Optimal Allocation and Sizing of Distributed Generation for Loss Minimization using a Multi-Population Genetic Algorithm

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***Abstract*—The paper introduces a evolutionary algorithm, based on Multi Population Genetic Algorithm (MPGA), to support decisions about allocation and power sizing of generation units within power systems. The effectiveness of the MPGA is tested over two different radial distribution systems taking into account five different scenario. The evaluated power systems are the 33 and 69-bus radial distribution systems, which are benchmark systems from literature. The promising results achieved are compared against recent literature results for the same problem.**

***Index Terms*—Allocation, Sizing, Distribution Networks, Distributed Generation, Multi-Population Genetic Algorithm**

I. Introduction

The electric power system delivers electric power from a substation to final customers through distribution lines, where radial, ring and mesh are the usual topologies for such network system. According to the International Renewable Energy Agency (IRENA), CO2 emissions have risen 1.3% over the last five years. International policies have focused on renewable energy sources to reduce such emissions. In the case of electric power systems, the inclusion of distributed generation (DG), based on renewable energy sources, has increased worldwide [1]. The decentralized power systems have become an option where distributed generator (DG) units are connected directly to the power system as a source of active electric power. The five major factors that have arouse interest over distributed generation are: development in distributed generation technologies, constraints for inclusion of new transmission lines, increasing of customer demand for highly reliable electricity, electricity market liberalisation and concerns about climate changes [2]. The benefits of the distributed generation must take into account its location in the power network system and the power size of the generating units. The best sizing of generator units can lead to energy losses reduction and increase the level of reliability for the whole electric power system. Also, the distribution power systems are traditionally based on a radial topology, which brings some technical challenges when adding a distributed generator (DG) unit such as: power flow inversion, fluctuations in voltage profile and increase of fault levels.

The present paper introduces a computational methodology, based on Multi Population Genetic Algorithm (MPGA), to support decisions about generation units placement and their power sizing. The effectiveness of the MPGA is tested over two different radial distribution systems at five different scenario. The promising results achieved are compared against recent literature results. This paper present a multi population genetic algorithm (MPGA) whose major objective is active power losss minimization in radial distribution system through the reconfiguration and simultaneous allocation and sizing of distributed generation. The MPGA is proposed of modular form, where a module referring to reconfiguration and another module is responsible by allocation and sizing of the distributed generations, allowing that way a separate analysis or together of the method.

The distributed generation allocation and sizing problem is a nonlinear mixed-integer optimization problem, where the authors in [3] identify solution approaches such as exact methods for Mixed Integer Non-Linear Programming (MINLP) models [4], Teaching-Learning based Optimization (TLBO) [5], and mainly metaheuristics: Ant Colony Search Algorithm (ACSA) [6], Firefly Algorithm (FA) [7], Bacterial Foraging Optimization (BFO) [8] and Particle Swarm Optimization (PSO) [9], among others. An application of Genetic Algorithm (GA) to solve the the distribution network reconfiguration (DNR) problem for loss minimization is early reported by [10]. The authors in [11] proposed a refined genetic algorithm (GA)

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for distribution network reconfiguration aiming to minimize the system power loss. In [12], a comparison between nonlinear optimization algorithm and genetic algorithm is reported for optimal allocation and sizing of DG units. GA searches for optimal size of DG in [13] within a radial distribution networks. GA is combined with PSO in [14] for allocation and sizing DG on distribution systems. GA was applied for allocation while PSO returned DG sizing. Non dominated sorting genetic algorithm (INSGA-II) is applied by [15] for optimal location and sizing of DG, minimizing the power system losses and introducing a multi-objective function to evaluate the voltage deviation and stability.

The paper is organized as follows: section II defines the allocation and sizing of DGs problem. The proposed method is introduced in section III and computational results are reported in section IV. The conclusions of this work follow in section V.

II. Problem Formulation

The insertion of DG units have not only positive impacts, but also negative impacts which depend strongly of the sizing and allocation of DG [16]. The location and sizing of DG within the electric power system can be influenced by several factors: weather, technical and economic criteria, regulation rules. Thus, appropriate tools to determine the locations and sizing of DG become useful for decision-makers [17].

The power loss is currently the most approached technical impact, when inserting a DG unit, as seen in [3]. It can be calculated following equations (1)-(7).

$$P_{i+1} = P_i - P_{Lossi} - P_{Li+1} + P_{DG+1} \tag{1}$$

$$Q_{i+1} = Q_i - Q_{Lossi} - Q_{Li+1} + Q_{DG+1} \tag{2}$$

$$V_{i+1}^2 = V_i^2 - 2.(r_{i+1}.P_i + x_{i+1}.Q_i) + \frac{(r_{i+1}^2 + x_{i+1}^2).(P_i^2 + Q_i^2)}{V_i^2} \tag{3}$$

$$P_{Lossi} = r_{i+1}.\frac{P_i^2 + Q_i^2}{V_i^2} \tag{4}$$

$$Q_{Lossi} = x_{i+1}.\frac{P_i^2 + Q_i^2}{V_i^2} \tag{5}$$

$$P_{Loss} = \sum_{i=1}^{n} P_{Lossi} \tag{6}$$

$$Q_{Loss} = \sum_{i=1}^{n} Q_{Lossi} \tag{7}$$

where,

r_{i+1} = Resistance of branch between bus i and $i+1$;
x_{i+1} = Reactance of branch between bus i and $i+1$;
V_i = Voltage of bus i;
P_i = Real power flowing out of bus i;
Q_i = Reactive power flowing out of bus i;
P_{Li+1} = Real power load connected in bus $i+1$;
Q_{Li+1} = Reactive power load connected in bus $i+1$;
P_{DGi+1} = Real Power generation of the DG connected at bus $i+1$;
Q_{DGi+1} = Reactive Power generation of the DG connected at bus $i+1$.
P_{Lossi} = Active power loss of branch between bus i and $i+1$;
Q_{Lossi} = Reactive power loss of branch between bus i and $i+1$;

The power balances are given by equations (1) and (2), while the voltage comes from Kirchhoff's law as given by equation (3). The active and reactive power losses on bus i is stated by equations (4) and (5), and the total losses follow equations (6) and (7). There are some problem constrains that must be handled which are describe by equations (8)-(13).

$$Q_{DG_i} \le P_{DG_i} \ . \ tan(\alpha), \quad \forall \ i \in \ N \setminus F; \tag{8}$$

$$Q_{DG_i} \ge -P_{DG_i} \ . \ tan(\alpha) \ \ \forall \ i \in \ N \setminus F. \tag{9}$$

$$\sum_i P_{DG_i} \le \beta \cdot \sum_i P_{L_i}, \qquad i \in N \setminus F. \tag{10}$$

$$\sum_i |Q_{DG_i}| \le \beta \cdot \sum_i Q_{L_i}, \qquad i \in N \setminus F. \tag{11}$$

$$\sum_{<i,j> \in arcs} y_{i,j} = Nnos - Card(F); \tag{12}$$

$$v_{min} \le v_{Ri}, \qquad \forall \ i \in \ N \setminus F. \tag{13}$$

The equations (8) and (9) state limits for Q_{DG_i}, where pf is the DG power factor and $\alpha = arccos(pf)$ [18], [19]. The distributed generation penetration is described by equations (10) and (11). The parameter β sets the percentage that GD power should not run against the feeder load. For instance, $\beta = 0.5$ means that the DG power must not exceed 50% of the feeder load. In equation (12), the decision variable $x_{i,j} \in \{0, 1\}$ defines if the switch is closed, $x_{i,j} = 1$, between nodes i and j, $x_{i,j} = 0$; otherwise. Parameters $Nnos$ and F are the set of nodes and feeders, respectively. The minimal voltage must hold following equation (13).

III. MultiPopulation Genetic Algorithm

A multi population genetic algorithm (MPGA) is proposed in this section to solve the allocation and sizing of DG problem. The MPGA's pseudocode follows in Algorithm 1.

The procedure $initialize()$ generates new individuals for each population during its first execution. The next executions of this procedure will initialize all individuals again, except by the best one and that migrated from other population. The fitness value of each individual is calculated by $evaluate()$ and the individuals are structured as a ternary tree by $organize()$, based on their fitness value. The individuals are hierarchically disposed within several clusters, where a cluster is compounded by three individuals following two levels. The cluster leader is positioned in the upper level, while two supporters are in the lower level. The fittest individual is always the leader of the cluster as shown by Figure 1. There are 13 individuals hierarchically structured in a ternary tree, where the root node

Algorithm 1: MultiPopulation Genetic Algorithm

```
begin
    repeat
        for i = 1 to number of populations do
            for j = 1 to population size do
                initialize(pop(i).ind(j));
                evaluate(pop(i).ind(j));
            organize(pop(i));
            repeat
                for j = 1 to number of crossovers do
                    selectparents(ind1,ind2);
                    child ← crossover (ind1,ind2);
                    if mutation rate then
                        mutation(child);
                    repair(child);
                    evaluate(child);
                    add(child, pop(i));
                organize(pop(i));
            until converge(pop(i));
        for i = 1 to number of populations do
            migrate(pop(i));
    until reach(stopping criterion);
    bestIndividual ← getBestIndividual(pop);
    return bestIndividual;
```

stores the individual with best fitness value over the whole population.

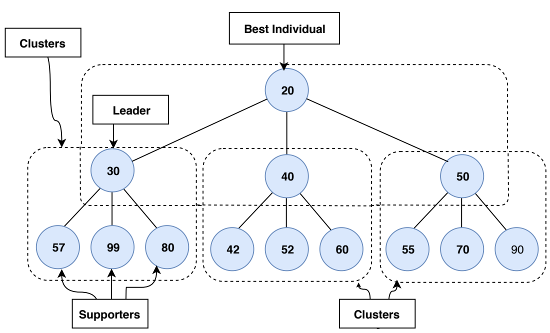

Fig. 1. Individuals structures in a ternary tree. Source: [20]

The procedure $select()$ takes two individuals from a randomly chosen cluster: one is always the leader of the cluster and the other is randomly selected from its supporters. A new individual is generated by $crossover()$ and it can be modified by $mutation()$, if the *mutation rate* holds. A $repair()$ is applied to remove unfeasibility from the new representation of individual ($child$). The $child$ is evaluated next and it will replace its worst parent, if it has a better fitness value.

A total of *number of crossovers* new individuals are created for each population. The evolution process over a population converges when no new individuals are added after *number of crossovers* executions. If the convergence happens, the procedure $migrate()$ send the best individuals from the current population to the next one. The stop criterion of Algorithm 1 is the time limit, returning the best route found within such period.

A. Representation of Solution and Initialization

Figure 2 illustrates a solution of the DG problem encoded as individual (chromosome).

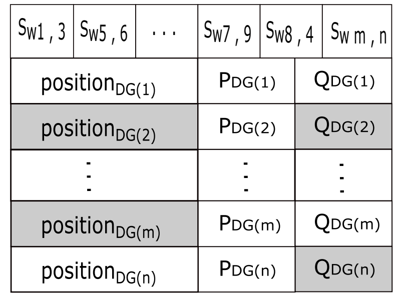

Fig. 2. Structure of Individual Reconfiguration & DG

First, there is a sequence of genes storing the number of tie switches which are normally open within the radial distribution system: $Sw_{1,3}$, $Sw_{5,6}$,..., $Sw_{m,n}$. The other entries store three components. The first one represents the allocation, which means the bus i where the DG should be connected in the power system network ($Position_{DG(i)}$). The second component is the active power generation of the DG at bus i ($P_{DG(i)}$), and the third component is the DG reactive power generation at bus i ($Q_{DG(i)}$).

The individual will be randomly generated, but some constraints must be handled. The sequence of normally open switches is randomly selected since the radial structure of the power system is kept. For instance, the initialization will not lead to disconnected nodes or cycles in the power network system. The values of $P_{DG(i)}$ and $Q_{DG(i)}$ are generated following an uniform distribution within $[P_{DG}^{min}, P_{DG}^{max}]$ and $[Q_{DG}^{min}, Q_{DG}^{max}]$, respectively.

B. Crossover, Mutation and Repair

One crossover is proposed to deal with the sequence of normally open switches and another to the entries with DG allocation and sizing. The crossover for the sequence of normally open switches follows two steps:

- Step 1: The child is created adding each gene of the Ind1 and Ind2 as illustrated in figure 3.

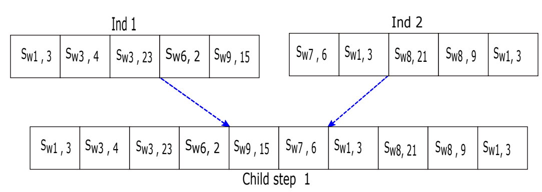

Fig. 3. Child in Step 1

- Step 2: The genes are randomly selected until reaching the size of tie switches as Illustrated in figure 4.

An uniform crossover is applied over Ind_1 e Ind_2 to select genes from entries ($Position_{DG(i)}$, $P_{DG(i)}$, $Q_{DG(i)}$) as illustrated in Figure 5.

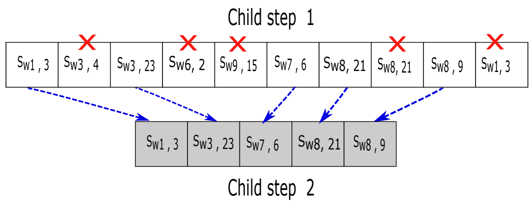

Fig. 4. Child in Step 2

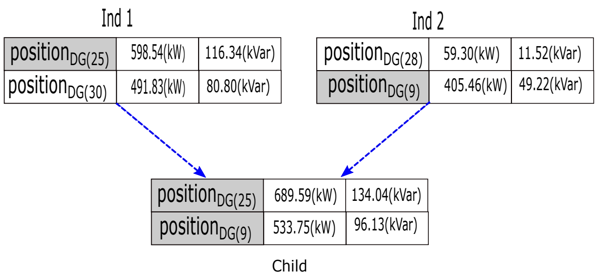

Fig. 5. Allocation and Sizing Crossover

Finally, BLX-α crossover [21] defines the new sizing for $P_{DG(i)}$ and $Q_{DG(i)}$ in *child*. The mutation operator is applied only over the sequence of normally open switches. An entry is randomly selected from the sequence and its switch is replaced by another one as shown by Figure 6

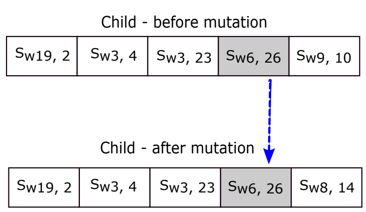

Fig. 6. mutation example

A $repair()$ is executed to deal with unfeasible representation of solution (*child*). First, the duplicate switches are removed from the sequence of switches as illustrated by Figure 7. Next, the $repair()$ also ascertain if the problem constraints

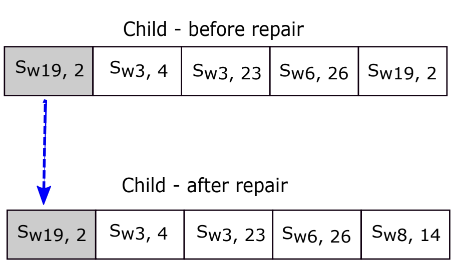

Fig. 7. Repair in Reconfiguration

given by equations (8)-(9) holds. If these constraints are violated, $repair()$ will randomly select a new value for Q_{DG_i} within those limits. For equations (10)-(11), new values of Q_{DG_i} and P_{DG_i} are randomly set when the left hand side exceed the right side on these equations.

C. Fitness Function

The main objective in this optimization problem is to reduce the active power losses of the distribution networks after the allocation and sizing of the DGs. However, constraints radial structure (equation (12)) and minimum voltage (equation (13)) must be satisfied. Thus, the fitness will reduce power losses (see equation (4)) and penalize constrains violation as describe by equations (14)-(16), where M is a big number.

$$Fitness = \sum_i \left(r_{i+1}.\frac{P_i^2 + Q_i^2}{V_i^2} \right) + M.(\Gamma + \sum_i \Lambda_i) \quad (14)$$

$$\Gamma = \left| \sum_{<i,j>\in arcs} y_{i,j} - (Nnos - Card(F)) \right|; \quad (15)$$

$$\Lambda_i = \begin{cases} v_{min} - v_{Ri} & \text{If } v_{min} > v_{Ri}, \\ 0 & \text{otherwise.} \end{cases} \quad (16)$$

IV. Test Results

The proposed evolutionary algorithm for allocation and sizing of distributed generators will solve two benchmark systems from literature: 33 and 69 bus systems reported in [22] and [23], respectively. MPGA was coded using the Professional Optimization Framework (ProOF) [24] and it ran over a machine with Intel Core i7 processor, 1.80 GHz and 16 GB RAM.

The 33 bus-system is shown in Figure 8 and it has 12.66 kV of base voltage, 37 branches, 32 normally closed switches and 5 normally open. The normally open switches are numbered from 33 to 37, while the normally closed are numbered from 1 to 32. The total substation loads for the base configuration are 5084.26 kW and 2547.32 kVAr, and the total real and reactive power loads are 3715 kW and 2315 kVAr. The initial power loss of this system is 202.67 kW and, after reconfiguration to reduce losses, the active power loss is 139.55 kW, which means a loss reduction of 31.14%.

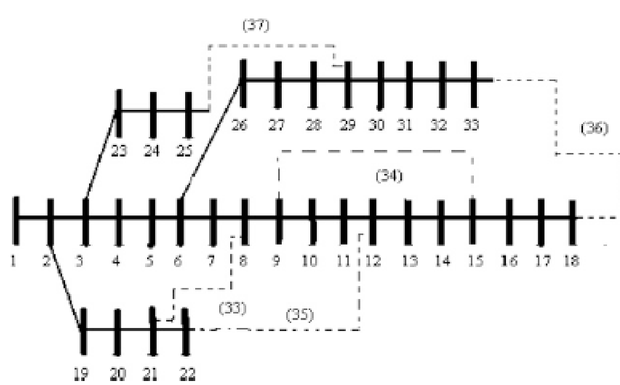

Fig. 8. The base configuration of the 33-bus radial distribution system

The 69 bus system has 12.66 kV of base voltage, 73 branches, 68 normally closed and 5 normally open switches as illustrated by Figure 9. The switches normally open are 69 to 73, while the closed ones are labeled from 1 to 68. The total real and reactive power loads on the systems are 3802.19 kW e 2694.06 kVAr. The initial power loss of this system is 224.95 kW and, after its reconfiguration, the power loss becomes 99.59 kW, which means a reduction of 55.72 %.

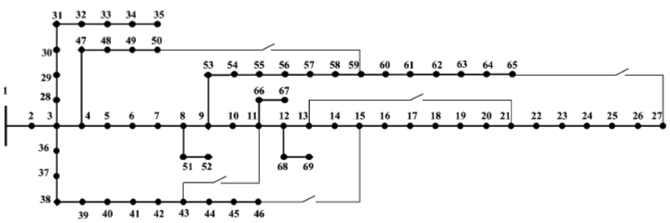

Fig. 9. Source: J. S. Savier and Debapriya Das, 2007.

The MPGA is validated following the same methodology described in [25], where five different scenarios are evaluated:

- Scenario 1: The initial configuration of the benchmark system is taken, which means without any reconfiguration and allocation of DG.
- Scenario 2: The benchmark system from Scenario 1 is now reconfigured to reduce power losses, but without the allocation of DG.
- Scenario 3: A total of 3 DG units is allocated to the benchmark system on Scenario 1.
- Scenario 4: A total of 3 DG units is allocated to the benchmark system on Scenario 2.
- Scenario 5: The decisions about 3 DG units allocation and reconfiguration are simultaneously made for the benchmark system from Scenario 1.

The limits of DG unit sizes up to 2 MW and distributed generators (DGs) operate with unit power factor (i.e, they are used for supplying active power only). The maximum allowed number of DGs unity are three with penetration factor level $\beta = 100\%$ (e.g, $\beta = 1$). DG can be connected to any bus, except by substation, and only one DG unit is attached to a bus. Table I, shows the results obtained by MPGA regarding the 33-bus system.

The active power loss in base scenario (Scenario I) is 202.67 that is reduced to 139.55, 71.45, 58.87 and 55.88 from scenarios 2 to 5, respectively. It can also been seen in Table I that the active power loss reduction in scenario 2, when compared to the active power loss in base scenario, is 31.14% of reduction. However, the allocation of DGs in Scenario 3 reaches 64.74% of reduction, even without a system reconfiguration. The reduction of power losses becomes better when the DGs are allocated after the system reconfiguration (70.95% in Scenario 4) and even better when simultaneously done with reconfiguration (72.42% in Scenario 5). Another aspect related to the allocation and sizing of DG units is the voltage profile. There is voltage profile improvement, where the minimal voltage of the Scenario 1 is 0.913112 p.u. at bus 18, while they are equal to 0.937835 (bus 32) in Scenario 2, 0.96864 p.u. (bus 33) in Scenario 3, 0.9630 p.u. (bus 31) in Scenario 4 and 0.97235 p.u (bus 33) in Scenario 5. This means an improvement of 2.70%, 6.08%, 5.46% and 6.48%, respectively. The voltage profile reached for each bus is shown in Figure 10.

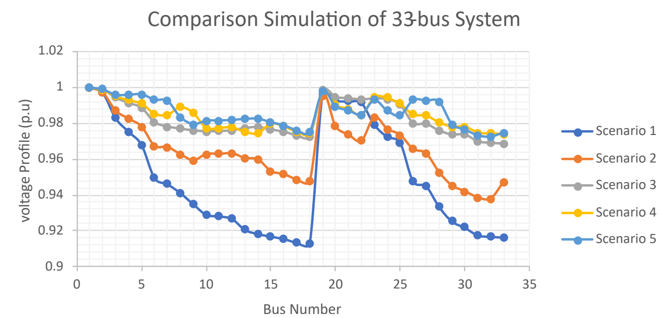

Fig. 10. Comparison of Simulation of 33-bus System

Table II shows the same results regarding the 69-bus system, which are similar to those reported for 33-bus system. For the base scenario, the active power loss is equal 224.93 that becomes 99.59 (55.72% of reduction) in Scenario 2, 69.98 (69.02% of reduction) in Scenario 3, 41.93 (81.35% of reduction) in Scenario 4 and 36.55 (83.75% of reduction) in Scenario 5. All scenarios with allocation and sizing of DG improved the voltage profile. The best voltage profile happens for Scenario 3 at bus 65 with voltage level increased by 1.14%. Figure 11 shows voltage profile for each bus.

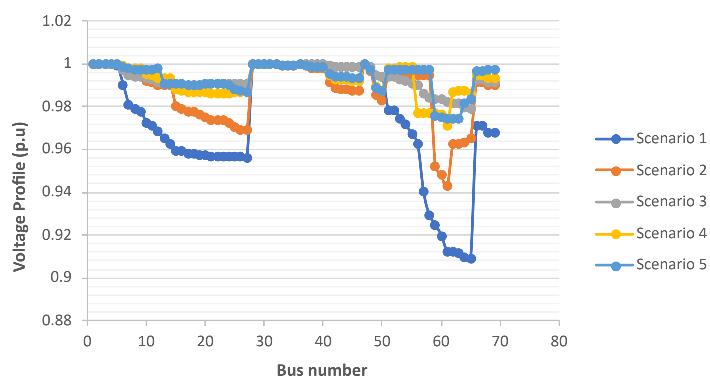

Fig. 11. Comparison of Simulation of 69-bus System

The lowest power loss is reached in scenario 5 for both benchmark systems. Thus, we have here an indication that the decisions made, taking into account the simultaneous reconfiguration and allocation of distributed generators, could yield better results.

In order to illustrate the performance of the proposed method, the MPGA is also compared against other techniques from the literature that deal with allocation and sizing of DGs: Meta-heurística Harmony Search Algorithm (HSA) [26], Uniform Voltage Distribution based constructive reconfiguration Algorithm (UVDA) [27] and Cuckoo Search Algorithm (CSA)

TABLE I
SIMULATION RESULTS OF 33-BUS

Item	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Real power loss (kW)	202.67	139.55	71.45	58.87	55.88
% Real power loss	-	31.14	64.74	70.95	72.42
$V_{min}(p.u)$ / Bus Nº.	0.9131121 / 18	0.937835 / 32	0.96864 / 33	0.9630 / 31	0.97235 / 33
Switches opened	33, 34, 35, 36, 37	7, 14, 9, 32, 37	33, 34, 35, 36, 37	7, 14, 9, 32, 37	32, 7, 9, 28, 8
DG Placement	-	-	14, 24, 30	8, 24, 30	5, 14, 25
Size of GD (MW)	-	-	0.75393, 1.0996, 1.07143	0.93157, 1.06819, 0.95043	0.76092, 0.84756, 1.46741

TABLE II
SIMULATION RESULTS OF 69-BUS

Item	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Real power loss (kW)	224.93	99.59	69.98	41.93	36.55
% Real power loss	-	55.72	69.02	81.35	83.75
$V_{min}(p.u)$ / Bus Nº.	0.96785 / 69	0.94273 / 61	0.97898 / 65	0.971090 / 61	0.974249 / 61, 62, 63
Switches opened	69, 70, 71, 72, 73	69, 70, 14, 61, 58	69, 70, 71, 72, 73	69, 70, 14, 61, 58	58, 70, 69, 14, 61
DG Placement	-	-	10, 23, 61	53, 60, 63	12, 23, 61
Size of GD (MW)	-	-	0.57631, 0.35008, 1.71571	0.56927, 1.47749, 0.48965	0.43507, 0.63363, 1.45341

[28]. All methods were applied to simultaneous reconfiguration, allocation and sizing of DG at the same scenarios. Table III and IV compare the results achieved by these methods for 33 and 69-bus systems, respectively. In Table III, the results show that the MPGA outperforms the other methods in several scenarios. MPGA reaches better results than HSA and UVD for scenarios 3,4 and 5, while is better than CSA for scenarios 2 and 3. However, CSA and MPGA return a similar reduction in scenario 4. Table IV reports similar results. MPGA outperforms HSA in scenarios 3,4 and 5, UVD in scenarios 3 and CSA in scenario 3. The results in scenario 5 are close to each other for MPGA, UVDA and CSA.

V. CONCLUSIONS

In this paper, we introduce a MPGA to reduce active power loss minimization in radial distribution system. The method must execute the reconfiguration, allocation and sizing of distribution generated (DG) units. The method is validate by solving two benchmark systems from the literature over four different scenarios. The results achieved are compared against three methods from literature: HSA, UVDA and CSA. The proposed method is able to improve results when decisions about system reconfiguration, allocation ans sizing of DG units are done simultaneously. MPGA also report competitive results when compared with HSA, UVDA and CSA within those scenarios. As future works, MPGA will be applied to solve more complex benchmark systems as well as real-world power systems.

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TABLE III

COMPARISON OF SIMULATION RESULTS OF 33-BUS SYSTEM

Method	Item	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Proposed Method	DG Placement	-	-	14, 24, 30	8, 24, 30	5, 14, 25
	DG Size (MW)	-	-	2.92496	2.95019	3.07589
	Open Switches	33, 34, 35, 36, 37	7, 14, 9, 32, 37	33, 34, 35, 36, 37	7, 14, 9, 32, 37	32, 7, 9, 28, 8
	Real Power Loss (KW)	202.67	139.55	71.45	58.87	55.88
	% Real Power Loss	-	31.14	64.74	70.95	72.42
	$V_{min}(p.u)$	0.913112	0.93783	0.96864	0.9630	0.97235
HSA [26]	DG Placement	-	-	17,18,33	30,31,32	31,32,33
	DG Size (MW)	-	-	1.7256	1.0909	1.6684
	Open Switches	33,34,35,36,37	7,14,9,32,37	33,34,35,36,37	7,14,9,32,37	7,17,10,32,28
	Real Power Loss (KW)	202.67	138.06	96.76	97.13	73.05
	% Real Power Loss	-	31.88	52.26	52.07	63.95
	$V_{min}(p.u)$	0.9131	0.9310	0.9670	0.9479	0.9700
UVDA [27]	DG Placement	-	-	11, 29, 24	30, 15, 12	29, 15, 21
	DG Size (MW)	-	-	2.731	2.243	2.689
	Open Switches	33, 34, 35, 36, 37	7,9,14,32,37	33, 34, 35, 36, 37	7,9,14,32,37	7,10,13,27,32
	Real Power Loss (KW)	202.685	139.55	74.213	66.602	57.287
	% Real Power Loss	-	31.15	63.39	67.14	71.74
	$V_{min}(p.u)$	0.9131	0.9378	0.962	0.9758	0.976
CSA [28]	DG Placement	-	-	14, 24,30	12,16, 29	18, 25, 7
	DG Size (MW)	-	-	3.2545	2.7978	3.2995
	Open Switches	33, 34,35, 36, 37	7,14, 9, 32, 28	33, 34,35, 36, 37	7,14, 9, 32, 28	33, 34, 11, 31, 28
	Real Power Loss (KW)	202.68	139.98	74.26	58.79	53.21
	% Real Power Loss	-	30.93	63.26	71.00	73.75
	$V_{min}(p.u)$	0.9108	0.9413	0.9778	0.9802	0.9806

TABLE IV

COMPARISON OF SIMULATION RESULTS OF 69-BUS SYSTEM

Method	Item	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5
Proposed Method	DG Placement	-	-	10, 23, 61	53, 60, 63	12, 23, 61
	DG Size (MW)	-	-	2.6421	2.53641	2.52211
	Open Switches	69, 70, 71, 72, 73	69, 70, 14, 61, 58	69, 70, 71, 72, 73	69, 70, 14, 61, 58	58, 70, 69, 14, 61
	Real Power Loss (KW)	224.93	99.59	69.98	41.93	36.55
	% Real Power Loss	-	55.72	69.02	81.35	83.75
	$V_{min}(p.u)$	0.96785	0.4273	0.97898	0.971090	0.974249
HSA [26]	DG Placement	-	-	63,64,65	58,60,61	60,61,62
	DG Size (MW)	-	-	1.7732	1.8448	1.8718
	Open Switches	69,70,71,72,73	69, 18,13, 56, 61	69,70,71,72,73	69,18,13,56,61	69,17,13,58,61
	Real Power Loss (KW)	225.00	99.35	86.77	51.30	40.30
	% Real Power Loss	-	55.85	61.43	77.20	82.08
	$V_{min}(p.u)$	0.9092	0.9428	0.9677	0.9619	0.9736
UVDA [27]	DG Placement	-	-	61, 11, 17	61, 11, 64	61, 11, 17
	DG Size (MW)	-	-	2.431	2.72	2.683
	Open Switches	69, 70, 71, 72, 73	14, 58, 61, 69, 70	69, 70, 71, 72, 73	14, 58, 61, 69, 70	14, 58, 63, 69, 70
	Real Power Loss (KW)	225.0	98.58	72.626	37.84	37.11
	% Real Power Loss	-	56.19	67.72	83.18	83.51
	$V_{min}(p.u)$	0.9092	0.9495	0.9688	0.9801	0.9816
CSA [28]	DG Placement	-	-	11, 18, 61	61, 64, 12	11, 65, 61
	DG Size (MW)	-	-	2.9826	2.5606	2.8189
	Open Switches	69, 70, 71, 72 73	69,70, 14, 57, 61	69, 70, 71, 72 73	69,70, 14, 57, 61	69, 70, 14, 58, 61
	Real Power Loss (KW)	224.89	98.56	72.44	37.23	37.02
	% Real Power Loss	-	56.16	67.79	83.45	83.54
	$V_{min}(p.u)$	0.9092	0.9495	0.9890	0.9870	0.9869

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