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Distribution Network Performance Enhancement Using Reconfiguration Technique based on Gravitational Search Algorithm

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Abstract

Objectives: The main goals of this work are to minimize network power loss and enhance the system's voltage profile (VF).

Methods: This work presents a novel methodology that simultaneously optimizes Distribution Network Reconfiguration (DNR), Distributed Generation (DG) sizing, and DG placement using the Gravitational Search Algorithm (GSA) optimization technique. The DNR approach helps reduce power loss, but its effectiveness is limited when applied alone. Similarly, optimizing DG sizing and placement can further minimize power loss, but improper integration with DNR may lead to increased power loss and voltage fluctuations. Hence, it is essential to develop an efficient optimization strategy that simultaneously determines the optimal DG size and location while achieving optimal DNR.

Results: For the IEEE 33-bus network, active and reactive power losses were reduced by 67.488% and 64.88%, respectively. Similarly, for the IEEE 69-bus network, the reductions in active and reactive power losses were 82.55% and 62.25%, respectively.

Conclusions: The findings show that adjusting the size and location of distributed generation units (DGs) while configuring the network significantly improves the voltage profile and reduces losses.

Keywords: Gravitational Search Algorithm, Optimization Technique, Voltage Profile, Network Reconfiguration, Power Loss.

تحسين أداء شبكة التوزيع الكهربائية باستخدام تقنية إعادة التشكيل بالاعتماد على خوارزمية الجاذبية

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الملخص

الأهداف: أهداف هذا العمل الرئيسية هي تقليل خسارة الطاقة في الشبكة وتعزيز منحى الجهد الكهربائي.

المنهجية: يوفر هذا العمل منهجية جديدة تحقق إعادة تشكيل مثلى لشبكة التوزيع (DNR) والتحديد الامثل لحجم وموقع مولدات التوزيع باستخدام تقنية خوارزمية بحث الجاذبية .(GSA) تُستخدم تقنية إعادة تشكيل شبكة التوزيع (DNR) لتقليل فقد الطاقة. ومع ذلك، فإن تطبيق هذه الطريقة وحدها سيقلل من فقد الطاقة إلى قيمة محددة. التقنية الأخرى المستخدمة لتقليل فقد الطاقة هي تحديد حجم وموقع مولدات التوزيع. ومع ذلك، فإن استخدام تقنية إعادة تشكيل المشتركة مع تحديد حجم وموقع مولدات التوزيع بطريقة غير مثلى قد يؤدي إلى زيادة فقد الطاقة وتباين الجهد. لذلك، فمن المهم تطوير منهجية تحسين فعالة تحدد حجم وموقع مولدات التوزيع المثلى وتضمن إعادة تشكيل مثلى للشبكة في نفس الوقت.

النتائج: تم تقليل خسارة الطاقة الفعالة وغير الفعالة بنسبة 67.488% و64.88% على التوالي لشبكة-IEEE 33 bus. بينما تم تقليل فقد الطاقة الفعالة وغير الفعالة بنسبة 82.55% و62.25% على التوالي لشبكة .IEEE 69-bus

الخلاصة: أثبتت النتائج أن دمج عملية التحديد المثلى لحجم وموقع مولدات التوزيع مع عملية إعادة التشكيل المثلى للشبكة بشكل متزامن يؤدي إلى تحسين ملحوظ في منحنى الجهد الكهربائي والحد الأدنى للخسائر.

الكلمات الدالة: خوارزمية بحث الجاذبية، تقنية التحسين، منحنى الجهد، إعادة تشكيل شبكة التوزيع، فقدان الطاقة.

Introduction

In today's distribution networks (DN), power loss is a significant concern due to the growing demand for electricity. According to the companies of electrical distribution, it may cause increased operating costs and decrease the voltage profile of the network (Yan, Shamim, Chou, Desideri, & Li, 2017). Therefore, different methods are studied by researchers to solve the electrical distribution network problems (Ola Badran, Mekhilef, Mokhlis, & Dahalan, 2017).

Power loss in distribution networks (DN) is a critical challenge in power systems. Network reconfiguration is one of the most effective methods for reducing power loss and improving reliability indices (Nguyen & Truong, 2015). This technique involves altering the status of switches to relieve network overload and minimize power loss. In (Abdelaziz, 2017), The authors introduced a novel approach to solving the Reconfiguration problem utilizing GA. This algorithm effectively handles the non-linear constraints and complex combinations associated with the reconfiguration proces. A discrete form of PSO was used in (Sivanagaraju, Rao, & Raju, 2008) for load balancing during DNR. Similar to this, GA was used in (Eldurssi & O'Connell, 2014) to solve the DNR issue with the goals of lowering power losses, raising the load index, and raising the VF. Network reconfiguration (NR) was used in (Kashem, Ganapathy, & Jasmon, 2000) to improve the VF of the radial network and maximize loadability, both of which boosted network reliability. Additionally, NR was utilized in a two-stage algorithm in (Tyagi, Verma, & Bijwe, 2018) to lower reactive power loss (REC) and enhance loadability. In (Pegado, Ñaupari, Molina, & Castillo, 2019), The authors introduced an alternative methodology to solve the DNR problem using Binary Particle Swarm Optimization (BPSO). They proposed a novel sigmoid function to enhance result convergence and regulate the rate of change in particles. The obtained results demonstrated high efficiency and reliability in identifying the optimal solution.

Voltage profile is also an important issue in the distribution system. Therefore, DG units are incorporated into the network system (Avchat & Mhetre, 2020). Thus, it is used to limit the major central power plants at peak loads and improve the system's reliability and stability (Karunarathne, Pasupuleti, Ekanayake, & Almeida, 2021). In (Moradi & Abedini, 2012), GA and PSO algorithms were proposed to find the best DG sizing (DGS) and DG location (DGL). In (O Badran & Jallad, 2014), storage batteries were integrated to the network with renewable DGs to enhance the VF. In (Mohandas, Balamurugan, & Lakshminarasimman, 2015), the authors presented a new approach to modify the voltage stability of the network. In (Ola Badran, 2023), the author used the FA algorithm to reduce power loss and improve the system voltage. Additionally, by building renewable energy DGs, (Yang et al., 2021) managed pollution emissions, power outages, DG costs, and VF in addition to addressing the issues of DG energy consumption and environmental pollution.. An algorithm combining PSO and GA was introduced in (Ha, Nazari-Heris, Mohammadi-Ivatloo, & Seyedi, 2020) to minimize active (ACT) and reactive (REC) power losses while improving voltage management. Moreover, to measure ACT and REC power loss, increase voltage stability, and boost power system security and dependability, a differential evolution method and voltage stability index were created in (Karuppiah, 2021).

Thus, DNR, DGS, and DGL techniques were combined to improve the system performance. In (Rao, Ravindra, Satish, & Narasimham, 2012), the authors solve the DGS, DGL, and DNR simultaneously to reduce power loss and enhance VF. The Harmony Search Algorithm (HSA) was used to solve the proposed problem. The obtained results were effective. Moreover, in (Imran, Kowsalya, & Kothari, 2014) a new methodology utilizing the FWA was introduced to solve the DNR and DG location problem, aiming to enhance system stability and reduce power loss. The simulated results validated the effectiveness of the proposed technique. Furthermore, (Ola Badran, Mokhlis, Mekhilef, & Dahalan, 2018), the authors minimize network power loss, reduce DG output, and improve the voltage profile (VF) index. Various metaheuristic algorithms were utilized, and the results successfully validated the effectiveness of the proposed approach.. While in (Ola Badran & Jallad, 2023a), the authors integrated a shunt capacitor to the network to reduce losses in both ACT and REC power, as well as to improve the VF by applying a multi-objective decision-making technique.

Unlike previous studies, the main contribution of this paper is the simultaneous optimization of Distribution Network Reconfiguration (DNR), Distributed Generation Sizing (DGS), and Distributed Generation Location (DGL) using the Gravitational Search Algorithm (GSA).

2. Objective Fitness and constraints

The proposed methodology aims to achieve optimal reconfiguration while simultaneously determining the best DG sizing and location.

The fitness is defined as the active power loss (P_{loss}):

$$F = \left(P_{loss}\right) \tag{1}$$

The power loss is given by:

$$P_{loss} = \sum_{N=1}^{M}(R_N \times |I_N|^2) \tag{2}$$

where N is the branch number, RN is the resistance in branch N, and IN is the branch current.
The presented method must fulfill these constraints:

1. The DG output Capacity (P_{DG}):

$$P_i^{min} \leq P_{DG,i} \leq P_i^{max} \quad (3)$$

where the allowable upper and lower bounds of the DG are denoted by P_i^{max} and P_i^{min}, respectively.

2. Injection Power:

$$\sum_{i=1}^{k} P_{DG,i} < (P_{Load} + P_{loss}) \quad (4)$$

where P_{Load}: is the power load. This constraint is meant to stop power from returning to the grid from the DG units, as that can cause problems with protection..

3. Balance power:

$$\sum_{i=1}^{k} P_{DG,i} + P_{Substation} = P_{Load} + P_{loss} \quad (5)$$

where $P_{Substation}$ the main substation active power. Both power load and power supply must be equal. This limitation guarantees the equilibrium principle, necessitating a balance between the supply and demand of power. In other words, the aggregate power produced by the DG units and substation needs to match the total of the power load and the power loss.

4. Magnitude Voltage

$$V_{min} \leq V_{bus} \leq V_{max} \quad (6)$$

where VMin and VMax are the voltage minimum (Min) and maximum (Max) values, respectively, and Vbus is the voltage bus. The range of any bus voltage must be 0.95 p.u. to 1.05 p.u. (±5% of the rated value) (Rahim et al., 2019).

5. Configuration Form:

The most significant restriction is that the distribution network must continue to be configured radially. (Ola Badran & Jallad, 2023c).

6. Isolation load:

Ensured that all nodes are energized to connect power to each node.

3. Proposed methodology

The optimization process involves reconfiguring the network while simultaneously determining the optimal DG sizing and placement using the Gravitational Search Algorithm (GSA). The GSA is a stochastic search technique that models agent interactions using the law of gravity to solve optimization issues. Within GSA, agents are viewed as objects whose properties are dictated by their gravitational force and masses attracting objects in the direction of larger masses, which directs the system's global motion. The following are the steps to apply the suggested GSA to DGS, DGL, and DNR:

Step 1: The parameters that make up the input data are defined, including the voltage, resistance, and reactance values of the lines as well as the bus load. The number of masses (N_{mass}) is the set up parameter through the GSA.

Step 2: By choosing switches at random to open in the distribution network and figuring out the size and placement of the DGs to form the masses, the first population is created. The first portion of the mass, which represents network reconfiguration, will have a length of N_{opened} if the number of switches that need to be opened is N_{opened}. In a similar vein, N_{DG}, the second component of mass represents the quantity of DGs that must be added to the distribution system. In the simultaneous case, the switches to be opened and the DG sizes are configured as follows:

$$Mass_i = \left[S_1^1, S_2^2, \cdots, S_{N_{opened}}^d, D_{L1}^{d+1}, D_{L2}^{d+2}, \cdots, D_{LN_{DG}}^{N_d}, D_{S1}^{d+1}, D_{S2}^{d+2}, \cdots, D_{SN_{DG}}^{N_d}\right] \quad (7)$$

where $i = 1, 2, \cdots, N_{mass}, N_d$ is the variables or dimensions to be optimized, and $Mass_i$ is the position of $i-th$ mass in the $d-th$ dimension. S_1^1, S_2^2 and $S_{N_{opened}}^d$ are the opened switched in $d-th$ dimension, and $D_{L1}^{d+1}, D_{L2}^{d+2}$ and $D_{LN_{DG}}^{N_d}$ are the location of the DG units, and $D_{S1}^{d+1}, D_{S2}^{d+2}$ and $D_{SN_{DG}}^{N_d}$ are the sizes of the DG units in MW of $d-th$ dimension.

Step 3: To determine the bus's voltages and the power flow across each network line, start the first iteration by executing the power flow program. You may then calculate the power losses and the lowest voltage across all buses using these data.

$$F_i^d(iter) = \sum_{j\in Kbest, j\neq i}^{N_{mass}} rand_j F_{ij}^d(iter) \tag{17}$$

In GSA, a random number within the interval [0, 1], represented as $rand_j$, is introduced. The algorithm should gradually enhance exploitation while decreasing exploration to strike a balance between the two. By the beginning of the algorithm, every mass exerts force on every other mass, but by the conclusion, only one mass remains in contact with the others. This is accomplished by introducing the idea of $Kbest$, a function of iteration. The collection of the first K masses with the biggest mass and the least power loss is denoted as $Kbest$. The initial value of $Kbest$, or K_0, is set at the beginning and lowers as the number of iterations increases, causing Kbest to decrease linearly over time. The next velocity of a mass is given by:

$$V_i^d(iter+1) = rand_i \times v_i^d(iter) + a_i^d(iter) \tag{18}$$

Step 6: Update the masses' positions as indicated below:

$$Mass_i^d(iter+1) = Mass_i^d(iter) + v_i^d(iter+1) \tag{19}$$

Step 7: Till the maximum number of iterations is achieved, carry out the actions from step 3 again.

Step 8: When the allotted number of iterations is reached, end the procedure and produce the best result, which includes the voltage at each bus, the locations and sizes of the DGs, the switch numbers defining the new network configuration, the power losses for the process, and the corresponding fitness value.

Figure. 1 illustrates the flowchart of the proposed methodology utilizing the Gravitational Search Algorithm (GSA).

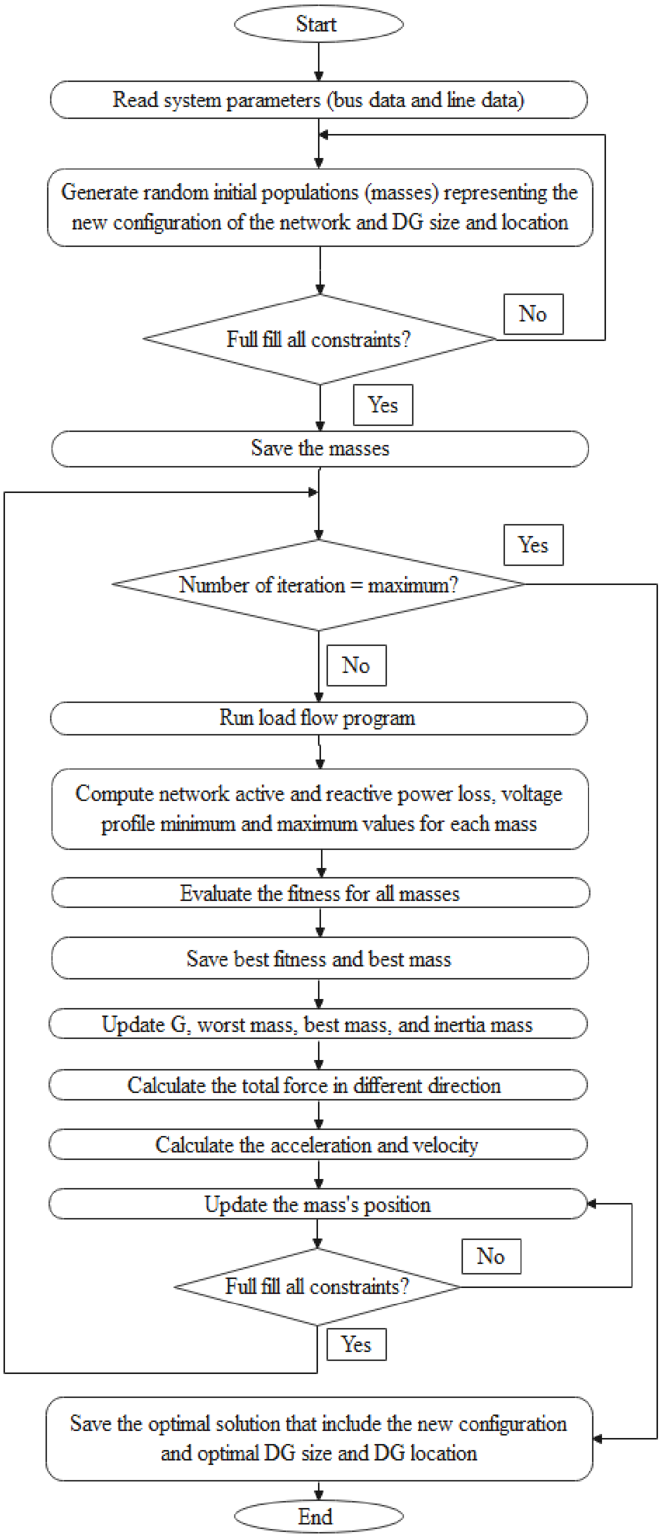

Figure (1): Flow chart of DNR and DG_LS using GSA

4. Simulation Results and Discussion

The results of the suggested approach for concurrently addressing the DG location, sizing, and system reconfiguration issues are shown in this section. MATLAB was used to implement and solve the methodology because of its robustness and speed. Every code was ran 20 times for 100 population sizes and 300 iterations during the simulation, which was executed on a laptop equipped with an Intel Core i7 processor. Two IEEE 33-bus systems (Figure 2) and an IEEE 69-bus system (Figure 3) were used to test the methodology. There were 37 switches in the IEEE 33-bus distribution network: 32 sectionalizing switches and 5 tie switches. As shown in Figure 2, the original network had switches 33, 34, 35, 36, and 37 that were generally open and the other switches that were normally closed. The voltage of the system was 12.66 kV, and the total real load demand was 3715 kW. There was 100 MVA as the base apparent power value. At the beginning, the network experienced 202.677 kW of power losses, with 0.913 pu being the lowest bus voltage. Switches 69 through 73 were initially left open in the IEEE 69-bus distribution network, which included 73 branches, 5 tie switches, and 68 sectionalizing switches. The minimum voltage magnitude of the system is 0.9092 p.u., while its nominal voltage is 12.66 kV. The system's apparent power demand is (3,802.19 + j2, 694.6) kVA, with corresponding ACT and REC power losses of 39.16 kVAR and 224.99 kW. The complete bus and line data are given in (Ola Badran & Jallad, 2023b; Ola Badran, Jallad, Mokhlis, & Mekhilef, 2020). It was supposed that the DG in this test setup was a mini-hydro generator. Every DG had a capacity of 2 MW.

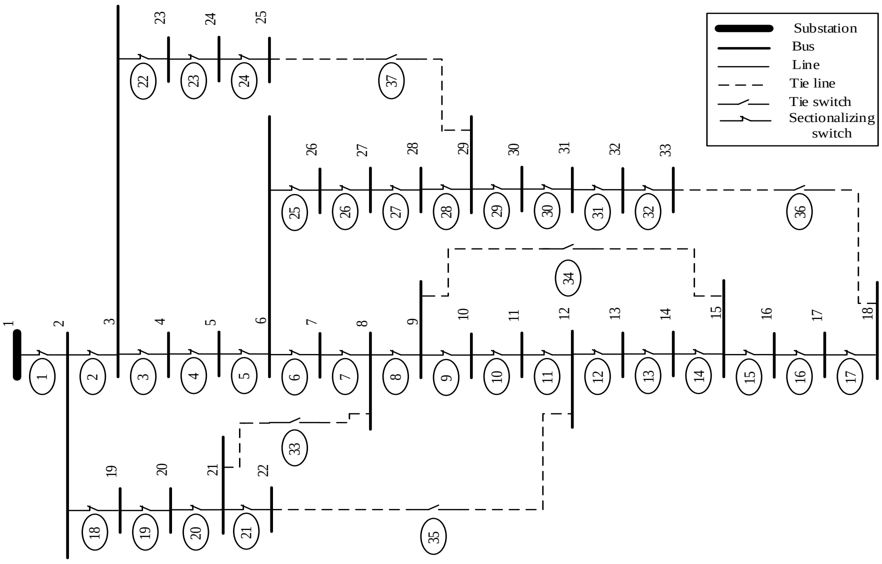

Figure (2): IEEE 33-bus system

4.1 Effect of the Optimization Technique on Power Loss

Table 1 illustrates the output results obtained by using GSA and compared to the initial form for the IEEE 33 bus system. It's seen that the optimization technique provides a better result according to the initial form. The active power loss was 65.87 kW compared to the initial case of 202.6 kW so the active power loss reduction was 67.488 %. The reactive power loss is 47.41 kVAR compared to the initial case of 135 kVAR and so the reactive power loss reduction is 53.52 %. The minimum voltage value of the voltage profile (VF) is 0.9695 p.u., an improvement over the initial case, where the minimum voltage was 0.913 p.u. Additionally, Table 2 presents the output results obtained using GSA, compared to the initial values for the IEEE 69-bus system. It's seen that the optimization technique provides a better result according to the initial form. The active power loss was 39.20 kW compared to the initial case of 224.6 kW so the active power loss reduction was 82.55 %. The reactive power loss is 38.5 kVAR compared to the initial case of 102 kVAR and so the reactive power loss reduction is 62.25 %. The minimum voltage value of the VF is 0.9807 p.u compared to the initial case where the minimum voltage is 0.9093 p.u.

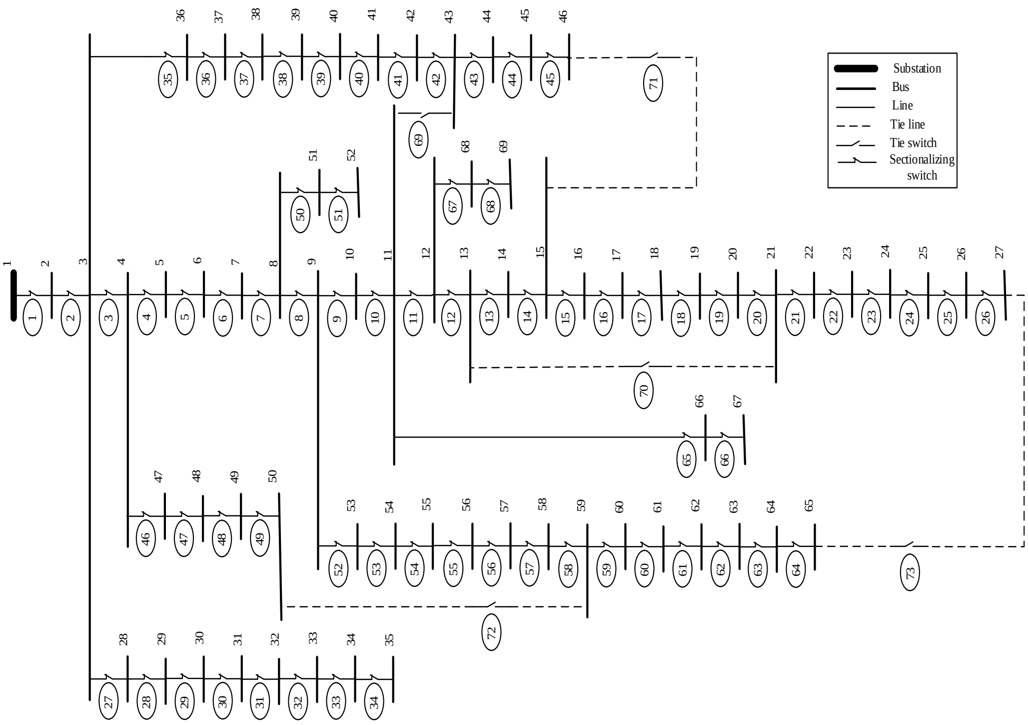

Figure (3): IEEE 69-bus system

Table 1: Proposed method results for IEEE 33 bus system

Item	Initial Form	DNR and DG_S and DG_L Form
Tie switch	33, 34, 35, 36, 37	32, 34, 27, 33, 9
		32
DG Location	---	25
		13
		.541
DG Sizing (MW)	---	.656
		.625
Fitness P_loss (kW)	202.6	65.87
Q_loss (kVAR)	135	47.41
P_loss (%)	---	67.488
Q_loss (%)	---	64.88
Min Voltage (p.u)	.9132	.9695
Max Voltage (p.u)	1	1

Table 2: Proposed method results for IEEE 69 bus system

Item	Initial Form	DNR and DG_S and DG_L Form
Tie switch	69, 70, 71, 72, 73	13, 12, 10, 57, 62
DG Location	---	22, 16, 61
DG Sizing (MW)	---	.507, .41, 1.512
Fitness P_loss (kW)	224.6	39.20

Item	Initial Form	DNR and DG_S and DG_L Form
Q_loss (kVAR)	102	38.5
P_loss (%)	---	82.55
Q_loss (%)	---	62.25
Min Voltage (p.u)	.9093	.9807
Max Voltage (p.u)	1	1

4.2 Effect of the Optimization Technique on Voltage Profile

The voltage profiles after applying the optimization technique are displayed in Figure 4 for the IEEE 33-bus distribution network and Figure 5 for the IEEE 69-bus distribution network. The voltage magnitudes of all buses show significant improvement compared to the initial case. After network reconfiguration, along with optimal DG location and sizing, all bus voltages are closer to unity.

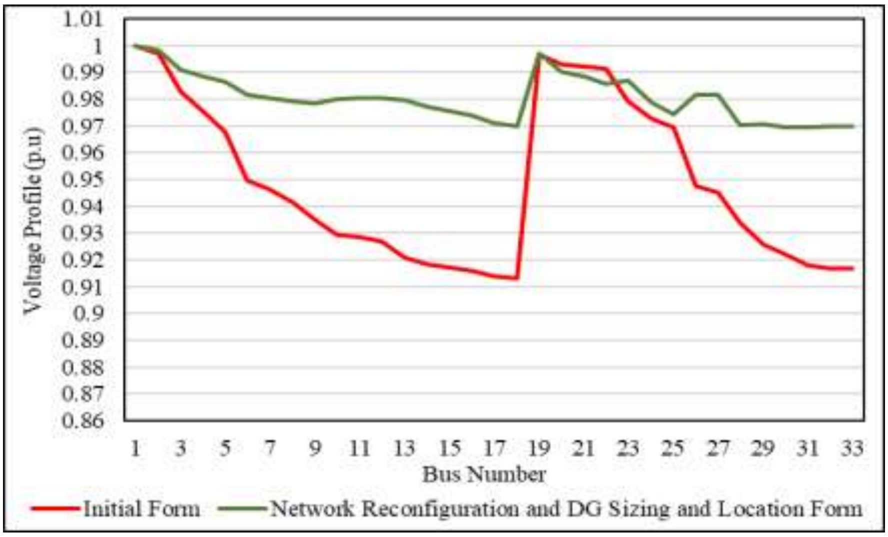

Figure (4): IEEE 33-bus distribution network voltage profile

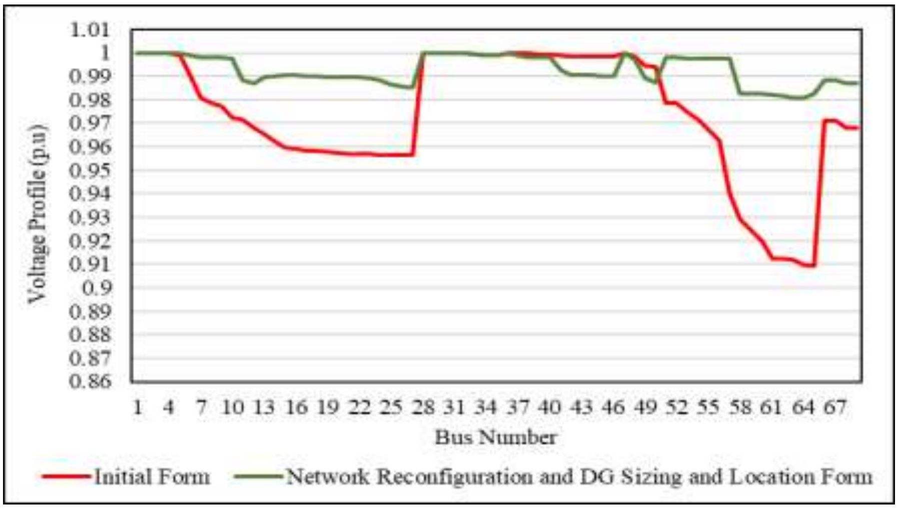

Figure (5): IEEE 69-bus distribution network voltage profile

4.3 The overall performance of GSA

Additionally, Figures 6 and 7 (corresponding to the IEEE 33-bus and IEEE 69-bus distribution networks, respectively) show results of a robustness test. The optimization method was used 20 times in this test. Every run of the GSA generated findings that were consistently similar and resulted in a locally optimal solution. The global optimal solution was shown to be the best of these local optima. In addition to DG sizing and location, the GSA showed significant and robust convergence performance, demonstrating its efficacy in identifying both local and global optimal solutions for complex problems like DNR.

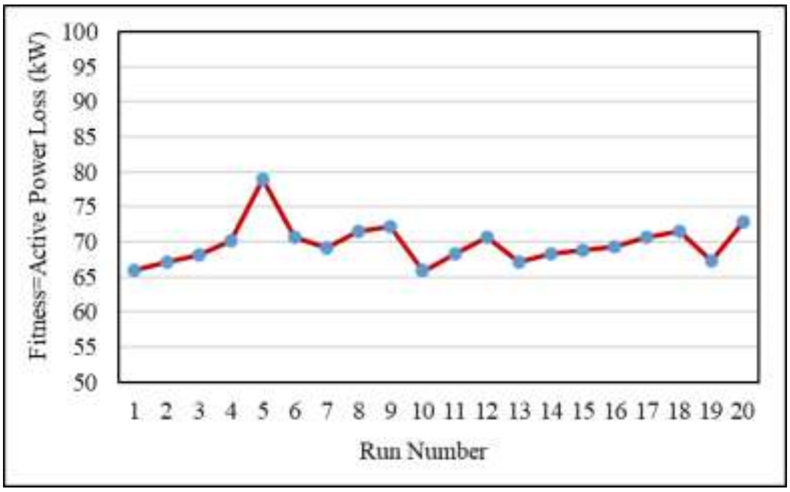

Figure (6): GSA robustness test curve for IEEE 33 bus system

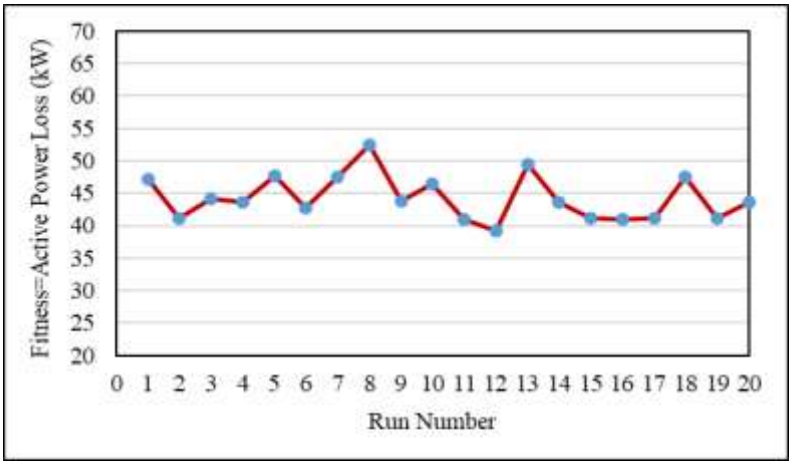

Figure (7): GSA robustness test curve for IEEE 69 bus system

The convergence performance of GSA for the IEEE 33-bus distribution network is illustrated in Figure 8, while Figure 9 presents the results for the IEEE 69-bus distribution network. The code was executed 20 times, and the best run was selected as the global solution. The global convergence performance was achieved with 300 iterations and a population size of 100.

The powerful of the presented optimization technique was compared with other work results as illustrated in Table 3 for the IEEE 33 bus system and in Table 4 for the IEEE 69 bus system. The presented optimization technique based on GSA provides results better than another algorithm.

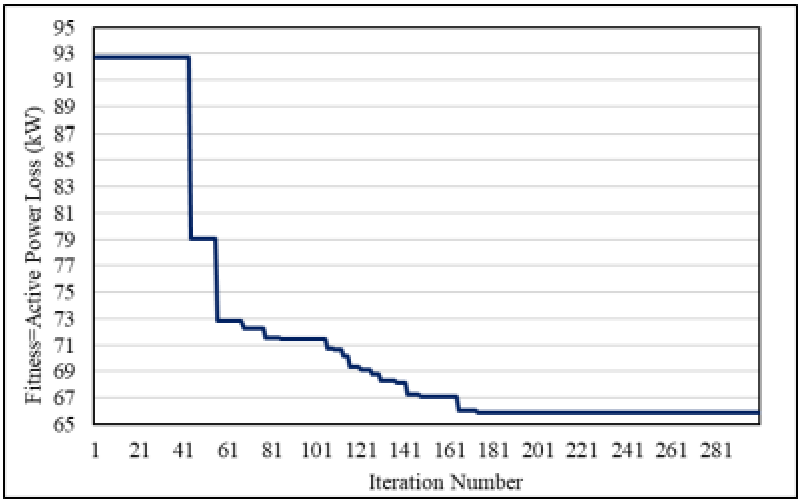

Figure (8): GSA convergence performance curve for IEEE 33 bus system

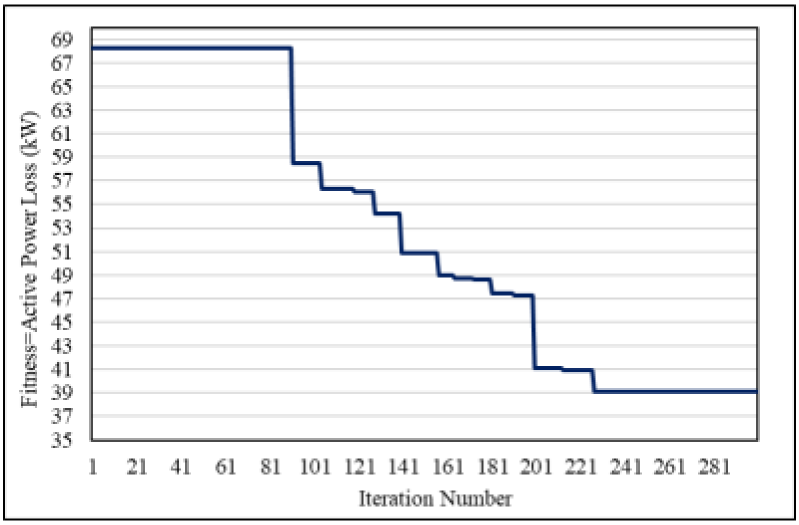

Figure (9): GSA convergence performance curve for IEEE 69 bus system

Table 3: Simulation result comparison for IEEE 33 bus system

Reconfiguration and DG Sizing and Allocation	Open Switch	Total DG Output (MW)	Lowest Bus Voltage (pu)	Power Loss (kW)	Loss Reduction (%)
GA (Rao, et al., 2012)	7, 10, 34, 28, 32	1.963	.977	75.13	62.9
RGA (Rao, et al., 2012)	7, 9, 32, 12, 27	1.774	.969	74.32	63.3
HSA (Rao, et al., 2012)	7, 32, 10, 14, 28	1.668	.970	73.05	63.9
FWA (Imran, et al., 2014)	7, 1132, 14, 28,	1.684	.971	67.1	66.89
EP (Ola Badran, et al., 2018)	7, 8, 9, 28, 32	1.964	.971	73.97	63.49
PSO (Ola Badran, et al., 2018)	7, 10, 13, 28, 32	1.766	.974	72.42	64.3
FA (Ola Badran, et al., 2018)	7, 10, 13, 28, 32	1.825	.975	72.36	64.28
ISCA (Raut & Mishra, 2020)	7, 14, 28. 31, 9	1.69120	-	66.81	67.03
The Proposed Method by GSA	32, 34, 27, 33, 9	1.822	.9695	65.87	67.488

Table 4: Simulation result comparison for IEEE 69 bus system

Reconfiguration and DG Sizing and Allocation	Open Switch	Total DG Output (MW)	Lowest Bus Voltage (pu)	Power Loss (kW)	Loss Reduction (%)
GA (Rao, et al., 2012)	10, 45, 55, 62, 15	2.02920	.97270	46.5	73.380
GA (Rao, et al., 2012)	10, 14, 55, 62, 16	2.06540	.97420	44.230	8.320
HSA (Rao, et al., 2012)	69, 13, 58, 61, 17	1.87180	.97360	4.3	82.080
MPSO (Essallah & Khedher, 2020)	14, 58, 61, 69, 70	2.2736	.98994	42.2	81.1
ISCA (Raut & Mishra, 2020)	12, 9, 57, 63, 69	1.8731	-	39.73	82.34
The Proposed Method by GSA	69, 70, 71, 72, 73	2.429	.9807	39.20	82.55

5. Conclusion

This paper presents an optimization methodology to simultaneously determine the optimal Distribution Network Reconfiguration (DNR), Distributed Generation (DG) sizing, and DG placement. The proposed approach aims to achieve the best voltage profile while minimizing active power loss in the distribution system. The Gravitational Search Algorithm (GSA) was employed to obtain the lowest fitness value. The effectiveness of the proposed technique was validated using a 33-bus distribution network, demonstrating its efficiency in simultaneously achieving optimal DNR, DG sizing, and DG placement. A portion of the obtained results was compared with existing published studies, demonstrating that the proposed optimization methodology achieved superior performance. Additionally, the results indicate that GSA outperforms other methods presented in previous research. Additionally, the limitations of the proposed methodology will appear in the case of dynamic load. The configuration of the network must change during the change of the load which may affect the network switches. This issue could be a future work. Authors should look forward to finding one configuration that is suitable during load change.

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