offer significant advantages in terms of power loss mitigation, and voltage drop reduction.[3,4] Due to such numerous advantages proffered by DGs via the use of local resources, their popularity is rising. In the pursuit of reliable energy, distributed generation is usually favored near large load centers and isolated places to supply electricity at an affordable price while making optimum use of the locally abundant resources and reducing the transmission losses.[4] Generally, this implies on-site production of electricity, thus avoiding the necessity of long-distance transmission of power. DGs promulgate diversification of energy while reducing the emission of greenhouse gases.[5,6] Therefore, refinement of voltage profile, enhancement in power quality, reduction of operating costs, better security of the critical loads, development of sustainable energy systems, relief of transmission congestion, etc. are all achievable via deployment of DGs.[1,2,7]

Regarding the efficiency of power system, researches have revealed that more than 10% of the generated power is wasted in the existing radial distribution systems.[8] As each unit of energy has a production cost, such huge losses of power mean an immense economic loss to the power companies. The traditional approach for remediating power loss is to add reactive power compensation devices, particularly the shunt capacitors. However, frequent variation of loads limits the effectiveness of such methods. In order to overcome such limitations, a large number of modern approaches for the minimization of power losses have been recently devised. In Reference [9], a power loss mitigation approach based on reducing the number of transformer tap changings and capacitor regulators is proposed. The proposed method is suitable for minimizing the necessity of frequent changing of taps and regulators; however, it does not encompass any mechanism to optimally allocate the DGs. Reference [7] proposes indices like voltage profile improvement index, DG benefit index, line loss reduction index, and environmental impact reduction index to gauge the technical merits of DGs. In addition, it analyzes various merits and challenges related to the deployment of distributed resources. Nonetheless, the size of DGs and their allocation for loss mitigation are not discussed. For the similar objective of mitigating power loss, the use of step size DGs is discussed in Reference [10]. In the study, a radial distribution system is considered and the power flow solution based on Bus Injection to Branch Current (BIBC) matrix formulation is adopted. However, the performed analysis is based on the mathematical approach, which is not very effective as compared to the optimization algorithms due to the continuously varying parameters of large distribution networks. The study conducted in Reference [11] discusses control of reactive power in distribution networks to reduce the active power loss and enhance the load voltage profile. To achieve this, the role of distributed reactive power regulators is elaborated in terms of various aspects. Nonetheless, this method focuses more on the control coordination among reactive power regulators. Moreover, no mechanism for optimal allocation and sizing of distributed generations is considered in this study. In Reference [12] mitigation of real power losses is discussed employing the interior point method. Even though the proposed method has a higher execution speed, it uses an approximation approach to locate the optimal solutions, thereby reducing the accuracy of the results. Reference [13] employs the decomposition method in order to minimize the real power losses via reactive power optimization in a large network. In the research, adaptation of transformer taps, generator voltages, capacitors, and inductors is implemented to fulfill the objective. However, in the presented strategy, the allocation of DGs is not properly entailed. Reference [14] renders a comparative review of evolutionary strategy, evolutionary programming, and GA for reactive power planning so that the losses and operating costs are minimized. In the study, first, the main optimization problem is disintegrated into active and reactive power sub-problems, and subsequently, the sub-problems are analyzed employing linear programming algorithm. Nonetheless, the allotment of DGs for loss minimization is not discussed. In Reference [15], a Fuzzy multi-objective formulation is proposed with the objective of power loss mitigation. The proposed method can satisfactorily minimize the losses but its fully automatic decision-making structure precludes grid managers from allocating weights to the active and reactive power losses. Reference [16] employs particle swarm optimization (PSO) for reactive power planning and encompasses computer-aided optimization for power loss minimization. However, PSO algorithm is vulnerable to being trapped in local optima while searching for the global optimum value. In Reference [17], a combined approach is proposed to find optimal setting values of transformer taps and capacitor banks to control the reactive power and lower the power system losses. To fulfill the intended purpose, successive linear programming (SLP) technique is adopted to control the capacitor switching, whereas transformer tap changing is governed via a simplified non-analytical approach. Nonetheless, the adopted technique focuses more on the control coordination. Apart from that, allocation of DGs is not considered in this study. In Reference [18], a network configuration method based on GA is proposed in order to alleviate the power loss of distribution systems. However, in the presented approach, only reconfiguration of the network is concentrated, and optimal location and size of DGs are not considered.

Increasing the number of DGs in a network can reinforce the power system performance through power loss reduction and voltage profile improvement. However, if they are not properly allotted, their incorporation in the power system may even lead to the further enhancement of total network losses or voltage profile aggravation.[19] In this paper, a power loss minimization strategy based on GA is proposed, in which both active and reactive power losses are mitigated through optimal location and size of DGs. In addition, the effect of adding new DGs on the network voltage profile is investigated.

The remainder of this paper is organized as follows: Section 2 describes the mechanism of GA and discusses the main parts of this algorithm including selection, crossover, mutation, as well as the stop criterion; Section 3 formulates the optimization problem for active and reactive power loss mitigation through optimal allocation of DGs; in Section 4, the efficacy of the proposed simulation results is appraised; and finally, Section 5 delineates the conclusion.

2 | MECHANISM OF GENETIC ALGORITHM

Genetic Algorithm (GA) was initially proposed in 1992 by Holland.[20] However, nowadays there are multiple modified versions of GA. This algorithm is considered as one of the most powerful optimization algorithms, which is based on the principles of genetics and natural selection.[21] This algorithm has a much higher speed in searching for the optimal solution in comparison with traditional methods.[22] Compared to other metaheuristic algorithms, the GA is much more robust,[23] requires a few mathematical models,[24] and has a lower chance of trapping in the local optima while searching for the global optimum.

A typical GA consists of a random population of individuals, which are the possible solutions to that problem. Subsequently, these individuals undergo selection, crossover, and mutation processes in a large number of iterations so that the optimal solution is found.[25,26] In this algorithm, for each individual, a fitness value is assigned, and finally, all individuals are sorted based on their fitness values. In the process of optimization, a chromosome is assigned for each individual in the random population. Chromosomes consist of one or more gene(s), which are specific data about the solution in codified form. The genes can be of real or integer type, as per the requirement of the optimization objective. In the first iteration (generation), each individual is generated randomly, whereas in the next iterations, individuals are selected among the ones with better fitness values. The selection process is such that the individuals with better fitness values are given a higher chance to procreate, whereas the candidates with worse fitness values have a lower chance. In this paper, the Boltzmann method is applied for selecting the best individuals among the population. Following the selection process by the Boltzmann method, different types of crossover and mutation are applied to the individuals to search for more possible solutions by creating new individuals. Therefore, in each iteration, three different populations are created after applying selection, crossover, and mutation processes; the first population is pop which represents the original population in the first generation and it is updated by the selection process in the next iterations; the second population is pop_c which includes the children produced by the parents on which crossover is applied; and the third population is pop_m which includes the new individuals formed after the mutation process. After creation of populations pop, pop_c, and pop_m in each iteration (generation), the best N_pop individuals among all populations which have better fitness values are selected as pop for the next generation. Such procedure continues until the stop criterion is met. Finally, the individual which has the best possible fitness value is considered as the solution of the optimization problem.

2.1 | Selection process using Boltzmann and roulette wheel selection methods

As mentioned above, the selection process should be performed such that only individuals with better fitness values have the chance to be parents and create a new generation. To fulfill the purpose, in this paper, the Boltzmann method is deployed which provides a higher chance of selection for the individuals with better fitness values. According to the Boltzmann method, the selection probability of the ith individual, P_i, is calculated as:

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

where P_i has a value between 0 and 1, and sum of the probabilities of all individuals is equal to 1; P_n represents the selection probability of the nth individual; β denotes the pressure constant; Z_i is the fitness value of the ith individual; and Z_worst is the worst fitness value in each iteration.

After the selection probability for each individual is assigned by the Boltzmann method, the individuals are selected by deployment of the roulette wheel selection (RWS) method. The RWS is a stochastic method that randomly selects the individuals according to their assigned probability. To understand the operating principle of this method, an actual roulette wheel can be considered. The circular wheel can be divided into n pies (like a pie chart), where n represents the number of individuals in the population. Since the selection process considers the selection probability of these individuals, the ones with better fitness values occupy larger spaces on the wheel, and therefore, they have higher chances to be selected as parents by the roulette wheel selector. However, in order to preserve the diversity, a chance is also considered for selecting the individuals with worse fitness values. In other words, the majority of the selected individuals are among those who have better fitness values, and only a small number of them are with worse fitness values. Considering random number r in the range between 0 and 1 as the selected value by the selector of roulette wheel, the ith individual is chosen as a parent if the following condition is met:

$$\frac{\sum_{i=1}^{i} P_i}{\sum_{n=1}^{N_{pop}} P_n} < r \le \frac{\sum_{i=1}^{i+1} P_i}{\sum_{n=1}^{N_{pop}} P_n}, \tag{2}$$

where P_i and P_n are selection probabilities of the ith and nth individuals, respectively.

2.2 | Crossover

Crossover is the partial exchange of information between two individuals, similar to the real chromosomes in biology. Depending on the requirement of objective function, crossovers can be of real type or integer type. Real type crossover can be represented as:

$$\begin{aligned} y_{1i} &= \alpha_i x_{1i} + (1-\alpha_i) x_{2i} \\ y_{2i} &= \alpha_i x_{2i} + (1-\alpha_i) x_{1i}, \end{aligned} \tag{3}$$

where x_{1i} and x_{2i} represent the ith gene of first and second parent, respectively; similarly, y_{1i} and y_{2i} represent the ith gene of first and second child, respectively; and α is a random real number between 0 and 1.

Figure 1 illustrates the process of different types of integer crossovers including single-point, double-point, and uniform crossovers. As can be seen from the figure, in the single-point crossover, a crossover point on the parent chromosomes is selected, and then all data beyond that point in the chromosome is swapped between the two parent organisms; in the double-point crossover, two random points are chosen on the parent chromosomes and the genetic material is exchanged between these points; and for the uniform crossover, each gene is selected randomly from one of the corresponding genes of the parent chromosomes. Since each of the above-mentioned crossover types has its own merits, in order to take advantage of all of them, the crossover type can be randomly selected in every crossover process through the RWS method.

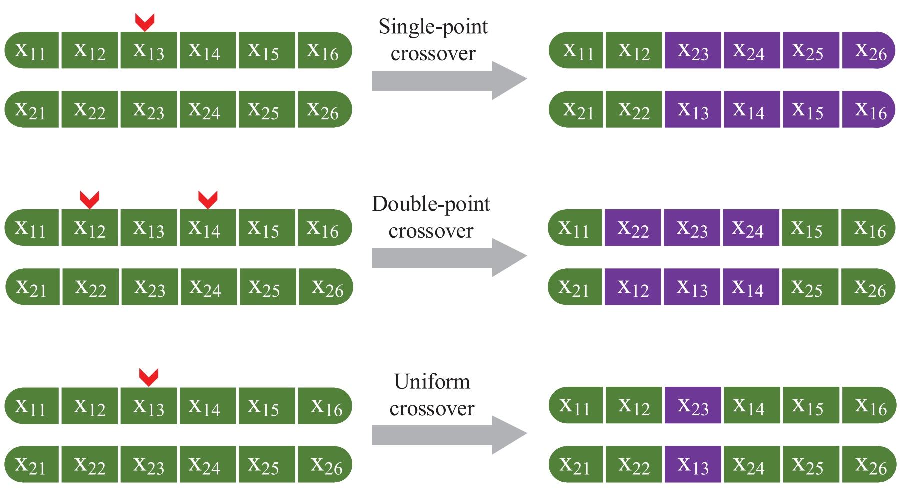

FIGURE 1 Process of different types of integer crossovers

2.3 | Mutation

Mutation is a random change in the gene(s) of a chromosome within a prescribed limit. Mutations increase diversity in a population and provide completely new solutions which may not be produced via crossover process. Therefore, it enhances the exploration feature of the GA and it has been proved essential during convergence. However, a low mutation probability, P_m, is usually applied to the algorithm. Otherwise, the excessive exploration of algorithm prevents the convergence of the algorithm; on the contrary, in case P_m is selected too low, then the exploration feature is significantly limited and the algorithm may be trapped in the local optima.

Figure 2 demonstrates the process of different types of mutation including random resetting, swap mutation, scramble mutation, and inversion mutation. As can be seen in the figure, in the strategy of random resetting, a random permissible value is assigned to the chosen gene; in case of swap mutation, two genes of the chromosome are selected randomly, and their values are interchanged; in scramble mutation, a subset of genes is chosen from the entire chromosome and their values are shuffled randomly; and in the inversion mutation type, a selected subset of the genes is inverted. Similar to the crossover process, different mutation types can be randomly selected in each mutation process through the RWS method.

2.4 | Stop criterion

The GA requires a large number of iterations to find the optimal solution. Therefore, an appropriate stop strategy must be devised such that it neither terminates the algorithm prior to reaching the global optimum point nor continues it after the solution is already found. There are three prevalent strategies for designing the stop criterion of GA which are as follows:

1. Setting a maximum number of iterations such that the algorithm automatically stops once it completes the last iteration. The advantage of this strategy is that the GA terminates after a specific number of iterations in various computers with different execution times. Nonetheless, for various optimization problems, different numbers of iterations should be set in order to ensure that the optimal solution is found.
2. Setting a maximum run time such that the algorithm automatically stops once the execution time reaches it. However, the main disadvantage of this strategy is that if the execution speed is not rapid enough, then the algorithm stops before reaching the optimal point, thereby producing inaccurate results.
3. The third strategy is to stop the algorithm when no better result is found after n iterations or Δt time period. This strategy has the highest reliability among all the stop criterion strategies, as it can ensure finding the global optimal point.

3 | POWER LOSS MINIMIZATION USING GENETIC ALGORITHM

In recent decades, DGs have been extensively utilized around the world as an effective way to reduce the environmental impacts in energy production. Even though DGs provide numerous benefits, their inappropriate

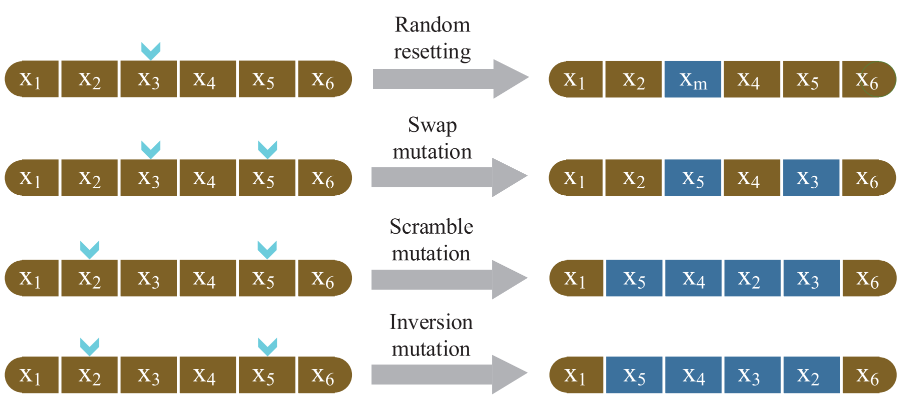

FIGURE 2 Process of different types of mutations

utilization may lead to excessive power losses in the distribution networks. In order to address this issue, this paper proposes a power loss minimization strategy based on GA in which the size and location of DGs are optimally allocated.

The current flowing from bus k to bus n and from bus n to bus k in branch kn of the network can be respectively calculated by:

$$\begin{aligned} \vec{I}_{kn} &= \left(\frac{y}{a^2}+j\frac{b}{2}\right)\vec{V}_k + \left(\frac{-y}{a}\right)\vec{V}_n \\ \vec{I}_{nk} &= \left(\frac{-y}{a}\right)\vec{V}_k + \left(y+j\frac{b}{2}\right)\vec{V}_n, \end{aligned} \tag{4}$$

where y denotes the total series admittance of line or transformer kn; b represents the shunt susceptance of line kn; a is the turns ratio of transformer kn; and, $\vec{V}_k$ and $\vec{V}_n$ are respectively the voltage phasors of busses k and n, which are calculated by the power flow algorithm. The complex power loss in branch kn can be determined as:

$$\vec{S}_{\text{loss},kn} = \vec{S}_{k,kn} + \vec{S}_{n,nk} = \vec{V}_k \vec{I}_{kn}^{\,*} + \vec{V}_n \vec{I}_{nk}^{\,*}, \tag{5}$$

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 busses are respectively computed as:

$$\begin{aligned} P_{\text{loss,tot}} &= \text{Re}\left(\vec{S}_{\text{loss,tot}}\right) = \text{Re}\left(\sum_{k=1}^{N} \sum_{\substack{n=1 \\ n\neq k}}^{N} \vec{V}_k \vec{I}_{kn}^{\,*} + \vec{V}_n \vec{I}_{nk}^{\,*}\right) \\ Q_{\text{loss,tot}} &= \text{Im}\left(\vec{S}_{\text{loss,tot}}\right) = \text{Im}\left(\sum_{k=1}^{N} \sum_{\substack{n=1 \\ n\neq k}}^{N} \vec{V}_k \vec{I}_{kn}^{\,*} + \vec{V}_n \vec{I}_{nk}^{\,*}\right). \end{aligned} \tag{6}$$

In this paper, since the mitigation of both network active and reactive power losses is considered, the optimization problem includes two objectives. However, it can be converted to a single-objective problem through Weighted Sum Method (WSM) so that it can be solved using GA as:

$$Z = \frac{P_{\text{loss,tot}}}{|P_{\text{loss,tot,org}}|} W_P + \frac{Q_{\text{loss,tot}}}{|Q_{\text{loss,tot,org}}|} \underbrace{W_Q}_{(1-W_P)}, \tag{7}$$

where Z is the fitness function; $P_{\text{loss,tot,org}}$ and $Q_{\text{loss,tot,org}}$ are respectively the original total active and reactive power losses of the network before adding new DGs; and W_{P} and W_{Q} respectively denote weights of the active and reactive power losses which sum of them equals 1.

In order to implement the optimization problem using GA, first, the type, number, and range of genes (decision variables) must be determined. For the mitigation of power losses by 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 busses, these genes can only take positive integers and their maximum value is the number of PQ busses in the power system, that is, N_{PQ}. The second m genes denote the decision variables for the capacity of each DG. According to the definition of DGs, these genes can take real numbers between 0 and 150 MW. As a result, the power loss minimization problem can be formulated by GA as follows:

$$\begin{cases} \text{Minimize } Z(x) \\ \text{where} \\ x = [x_{\text{int},1}, x_{\text{int},2}, x_{\text{int},3}, \ldots, x_{\text{int},m}, x_{real,1}, x_{real,2}, x_{real,3}, \ldots, x_{real,m}] \\ \text{subject to:} \\ 1 \le x_{\text{int},i} \le N_{PQ}; i = 1,2,3,\ldots,m \\ 0 \le x_{real,i} \le 150; i = 1,2,3,\ldots,m \end{cases}, \tag{8}$$

where x is the vector of decision variables, and $Z(x)$ is the fitness function. Figure 3 depicts the flowchart of the proposed strategy. As can be seen from the figure, in this strategy, the fitness function is calculated for different weights of active power, W_P. To fulfill this, W_P is set to 1 in the first iteration, and it decreases by 0.05 in each iteration until it reaches zero. After setting W_P, the GA parameters and stop criterion are set, and then population pop including N_{pop} random individuals is created. In the next stage, selection, crossover, and mutation processes are applied so that populations pop_c and pop_m are formed as well. Afterward, the information of each individual's chromosome is sent to the Newton–Raphson power flow program. The power flow program interprets the information of the chromosomes, and then reconfigure the network structure accordingly. Finally, the fitness values for all individuals are computed by the power flow program and sent back to the main algorithm. In the main algorithm, the fitness values are sorted in ascending order, and then the best N_{pop} individuals are taken to the next iteration (generation). This procedure continues until the GA stop criterion is met. Finally, after execution of the last iteration, the best scheme including the location and capacity of DGs and their corresponding active and reactive power losses are determined.

4 | SIMULATION RESULTS

In order to verify the effectiveness of the proposed strategy, several simulations have been performed in MATLAB software on both IEEE 30 and 118 bus systems under different conditions, i.e. random allocation of DGs, optimal allocation of DGs using GA, and optimal allocation of DGs using CS algorithm, as follows:

4.1 | Simulation results obtained from random allocation of DGs

As mentioned earlier, DGs are basically added to the distribution networks to generate additional power and improve the reliability of the grid. However, in case the DGs are not properly allocated, the total power losses emanating from the network may even increase. This can be explained using Figures 4 and 5 in which two DGs (of capacity 0–150 MW) are randomly allocated to two PQ busses of test networks IEEE 30 and 118 bus systems, respectively. According to the figures, it can be seen that improper allocation of DGs significantly affects the total network active and reactive power losses, and it may even lead to the further increment of their values.

4.2 | Simulation results obtained from optimal allocation of DGs using GA

For optimal allocation of DGs using GA, a random population with 100 individuals is considered, and the crossover and mutation percentages are set to 80% and 30%, respectively. For each individual on which mutation is applied, a mutation rate of 5% is considered, implying that only 5% of the genes are changed during the mutation process. Also, the pressure constant of $\beta = 0.8$ is considered, which is used for the Boltzmann method in the selection process.

Figures 6 and 7 indicate the mitigation of total network active and reactive power losses through optimal allocation of two DGs using GA under different values of W_P in IEEE 30 and 118 bus systems, respectively. The corresponding data for each solution in Figures 6 and 7 are respectively listed in Tables 1 and 2. From both tables, it can be seen that the proper allotment of DGs can considerably reduce the active and reactive power losses. To be more precise, for IEEE 30 bus test system with $P_{\text{loss,tot,org}} = 8.0714$ MW and $Q_{\text{loss,tot,org}} = 5.8099$ MVAR, among 21 optimization results obtained

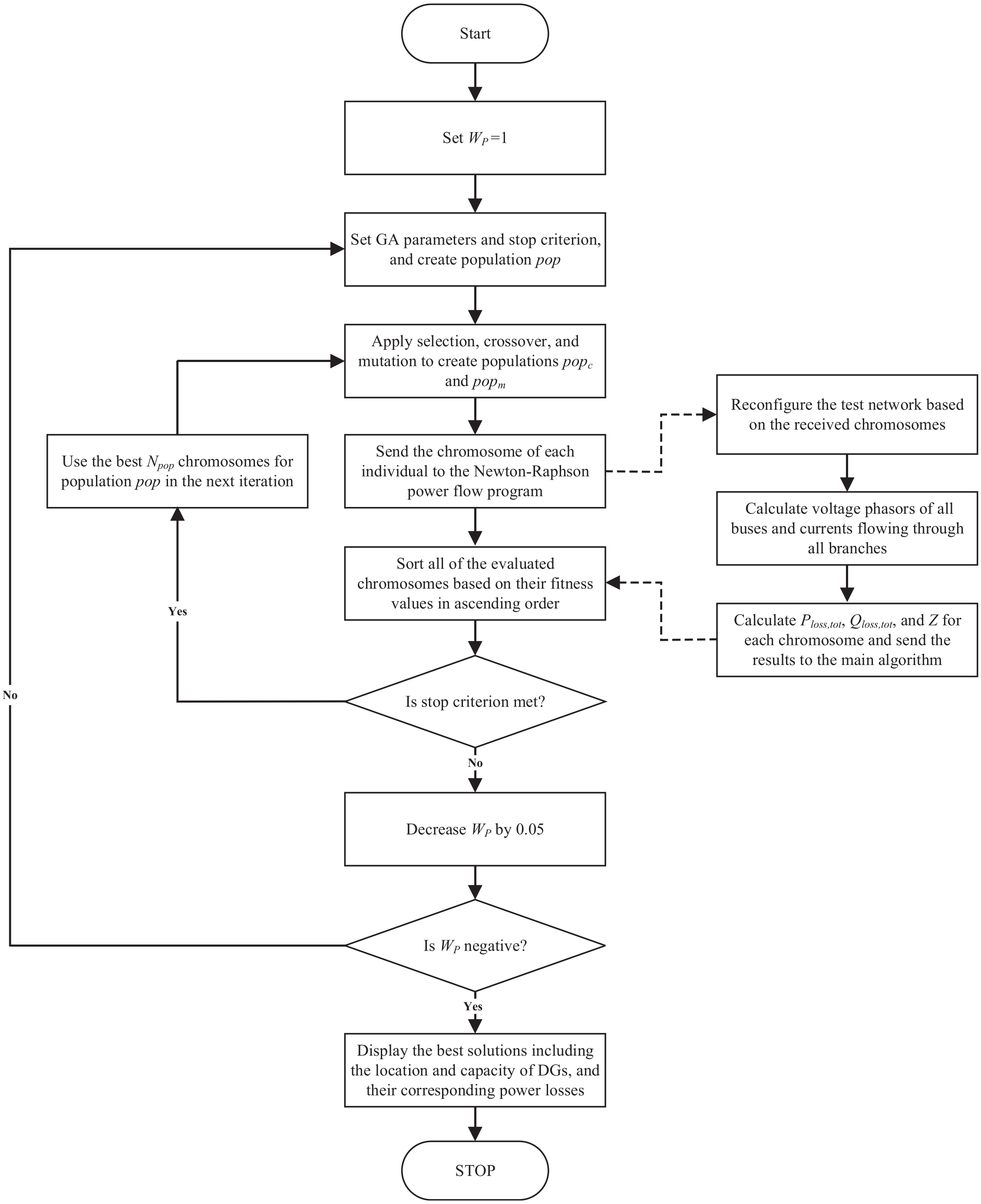

FIGURE 3 Flowchart of the proposed strategy

under different values of W_P, the minimum and maximum total network active power losses are 3.5068 and 3.9178 MW, and the total network reactive power losses range from −16.4091 MVAR to −11.8936 MVAR. In terms of the location of DGs, the obtained optimal solutions can be classified into four clusters, i.e. (bus 7, bus 9), (bus 7, bus 21), (bus 7, bus 22) and (bus 7, bus 24). Similarly, for IEEE 118 bus system with $P_{\text{loss,tot,org}} = 133.5305$ MW and $Q_{\text{loss,tot,org}} = -570.2474$ MVAR, the minimum and maximum total network active power losses are 111.7246 MW and 114.9223 MW, and the total network reactive power losses range from −691.1399 MVAR to −687.7827 MVAR. In addition, the optimal locations for installation of DGs are clusters (bus 41, bus 53) and (bus 41, bus 37). The results shown in Tables 1 and 2 also indicate that the average values of bus voltage magnitude in IEEE 30 and 118 bus networks are significantly improved from their original values, that is, 1.0012 and 0.9879 p.u., respectively.

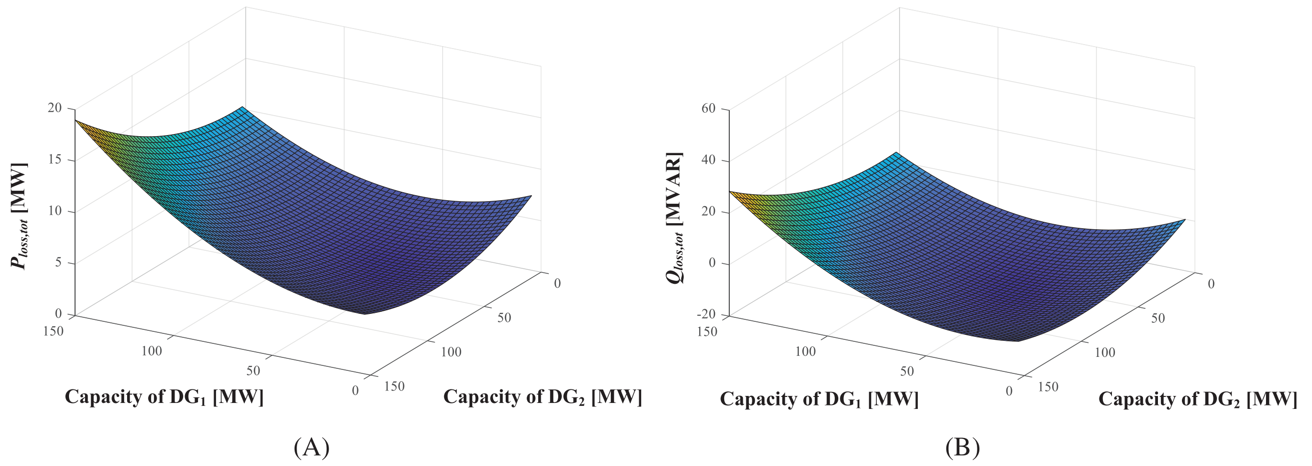

FIGURE 4 Impact of random allocation of two distributed generators (of capacity 0–150 MW) to two PQ busses of IEEE 30 bus system on: (A) total network active power losses, and (B) total network reactive power losses

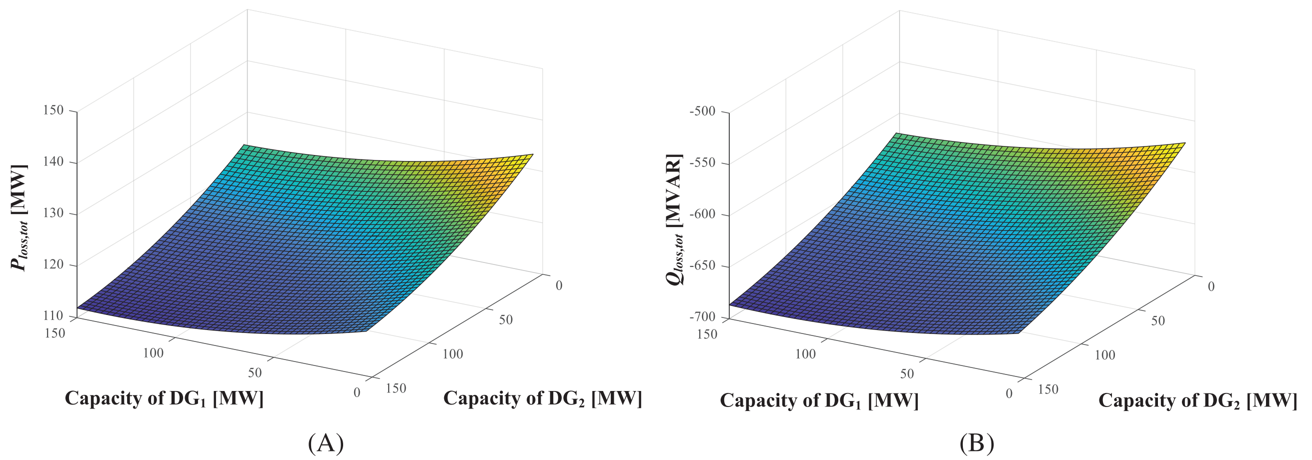

FIGURE 5 Impact of random allocation of two distributed generators (of capacity 0–150 MW) to two PQ busses of IEEE 118 bus system on: (A) total network active power losses, and (B) total network reactive power losses

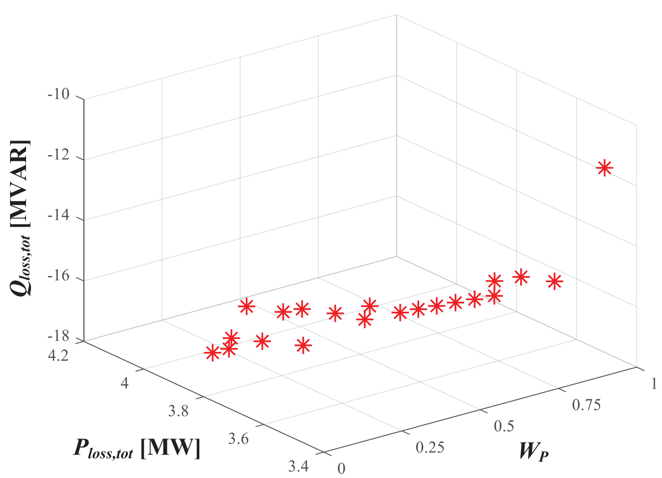

FIGURE 6 Mitigation of total network active and reactive power losses through optimal allocation of two distributed generators using genetic algorithm under different values of W_P in IEEE 30 bus system

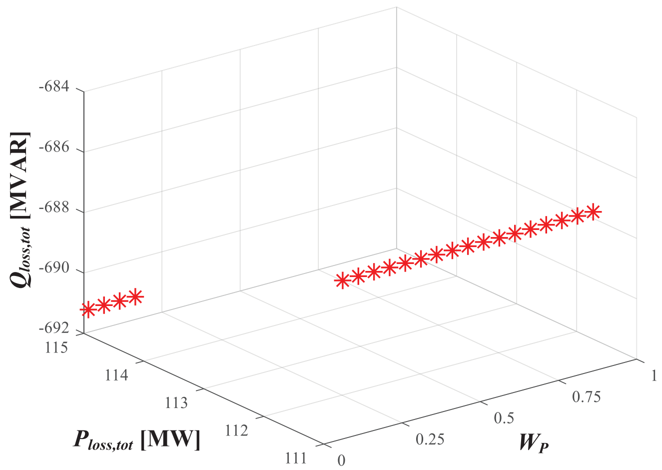

FIGURE 7 Mitigation of total network active and reactive power losses through optimal allocation of two distributed generators using genetic algorithm under different values of W_P in IEEE 118 bus system

TABLE 1 Corresponding data for each solution in Figure 6

				DG_1		DG_2		
Wp	P_{loss} (MW)	Q_{loss} (Mvar)	*Z* (p.u.)	Location	Capacity (MW)	Location	Capacity (MW)	V_{avg} (p.u.)
1.00	3.5068	−11.8936	0.43447	Bus 7	59.6215	Bus 9	44.7747	1.0075
0.95	3.6214	−16.0346	0.28825	Bus 7	66.6777	Bus 21	34.8167	1.0110
0.90	3.6810	−16.0202	0.13472	Bus 7	63.5745	Bus 22	37.2663	1.0106
0.85	3.7171	−16.1821	−0.02633	Bus 7	65.2611	Bus 21	40.4557	1.0104
0.80	3.6658	−16.2961	−0.19762	Bus 7	66.6093	Bus 21	40.2296	1.0107
0.75	3.6793	−16.3315	−0.36085	Bus 7	65.6193	Bus 21	41.5950	1.0107
0.70	3.6910	−16.3538	−0.52432	Bus 7	65.5323	Bus 21	42.4662	1.0106
0.65	3.7013	−16.3694	−0.68803	Bus 7	65.4697	Bus 21	43.1838	1.0106
0.60	3.7105	−16.3805	−0.85191	Bus 7	65.4241	Bus 21	43.7845	1.0105
0.55	3.7188	−16.3885	−1.0159	Bus 7	65.2059	Bus 21	44.3512	1.0105
0.50	3.7681	−16.2612	−1.166	Bus 7	66.2066	Bus 22	43.4826	1.0102
0.45	3.7327	−16.3987	−1.3443	Bus 7	65.3457	Bus 21	45.1161	1.0105
0.40	3.7789	−16.2692	−1.4928	Bus 7	66.2297	Bus 22	44.0636	1.0101
0.35	3.8371	−16.2515	−1.6518	Bus 7	70.8063	Bus 24	36.8662	1.0127
0.30	3.8480	−16.2553	−1.8154	Bus 7	70.7374	Bus 24	37.2264	1.0126
0.25	3.9178	−16.2526	−1.9767	Bus 7	67.5923	Bus 24	39.7111	1.0123
0.20	3.6770	−16.2984	−2.1531	Bus 7	69.3697	Bus 21	40.0245	1.0108
0.15	3.7613	−16.4086	−2.3307	Bus 7	65.2958	Bus 21	46.6546	1.0104
0.10	3.8121	−16.3958	−2.4925	Bus 7	63.3349	Bus 21	49.5678	1.0102
0.05	3.7681	−16.4091	−2.6597	Bus 7	65.2910	Bus 21	46.9916	1.0104
0.00	3.7704	−16.4091	−2.8243	Bus 7	65.0571	Bus 21	47.1773	1.0103

4.3 | simulation results obtained from optimal allocation of DGs using CS algorithm

In this paper, in order to validate the accuracy of obtained results from GA, another nature-inspired optimization algorithm, cuckoo search (CS), is deployed which has attracted much attention in recent years due to its excellent performance in dealing with large, complex and dynamic real-world optimization problems. CS algorithm is a meta-heuristic optimization algorithm which is inspired by the obligate brood parasitism of some cuckoo species by laying their eggs in the nests of host birds of other species. Some host birds can engage direct conflict with the intruding cuckoos. To be more precise, in case the host bird discovers the eggs are not their own, it will either throw these alien eggs away or simply abandon its nest and build a new nest elsewhere. CS algorithm is based on the following

TABLE 2 Corresponding data for each solution in Figure 7

				DG$_1$		DG$_2$		
W_P	P_{loss} (MW)	Q_{loss} (Mvar)	Z (p.u.)	Location	Capacity (MW)	Location	Capacity (MW)	V_{avg} (p.u.)
1.00	111.7250	−687.7860	0.8367	Bus 41	149.9490	Bus 53	130.6560	0.9892
0.95	111.7256	−687.7827	0.7346	Bus 41	149.9109	Bus 53	130.4405	0.9892
0.90	111.7251	−687.7906	0.6324	Bus 41	149.9466	Bus 53	130.2235	0.9892
0.85	111.7249	−687.7925	0.5303	Bus 41	149.9555	Bus 53	130.0626	0.9892
0.80	111.7251	−687.7951	0.4281	Bus 41	149.9539	Bus 53	129.9326	0.9892
0.75	111.7248	−687.8008	0.3260	Bus 41	149.9733	Bus 53	129.7356	0.9892
0.70	111.7246	−687.8046	0.2239	Bus 41	149.9890	Bus 53	129.6578	0.9892
0.65	111.7255	−687.8008	0.1217	Bus 41	149.9552	Bus 53	129.3181	0.9892
0.60	111.7259	−687.8000	0.0196	Bus 41	149.9447	Bus 53	129.1602	0.9892
0.55	111.7248	−687.7978	−0.0826	Bus 41	149.9677	Bus 53	128.9360	0.9892
0.50	111.7268	−687.7978	−0.1847	Bus 41	149.9226	Bus 53	128.8324	0.9892
0.45	111.7268	−687.8002	−0.2868	Bus 41	149.9305	Bus 53	128.6868	0.9892
0.40	111.7274	−687.7994	−0.3890	Bus 41	149.9199	Bus 53	128.4404	0.9892
0.35	111.7275	−687.8029	−0.4911	Bus 41	149.9327	Bus 53	128.2250	0.9892
0.30	111.7274	−687.8057	−0.5933	Bus 41	149.9450	Bus 53	128.1531	0.9892
0.25	111.7272	−687.8100	−0.6954	Bus 41	149.9650	Bus 53	128.0574	0.9892
0.20	111.7276	−687.8114	−0.7975	Bus 41	149.9683	Bus 53	127.8376	0.9892
0.15	114.9221	−691.1371	−0.9011	Bus 41	149.9057	Bus 37	149.9853	0.9888
0.10	114.9222	−691.1379	−1.0047	Bus 41	149.9477	Bus 37	149.9630	0.9888
0.05	114.9223	−691.1341	−1.1083	Bus 41	149.9123	Bus 37	149.9387	0.9888
0.00	114.9221	−691.1399	−1.2120	Bus 41	149.9625	Bus 37	149.9789	0.9888

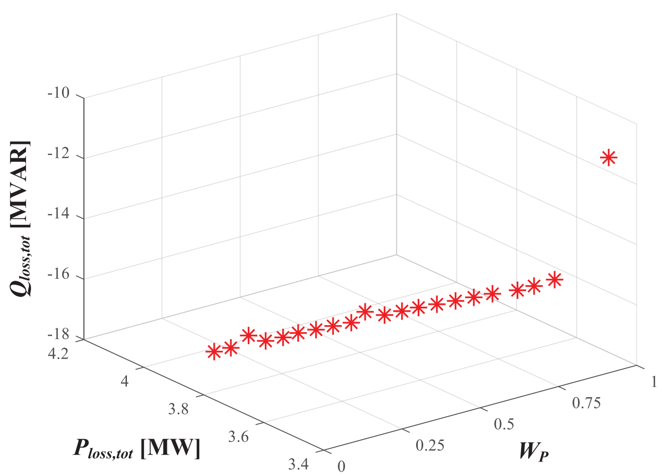

FIGURE 8 Mitigation of total network active and reactive power losses through optimal allocation of two distributed generators using cuckoo search algorithm under different values of W_P in IEEE 30 bus system

idealized rules, i.e. (a) Each cuckoo lays only one egg at a time and places it in a randomly selected nest (b) Best nest with high quality of eggs will carry over to the next generation, and (c) The number of available host nests is fixed; host bird discovers cuckoo eggs with probability of $P_a \in [0,1]$. In this case, the host bird either throws the egg away or leaves its nest and builds a new one.

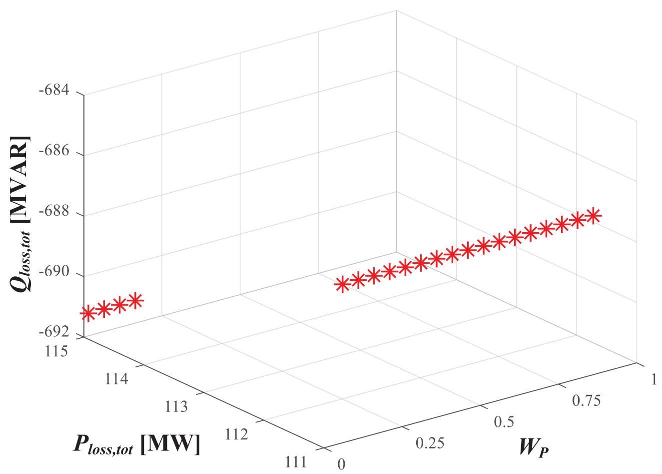

FIGURE 9 Mitigation of total network active and reactive power losses through optimal allocation of two distributed generators using cuckoo search algorithm under different values of W_P in IEEE 118 bus system

TABLE 3 Corresponding data for each solution in Figure 8

				DG$_1$		DG$_2$		
W_P	P_{loss} (MW)	Q_{loss} (Mvar)	Z (p.u.)	Location	Capacity (MW)	Location	Capacity (MW)	V_{avg} (p.u.)
1.00	3.4932	−11.5381	0.4328	Bus 7	55.1837	Bus 9	52.5816	1.0075
0.95	3.6213	−16.0325	0.2882	Bus 7	66.8490	Bus 21	34.7408	1.0111
0.90	3.6376	−16.1784	0.1271	Bus 7	66.2703	Bus 21	37.4863	1.0109
0.85	3.6407	−16.1928	−0.0347	Bus 7	65.0170	Bus 21	38.1346	1.0108
0.80	3.6720	−16.3126	−0.1976	Bus 7	66.6071	Bus 21	40.7341	1.0107
0.75	3.6820	−16.3352	−0.3608	Bus 7	65.6159	Bus 21	41.5000	1.0107
0.70	3.6908	−16.3536	−0.5244	Bus 7	65.5392	Bus 21	42.4537	1.0106
0.65	3.7008	−16.3687	−0.6881	Bus 7	65.4694	Bus 21	43.1516	1.0106
0.60	3.7099	−16.3798	−0.8519	Bus 7	65.4219	Bus 21	43.7483	1.0105
0.55	3.7129	−16.3713	−1.0157	Bus 7	65.2030	Bus 21	44.3588	1.0105
0.50	3.7188	−16.3882	−1.1800	Bus 7	64.8663	Bus 21	44.4428	1.0105
0.45	3.7314	−16.3979	−1.3443	Bus 7	65.3445	Bus 21	45.0451	1.0105
0.40	3.7254	−16.3912	−1.5081	Bus 7	64.0127	Bus 21	45.0436	1.0105
0.35	3.7340	−16.3992	−1.6728	Bus 7	64.9138	Bus 21	45.3144	1.0104
0.30	3.7386	−16.4016	−1.8372	Bus 7	64.8985	Bus 21	45.5731	1.0104
0.25	3.7460	−16.4047	−2.0017	Bus 7	64.9318	Bus 21	45.9617	1.0104
0.20	3.7443	−16.4031	−2.1659	Bus 7	64.3624	Bus 21	46.0245	1.0104
0.15	3.7502	−16.4049	−2.3304	Bus 7	64.2946	Bus 21	46.3546	1.0103
0.10	3.7549	−16.4063	−2.4949	Bus 7	64.3349	Bus 21	46.5899	1.0102
0.05	3.7618	−16.4072	−2.6595	Bus 7	64.2345	Bus 21	46.9736	1.0102
0.00	3.7652	−16.4073	−2.8240	Bus 7	64.0979	Bus 21	47.1764	1.0102

In this algorithm, for each iteration, t, a cuckoo egg, i, is randomly selected using Lévy flights and new solutions, x_i^{t+1}, are generated. The Lévy flights are a kind of random walk in which the steps are defined in terms of the step lengths, which have a certain probability distribution, with isotropic and random step directions. The general equation for the Lévy flight is expressed as:

$$x_i^{t+1} = x_i^t + \alpha \oplus \mathrm{Levy}(\lambda), \tag{9}$$

where α represents the step size, and symbol $\oplus$ denotes the entry-wise multiplication. The transition probability of the Lévy flights in this equation is modulated by the Lévy distribution as:

$$\mathrm{Levy}(\lambda) = t^{-\lambda}, \qquad (1 < \lambda \leq 3). \tag{10}$$

From the computational point of view, the generation of random numbers using Lévy flights is comprised of two main steps, that is, the choice of a random direction and the generation of step which obeys the chosen Lévy distribution. In this paper, Mantegna's algorithm for symmetric distributions is deployed. This approach calculates the factor:

$$\hat{\phi} = \left(\frac{\Gamma(1+\hat{\beta}) \sin \frac{\pi \hat{\beta}}{2}}{\hat{\beta} \Gamma\left(\frac{1+\hat{\beta}}{2}\right) 2^{\frac{\hat{\beta}-1}{2}}} \right)^{\frac{1}{\hat{\beta}}}, \tag{11}$$

where Γ denotes the Gamma function. In addition, the value of 1.5 is considered for factor $\hat{\beta}$. This factor is used in Mantegna's algorithm for calculation of step length ζ as:

TABLE 4 Corresponding data for each solution in Figure 9

				DG$_1$		DG$_2$		
W_P	P_{loss} (MW)	Q_{loss} (Mvar)	Z (p.u.)	Location	Capacity (MW)	Location	Capacity (MW)	V_{avg} (p.u.)
1.00	111.7240	−687.7960	0.8367	Bus 41	150.0000	Bus 53	130.6571	0.9892
0.95	111.7240	−687.7986	0.7346	Bus 41	150.0000	Bus 53	130.4399	0.9892
0.90	111.7240	−687.8012	0.6324	Bus 41	150.0000	Bus 53	130.2154	0.9892
0.85	111.7241	−687.8033	0.5303	Bus 41	150.0000	Bus 53	130.0212	0.9892
0.80	111.7242	−687.8053	0.4281	Bus 41	150.0000	Bus 53	129.8120	0.9892
0.75	111.7244	−687.8074	0.3260	Bus 41	150.0000	Bus 53	129.5846	0.9892
0.70	111.7246	−687.8093	0.2238	Bus 41	150.0000	Bus 53	129.3687	0.9892
0.65	111.7248	−687.8110	0.1217	Bus 41	150.0000	Bus 53	129.1521	0.9892
0.60	111.7250	−687.8125	0.0196	Bus 41	150.0000	Bus 53	128.9365	0.9892
0.55	111.7253	−687.8138	−0.0826	Bus 41	150.0000	Bus 53	128.7241	0.9892
0.50	111.7257	−687.8150	−0.1847	Bus 41	150.0000	Bus 53	128.5046	0.9892
0.45	111.7260	−687.8160	−0.2869	Bus 41	150.0000	Bus 53	128.2887	0.9892
0.40	111.7264	−687.8169	−0.3890	Bus 41	150.0000	Bus 53	128.0725	0.9892
0.35	111.7269	−687.8176	−0.4912	Bus 41	150.0000	Bus 53	127.8566	0.9892
0.30	111.7274	−687.8182	−0.5933	Bus 41	150.0000	Bus 53	127.6469	0.9892
0.25	111.7278	−687.8185	−0.6955	Bus 41	150.0000	Bus 53	127.4246	0.9892
0.20	111.7284	−687.8188	−0.7976	Bus 41	150.0000	Bus 53	127.2105	0.9892
0.15	114.9219	−691.1435	−0.9011	Bus 41	150.0000	Bus 37	150.0000	0.9888
0.10	114.9219	−691.1435	−1.0047	Bus 41	150.0000	Bus 37	150.0000	0.9888
0.05	114.9219	−691.1435	−1.1084	Bus 41	150.0000	Bus 37	150.0000	0.9888
0.00	114.9219	−691.1435	−1.2120	Bus 41	150.0000	Bus 37	150.0000	0.9888

$$\zeta = \frac{u}{|v|^{\frac{1}{\beta}}}, \tag{12}$$

where u and v are normal distributions of zero mean and variances σ_u^2 and σ_v^2, respectively. Here, σ_u obeys the Lévy distribution given by (11), and $\sigma_v = 1$. Subsequently, the step size, η, is determined as:

$$\eta = 0.01\zeta(x_i - x_{\text{best}}). \tag{13}$$

In this paper, in order to simulate the proposed strategy using CS algorithm, parameters η and P_a are set to 100 and 0.25, respectively. Figures 8 and 9 indicate the mitigation of total network active and reactive power losses through optimal allocation of two DGs using CS algorithm under different values of W_{P} in IEEE 30 and 118 bus systems, respectively. The corresponding data for each solution in Figures 8 and 9 are respectively listed in Tables 3 and 4. From Table 3, it can be seen that the minimum and maximum total network active power losses after optimal allotment of DGs in IEEE 30 bus system using CS algorithm are 3.4932 and 3.7652 MW; also, the total reactive power losses range from −16.4073 to −11.5381 MVAR. This table also depicts that the optimal places for allocation of DGs are clusters (bus 7, bus 9) and (bus 7, bus 21). Likewise, for IEEE 118 bus system, Table 4 shows that the minimum and maximum total network active power losses are 111.7240 and 114.9219 MW; and the total network reactive power losses range from −691.1435 to −687.7690 MVAR. In addition, the optimal locations for installation of DGs are clusters (bus 41, bus 53) and (bus 41, bus 37). Moreover, the obtained results in both Tables 3 and 4 illustrate that the average values of bus voltage magnitude in both test networks are remarkably enhanced.

5 | CONCLUSION

Escalation in power demand and ecological hazards has motivated research studies to seek disparate power loss mitigation techniques. Deployment of DGs is among these approaches which can significantly lead to the reduction in total network active and reactive power losses. However, improper allotment of DGs may lead to excessive power losses in the distribution networks. In this paper, a power loss reduction strategy based on the optimal allocation of DGs is devised, in which the location and size of DGs are determined by deploying the genetic algorithm. In addition, to verify the accuracy of the obtained results using GA, another optimization algorithm, i.e. CS algorithm, is applied. Lastly, to validate the adequacy of the developed strategy, several simulations were undertaken on IEEE 30 and 118 bus systems. The obtained results indicate that the proposed approach can be effective in mitigation of total network power losses, as well as enhancement of the network bus voltage magnitudes.

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DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

REFERENCES

1. Fathabad AM, Cheng J, Pan K, Qiu F. Data-driven planning for renewable distributed generation integration. *IEEE Trans Power Syst*. 2020;35(6):4357-4368.
2. Gupta Y, Doolla S, Chatterjee K, Pal BC. Optimal DG allocation and Vol–Var dispatch for a droop-based microgrid. *IEEE Trans Smart Grid*. 2021;12(1):169-181.
3. Pamshetti VB, Singh S, Thakur AK, Singh SP. Multistage coordination volt/VAR control with CVR in active distribution network in presence of inverter-based DG units and soft open points. *IEEE Trans Ind Appl*. 2021;57(3):2035-2047.
4. Yazdavar AH, Shaaban MF, El-Saadany EF, Salama MMA, Zeineldin HH. Optimal planning of distributed generators and shunt capacitors in isolated microgrids with nonlinear loads. *IEEE Trans Sustainable Energy*. 2020;11(4):2732-2744.
5. Kalakova A, Nunna HK, Jamwal PK, Doolla S. A novel genetic algorithm based dynamic economic dispatch with short-term load forecasting. *IEEE Trans Ind Appl*. 2021;57(3):2972-2982.
6. Murthy VVSN, Kumar A. Comparison of optimal DG allocation methods in radial distribution systems based on sensitivity approaches. *Int J Electr Power Energy Syst*. 2013;53(1):450-467.

7. Chiradeja P, Ramakumar R. An approach to quantify the technical benefits of distributed generation. *IEEE Trans Energy Conv*. 2004; 19(4):764-773.
8. Rukmani DK, Thangaraj Y, Subramaniam U, Ramachandran S, Elavarasan R, Das N. A new approach to optimal location and sizing of DSTATCOM in radial distribution networks using bio-inspired cuckoo search algorithm. *Energies*. 2020;13(4615):1-20.
9. L. Y. Wang, B. H. Zhang, J. F. Ren, D. Zhou, F. Yao, W. Zhang, H. Xie, G. Yu, A solution to lower tap changing or capacitors regulator times in reactive power control in distribution systems. Proceedings of the 2005 IEEE/PES Transmission and Distribution Conference and Exposition: Asia and Pacific, Dalian, China, 2005, pp. 1–5.
10. A. Alam, M. Zaid, A. Gupta, P. Bindal, A. Siddiqui, Power loss reduction in a radial distribution network using distributed generation. Proceedings of the International Conference on Computing, Power and Communication Technologies (GUCON), Greater Noida, India, 2018, pp. 1142–1145.
11. Zhong L, Guan L, Zhang J, Gong Y, Chung CY. Distributed reactive power regulation considering load voltage and power loss. *IEEE Access*. 2020;8(1):24334-24343.
12. Rezania E, Shahidehpour SM. Real power loss minimization using interior point method. *Int J Electr Power Energy Syst*. 2001;23(1): 45-56.
13. Deeb N, Shahidehpour SM. Linear reactive power optimization in a large power network using the decomposition approach. *IEEE Trans Power Syst*. 1990;5(2):428-438.
14. Lee KY, Yang FF. Optimal reactive power planning using evolutionary algorithms: a comparative study for evolutionary programming, evolutionary strategy, genetic algorithm, and linear programming. *IEEE Trans Power Syst*. 1998;13(1):101-108.
15. X. Guiguang, W. Xing, Y. Erkeng, A fuzzy multi-objective approach to optimal voltage/reactive power control, in: POWERCON′98. Procedings of the International Conference on Power System Technology (Cat. No. 98EX151), Beijing, China, 1998, pp. 1443–1447.
16. H. Liu, G. Huang, C. Wang, H. Liu, Z. Wang, Z. Xu, L. Shi, Reactive power optimization of power grid with photovoltaic generation based on improved particle swarm optimization, Proceedings of the IEEE Innovative Smart Grid Technologies-Asia (ISGT Asia), Chengdu, China, 2019, pp. 1536–1540.
17. Deng Y, Ren X, Zhao C, Zhao D. A heuristic and algorithmic combined approach for reactive power optimization with time-varying load demand in distribution systems. *IEEE Trans Power Syst*. 2002;17(4):1068-1072.
18. Y. Y. Hong, S. Y. Ho, Genetic algorithm based network reconfiguration for loss minimization in distribution systems, Proceedings of the IEEE Power Engineering Society General Meeting (IEEE Cat. No. 03CH37491), Toronto, Canada, 2003, pp. 486–490.
19. P. P. Barker, R. W. De Mello, Determining the impact of distributed generation on power systems. I. Radial distribution systems. Proceedings of the Power Engineering Society Summer Meeting (Cat. No. 00CH37134), Seattle, WA, USA, 2000, pp. 1645–1656.
20. Holland JH. Genetic algorithms. *Sci Am*. 1992;267(1):66-73.
21. Sun M, Wang Y, Xu S, Yang H, Zhang K. Indoor geomagnetic positioning using the enhanced genetic algorithm-based extreme learning machine. *IEEE Trans Instrum Meas*. 2021;70(1):1-11.
22. Jinlei S, Wei L, Chuanyu T, Tianru W, Tao J, Yong T. A novel active equalization method for series-connected battery packs based on clustering analysis with genetic algorithm. *IEEE Trans Power Electron*. 2021;36(7):7853-7865.
23. Tavares YA, Lee M. A foreground calibration for M-channel time-interleaved analog-to-digital converters based on genetic algorithm. *IEEE Trans Circuits Syst I: Regul Pap*. 2021;68(4):1444-1457.
24. Ananda S, Lakshminarasamma N, Radhakrishna V, Srinivasan MS, Satyanarayana P, Sankaran M. Genetic algorithm driven generic estimation model of lithium-ion battery for energy balance calculation in spacecraft. *IEEE Trans Ind Appl*. 2021;57(3):2726-2736.
25. Ponciroli R, Stauff NE, Ramsey J, Ganda F, Vilim RB. An improved genetic algorithm approach to the unit commitment/economic dispatch problem. *IEEE Trans Power Syst*. 2020;35(5):4005-4013.
26. Song J, Wang Z, Niu Y, Dong H. Genetic-algorithm-assisted sliding-mode control for networked state-saturated systems over hidden Markov fading channels. *IEEE Trans Cybern*. 2021;51(7):3664-3675.

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