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A Comprehensive Review of Metaheuristic Methods for the Reconfiguration of Electric Power Distribution Systems and Comparison With a Novel Approach Based on Efficient Genetic Algorithm

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ABSTRACT The distribution system reconfiguration (DSR) is a complex large-scale optimization problem, which is usually formulated with one or more objective functions and should satisfy multiple sets of linear and non-linear constraints. As the exploration of feasible solutions in large and nonconvex search space of DSR is typically hard, it is important to develop efficient algorithms and methods for finding optimal solutions for DSR problem in reasonably short computational times. In traditional DSR, the configuration of distribution network can be changed by opening and closing sectional and tie switches, where active power losses are minimized, while radial network configuration and supply to all connected loads are both preserved. Accordingly, this paper provides a comprehensive review of a number of existing metaheuristic reconfiguration methods and introduces a novel efficient genetic algorithm (efficient GA) for DSR with loss minimization. In order to demonstrate benefits and effectiveness of the proposed efficient GA for DSR, the paper also provides a detailed comparison of results with an improved genetic algorithm (improved GA) for several test systems and real distribution networks. The obtained simulation results clearly show higher accuracy and improved convergence performance of the proposed efficient GA method, compared to the improved GA and other considered reconfiguration methods.

INDEX TERMS Distribution system, efficient genetic algorithm, loss minimization, network reconfiguration.

I. INTRODUCTION

Distribution networks are essential part of the electric power system [1], linking transmission part of the system [2], [3] to each and every end-user or electricity customer [4]. Distribution networks in urban areas are typically constructed as a meshed structure and are usually operated in a suitable radial topology, which can be set or changed by opening normally closed sectional switches and closing normally open tie line switches, which is commonly denoted as distribution system reconfiguration (DSR). Tie line switches interconnect ends of radial feeders and/or provide connections to alternative supply points, while sectionalizing switches provide interconnections for the main sections or branches of each

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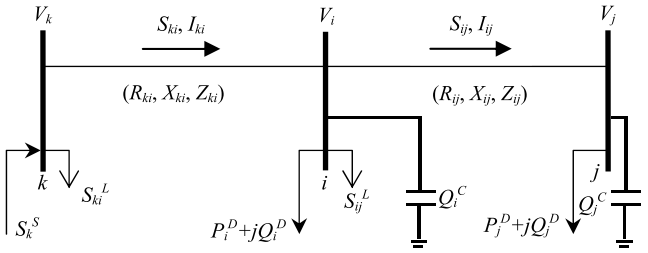

FIGURE 1. General representation of the basic 3-bus network.

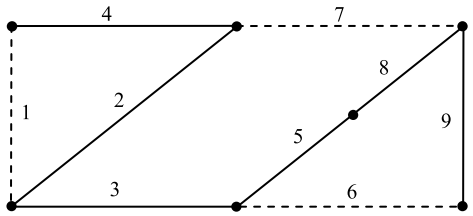

FIGURE 2. Example system.

radial feeder. Both types of switches may be controlled manually, or may be operated automatically, as remotely controlled switches [5]–[7].

Modern power distribution networks feature a number of remotely controlled switches, which are activated to provide emergency supply connections for reliability improvement, or to allow for maintenance and servicing works, or to adjust optimal system configuration during normal operation. In term of both system protection and normal operation, sectionalizing switches along the feeders are automated and can be controlled using dedicated communication links [8], [9].

Historically, the DSR problem was considered for minimizing active power losses during normal operating conditions, as these losses directly affect the operational cost and the system voltage profile and are therefore important for increasing the distribution system efficiency and improving operational performance [10].

The DSR can be approached as a combinatorial optimization problem with one or more objective functions and decision variables, which should satisfy multiple sets of linear and non-linear constraints. The exploration of feasible solutions in a typically large and nonconvex DSR search space for normal operating conditions is hard and finding optimal solutions for the DSR problem is a challenging task, particularly in the case of large networks [11].

Since the DSR was first introduced in [12], classic optimization methods have been used to determine good quality solutions. However, more than five decades of the previous work proved that solving the DSR through classical optimization methods is usually time-consuming, due to the nonconvexity of the search spaces, and indicated further issues when integer decision variables are considered. In order to avoid these limitations of the classic optimization methods, heuristic techniques were employed for the DSR problem. Heuristic methods can often find feasible solutions with much lower computational efforts, but their solutions are usually not

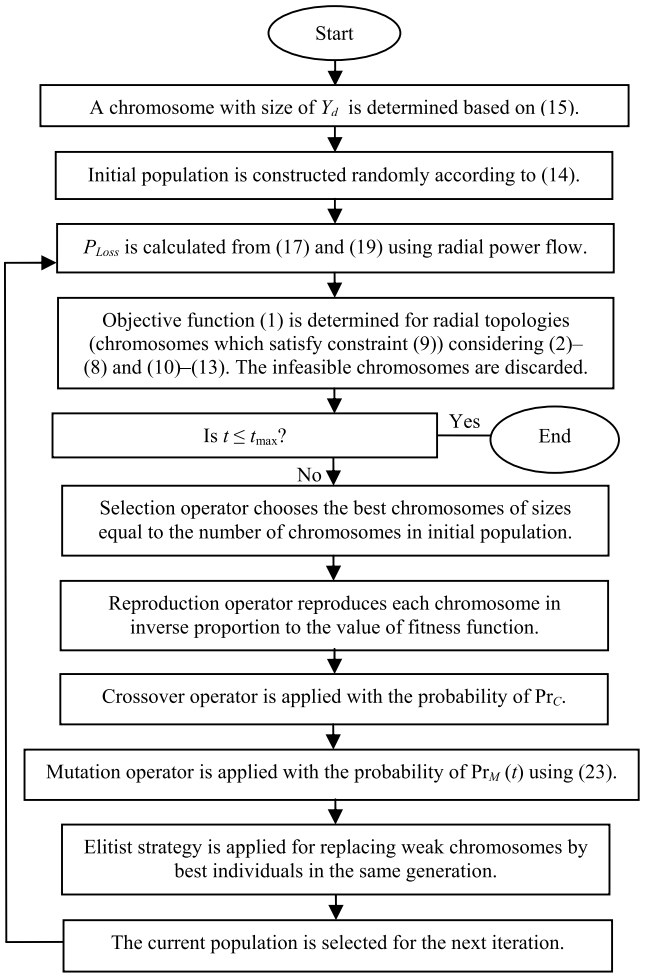

FIGURE 3. Flowchart of the improved GA.

accurate as the classic ones. Later, metaheuristic approaches were proposed to solve the DSR problem. Metaheuristic methods build on the same mechanism of heuristic approaches, but they define and use certain search criteria during the optimization process, typically resulting in better solutions than heuristic approaches and in shorter computational time than classic methods. As the metaheuristic methods are the most commonly used optimization techniques for solving DSR problem, further text provides their review.

In [13], simulated annealing (SA) method was proposed to solve the DSR problem with power loss and load balancing optimization as objective functions. The SA is a robust search algorithm based on a well-developed theory that has been adopted from the physical process of solids annealing. Although the SA can provide an optimal switching strategy for DSR, the repeated runs of power flow calculations during the annealing process make this approach very time-consuming. To reduce the computing time of SA methods, the power flow equations of [13] were replaced by a simplified set of equations in [14], but these modifications reduced the quality of the DSR solutions. To overcome this issue, an efficient SA (ESA) method was developed to minimize the losses through DSR in [15]. This method presents better

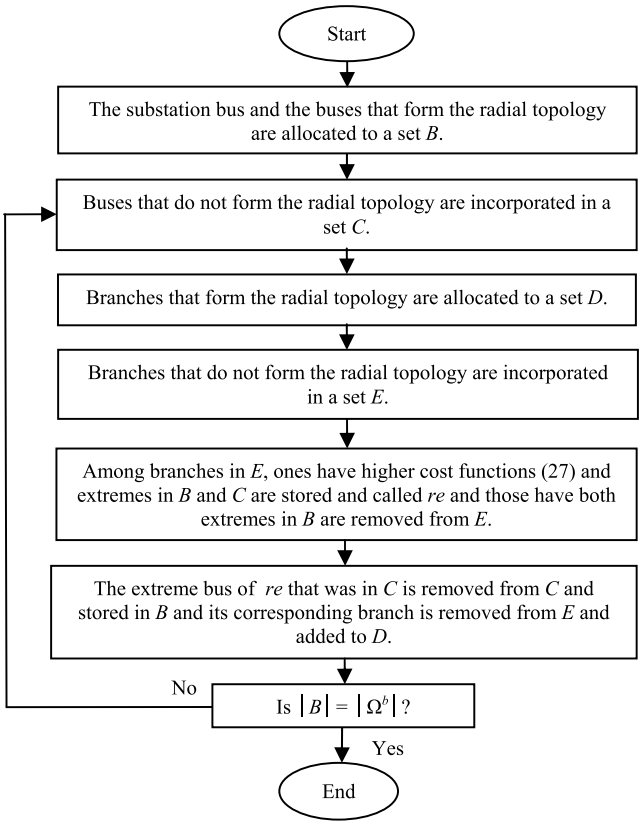

FIGURE 4. Flowchart of the modified prim's algorithm.

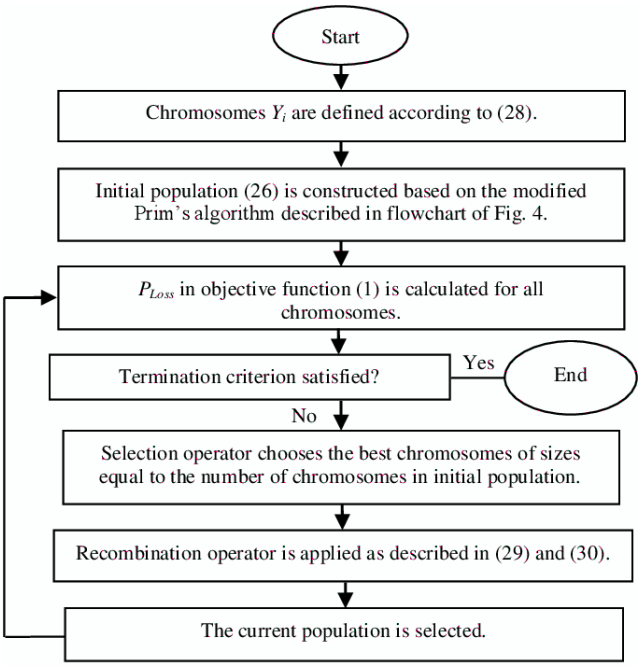

FIGURE 5. Flowchart of the proposed method.

solutions than SA because the algorithm can "escape" local minima, but its implementation on the large-scale distribution networks is difficult.

TABLE 1. Parameters of EGA.

Cases	Parameters	Values
System 1	Maximum number of generations	7
	Size of chromosomes	7
	Maximum value of each gen	7
System 2	Maximum number of generations	7
	Size of chromosomes	12
	Maximum value of each gen	12
System 3	Maximum number of generations	7
	Size of chromosomes	16
	Maximum value of each gen	16
System 4	Maximum number of generations	10
	Size of chromosomes	31
	Maximum value of each gen	31
System 5	Maximum number of generations	10
	Size of chromosomes	34
	Maximum value of each gen	34
System 6	Maximum number of generations	11
	Size of chromosomes	37
	Maximum value of each gen	37
System 7	Maximum number of generations	10
	Size of chromosomes	53
	Maximum value of each gen	53
System 8	Maximum number of generations	10
	Size of chromosomes	63
	Maximum value of each gen	63
System 9	Maximum number of generations	10
	Size of chromosomes	73
	Maximum value of each gen	73
System 10	Maximum number of generations	10
	Size of chromosomes	79
	Maximum value of each gen	79
System 11	Maximum number of generations	15
	Size of chromosomes	96
	Maximum value of each gen	96
System 12	Maximum number of generations	20
	Size of chromosomes	132
	Maximum value of each gen	132
System 13	Maximum number of generations	11
	Size of chromosomes	156
	Maximum value of each gen	156
System 14	Maximum number of generations	11
	Size of chromosomes	216
	Maximum value of each gen	216

In [16], tabu search (TS) algorithm was used to solve the DSR problem in networks with distributed generation (DG). The TS is a random search algorithm that utilizes movements and memory operations. The movement operator is used for "jumping" from one solution to another, while memory operator guides the search to avoid cycling between solutions. The obtained simulation results in [16] confirm better performance of TS algorithm compared to SA from both computational time and solution accuracy points of view. Nevertheless, the global search ability of TS depends on tabu list length: small size tabu lists cause the algorithm to be captured in some of local minima easily, while large size lists increase the processing time of TS method. To resolve this problem, improved and modified TS algorithms were proposed in [17] and [18], respectively. In improved TS (ITS) method [17], mutation operator of genetic algorithm (GA) [19] was used to weaken the dependence of global search ability on tabu list length. In modified

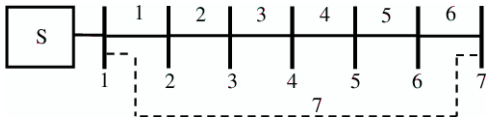

FIGURE 6. The 7-bus test system [73].

TABLE 2. Numerical results of EGA and IGA after 30 independent runs for system 1.

Items	Solutions	Methods	
		EGA	IGA
Best Open Switches		5	5
Losses (kW)	Best	0.82	0.82
	Worst	0.82	0.82
	Mean	0.82	0.82
	Standard deviation	0	0
	Final	0.82±0=**0.82**	0.82±0=**0.82**
Time (s)	Minimum	0.073	0.12
	Maximum	0.117	0.32
	Average	0.08	0.18
	Standard dev. (SD)	0.008	0.06
	Final	0.08±0.008	0.18±0.06

TABLE 3. Final solutions for system 1.

Methods	Open Switches	Losses (kW)	Time (s)
Classic [73]	4	1.2	-
IGA	5	0.82	0.24
EGA	5	0.82	0.088

TS (MTS) method [18], the size of tabu list is set to vary with the system size and a random multiplicative move is used in the searching process to diversify the search toward unexplored regions, to escape local optimums and to prevent cycling around the sub-optimum solutions. The simulation results show that accuracy of ITS and MTS is higher than that of TS and SA methods.

In [20], an evolutionary algorithm (EA) method was presented to minimize active power losses in the DSR problem. The EA method is a random search algorithm using principles of natural selection and recombination, which has simpler implementation than SA and TS. However, its performance is drastically reduced by inadequate tree representation of distribution network graph, resulting in appearance of non-radial solutions (branches that cannot create a tree) during algorithm search.

Therefore, in [21], a differential evolution algorithm (DEA) was proposed for loss minimization in DSR, showing that DEA has lower computational burden than EA. However, EA-based methods highly depend on chose of the operator values and suffer high computational time, stagnation, and premature convergence. In order to overcome these drawbacks, an adaptive quantum inspired EA (adaptive QiEA) was proposed in [22] for power loss minimization through DSR. The QiEA method by integrating some roles of quantum mechanics into EA algorithm, establishes good balance between exploration and exploitation. In standard QiEA, two quantum-bits (qubits) are employed instead of classical bits

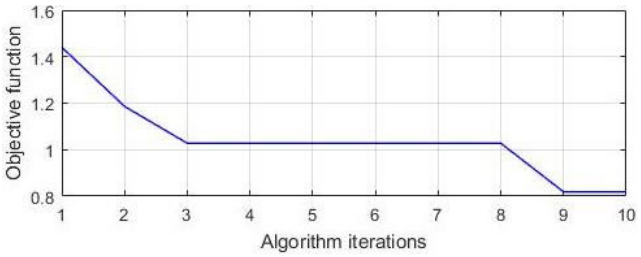

FIGURE 7. Worst convergence plot of IGA for system 1.

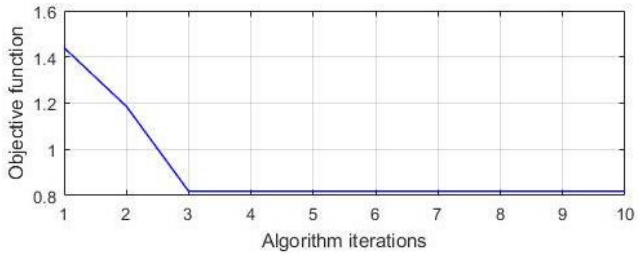

FIGURE 8. Best convergence plot of IGA for system 1.

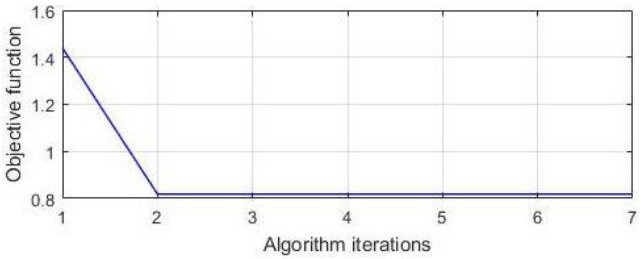

FIGURE 9. Best and worst convergence plot of EGA for system 1.

of EA, in which first qubit includes the decision variables and the second one contains the scaled values of objective function. In adaptive QiEA (AQiEA) method, performance of an operation on one of the qubits does not affect the state of other one. In order to apply EA to solve multi-objective DSR problems, a fuzzy EA (FEA) was developed in [23]. The simulation results confirmed that the FEA is an appropriate method for solving such problems, but its performance is highly affected by fuzzy membership functions. In fuzzy theory, different objectives are embedded in a single function as weighted-sum values using membership functions. However, accurate defining of fuzzy membership functions is not easy in complex optimization problems. For resolving this issue, gray correlation analysis (GCRA) was used in [24] instead of fuzzy theory, where presented results showed better performance of the proposed method compared to FEA.

In [25], a particle swarm optimization (PSO) algorithm [26] was applied to loss reduction in DSR, but this method in its standard form is very time-consuming for large distribution networks. Therefore, a modified PSO (MPSO) was presented in [27], where some parameters of standard PSO methods, such as inertia weight, number of iterations and population size, were modified. The modified settings allow the PSO to explore a larger area at the start of the

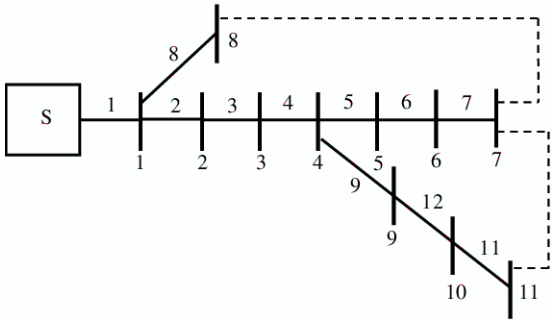

FIGURE 10. Distribution network of AL-mansoor no.11.

TABLE 4. Numerical results of EGA and IGA after 30 independent runs for system 2.

Items	Solutions	Methods	
		EGA	IGA
Best Open Switches		5,11	5,11
Losses (kW)	Best	1.31	1.31
	Worst	1.31	1.31
	Mean	1.31	1.31
	SD	0	0
	Final	1.31+0=**1.31**	1.31+0=**1.31**
Time (s)	Minimum	0.10	0.18
	Maximum	0.12	0.67
	Average	0.106	0.41
	SD	0.006	0.13
	Final	0.106+0.002= **0.108**	0.25+0.13= **0.38**

TABLE 5. Final solutions for system 2.

Methods	Open Switches	Losses (kW)	Time (s)
Classic [74]	12,13	3.5	0.4
IGA	5,11	1.31	0.38
EGA	5,11	1.31	0.108

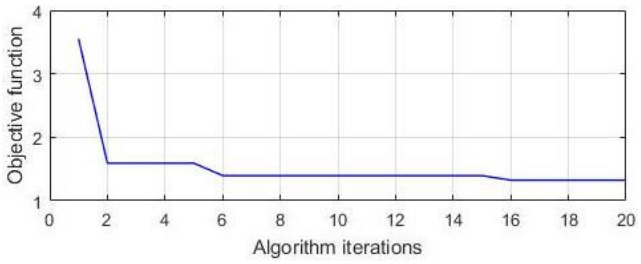

FIGURE 11. Worst convergence plot of IGA for system 2.

simulation and to continue its searching in a smaller area nearer to global optimum. This feature makes the algorithm faster than standard PSO, SA, and TS, but it increases the probability of capturing in the local minima. In order to decrease computational time of PSO method and increase MPSO method accuracy, the enhanced integer coded PSO (EICPSO) was developed for loss minimization in DSR problem in [28]. In the EICPSO method, the modified inertia weight of MPSO was employed and binary numbers (0 for open and 1 for closed switches) were used instead of integer

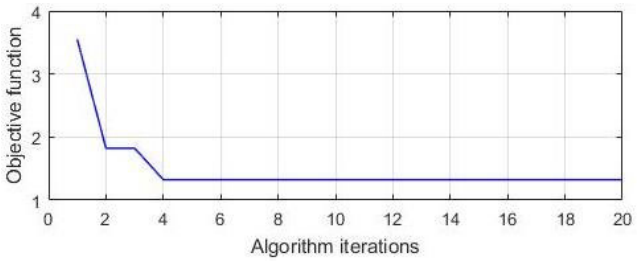

FIGURE 12. Best convergence plot of IGA for system 2.

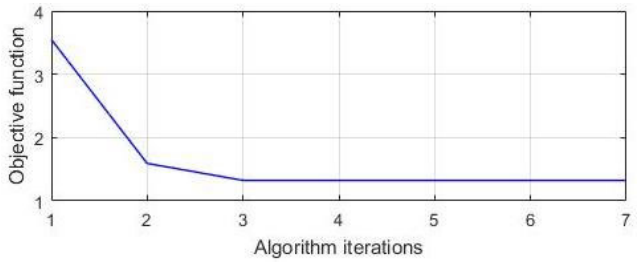

FIGURE 13. Best and worst convergence plot of EGA for system 2.

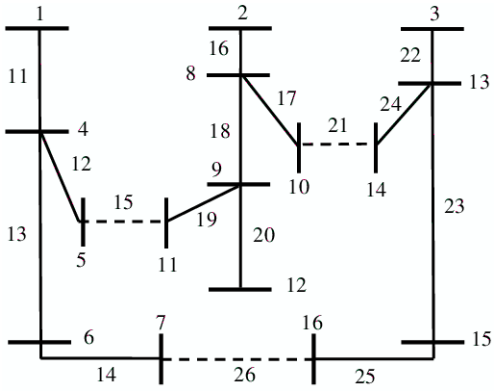

FIGURE 14. The 16-bus test system [66].

values (bus numbers) for the representation of each particle. The presented results show that EICPSO method is much faster than PSO and MPSO, but its accuracy is lower than in the standard PSO methods.

In [29], ant colony optimization (ACO) algorithm was suggested for solving the DSR problem, where presented results show better performance of ACO when compared to SA. Later, in [30], hyper cube ACO (HC-ACO) method was proposed to minimize active power losses through DSR. In this method, two heuristic rules were used to improve ACO performance. The aim of local heuristic rule is to prepare the candidate configurations for successive random selection, whereas the aim of global rule is to maintain some already found successful configurations. Simple implementation and shorter computational time are two important features of HC-ACO algorithm when compared to ACO and SA.

In [31], an adaptive ACO (AACO) method was presented to solve the traditional DSR problem, demonstrating better performance than ACO and ITS methods. The ACO was

TABLE 6. Numerical results of EGA and IGA after 30 independent runs compared to other metaheuristic approaches for system 3.

Items	Solutions	Methods									
		EGA	IGA	SA [14]	SA [29]	GA [29],[67]	ACO [29],[67]	GA [25]	PSO [25]	GMT [49]	SA [67]
Best Open Switches		17,19,26	17,19,26	17,19,26	17,19,26	17,19,26	17,19,26	17,19,26	17,19,26	17,19,26	17,19,26
Losses (kW)	Best	466.1	466.1	466.1	466.1	466.1	466.1	466.1	466.1	466.1	466.1
	Worst	466.1	466.1	483.9	511.4	493.2	483.3	511.43	483.87	-	501.3
	Mean	466.1	466.1	475	482.3	474.8	470.2	483.04	466.3	473	482.3
	SD	0	0	8.9	-	-	-	-	-	9.76	-
	Final	**466.1**	**466.1**	475+8.9 = **483.9**	**482.3**	**474.8**	**470.2**	**483.04**	**466.3**	473+9.76 = **482.76**	**482.3**
Time (s)	Minimum	0.11	0.24	6	-	-	-	-	-	-	-
	Maximum	0.19	1.3	7	-	-	-	-	-	-	-
	Average	0.13	0.57	6.5	2.07	2.32	1.81	2.027	0.16	2.1	2.07
	SD	0.02	0.25	0.5	-	-	-	-	-	-	-
	Final	0.13+0.02 = **0.15**	0.57+0.25 = **0.82**	6.5+0.5 = **7**	**2.07**	**2.32**	**1.81**	**2.027**	**0.16**	**2.1**	**2.07**

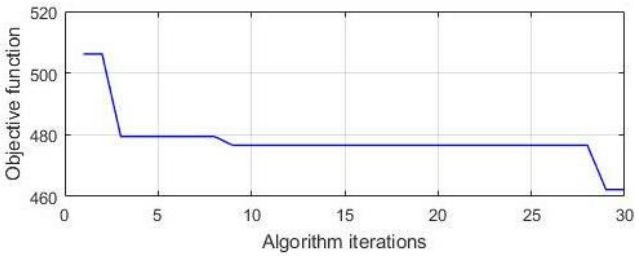

FIGURE 15. Worst convergence plot of IGA for system 3.

adapted by using the graph theory to ensure radial solutions during the optimization. Nevertheless, the performance of ACO algorithm has not been tested on large distribution systems. In [32], a hybrid ACO (HACO) was also applied to minimize power losses in DSR, where crossover operator of GA was used to improve the ACO method. It was shown that efficiency of the proposed method is better than DEA. However, there is no comparison between performance of proposed method and other ACO-based approaches.

In [33], artificial immune system (AIS) method was applied to minimize power losses and loading unbalances in a multi-objective DSR problem. The AIS is a random search method based on an initial population of antibodies containing several antigens, representing positions of open tie line switches. The algorithm guides the antibodies toward the best objective functions using selection, crossover and mutation operators. The best switching scenarios can be obtained through interactions between multi-objective decision maker (DM) and immune algorithm (IA). Although the AIS decreases computing time of the proposed multi-objective problem, its performance has not been evaluated for DSR in large distribution networks. In [34], a method based on AIS and clonal selection (CLONR) was presented to minimize losses through DSR, with the simulation results showing better performance of the proposed method compared to AIS.

In [35], the bacterial foraging optimization algorithm (BFOA) was proposed to minimize power losses in

TABLE 7. Final solutions for system 3.

Methods	Open Switches	Losses (kW)	Time (s)
Heuristic [75]	15,17,26	483.9	-
Heuristic [76]	15,17,26	483.9	-
Heuristic [77]	15,17,26	483.9	-
SA [14]	17,19,26	483.9	7
GA [25]	17,19,26	483.04	2.027
GMT [49]	17,19,26	482.76	2.1
SA [29],[67]	17,19,26	482.3	2.07
GA [29],[67]	17,19,26	474.8	2.32
ACO [29],[67]	17,19,26	470.2	1.81
PSO [25]	17,19,26	466.3	0.16
SA+TS [78]	17,19,26	466.1	-
VSDEA [66]	17,19,26	466.1	-
Heuristic [79]	17,19,26	466.1	-
Heuristic [80]	17,19,26	466.1	-
Heuristic [81]	17,19,26	466.1	-
NrGA [62]	17,19,26	466.1	-
Heuristic [82]	17,19,26	466.1	-
RGA [47]	17,19,26	466.1	-
Classic [83]	17,19,26	466.1	-
Dragonfly [72]	17,19,26	466.1	-
Standard GA [49]	17,19,26	466.1	30
SA [21]	17,19,26	466.1	8.3
DEA [21]	17,19,26	466.1	7.7
SA [63]	17,19,26	466.1	7.5
MTS [18]	17,19,26	466.1	5
ReGA [50]	17,19,26	466.1	1.3
Heuristic [52]	17,19,26	466.1	0.841
IGA	17,19,26	466.1	0.82
FNSGA [61]	17,19,26	466.1	0.27
SOReco [52]	17,19,26	466.1	0.212
Classic [84]	17,19,26	466.1	0.16
EGA	17,19,26	466.1	0.15

DSR. The BFOA is a global optimization algorithm that uses chemotaxis, reproduction, elimination and dispersal operators to guide the particles/bacterium toward the best solution using appropriate fitness function. The simulation results indicate that the BFOA can reduce losses more than ACO, but the computing time of this method has not been compared to other DSR algorithms.

In [36], the harmony search algorithm (HSA) was employed to solve the DSR problem, with results demonstrating that the HSA converged to optimal solution (minimum losses) more quickly than TS. In [37], an improved

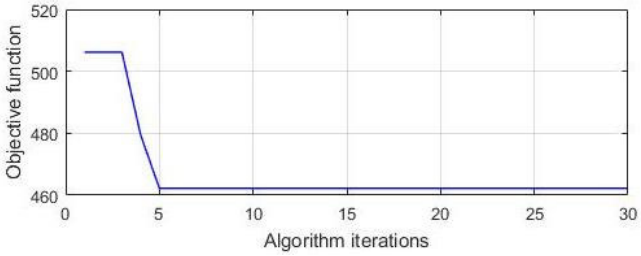

FIGURE 16. Best convergence plot of IGA for system 3.

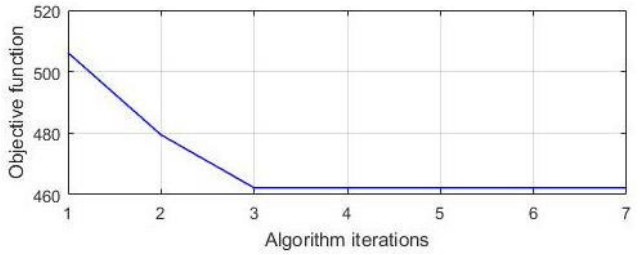

FIGURE 17. Best and worst convergence plot of EGA for system 3.

HSA (IHSA) method was presented to minimize reactive power losses in network reconfiguration. In the proposed approach, reactive power losses are minimized first using branch exchange (BE) method. Afterwards, if the system loadability is near the critical limit, the HSA method is used for further optimization. The presented simulation results confirm that the proposed solution methodology is much faster than HSA. However, in HSA-based methods, determination of the penalty coefficients of fitness function is harder than other metaheuristic algorithms.

In [38], a teaching-learning based optimization (TLBO) algorithm was proposed to solve the DSR problem, showing that this method decreases network power losses and improves network voltage profiles better than PSO. In [39], a big bang-big crunch (BB-BC) algorithm was employed to optimize power losses, DG costs, and greenhouse gas emissions in DSR problem. The BB-BC is a combination of Big Bang (BB) and Big Crunch (BC) methods that converges to optimal solution using center of mass and the best position of each solution operators. The simulation results indicated that the BB-BC minimizes losses better than HSA and ACO.

In [40], a combination of TLBO and epsilon-constraint method [41] was used to solve simultaneous DSR and DG allocation problem, indicating better performance of proposed method compared to PSO. In this approach, all possible solutions were listed and ranked by ε-constraint method and then TLBO employed to find the best solution of the list. In order to reduce the computational time of the multi-objective DSR problems, a chaos disturbed beetle antennae search (CDBAS) algorithm was presented in [42] to minimize power losses, loading unbalances, and nodal voltage deviations. The beetle antennae search (BAS) algorithm was inspired by the foraging principle of beetles. Grey target decision-making technology was used to adopt CDBAS for multi-objective frameworks. The results confirmed better performance of the proposed methodology compared to other reconfiguration methods for multi-objective DSR applications. Also, in [43], a fuzzy modified PSO (FMPSO) based on Kruskal algorithm was employed to solve a multi-objective DSR problem. The Kruskal algorithm can generate a radial topology directly without checking the loops and islands. Later, an improved cuckoo search algorithm (CSA) was presented by [44] to solve a multi-objective DSR problem in presence of demand response (DR). In this method not-so-good solutions are replaced by new and potentially better solutions (cuckoos) in the nests.

Genetic algorithms (GAs) are efficient methods to solve complex non-linear optimization problems [45], mainly because of their simple implementation, flexibility, good performance, and high adaptation with other metaheuristic algorithms (e.g. genetic operators of mutation and crossover have been used in ITS [17] and AACO [31]). GA methods are popular metaheuristic approaches for solving the DSR problem and different types of GAs that have been proposed in existing literature are reviewed in further text.

In [46], standard GA was applied to minimize the power losses in DSR problem, indicating that it is a time-consuming method for reconfiguration of large distribution systems. In order to resolve this problem, the refined GA (RGA) method was proposed in [47]. In this method, the size of standard GA chromosomes is reduced to be equal to the number of tie line switches and a variable mutation is used instead of a fix one [48]. The simulation results show that RGA has better performance than standard GA. In order to create only radial solutions, crossover and mutation operators of standard GA were formulated using matroid and graph theories in [49]. In the GA based on matroid theory (GAMT), radiality of proposed topologies is maintained after applying genetic operators, but some non-radial solutions still appear during algorithm evolutionary process. In order to remove this shortcoming, search space of GA was restricted in [50] by defining fundamental loops for meshed network (when all switches are considered to be closed). However, this approach can check only the isolation of exterior buses and does not search for the isolation of interior ones. Therefore, this strategy does not guarantee connectivity of network and may produce radial topologies with isolated buses, which are effectively infeasible solutions.

In [51], a dedicated GA (DGA) method was used to solve the DSR and capacitor allocation problem, where the initial population was constructed by a heuristic algorithm based on sensitivity analysis. Although the sensitivity analysis significantly reduces the search space of DGA algorithm, it may decrease the accuracy of solutions, because all possible switching sequences are not evaluated.

In order to enhance the performance of GA for solving the DSR problem, new improvements for genetic operators were considered in [52]. In the proposed GA, after producing the initial population using BE method, the integer variables are decoded based on branch list, instead on nodes-branches

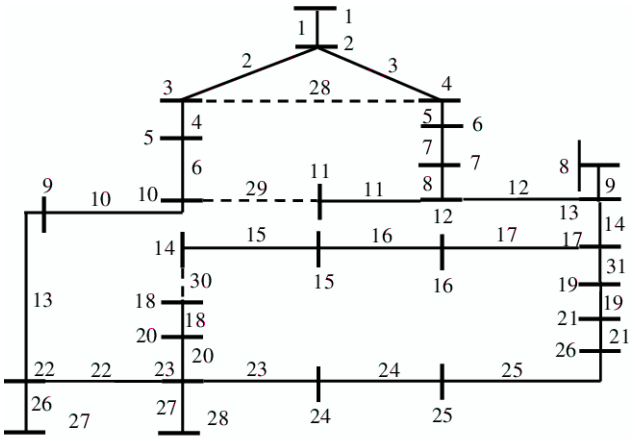

FIGURE 18. Distribution system of koprivnica [85].

TABLE 8. Numerical results of EGA and IGA after 30 independent runs for system 4.

Items	Solutions	Methods	
		EGA	IGA
Best Open Switches		11,20,21,28	11,20,21,28
Losses (kW)	Best	40	40
	Worst	40	40.16
	Mean	40	40.03
	SD	0	0.06
	Final	**40**	40.03+0.06=**40.09**
Time (s)	Minimum	0.38	1.18
	Maximum	1.4	10.89
	Average	0.9	4.59
	SD	0.08	2.66
	Final	0.9+0.08=**0.98**	4.59+2.66=**7.25**

TABLE 9. Final solutions for system 4.

Methods	Open Switches	Losses (kW)	Time (s)
IGA	11,20,21,28	40.09	7.25
Classic [85]	11,20,21,28	40	-
EGA	11,20,21,28	40	0.98

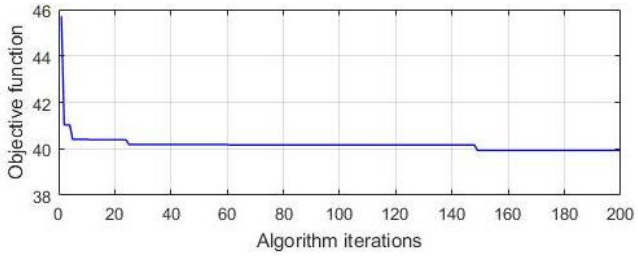

FIGURE 19. Worst convergence plot of IGA for system 4.

incidence matrix. Also, selection operator was defined as an exponential function using ecological niche method, instead of tournament mechanism [53]. It was shown that the proposed GA (SOReco) is simple enough to obtain a fast convergence and complex enough to obtain a good quality solution in comparison with other GAs. However, non-radial topologies may be created after applying genetic operators and

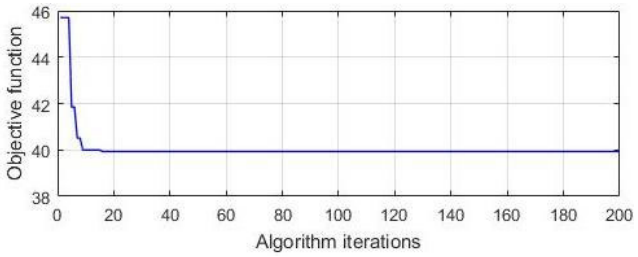

FIGURE 20. Best convergence plot of IGA for system 4.

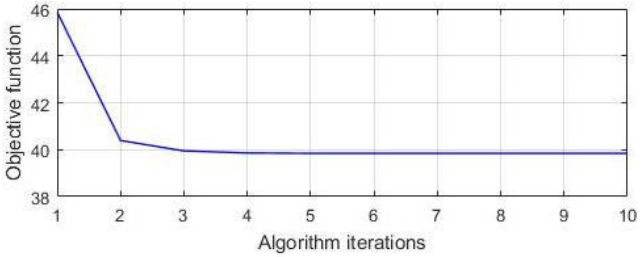

FIGURE 21. Best and worst convergence plot of EGA for system 4.

that will degrade efficiency of the proposed algorithm for reconfiguration of large distribution networks.

In order to increase the GA convergence speed in multi-objective reconfiguration applications, fuzzy logic was employed to control the mutation operator of standard GA method in [54]. In order to enhance the performance of fuzzy GA (FGA) presented in [54], a fuzzy adoptive GA (FAGA) was proposed in [55]. The adoptive GA (AGA) is a modified version of GA presented in [50] that, in addition to fundamental loops, uses common branches of each bus and prohibited group of switches to avoid the generation of any non-radial solutions. The proposed FAGA technique is more efficient than SA and FGA, but performance of fuzzy rules-based methods, such as FGA and FAGA, strongly depends on the selected fuzzy membership functions. Therefore, a non-dominated sorting GA (NSGA) was used in [56] to solve a multi-objective DSR problem. The NSGA is a combination of GA and pareto techniques that enables to evaluate different objectives without integrating them into one objective function. Although the proposed method gives various options to the decision makers, the accuracy of the obtained solutions has not been verified.

Regarding the advantages and disadvantages of above-mentioned GA methods, this paper presents an efficient GA algorithm for reconfiguration of radial distribution systems, which is simple to implement and is characterized by both high accuracy and short computational time. The robustness and effectiveness of the proposed method is tested on different types of distribution systems and directly compared with an improved GA. In contrast to the previous methods that were tested on specific networks, the proposed efficient GA method provides effective reconfiguration solutions for all considered distribution systems.

In addition, this paper aims to provide a good reference for future work on the DSR problem, as it includes a large

TABLE 10. Numerical results of EGA and IGA after 30 independent runs for system 5.

Items	Solutions	Methods	
		EGA	IGA
Best Open Switches		3,5,7,10,25,33	3,5,7,10,25,33
Losses (kW)	Best	361	361
	Worst	361	361
	Mean	361	361
	SD	0	0
	Final	**361**	**361**
Time (s)	Minimum	0.94	1.43
	Maximum	1.12	7.26
	Average	1.02	4.07
	SD	0.04	1.65
	Final	1.02+0.04 = **1.06**	4.13+1.65 = **5.72**

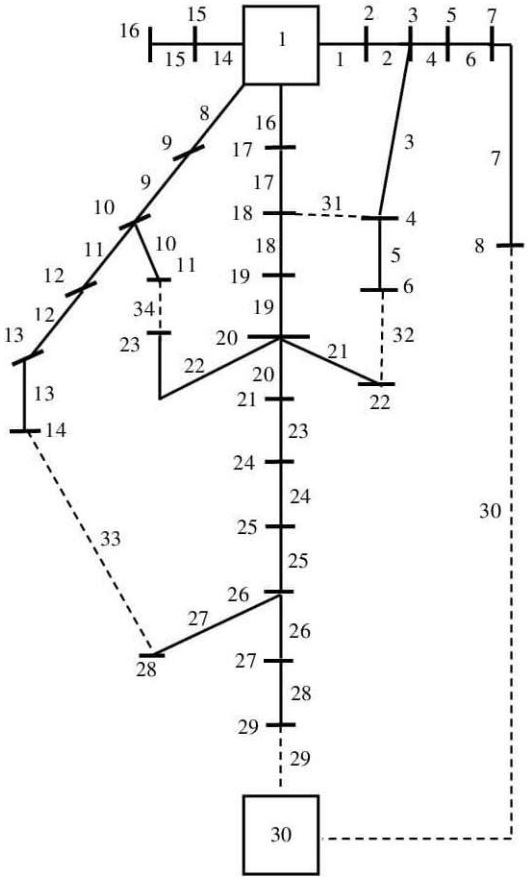

FIGURE 22. The 30-bus test system.

TABLE 11. Final solutions for system 5.

Methods	Open Switches	Losses (kW)	Time (s)
GA [86]	3,7,10,25,32,33	368	-
IGA	3,5,7,10,25,33	361	5.72
EGA	3,5,7,10,25,33	361	1.06

number of different types of test systems in the analysis and compares performance of the proposed method in terms of achieved reduction of losses and execution times with numerous methods in existing literature.

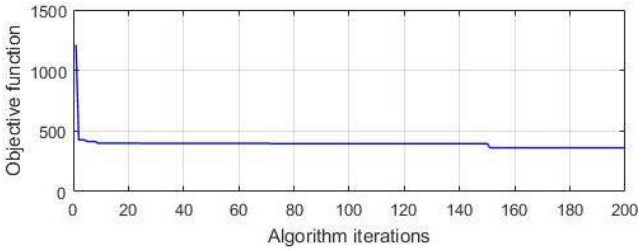

FIGURE 23. Worst convergence plot of IGA for system 5.

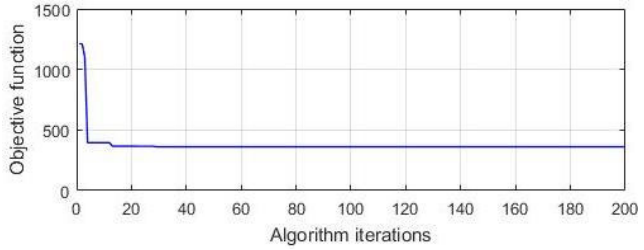

FIGURE 24. Best convergence plot of IGA for system 5.

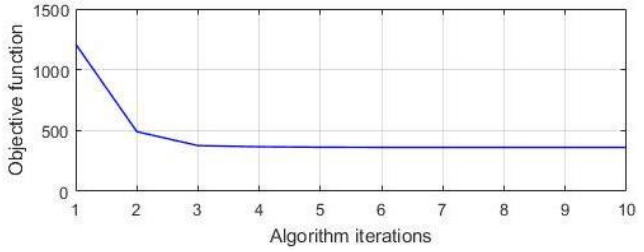

FIGURE 25. Worst and best convergence plot of EGA for system 5.

In summary, the paper presents an efficient GA for reconfiguration of radial distribution systems which is:

- Accurate and simple for implementation in commercial software packages.
- Efficient, as it requires short computing times and has good convergence characteristics.
- Providing only radial solutions during the whole evolutionary process (it guarantees network radiality).
- Prohibiting isolation of any node (interior and exterior buses) from proposed radial topologies (it guarantees network connectivity).
- Applicable for reconfiguration of distribution networks of any size (from small to very large systems).
- Implemented in several test systems, demonstrating superior performance.

II. PROBLEM FORMULATION

The considered DSR problem can be described as the determination of such switch status of branches (open or closed) which will minimize network losses (P_{Loss}) and satisfy stipulated constraints. Assuming the network is represented using pairs of receiving and sending buses, which are connected by branches (i.e., distribution lines and transformers), as shown

TABLE 12. Numerical results of EGA and IGA after 30 independent runs compared to other metaheuristic approaches for system 6.

Items	Solutions	Methods								
		EGA	IGA	GA [36],[46]	RGA [36],[47]	ITS [36]	HSA [36]	EICPSO [28]	MPSO [28]	SA [14]
Best Open Switches		7,9,14, 32, 37	7,9,14, 32, 37	7,9,14, 32,37	7,9,14, 32,37	7,9,14, 36,37	7,10,14, 36,37	7,9,14, 28,32	7,9,14, 28,32	7,9,14, 32,37
Losses (kW)	Best	139.5	139.5	139.5	139.5	142.68	142.68	139.98	139.98	139.5
	Worst	139.5	139.5	202.7	198.4	196.3	195.1	139.98	139.98	153.9
	Mean	139.5	139.5	166.2	164.9	163.5	152.33	139.98	139.98	145.35
	SD	0	0	14.53	13.34	12.11	11.28	0	0	5.27
	Final	**139.5**	**139.5**	**180.73**	**178.3**	**175.61**	**163.61**	**139.98**	**139.98**	**150.62**
Time (s)	Minimum	1	2.5	-	-	-	-	-	-	48
	Maximum	1.2	10.87	-	-	-	-	-	-	57
	Average	1.1	5.09	19.1	13.8	8.1	7.2	6.343	5.693	56.25
	SD	0.04	2.31	-	-	-	-	-	-	5.11
	Final	**1.14**	**7.4**	**19.1**	**13.8**	**8.1**	**7.2**	**6.343**	**5.693**	**61.36**

Items	Solutions	Methods								
		GA+BE [88]	HBMO [71],[88]	PSO [28]	RGA [88],[47]	SA [78],[88]	ACO [88]	MPSO [27]	HSA [88]	TLBO [38]
Best Open Switches		7,9,14, 32, 37	7,9,14, 32,37	7,9,14, 32,37	7,9,14, 32,37	7,9,14, 32,37	7,9,14, 32,37	7,9,14, 32,37	7,9,14, 32,37	7,9,14, 32,37
Losses (kW)	Best	139.5	139.5	139.5	139.5	139.5	139.5	139.5	139.5	139.5
	Worst	139.5	162.98	145.47	171.76	196.3	154.7	143	162.98	141.9
	Mean	139.5	142.16	143.29	149.61	163.5	144.39	141	147.8	139.7
	SD	0	-	-	-	-	-	-	-	-
	Final	**139.5**	**142.16**	**143.29**	**149.61**	**163.5**	**144.39**	**141**	**147.8**	**139.7**
Time (s)	Minimum	-	-	-	-	-	-	-	-	7
	Maximum	-	8	19.78	-	-	-	-	-	8
	Average	10.83	6	6.075	7.41	6.852	6.439	5.693	3.274	13
	SD	-	-	-	-	-	-	-	-	-
	Final	**10.83**	**6**	**6.075**	**7.41**	**6.852**	**6.439**	**5.693**	**3.274**	**8**

in Fig. 1, the DSR problem can be formulated by (1) to (13).

$$\text{Min } P_{Loss} = \sum_{ij\in\omega^l} R_{ij}\left|I_{ij}\right|^2 \tag{1}$$

$$\text{Subject to: } S_k^S = \sum_{ki\in\Omega^l} S_{ki} + \sum_{ki\in\Omega^l} S_{ki}^L \quad \forall k \in \Omega^b \tag{2}$$

$$\sum_{ki\in\Omega^l} S_{ki} = \sum_{ij\in\Omega^l} S_{ij} + \sum_{ij\in\Omega^l} S_{ij}^L + S_i^D \quad \forall i \in \Omega^b \tag{3}$$

$$S_i^D = P_i^D + j\left(Q_i^D - Q_i^C\right) \quad \forall i \in \Omega^b \tag{4}$$

$$S_{ij} = V_j I_{ij}^* \quad \forall i \in \Omega^b,\ \forall ij \in \Omega^l \tag{5}$$

$$Z_{ij} = R_{ij} + jX_{ij} \quad \forall ij \in \Omega^l \tag{6}$$

$$S_{ij}^L = R_{ij}\left|I_{ij}\right|^2 + jX_{ij}\left|I_{ij}\right|^2 \quad \forall ij \in \Omega^l \tag{7}$$

$$V_i = V_j + I_{ij}Z_{ij} + b_{ij} \quad \forall i,j \in \Omega^b,\ \forall ij \in \Omega^l \tag{8}$$

$$rank\ (\mathrm{A}) = \left|\Omega^b\right| - 1 \tag{9}$$

$$V_{\min} \le |V_i| \le V_{\max} \quad \forall i \in \Omega^b \tag{10}$$

$$\left|I_{ij}\right| \le I_{ij}^{\max} y_{ij} \quad \forall ij \in \Omega^l \tag{11}$$

$$\left|b_{ij}\right| \le (V_{\max} - V_{\min})\left(1 - y_{ij}\right) \quad \forall ij \in \Omega^l \tag{12}$$

$$y_{ij} \in \{0,1\} \quad \forall ij \in \Omega^{sw} \tag{13}$$

where: Ω^l, Ω^{sw}, and Ω^b are sets of all branches (all lines and transformers), switches, and buses, respectively. Also, V_i, $|V_i|$, V_{min}, and V_{max} are voltage of bus i, its magnitude, and its minimum and maximum allowed values, respectively. It should be mentioned that *rank* (A) is the number of linearly independent rows or columns of nodes-branches incidence matrix A. Moreover, S_{ij} and S_{ij}^L are complex power and power losses of branch ij, respectively. In addition, S_k^S, P_i^D, Q_i^D, and Q_i^C are complex power of substation, active and reactive demands, and reactive power of capacitor banks at buses k and i, respectively. It should be noted that I_{ij} is current flow of branch ij and I_{ij}^* is its conjugate value. $\left|I_{ij}\right|$ and I_{ij}^{max} are magnitude and maximum allowed current flow on branch ij, respectively. Furthermore, R_{ij}, X_{ij}, and Z_{ij} are resistance, reactance, and impedance of branch ij, respectively. Also, b_{ij} is a variable for representing the Kirchhoff's voltage law (KVL) in the planar loop formed by branch ij. Finally, y_{ij} is a binary variable representing status (based on switch states) of line ij (0 for open and 1 for closed switches).

Equations (2) to (4) show nodal power balance (Kirchhoff's current law, KCL). Equation (5) represents complex power in terms of nodal voltages and conjugate values of branch currents, while (6) shows relationship of impedance with resistance and reactance. Also, (7) shows active and reactive components of power losses. Equation (8) describes that net sum of voltage drops of all branches in a planar loop

TABLE 13. Final solutions for system 6.

Methods	Open Switches	Losses (kW)	Time (s)	Methods	Open Switches	Losses (kW)	Time (s)
GA [36],[46]	7,9,14,32,37	180.73	19.1	HC-ACO [68]	7,9,14,32,37	139.5	-
RGA [36],[47]	7,9,14,32,37	178.3	13.8	BFOA [35]	7,9,14,32,37	139.5	-
ITS [36]	7,9,14, 36,37	175.61	8.1	Heuristic [82]	7,9,14,32,37	139.5	-
HAS [36]	7,10,14, 36,37	163.61	7.2	NrGA [62]	7,9,14,32,37	139.5	-
SA [78],[88]	7,9,14, 32,37	163.5	6.852	CLONR [34]	7,9,14,32,37	139.5	-
SA [14]	7,9,14, 32,37	150.62	61.36	DCGA [93]	7,9,14,32,37	139.5	-
RGA [47]	7,9,14,32,37	149.61	7.41	BB-BC [39]	7,9,14,32,37	139.5	-
Heuristic [87]	11,28,31,33,34	148.858	-	Heuristic [52]	7,9,14,32,37	139.5	1667
HSA [88]	7,9,14,32,37	139.5	3.274	Heuristic [94]	7,9,14,32,37	139.5	647.03
ACO [88]	7,9,14,32,37	144.39	6.439	FEA [23]	7,9,14,32,37	139.5	55.04
GA [22]	7,9,14,28,31	144.181	-	Heuristic [76]	7,9,14,32,37	139.5	48
PSO [22]	7,9,14,27,32	143.296	-	Classic [83]	7,9,14,32,37	139.5	35.2
PSO [28]	7,9,14,32,37	143.29	6.075	Classic [95]	7,9,14,32,37	139.5	19
GSA [22]	7,11,28,32,34	143.138	-	NSGA [56]	7,9,14,32,37	139.5	18
Heuristic [89]	6,9,14,32,37	142.83	-	Classic [96]	7,9,14,32,37	139.5	12.8
Standard GA [49]	7,10,14,36,37	142.68	160	GA+BE [88]	7,9,14,32,37	139.5	10.83
HBMO [71]	7,9,14,32,37	142.16	6	HAS [91]	7,9,14,32,37	139.5	9
MPSO [27]	7,9,14,32,37	141	5.693	PSO+HBMO [97]	7,9,14,32,37	139.5	8
GWO [22]	7,10,14,28,32	140.705	-	IGA	7,9,14,32,37	139.5	7.4
FACO [69]	7,10,14,32,37	140.26	-	GAMT [49]	7,9,14,32,37	139.5	7.2
FGA [59]	9,28,33,34,36	140.6	900	TS [78]	7,9,14,32,37	139.5	7.106
Heuristic [79]	7,10,14,32,37	140.26	1.55	SA+TS [78]	7,9,14,32,37	139.5	6.851
Heuristic [90]	7,10,14,32,37	140.26	0.87	ReGA [50]	7,9,14,32,37	139.5	6.3
GA [91]	9,28,33,34,36	140.6	-	SOReco [52]	7,9,14,32,37	139.5	5.704
ReGA [92]	7,9,14,28,32	139.98	7.05	Heuristic [98]	7,9,14,32,37	139.5	3.7
EICPSO [28]	7,9,14,28,32	139.98	6.343	Classic [99]	7,9,14,32,37	139.5	3.2
MPSO [28]	7,9,14,28,32	139.98	5.693	Heuristic [100]	7,9,14,32,37	139.5	1.99
TLBO [38]	7,9,14,32,37	139.7	8	Heuristic [80]	7,9,14,32,37	139.5	1.66
AQiEA [22]	7,9,14,32,37	139.5	-	EGA	7,9,14,32,37	139.5	1.14
RGA [91]	7,9,14,32,37	139.5	-	-	-	-	-

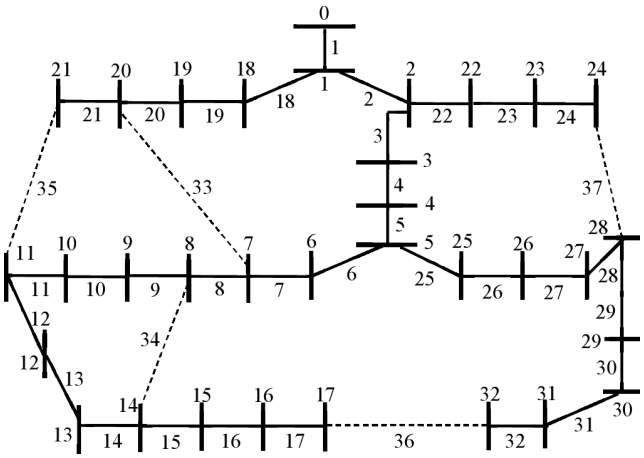

FIGURE 26. The 33-bus test system.

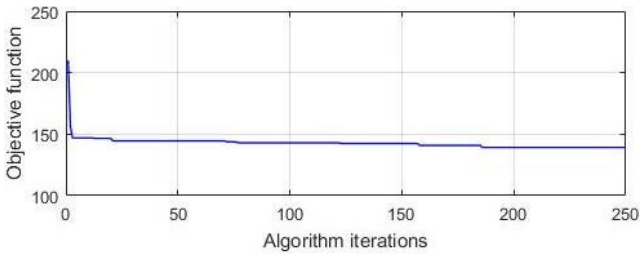

FIGURE 27. Worst convergence plot of IGA for system 6.

has to be equal to zero (KVL). In this equation, b_{ij} will be zero, when switch of line ij is closed (KVL must be established) and will be a real number for open switches (KVL is not necessary). Equation (9) indicates radiality constraint. Accordingly, the total number of branches under operation (total number of linearly independent rows or columns of matrix A) has to be equal to the total number of buses minus one (according to graph theory). Moreover, (10) and (11) show the nodal voltage and branch current magnitude constraints, respectively. While (12) ensures that the value of b_{ij} will be zero, if the switch of branch ij is closed ($y_{ij} = 1$) and a real number between $V_{\max} - V_{\min}$ and $V_{\min} - V_{\max}$, when the corresponding branch is open ($y_{ij} = 0$).

III. SOLUTION METHOD

The proposed mathematical formulation by (1)−(13) is a mixed-integer non-linear programing (MINLP) problem, as it includes integer variables for branch numbers (identifiers), real variables for branch currents (I_{ij}) and bus voltages (V_i), non-linear objective function (1), and linear and non-linear equations (4)–(9) and constraints (2), (3), (10)–(13). The DSR MINLP problem can be solved by different approaches—using analytical methods, heuristic techniques, or metaheuristic algorithms.

Solving proposed MINLP problem by classic analytical methods is time-consuming and requires considerable computational resources, because of a large number of integer variables (branches), nonconvexity of (5) and non-linear

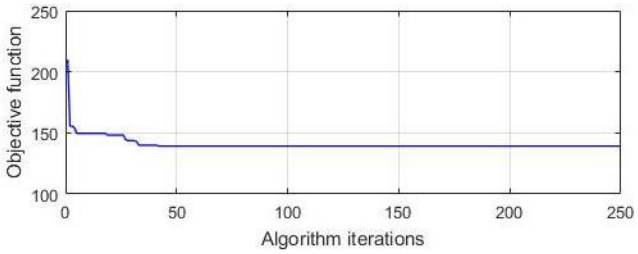

FIGURE 28. Best convergence plot of IGA for system 6.

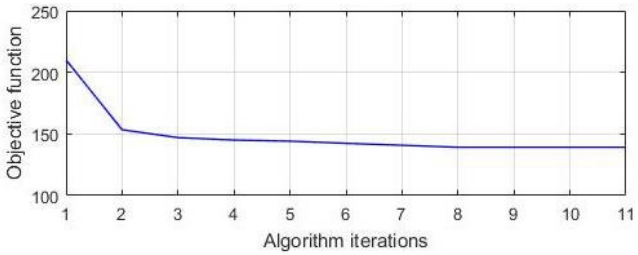

FIGURE 29. Best and worst convergence plot of EGA for system 6.

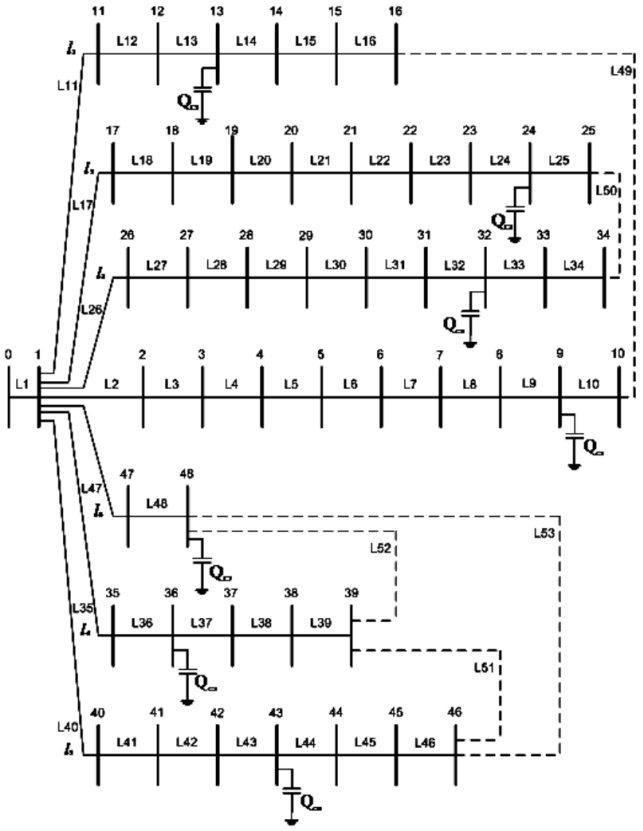

FIGURE 30. Baghdad distribution system [101].

terms in (1), (5), and (7). This also impacts that heuristic methods generally cannot be easily applied and used to provide good solutions for large-scale DSR problems. Metaheuristic methods, however, typically can find better solutions than heuristic approaches and require lower computational efforts than classical methods.

TABLE 14. Numerical results of EGA and IGA after 30 independent runs for system 7.

Items	Solutions	Methods	
		EGA	IGA
Best Open Switches		34,39,45,49,51	34,39,45,49,51
Losses (kW)	Best	8	8
	Worst	8	8
	Mean	8	8
	SD	0	0
	Final	**8**	**8**
Time (s)	Minimum	0.58	1.97
	Maximum	0.76	8.79
	Average	0.66	4.11
	SD	0.05	1.62
	Final	**0.71**	**5.73**

TABLE 15. Final solutions for system 7.

Methods	Open Switches	Losses (kW)	Time (s)
GA [101]	15,34,38,45,52	8.976	-
IGA	34,39,45,49,51	8	5.73
EGA	34,39,45,49,51	8	0.71

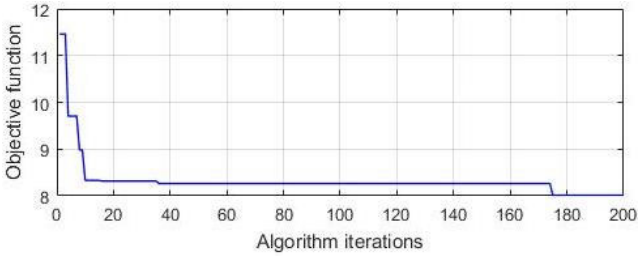

FIGURE 31. Worst convergence plot of IGA for system 7.

In this paper, an efficient GA is employed to solve the considered non-convex and non-linear DSR problem, because of its simple implementation, high efficiency and short computation time compared to other metaheuristic methods. In order to highlight the efficiency of the proposed genetic algorithm and prove the results, an improved GA was applied to the problem in addition to the efficient one.

A. IMPROVED GA (IGA)

Standard genetic algorithm is a random search method that can be used to solve non-linear system of equations and optimize complex problems, including DSR. The basic principle of GA is the selection process of individuals (chromosomes), on which three fundamental genetic operators are applied. The operators are reproduction, crossover and mutation, and they guide the chromosomes toward better fitness. There are two methods for coding the distribution branches based on the GA methods.

1) Binary coding for each branch (standard GA) [46].
2) Decimal coding for each branch (DCGA) [57].

Chromosomes of standard GA are coded by binary numbers 0 and 1, while in the DCGA problem variables are directly inserted in chromosome strings as integer numbers. Although binary coding is conventional in genetic algorithms,

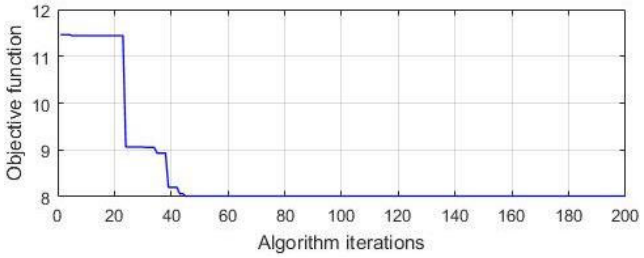

FIGURE 32. Best convergence plot of IGA for system 7.

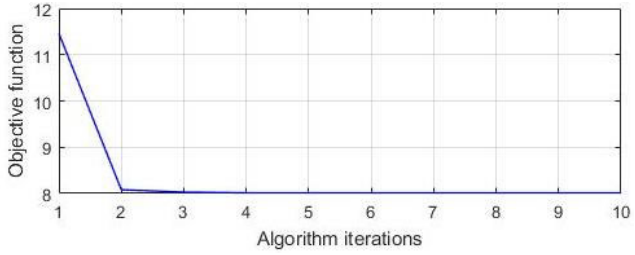

FIGURE 33. Best and worst convergence plot of EGA for system 7.

the DCGA is more efficient than standard GA, as it avoids difficulties with coding and decoding problems and prevents production of completely different offspring from the parents and subsequent divergence.

It should be noted that high similarity between parents and offspring decreases ability of GA to escape from local minimum, while low similarity causes divergence problems. Therefore, the proposed DCGA prevents only creation of very different children, while normal similarity is considered. In this method, an initial population with d chromosomes can be constructed randomly as a column matrix/vector (14):

$$Y = \begin{bmatrix} Y_1 \\ Y_2 \\ \vdots \\ Y_d \end{bmatrix} \tag{14}$$

where: Y_d is the d^{th} chromosome of the population Y. This vector consists of integer numbers, called genes, which describe the problem variables (branch numbers).

$$Y_d = \left[n_1, n_2, \ldots, n_i, \ldots, n_{|\Omega^t|}\right] \tag{15}$$

where: n_i and Ω^t indicate the number of branch i and set of tie line switches (subset of Ω^{sw}), respectively.

Equation (16) describes a typical population with three chromosomes ($d = 3$) for an example system in Fig. 2. This 7-bus example network includes six normal branches (solid lines, each with a sectional switch) and three tie line switches (indicated with dashed lines).

$$\begin{aligned} Y_1 &= [2, 6, 8] \\ Y_2 &= [1, 7, 6] \\ Y_3 &= [1, 6, 8] \end{aligned} \tag{16}$$

TABLE 16. Numerical results of EGA and IGA after 30 independent runs compared to TLBO method for system 8.

Items	Solutions	Methods		
		EGA	IGA	TLBO [38]
Best Open Switches		25,31,39,40, 62	25,31,39,40, 62	25,31,39,40, 62
Losses (kW)	Best	131.69	131.69	131.69
	Worst	131.69	131.69	131.69
	Mean	131.69	131.69	131.69
	SD	0	0	0
	Final	**131.69**	**131.69**	**131.69**
Time (s)	Minimum	1.7	2.85	7
	Maximum	2.3	14.13	20
	Average	1.96	5.98	14
	SD	0.14	2.7	-
	Final	**2.1**	**8.68**	**14**

TABLE 17. Final solutions for system 8.

Methods	Open Switches	Losses (kW)	Time (s)
TLBO [38]	25,31,39,40,62	131.69	14
IGA	25,31,39,40,62	131.69	8.68
EGA	25,31,39,40,62	131.69	2.1

Y_1 proposes that switches 2 (normal branch), 6 (tie line), and 8 (normal branch) have to be open and others (switches 1, 3, 4, 5, 7, and 9) should be closed.

The branch currents and nodal voltage magnitudes ($|I_{ij}|$ and $|V_i|$) of radial topologies (chromosomes which satisfy radiality constraint (9)) are computed by backward- forward sweep load flow (radial power flow). Using radial power flow in metaheuristic algorithms is a common way in reconfiguration studies, because of its simplicity and shorter computational time, compared to conventional power flow methods [22]. In the proposed power flow, load currents are computed iteratively with the updated voltages of each bus, while currents summation is calculated in the backward way and voltage drops are determined by the forward sweep from far end to sending end of a radial feeder/lateral. The maximum difference of voltage magnitudes in successive iterations of power flow program is taken as convergence criteria and Δ is considered as tolerance value. According to Fig. 1, the following set of iterative equations can be employed to calculate nodal voltages and branch currents.

$$I_{ij} = \left(\frac{S_j^D}{V_j}\right)^* = \left(\frac{P_j^D + j(Q_j^D - Q_j^C)}{V_j}\right)^* \quad \begin{matrix} \forall ij \in \Omega^l \\ \forall j \in \Omega^b \end{matrix} \tag{17}$$

$$V_j = V_i - Z_{ij} I_{ij} \quad \forall i, j \in \Omega^b,\ ij \in \Omega^l \tag{18}$$

$$I_{ki} = I_{ij} + \left(\frac{P_i^D + j(Q_i^D - Q_i^C)}{V_i}\right)^* \quad \forall ij,\ ki \in \Omega^l \tag{19}$$

$$V_i = V_k - Z_{ki} I_{ki} \quad \forall i, k \in \Omega^b,\ ki \in \Omega^l \tag{20}$$

Then, active power losses (P_{Loss}) of all branches are calculated, and consequently objective function (1) is determined for feasible chromosomes (radial topologies).

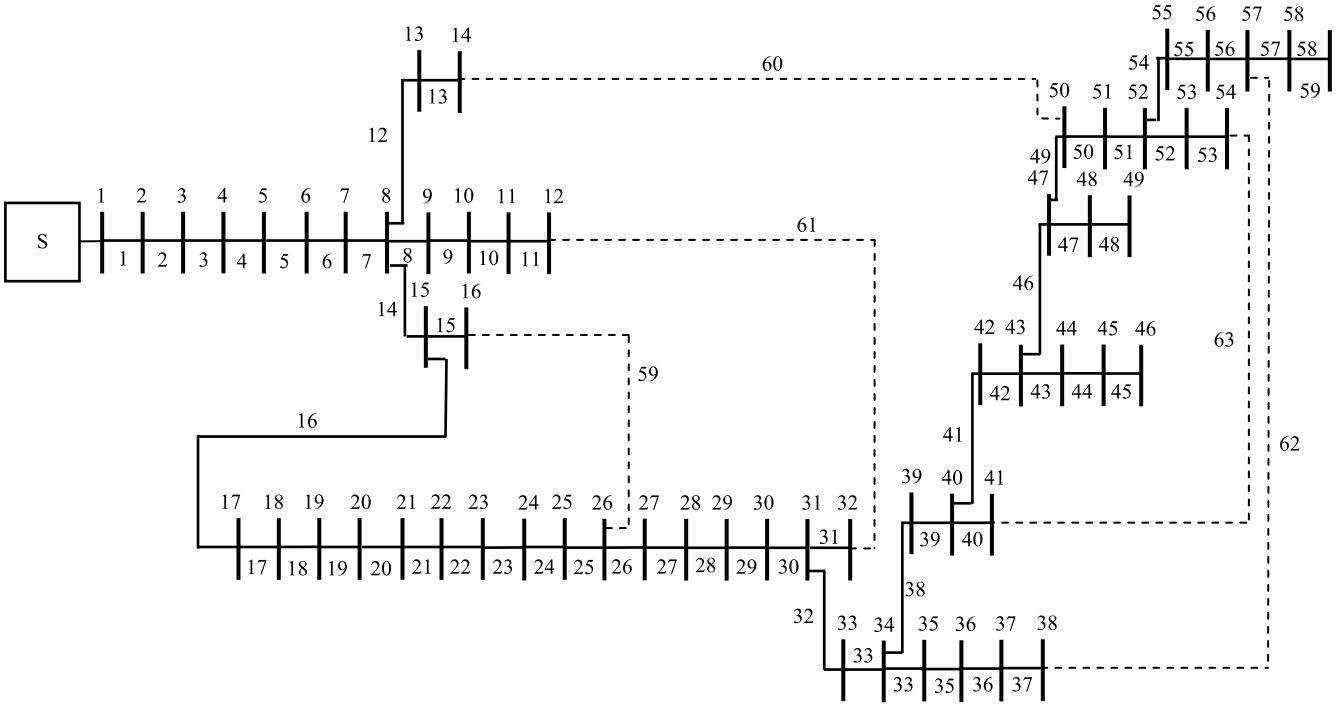

FIGURE 34. The 59-bus distribution system [38].

TABLE 18. Numerical results of EGA and IGA after 30 independent runs compared to other metaheuristic approaches for system 9.

Items	Solutions	Methods							
		EGA	IGA	TLBO [38]	SA [14]	MPSO [27]	SAPSO [64]	SFLA [64]	SAPSO+SFLA [64]
Best Open Switches		14,58,61, 69,70	14,55,61, 69,70	14,57,61, 69,70	14,55,61, 69,70	14,55,61, 69,70	14,58,61, 69,70	14,58,61, 69,70	14,58,61, 69,70
Losses (kW)	Best	99.62	99.62	99.62	99.62	99.62	99.62	99.62	99.62
	Worst	99.62	99.62	100.8	134.06	130	115.9	106.63	99.62
	Mean	99.62	99.62	99.8	118.89	100	102.39	101.95	99.62
	SD	0	0	0	14.35	-	1.99	1.19	0
	Final	**99.62**	**99.62**	**99.8**	**133.24**	**100**	**104.38**	**103.14**	**99.62**
Time (s)	Minimum	2.19	7.16	4	165	-	-	-	-
	Maximum	3.2	27.33	20	175	-	-	-	-
	Average	2.76	16.33	13	170.33	8	10	4	5
	SD	0.23	6.074	0	4.1	-	-	-	-
	Final	**2.99**	**22.404**	**13**	**174.43**	**8**	**10**	**4**	**5**

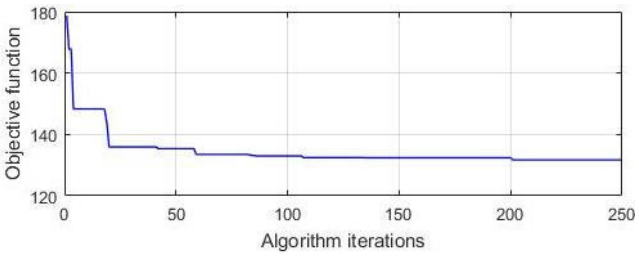

FIGURE 35. Worst convergence plot of IGA for system 8.

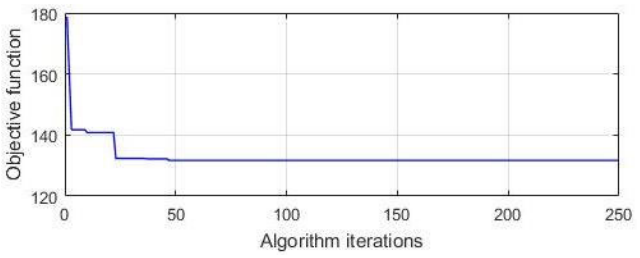

FIGURE 36. Best convergence plot of IGA for system 8.

Afterward, the reproduction operator selects the chromosomes (Y_d) in the population that are more fit for reproduction, so for minimization problem, chromosomes are reproduced in inverse proportion to the value of their fitness function. After the pairs of parent chromosomes have been selected, the crossover operator is applied to each pair, so crossover can take place at the boundary of two integer numbers (between two variables). Based on a predefined probability, known as the crossover probability (Pr_C), an even number of chromosomes are chosen at random. Random

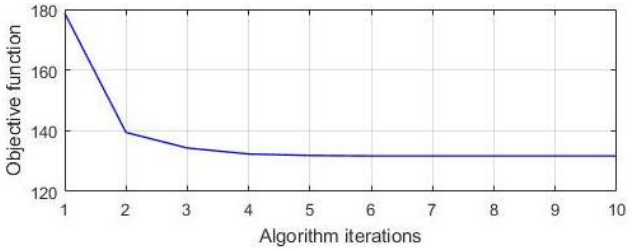

FIGURE 37. Worst and best convergence plot of EGA for system 8.

TABLE 19. Final solutions for system 9.

Methods	Open Switches	Losses (kW)	Time (s)
SA [14]	14,55,61,69,70	133.24	174.43
NSGA [56]	14,23,51,60,72	136.87	37
FGA [60]	12,20,58,64,69	113.8	3.19
GA [60]	12,20,58,64,69	113.8	25
HAS [91]	13,18,61,56,69	106.18	-
SAPSO [64]	14,58,61,69,70	104.38	10
GA [91]	14,53,61,69,70	103.29	-
SFLA [64]	14,58,61,69,70	103.14	4
RGA [91]	13,17,55,61,69	100.28	-
MPSO [27]	14,55,61,69,70	100	8
FACO [69]	12,57,61,69,70	99.82	-
TLBO [38]	14,57,61,69,70	99.8	-
Heuristic [82]	14,59,62,70,71	99.72	-
Heuristic [102]	15,56,62,70,71	99.70	-
Heuristic [82]	15,59,62,70,71	99.62	-
Heuristic [103]	14,58,61,69,70	99.62	-
Heuristic [104]	14,55,61,69,70	99.62	-
Heuristic [105]	14,58,61,69,70	99.62	-
NrGA [62]	14,57,61,69,70	99.62	-
Dragonfly [72]	14,57,61,69,70	99.62	-
DCGA [93]	14,58,61,69,70	99.62	1181
MTS [18]	14,55,61,69,70	99.62	150
IGA	14,55,61,69,70	99.62	22.404
NSGA [61]	14,57,61,69,70	99.62	20.2
ReGA [92]	14,58,61,69,70	99.62	10.33
SAPSO+SFLA [64]	14,58,61,69,70	99.62	5
EGA	14,58,61,69,70	99.62	2.99

positions are chosen for each pair of the selected chromosomes, and then chromosomes of each pair swap their genes (variables). In this paper, the crossover is used with a probability of 0.7 ($\Pr_C = 0.7$) for all study cases and test systems, because of its good impacts on solutions. Equations (21) and (22) show a pair of the selected chromosomes, Y_1 and Y_2, before and after applying the multi-position crossover operator, respectively. In (21), the crossover is applied to two positions between integer variables. A single-position crossover can be employed, but its efficiency is less than multiple-crossover operator in large-scale DSR problems.

$$\begin{aligned} Y_1 &= [2,6,8] \\ &\quad\updownarrow\updownarrow \\ Y_2 &= [1,7,6] \end{aligned} \tag{21}$$

$$\begin{aligned} Y_1' &= [2,7,6] \\ Y_2' &= [1,6,8] \end{aligned} \tag{22}$$

Each chromosome after the crossover operation is then subjected to the mutation operator. This operator selects a few existing integer numbers (variables) in the chromosome and then changes their values at random, according to a small mutation probability ($\Pr_M$). In order to improve the convergence speed and accuracy of DCGA method, mutation operator is applied with a variable probability of $\Pr_M(t)$, instead of a constant value of $\Pr_M$:

$$\Pr_M(t) = \Pr_M^0 - \frac{\left(\Pr_M^0 - \Pr_M^{\max}\right)}{t_{\max} t} \tag{23}$$

where: t and t_{max} are current iteration number and maximum number of iterations in GA algorithm, respectively, with $\Pr_M(t)$ variable mutation probability at iteration t. $\Pr_M^0$ and $\Pr_M^{\max}$ are initial and maximum values of $Pr_M(t)$, respectively. In this study, initial and maximum probabilities of mutation were set to 0.1 and 0.2 for all case studies, respectively, because of its good results. In this way, mutation is starting to be implemented on chromosomes of initial population at the end of the first iteration ($t = 1$) and this procedure continuing in other iterations (i.e. mutation operator is applied to chromosomes at the end of each iteration). Equations (24) and (25) illustrate Y_2' before and after mutation of two genes, respectively. At least one gene has to be mutated depending on the selected strategy.

$$Y_2' = [1, 6, 8] \tag{24}$$

$$\hat{Y}_2 = \left[\overbrace{4}^{1}, 6, \overbrace{5}^{8}\right] \tag{25}$$

In the final step of forming a new generation, ''weak chromosomes'' are replaced by ''elite chromosomes'' in the same generation (elitist strategy). After replacement, the production of the new generation is complete, and the process can begin all over again with the evaluation of objective function (1) for each chromosome. The process continues and it is terminated when algorithm reaches the maximum number of iterations (t_{max}). The flowchart of the GA method improved by using variable mutation probability of (23) and elitist strategy is shown in Fig. 3.

Equation (23) effectively increases both convergence speed and accuracy of DCGA algorithm in improved GA (IGA).

B. EFFICIENT GA (EGA)

In order to improve both accuracy and convergence speed of IGA method, an efficient GA (EGA) is proposed for solving the DSR problem. The EGA implemented in this section has significantly different characteristics when compared to the traditional GAs and is particularly suitable for solving large-scale multi-constraint DSR problems, in which several unfeasible solutions (non-radial topologies) may be generated.

In the first step ($t = 1$), an initial population with d feasible chromosomes (radial topologies) is constructed randomly as (26), in which constraint (9) is satisfied.

$$Y = \begin{bmatrix} Y_1 \\ \vdots \\ Y_i \\ \vdots \\ Y_d \end{bmatrix} \tag{26}$$

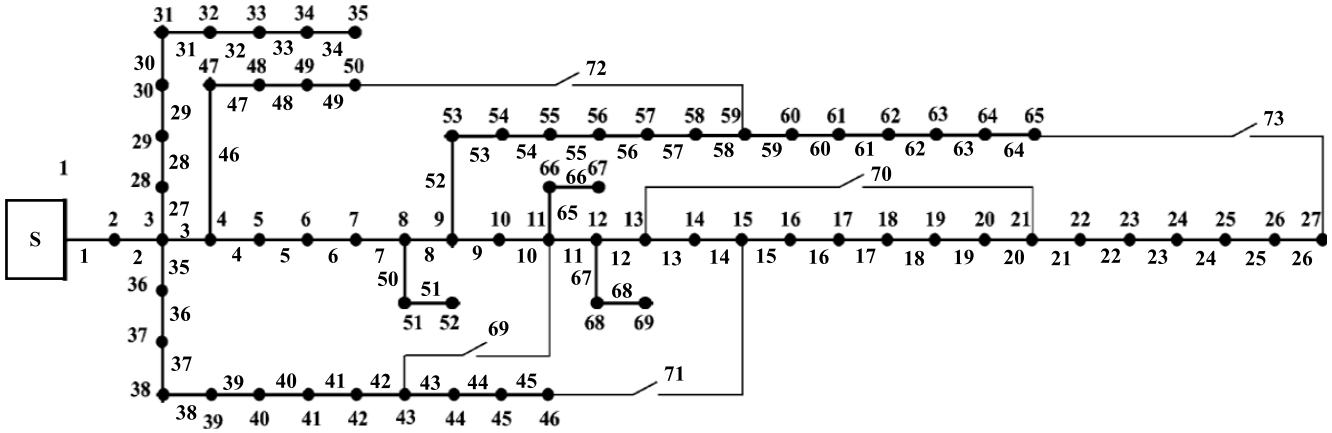

FIGURE 38. The 69-bus test system.

TABLE 20. Numerical results of EGA and IGA after 30 independent runs compared to other metaheuristic approaches for system 10.

Items	Solutions	Methods									
		EGA	IGA	Hybrid PSO (HPSO) [65]	Modified SFLA (MSLFA) [107]	SAPSO [107]	SAPSO+ MSLFA [107]	PSO [108]	HBMO [108]	PSO+ HBMO [108]	AACO [31]
Best Open Switches		13,30,45, 51,66,70, 75–79	13,30,45, 51,66,70, 75–79	14,28,39, 46,51,67, 70,71,73, 76,79	30,46,51, 66,70,71, 75–79	30,46,51, 66,70,71, 75–79	30,46,51, 66,70,71, 75–79	14,28,39, 46,51,67, 70,71,73, 76,79	14,28,39, 46,51,67, 70,71,73, 76,79	14,28,39, 46, 51,67, 70,71,73, 76,79	13,30,45, 51,66,70, 75–79
Losses (kW)	Best	201.36	201.36	205.32	202.18	202.18	202.18	205.32	205.32	205.32	201.36
	Worst	201.36	205.42	206.81	207.07	209.04	205.05	213.83	212.19	205.32	206.98
	Mean	201.36	203.14	205.68	203.84	204.47	202.27	210.66	207.68	205.32	205.7
	SD	0	1.28	0.003	-	-	-	4.03	3.02	0	0.5
	Final	**201.36**	**204.42**	**205.683**	**203.84**	**204.47**	**202.27**	**214.69**	**210.7**	**205.32**	**206.2**
Time (s)	Minimum	2.68	13.17	-	-	-	-	-	-	8	-
	Maximum	3.63	307.67	-	-	-	-	-	-	-	-
	Average	3.14	118.82	5	-	-	-	15	18	12	19.72
	SD	0.24	76.82	-	-	-	-	-	-	-	-
	Final	**3.38**	**195.64**	**5**	**-**	**-**	**-**	**15**	**18**	**12**	**19.72**

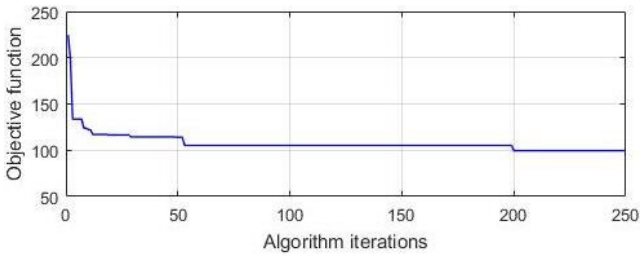

FIGURE 39. Worst convergence plot of EGA for system 9.

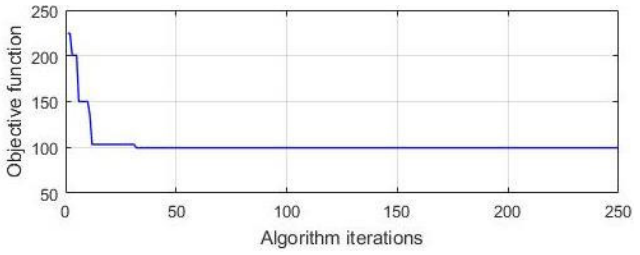

FIGURE 40. Best convergence plot of IGA for system 9.

The representation form (coding) of each chromosome (solution proposal) of initial population ((26)) is very important. This coding should allow for evaluating only feasible solutions (radial topologies), in which the implementation of genetic operators depends on this representation. Including only open switches and the identification of their independent loops in chromosomes is the best method for representation of solution proposals. This form of representation ensures that only radial topologies are generated.

A Prim's algorithm [58] is adopted to form initial population. In this method, the optimal solution can be found because of generation of minimum spanning tree of the graph. The proposed modified Prim's algorithm can generate randomly controlled radial topologies in each iteration without power flow calculations. Furthermore, this algorithm can find radial configurations where higher weighting values are chosen for the most important branches.

In the adopted algorithm, the minimization of active power losses in objective function (1) is converted to the

TABLE 21. Final solutions for system 10.

Methods	Open Switches	Losses (kW)	Time (s)
PSO [108]	14,28,39, 46,51,67,70,71,73, 76,79	214.69	15
HBMO [108]	14,28,39, 46,51,67,70,71,73, 76,79	210.7	18
AACO [31]	13,30,45,51,66,70,75–79	206.2	19.72
HPSO [65]	14,28,39,46,51,67,70,71,73, 76,79	205.68 3	5
PSO+HBMO [108]	14,28,39, 46,51,67,70,71,73, 76,79	205.32	12
Heuristic [106]	14,28,39,46,51,67,70,71,73, 76,79	205.32	3
SAPSO [107]	30,46,51,66,70,71, 75–79	204.47	-
IGA	13,30, 45,51,66,70,75–79	204.42	195.64
MSLFA [107]	30,46,51,66,70,71, 75–79	203.84	-
Heuristic [52]	13,28,45,51,67,70,73,75,76, 78,79	203.67	7633
SOReco [52]	13,28,45,51,67,70,73,75,76, 78,79	203.67	4.64
GAMT [49]	14,30,38,46,51,66,70,71,76, 77,79	203.17	160
SAPSO+ MSLFA [107]	30,46,51,66,70,71, 75–79	202.27	-
Classic [83]	14,30,45,51,66,70,75–79	201.44	485
Standard GA [49]	13,30,45,51,66,70,75–79	201.36	1900
EGA	13,30, 45,51,66,70,75–79	201.36	3.38

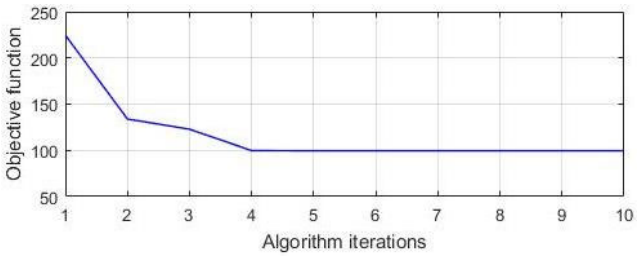

FIGURE 41. Best and worst convergence plot of EGA for system 9.

maximization of cost function J.

$$Max\ J = \sum_{ij \in \Omega^l} \frac{c_{ij}}{P_{Loss_{ij}}} \tag{27}$$

where: c_{ij} is the value (weight) of branch ij and $P_{Loss_{ij}}$ is active power loss of the same branch. This method and its steps are illustrated in a flowchart in Fig. 4.

A typical chromosome (Y_i) for example system of Fig. 2 is illustrated in (28). The chromosome consists of two parts. First part ($|\Omega^{sw}| - |\Omega^t|$) includes normal branches (normally closed switches) of the network and second part ($|\Omega^t|$) consists of tie lines (normally open switches).

$$Y_i = \left[\overbrace{2, 4, 3, 5, 8, 9}^{|\Omega^{sw}|-|\Omega^t|}, \overbrace{1, 7, 6}^{|\Omega^t|} \right] \tag{28}$$

The branch current and nodal voltage magnitude of all chromosomes, as well as P_{Loss} are calculated by the radial power flow using the set of equations (17)–(20). Then, the selection operator selects the chromosomes (Y_i) for

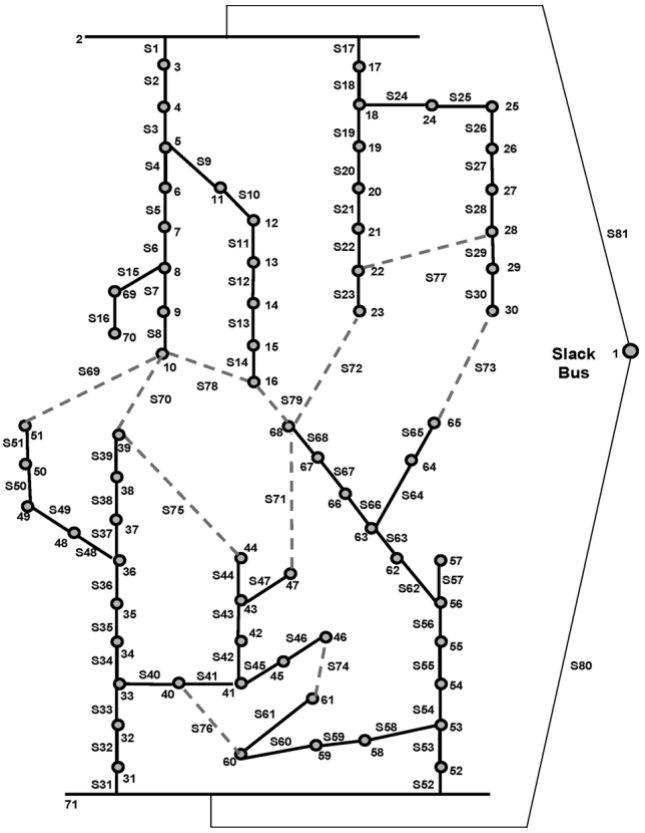

FIGURE 42. The 70-bus test system [49].

recombination. In the recombination process, two new radial topologies ((30)) are generated from each pair of existing ones ((29)). First, recombination position is selected in the first parts of Y_1 and Y_2 between points ($|\Omega^{sw}| - |\Omega^t|)/2$) and ($|\Omega^{sw}| - |\Omega^t| - 1$).

$$\begin{aligned} Y_1 &= \left[\overbrace{2,4,3,5,\underbrace{8,9}}^{\text{Part 1}}, \overbrace{1,\underbrace{7,6}}^{\text{Part 2}} \right] \\ Y_2 &= \left[\underbrace{1,3,4,5,\underbrace{7,9}}_{\text{Part 1}}, \underbrace{2,\underbrace{6,8}}_{\text{Part 2}} \right] \end{aligned} \tag{29}$$

$$Y_1' = [2,4,3,5,7,9,1,6,8]$$

$$Y_2' = [1,3,4,5,8,9,2,7,6] \tag{30}$$

In the offspring chromosomes (Y_1' and Y_2'), genes (branches) that form a loop are allocated to the second part and those that do not form a loop are incorporated in the first part. In this way, only radial offspring chromosomes are constructed.

For example, in (29), the recombination point was chosen between 4th and 5th gene. Thus, the branches 2, 4, 3, and 5 are copied directly into Y_1' and then elements of Y_2 are evaluated. Therefore, branch 1 is added to Part 2 of Y_1' and branches 3, 4, and 5 are discarded because they already have been in the first part of Y_1'. In this way, branches 7 and 9 are allocated to Part 1 of Y_1', because they do not contain a loop. Then,

TABLE 22. Numerical results of EGA and IGA after 30 independent runs compared to other metaheuristic approaches for system 11.

Items	Solutions	Methods								
		EGA	IGA	GA+BE [88]	GA [88]	RGA [88]	HSA [88]	HBMO [88]	SA [88]	GA [29]
Best Open Switches		7,13,34, 39,42,55, 62,72,83, 86, 89,90, 92	7,13,34, 39,42,55, 62,72,83, 86,89,90, 92	7,13,34, 39,42,55, 62,72,83, 86,89,90, 92	7,13,34, 39,63,72 ,83,84,86, 89,90,92, 95	7,13,34, 39,42,63, 72, 83,84, 86,89,90, 92	7,13,34, 39,42,55, 62,72,83, 86,89,90, 92	7,13,34, 39,42,55, 62,72,83, 86,89,90, 92	7,13,34, 39,42,62, 72,83,84, 86,89,90, 92	7,13,34,39 ,41,55,62, 72,83,86,8 9,90,92
Losses (kW)	Best	469.88	469.88	469.88	470.21	470.08	469.88	469.88	470.51	471.1
	Worst	469.88	469.88	471.28	498.72	492.57	484.37	474.14	514.28	489.25
	Mean	469.88	469.88	470.19	481.66	478.18	475.13	471.69	486.13	479.73
	SD	0	0	-	-	-	-	-	-	-
	Final	**469.88**	**469.88**	**470.19**	**481.66**	**478.18**	**475.13**	471.69	**486.13**	**479.73**
Time (s)	Minimum	6.3	42.19	-	-	-	-	-	-	-
	Maximum	8	209.95	-	-	-	-	-	-	-
	Average	7.1	112.51	37.98	30.52	27.41	9.87	17.1	22.06	303.7
	SD	0.4	45.38	-	-	-	-	-	-	-
	Final	**7.5**	**157.89**	**37.98**	**30.52**	**27.41**	**9.87**	**17.1**	**22.06**	**303.7**

Items	Solutions	Methods								
		ACO [88]	AACO [31]	MSLFA [107]	SAPSO+ MSLFA [64],[107]	SLFA [64]	SA [67]	GA [67]	ACO [67]	ACO [29]
Best Open Switches		7,13,34, 39,42,55, 62,72,83, 86,89,90, 92	7,13,34, 39,42,55, 62,72,83, 86,89,90, 92	7,14,34, 39,42,55, 62,72,83, 86,88,90, 92	7,14,34, 39,42,55, 62,72,83, 86,88,90, 92	7,14,34, 39,42,55, 62,72,83, 86,88,90, 92	7,13,34, 39,42,55, 62,72,83, 86, 89,90, 92	7,13,34, 39,42,55, 62,72,83, 86, 89,90, 92	7,13,34, 39,42,55, 62,72,83, 86, 89,90, 92	7,13,34, 39,41,55, 62,72,83, 86,89,90, 92
Losses (kW)	Best	469.88	469.88	482.14	482.14	482.14	469.88	469.88	469.88	471.1
	Worst	477.95	470	478.38	483.67	478.38	498.22	489.25	482.95	482.95
	Mean	473.04	470	474.63	482.9	474.63	489.82	479.73	471.41	471.41
	SD	-	0.0004	1.84	0.44	1.84	-	-	-	-
	Final	**473.04**	**470.0004**	**476.47**	**483.34**	**476.47**	**489.82**	**479.73**	**471.41**	**471.41**
Time (s)	Minimum	-	-	-	-	-	-	-	-	-
	Maximum	-	-	-	-	-	-	-	-	-
	Average	19.73	95.88	-	11	14	-	-	-	241.5
	SD	-	-	-	-	-	-	-	-	-
	Final	**19.73**	**95.88**	**-**	**11**	**14**	-	-	-	**241.5**

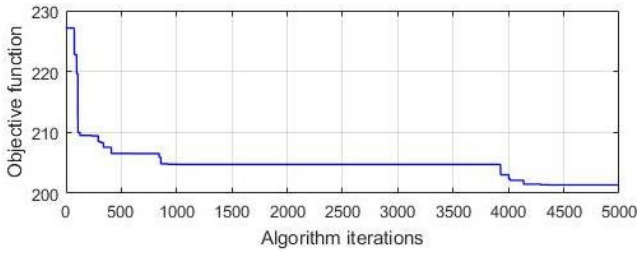

FIGURE 43. Worst convergence plot of IGA for system 10.

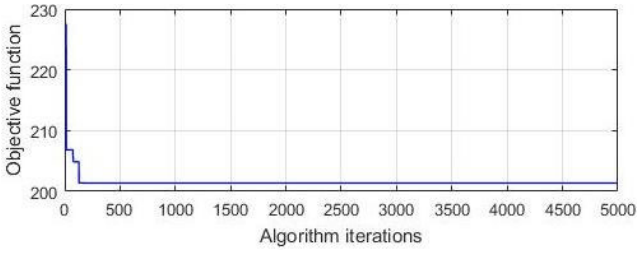

FIGURE 44. Best convergence plot of IGA for system 10.

branches 6 and 8 are allocated to Part 2 of Y_1', because of exchange of genes between the second parts of Y_1 and Y_2,

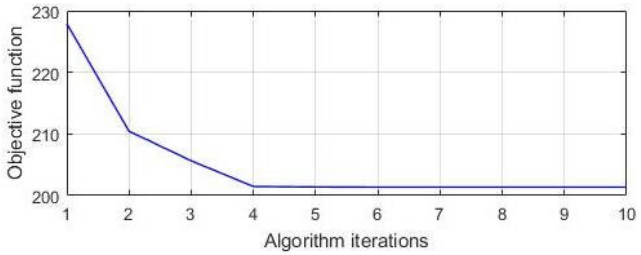

FIGURE 45. Best and worst convergence plot of EGA for system 10.

as it is seen in (29). Two important features of this type of recombination are:

1) Only new radial topologies are generated.
2) The most of the branches of the new radial solutions exist in initial chromosomes Y_1 or Y_2.

Afterwards, the process starts again with the evaluation of objective function (1) for each new chromosome. The process continues and it is terminated when the end criterion is satisfied, which can be a specific threshold for improvement between two generations, or maximum number of generations. The flowchart of the proposed EGA is shown in Fig. 5.

Numerical examples in the paper demonstrate superior performance of this technique compared to other

TABLE 23. Final solutions for system 11.

Methods	Open Switches	Losses (kW)	Time (s)	Methods	Open Switches	Losses (kW)	Time (s)
SA [67]	7,13,34,39,42,55,62,72,83,86,89,90, 92	489.82	-	Heuristic [111]	7,13,34,39,41,55,62,72,83,86,89,90,92	471.1	-
SA [29]	7,13,34,39,41,55,62,72,83,86,89,90,92	489.82	257.4	ACO [110]	7,13,34,39,41,55,62,72,83,86,89,90,92	471.1	-
SA [88]	7,13,34,39,42,62,72,83,84,86,89,90,92	486.13	22.06	VSDEA [66]	7,13,34,39,41,55,62,72,83,86,89,90,92	471.1	318
SAPSO+ MSLFA [107]	7,14,34,39,42,55,62,72,83,86,88,90, 92	483.34	11	GA+BE [88]	7,13,34,39,42,55,62,72,83,86,89,90,92	470.19	37.98
HBMO [71]	7,14,34,39,42,55,62,72,83,86,88,90,92	482.14	13	HSA [112]	7, 34, 39,42,55.62,72,83,86,88 –90,92	470.19	7.751
GA [88]	7,13,34,39,63,72,83,84,86,89,90,92,95	481.66	30.52	Heuristic [98]	7,13,34,39,42,63,72,83,84,86,89,90,92	470.1	69
GA [67]	7,13,34,39,42,55,62,72,83,86,89,90, 92	479.73	-	AACO [31]	7,13,34,39,42,55,62,72,83,86,89,90,92	470	95.88
GA [29]	7,13,34,39,41,55,62,72,83,86,89,90,92	479.73	303.7	Heuristic [94]	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	-
RGA [88]	7,13,34,39,42,63,72,83,84,86,89,90,92	478.18	27.41	NrGA [62]	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	-
MSLFA [107]	7,14,34,39,42,55,62,72,83,86,88,90, 92	476.47	-	Heuristic [104]	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	-
SLFA [64]	7,14,34, 9,42,55,62,72,83,86,88,90,92	476.47	14	Heuristic [52]	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	266,901
HSA [88]	7,13,34,39,42,55,62,72,83,86,89,90,92	475.13	9.87	Classic [113]	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	207.7
ACO [88]	7,13,34,39,42,55,62,72,83,86,89,90,92	473.04	19.73	SA [21]	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	195.2
AIS+ACO [109]	7,13,34,39,42,55,62,72,86,89,90,91,92	472.32	15	CLONR [34]	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	160
HBMO [88]	7,13,34,39,42,55,62,72,83,86,89,90,92	471.69	17.1	IGA	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	157.89
GA [110]	7,33,55,61,72,83,86,88,89,90,92,93,95	471.5	-	DEA [21]	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	36.15
ACO [67]	7,13,34,39,42,55,62,72,83,86,89,90, 92	471.41	-	SOReco [52]	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	7.809
ACO [29]	7,13,34,39,41,55,62,72,83,86,89,90,92	471.41	241.5	EGA	7,13,34,39,42,55,62,72,83,86,89,90,92	469.88	7.5

GA approaches. In this algorithm, only radial configurations appear in the final population. Consequently, it is possible to increase the size of the population for highly complex DSR problems and improve the algorithm accuracy with imposing a low additional computation time and burden. It should be noted that the number of chromosomes of initial population (d), radial power flow tolerance (Δ), and minimum amount of each chromosome are considered to be 4, 1, and 10^{-8} for all test systems, respectively. Other parameters used in EGA are listed in Table 1.

IV. SIMULATION RESULTS

The proposed method (EGA) and IGA were applied to a number of test systems and the results were compared with the solutions obtained by other GA approaches: standard GA [22], [46], RGA [47], GAMT [49], restricted GA (ReGA) [50], DGA [51], SOReco [52], FGA [54], [59], [60], FAGA [55], NSGA [56], fast NSGA (FNSGA) [61], and non-revisiting GA (NrGA) [62]. Comparisons also include classic methods, heuristic approaches, and metaheuristic algorithms such as SA [13], [14], [63], ESA [15], gravitational SA (GSA) [22], TS [16], ITS [17], MTS [18], EA [20], [64], [65], DEA [21], variable scaling DEA (VSDEA) [66], FEA [23], [24], PSO [22], [25], MPSO [27], EIPSO [28], self-adaptive PSO (SAPSO) [64], ACO [29], [67], HC-ACO [30], [68], AACO [31], HACO [32], fuzzy ACO (FACO) [69], AIS [33], [34], BFOA [35], HSA [36], TLBO [38], BB-BC [39], honey bee mating optimization (HBMO) [70], [71], shuffled frog leaping algorithm (SFLA) [64], dragonfly [72], and grey wolf optimizer (GWO) [22]. Available parameters of meta-heuristic approaches used for comparison with proposed method have been given in Appendix. Also, data of test systems used in the current literature have been shared with public at the repository: https://figshare.com/s/295f3a8e7e5b5492a005.

A. SYSTEM 1: 7-BUS DISTRIBUTION NETWORK

Figure 6 shows this test system with a single radial feeder and one substation bus (supply point), including six lines with closed switches and one tie line. All data related to this system are available in [73]. The base power is 1 MVA and the nominal voltage is 12.66 kV. The active power loss of original network (before reconfiguration) is 1.44 kW. The EGA and IGA were applied to this test system 30 times, with the best, worst, mean and standard deviation values reported in Table 2.

Also, the results of both EGA and IGA methods for best open switches, final losses (kW), and final computing time (s) were compared with method of [73] in Table 3. It should be noted that in all cases, mean values plus standard deviations (worst scenarios) are considered as final amounts

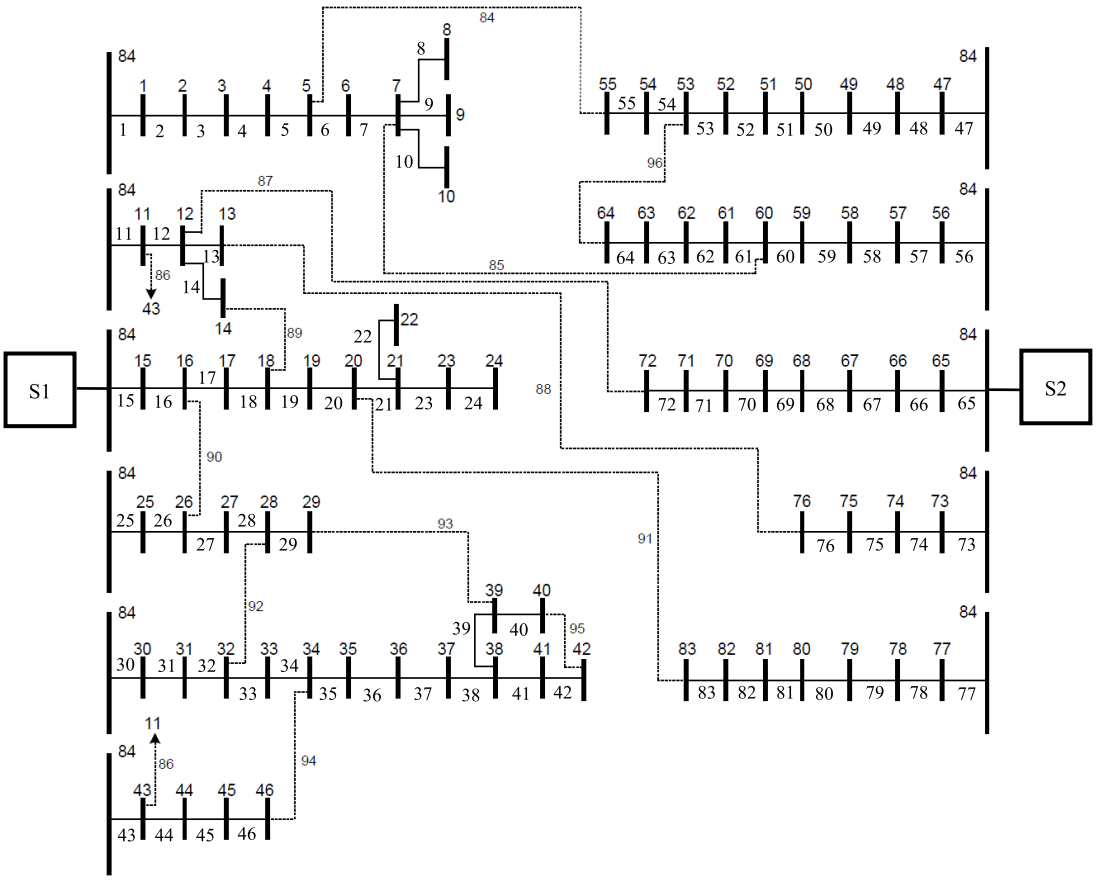

FIGURE 46. The 84-bus test system.

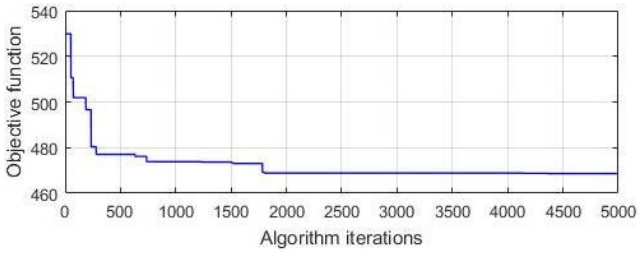

FIGURE 47. Worst convergence plot of IGA for system 11.

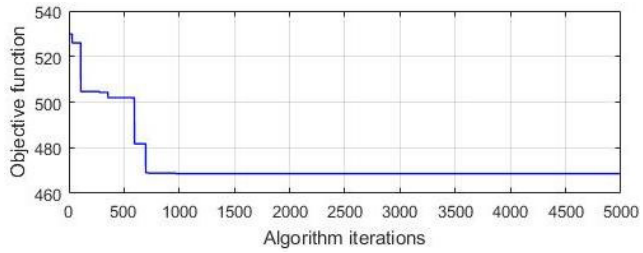

FIGURE 48. Best convergence plot of IGA for system 11.

instead of mean and standard deviation differences (Mean–SD), because of showing certain superior performance of EGA algorithm compared to other reconfiguration methods.

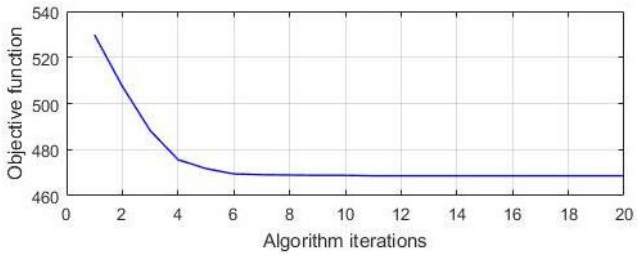

FIGURE 49. Best and worst convergence plot of EGA for system 11.

From Table 3, it can be seen that EGA and IGA can find better solution for open switches and lower power losses than the original classic method presented in [73]. Also, EGA can solve the DSR problem in shorter computation time than IGA method. Solving DSR problem in shorter time is very important for online (real time) reconfiguration tasks. In order to see the convergence process of both GA methods, plot of objective function with iterations is shown in Figs 7 to 9 for worst and best solutions of IGA and EGA methods, respectively.

From Figs 7 to 9, it can be seen that EGA has found optimal solution in the second iteration, while IGA has minimized losses at least in the third and maximum in the ninth iteration.

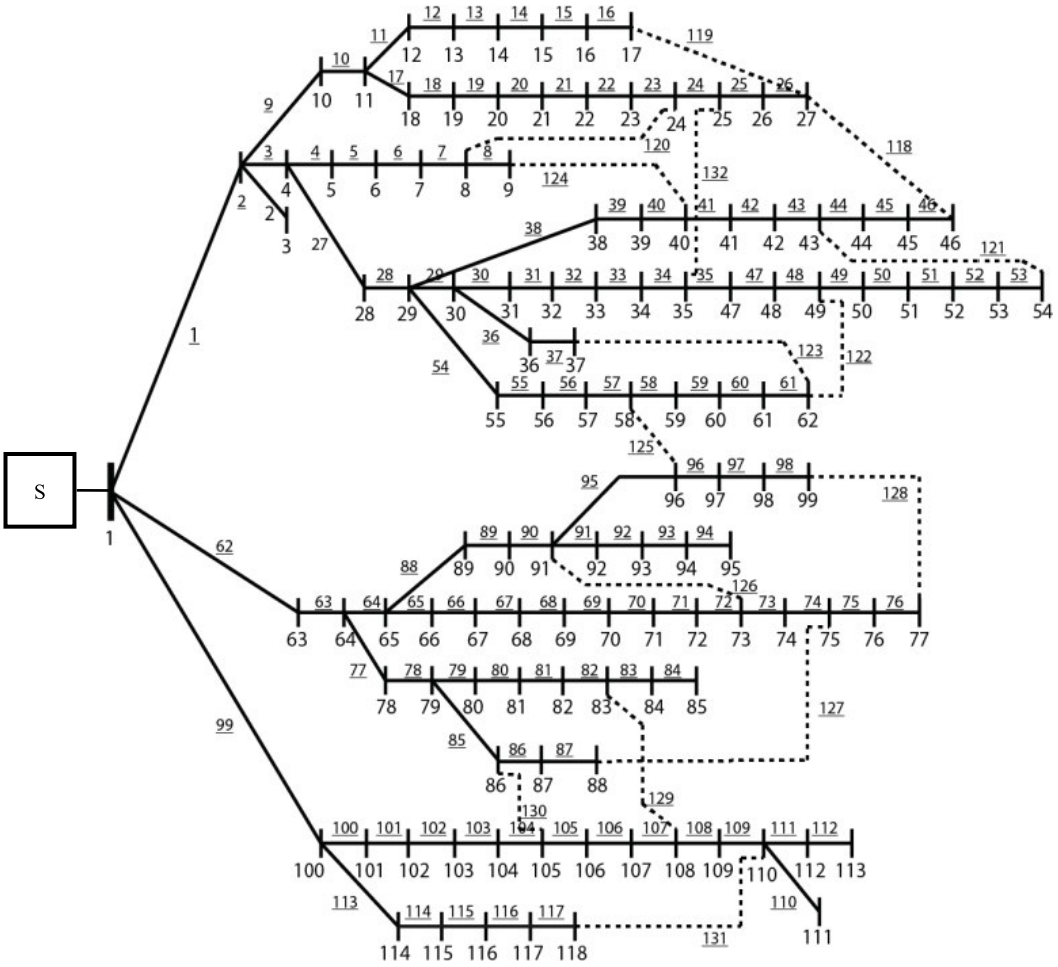

FIGURE 50. The 118-bus test system [114].

B. SYSTEM 2: 12-BUS DISTRIBUTION NETWORK

This model represents an actual system, which is part of the distribution network of Baghdad city in Iraq. Its single line diagram is shown in Fig. 10. The feeder is connected to the substation (supply point) S, which has a nominal (base) voltage of 11.1 kV and a capacity of 2250 kVA. The relevant data are given in [74]. There are two tie lines and 11 sectional switches in this network.

The results obtained by the EGA and IGA methods are provided in Table 4 after 30 independent runs and compared with results from [74] in Table 5. The convergence plots of EGA and IGA methods for best and worst solutions are shown in Figs 11 to 13.

From Table 5, it can be seen that both EGA and IGA find better configuration (5,11) for minimizing active power losses than classic method presented in [74]. Also, it can be seen that EGA and IGA methods have solved the DSR problem faster than the method of [74], and that EGA is much faster than IGA method. Also, Figs. 11 to 13 show improved convergence of EGA method, as compared to IGA: the EGA approached the optimal solution at least one iteration and 13 iterations maximum before the IGA method.

C. SYSTEM 3: 16-BUS DISTRIBUTION NETWORK

A three-feeder 23 kV distribution system connected to substation buses 1, 2 and 3 including 13 sectional switches and three tie lines is shown in Fig. 14. All data, such as resistances and reactances of branches, and nodal active and reactive power demands are reported in [66]. The base power and initial power losses (before reconfiguration) are 10 MVA and 511.44 kW, respectively.

The results of EGA, IGA, and some metaheuristic algorithms are given in Table 6.

The final results obtained by EGA, IGA, and methods listed in Table 6 are compared with a number of other methods using the same test system in Table 7. It should be noted that the computing time of some alternative methods has not been reported. Therefore, the methods are ranked in Table 7 first according to power losses reduction, then according to reported computational time, and afterwards regarding the date of their publications. Again, plots of objective function values versus number of iterations are shown in Figs 15 to 17 for both EGA and IGA methods.

The heuristic techniques proposed in [75], [76], and [77] do not provide the optimal solution for open switches

TABLE 24. Numerical results of EGA and IGA after 30 independent runs compared to other metaheuristic approaches for system 12.

Items	Solutions	Methods							
		EGA	IGA	MTS [18]	AACO [31]	GA [36],[46]	RGA [36],[47]	ITS [17], [36]	HSA [36]
Best Open Switches		23,26,34, 39,42,51, 58,71,74, 95,97,109, 122,129,130	23,26,34, 39,42,51, 58,71,74, 95,97,109, 122,129,130	23,26,34, 39,42,51, 58,71,74, 95,97,109, 122,129,130	23,26,34, 39,42,51, 58,71,74, 95,97,109, 122,129,130	23,30,34, 39,42,48, 50,61,72, 73,76,82, 109,119,125	22,26,32, 39,42,48, 51,61,72, 73,76,82, 109,125,130	23,26,34, 39,42,51, 58,71,74, 95,97,109, 119,129,130	22,26,32, 42,52,61, 71,74,122, 124,125, 128–131
Losses (kW)	Best	869.7	869.7	869.7	869.7	885.5	883.13	874.7	1078. 4
	Worst	869.7	869.7	888	889.62	1309.1	1297.34	1288.17	1282.73
	Mean	869.7	869.7	874	875.5	965.8	963.1	952.6	1108.87
	SD	0	0	-	0.003	78.5	77.4	73.2	69.3
	Final	**869.7**	**869.7**	874	**875.503**	**1044.3**	**1040.5**	**1025.8**	**1178.2**
Time (s)	Minimum	15.95	137.81	-	-	-	-	-	-
	Maximum	18.29	489.96	-	-	-	-	-	-
	Average	16.8	286.52	18000	430.75	24.45	17.53	9.038	8.61
	SD	0.61	99.07	-	-	-	-	-	-
	Final	**17.41**	**385.59**	**18000**	**430.75**	**24.45**	**17.53**	**9.038**	**8.61**

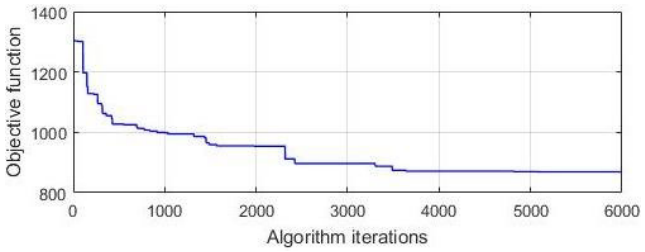

FIGURE 51. Worst convergence plot of IGA for system 12.

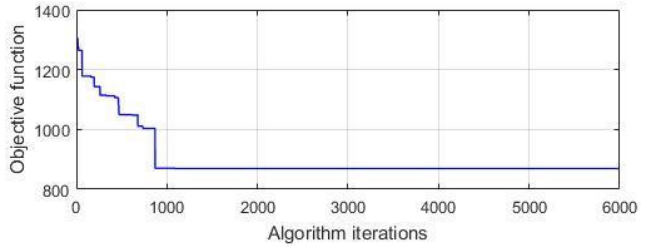

FIGURE 52. Best convergence plot of IGA for system 12.

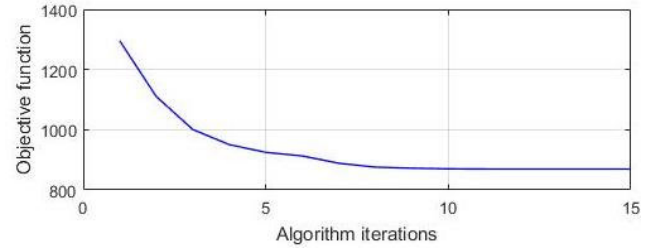

FIGURE 53. Best and worst convergence plot of EGA for system 12.

(17,19,26), in contrast to other approaches and EGA and IGA methods.

It can be seen that the EGA strategy provides optimal solution in shorter computing time compared to IGA and all other reconfiguration methods. As seen in Table 7, performance of IGA has degraded with increase in size of distribution

TABLE 25. Final solutions for system 12.

Methods	Open Switches	Losses (kW)	Time (s)
HSA [36]	23,26,34,39,42,51,58,71,74, 95,97,109,122,129,130	1178.2	8.61
GA [36], [46]	23,30,34,39,42,48,50,61,72, 73,76,82,109,119,125	1044.3	24.45
RGA [36],[47]	22,26,32,39,42,48,51,61,72, 73,76,82,109,125,130	1040.5	17.53
ITS [17], [36]	23,26,34,39,42,51,58,71,74, 95,97,109,122,129,130	1025.8	9.038
Standard GA [114]	4,26,33,42,46,53,60,70,73,82 ,95,98,109,124,130	980.54	38935
BE [17], [87]	23,30,34,39,42,48,50,61,72, 73,76, 82,109,119,125	885.56	-
TS [16] [17]	22,26,32,39,42,48,51,61,71, 73,76,84,109,125,130	884.163	-
AACO [31]	23,26,34,39,42,51,58,71,74, 95,97,109,122,129,130	875.503	430.74
Heuristic [104]	23,26,34,39,42,51,58,71,74, 95,98,109,122,129,130	870.5	-
CLONR [34]	23,26,34,39,42,51,58,71,74, 95,98,109,122,129,130	870.5	704.1
MTS [18]	23,26,34,39,42,51,58,71,74, 95,97,109,122,129,130	869.7	18000
Classic [83]	23,26,34,39,42,51,58,71,74, 95,97,109,122,129,130	869.7	1009
IGA	23,26,34,39,42,51,58,71,74, 95,97,109,122,129,130	869.7	385.59
ReGA [92]	23,26,34,39,42,51,58,71,74, 95,97,109,122,129,130	869.7	42.13
Classic [84]	23,26,34,39,42,51,58,71,74, 95,97,109,122,129,130	869.7	39.4
EGA	23,26,34,39,42,51,58,71,74, 95,97,109,122,129,130	869.7	17.41

network compared to EGA method. Comparing convergence plot of Figs. 15 and 16 with that of Fig. 17 shows that EGA again finds optimal solution in iteration 3 (IGA finds it in the 5th and 29th iteration in the best and worst cases, respectively).

D. SYSTEM 4: 28-BUS DISTRIBUTION NETWORK

This real network is part of the electrical power distribution system in the city of Koprivnica, Croatia. It consists

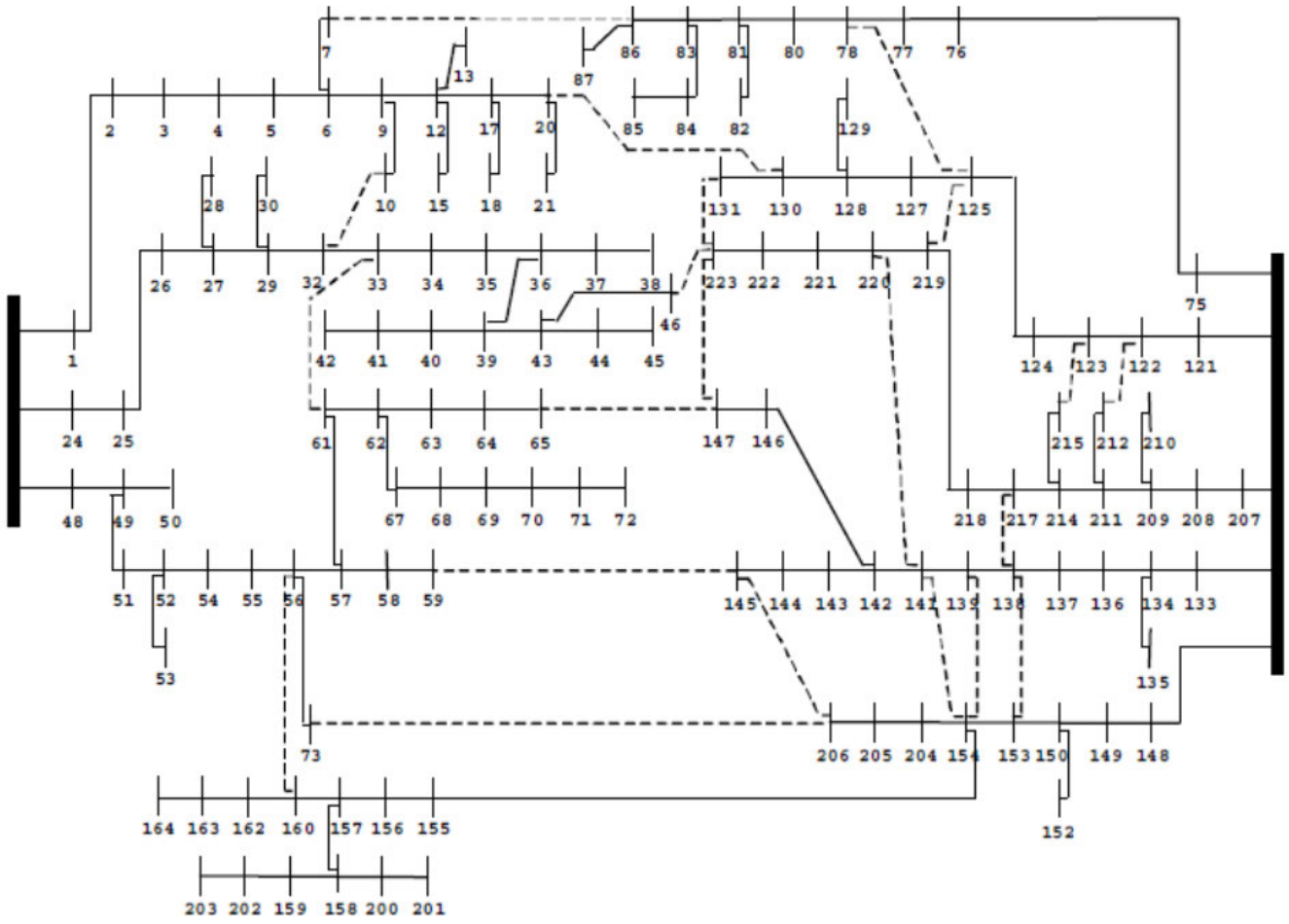

FIGURE 54. The 136-bus distribution system [115].

of 28 buses, two radial feeders with one substation bus, one 110/35 kV transformer between buses 1 and 2, two 35/10 kV transformers (one of them connects bus 2 to bus 3 and another buses 2 and 4), 22 load buses, and 24 distribution lines. The single-line diagram of the Koprivnica distribution system is shown in Fig. 18 and its data are available in [85]. Full lines represent distribution branches that are switched on, while dashed lines represent distribution lines that are switched off. The active power losses of initial network are 46 kW. The results are shown in Tables 8 and 9 and Figs 19 to 21.

Table 9 shows that the EGA method can find the optimal configuration as accurate as the method presented in [85], but with shorter computing time than improved GA. Figures 19 to 21 indicate that the same solution obtained by EGA method in fifth iteration is found by IGA after 16 and 149 iterations minimum and maximum, respectively.

E. SYSTEM 5: 30-BUS DISTRIBUTION SYSTEM

The diagram of this test system with four radial feeders, six tie lines, 28 sectionalizing switches, and two substations (substation 2 is a back-up/alternative supply point) is shown in Fig. 22 and its data are listed in [86]. The nominal values are 1 MVA and 18.6 kV and initial losses are 1240 kW. The final results of EGA and IGA methods presented in Table 10 are compared with original GA results of [86] in Table 11. Again, convergence plots of EGA and IGA methods are depicted in Figs 23 to 25.

The results show that GA method of [86] is not as accurate as EGA and IGA methods, which both find better configuration with lower power losses. In comparison with system 4, EGA method could find the best configuration less quickly than IGA algorithm for system 5, which has almost the same number of normal branches as system 4, but nearly twice the number of tie switches and substation buses. This shows that convergence speed of IGA has been reduced compared to EGA method in system 4 even with decrease in tie line switches and supply points.

Figures 23 to 25 illustrate a significant improvement in convergence characteristic of EGA method, as the IGA has found the best configuration in at least 22 iterations and a maximum of 144 iterations more than the EGA method.

F. SYSTEM 6: 33-BUS DISTRIBUTION NETWORK

The system shown in Fig. 26 includes two radial feeders with three 12.66 kV laterals, five tie line switches, and

TABLE 26. Numerical results of EGA and IGA after 30 independent runs compared to AACO and TS methods for system 13.

Items	Solutions	Methods			
		EGA	IGA	AACO [31]	TS [116]
Best Open Switches		7,35,51,90, 96,106,118, 126,135,137, 138,141,142, 144–148, 150,151,155	7,35,51,90, 96,106,118, 126,135,137, 138,141,142, 144–148, 150,151,155	7,35,51,90, 96,106,118, 126,135,137, 138,141,142, 144–148, 150,151,155	7,35,51,90, 96,106,118, 126,135,137, 138,141,142, 144–148, 150,151,155
Losses (kW)	Best	280.19	280.19	280.19	280.19
	Worst	280.19	280.19	284.04	280.25
	Mean	280.19	280.19	280.59	280.3
	SD	0	0	0.0009	-
	Final	**280.19**	**280.19**	**280.591**	**280.25**
Time (s)	Minimum	18.8	332.14	-	-
	Maximum	21.5	701.31	-	-
	Average	19.8	514.57	894.2	46.78
	SD	0.65	113.47	-	-
	Final	**20.45**	**628**	**894.2**	**46.78**

TABLE 27. Final solutions for system 13.

Methods	Open Switches	Losses (kW)	Time (s)	Methods	Open Switches	Losses (kW)	Time (s)
Heuristic [115]	51,106,136–139,141–152,154–156	285.5	-	NrGA [62]	7,35,51,90,96,106,118,126,135,137,138, 141,142,144–148,150,151,155	280.19	-
Heuristic [82]	7,38,51,55,90,97,106,118,126,137,138, 141,144–148,150–152,155	282.77	23.93	Classic [96]	7,35,51,90,96,106,118,126,135,137,138, 141,142,144–148,150,151,155	280.19	4473
FAGA [55]	51,53,90,96,106,118,136–139,141, 144–148, 150,151,154–156	281.7	40	Classic [113]	7,35,51,90,96,106,118,126,135,137,138, 141,142,144–148,150,151,155	280.19	1800
Heuristic [98]	7,38,51,54,84,90,96,106,119,126,135,137, 138,141,144,145,147,148,150,151,155	281.02	530	Classic [83]	7,35,51,90,96,106,118,126,135,137,138, 141,142,144–148,150,151,155	280.19	1785
AACO [31]	7,35,51,90,96,106,118,126,135,137,138, 141,142,144–148,150,151,155	280.591	894.2	IGA	7,35,51,90,96,106,118,126,135,137,138, 141,142,144–148,150,151,155	280.19	628
DGA [51]	7,38,51,53,90,96,106,118,126,128,137, 138,141,144–148,150,151,156	280.47	227	TS [116]	7,35,51,90,96,106,118,126,135,137,138, 141,142,144–148,150,151,155	280.19	46.78
Classic [99]	38,51,54,84,90,96,106,118,126,128,135,1 37,138,141,144,145,147,148,150,151,7	280.38	188.4	FNSGA [61]	7,35,51,90,96,106,118,126,135,137,138, 141,142,144–148,150,151,155	280.19	32.6
Classic [84]	38,51,54,84,90,96,106,118,126,128,135,1 37,138,141,144,145,147,148,150,151,7	280.38	132.5	Classic [117]	7,35,51,90,96,106,118,126,135,137,138, 141,142,144–148,150,151,155	280.19	24.8
HACO [32]	7,51,53,84,90,96,106,118,126,128,137–139,141,144,145,147,148,150,151,156	280.22	5120	EGA	7,35,51,90,96,106,118,126,135,137,138, 141,142,144–148,150,151,155	280.19	20.45
DCGA [57]	7,51,53,84,90,96,106,118,126,128,137–139,141,144,145,147,148,150,151,156	280.22	3600	-	-	-	-

32 normal branches. The data of this test system are available in [87]. The MVA and kV base are 1 and 12.66, respectively. The voltage of the substation bus (node 0) is assumed 1 per unit. The power losses of initial network are 202.68 kW. The results of EGA, IGA, and some metaheuristic methods for this test system are listed in Table 12 and compared with the results of other methods in Table 13. The convergence plots of IGA and EGA are represented in Fig. 27 to 29.

Table 13 shows that the EGA method finds the same optimal configuration and power losses as some other methods, including IGA, but computational time is the shortest of all methods.

In comparison with Table 11, processing time of IGA has significantly increased with the increase in number of normal branches and decrease in number of substation buses and tie line switches in system 6, while EGA algorithm exhibits almost the same performance in system 6 compared to system 5. Comparing Figs 27 to 29 with Figs 23 to 25 shows better convergence performance of EGA method, compared to IGA (8th vs 186th iteration maximum and 42nd iteration minimum).

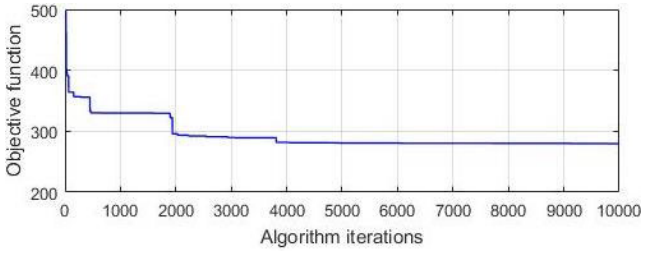

FIGURE 55. Worst convergence plot of IGA for system 13.

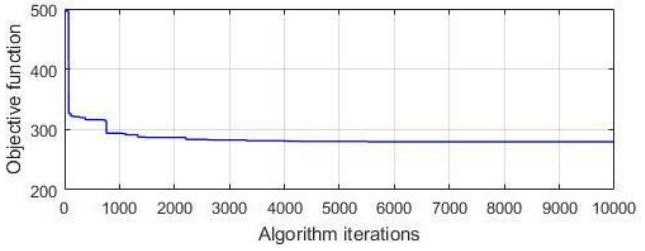

FIGURE 56. Best convergence plot of IGA for system 13.

G. SYSTEM 7: 49-BUS DISTRIBUTION NETWORK

Figure 30 shows the single-line diagram of part of the real distribution network of Baghdad city in Iraq.

The test system is an 11 kV network with one substation, 49 buses, five tie lines, 48 sectional switches, and a radial feeder with six laterals. The system data and power demand information are available in [101]. The active power loss of network before reconfiguration is 10.59 kW. The results are given in Tables 14 and 15, while iterations of loss minimization of objective function are shown in Figs 31 to 33 for EGA and IGA methods.

From Table 15, it can be seen that both EGA and IGA methods find better configuration with lower power losses than GA presented in [101]. In addition, the EGA could solve the problem faster than IGA method. Figures 31 to 33 illustrate that the proposed method needs only four iterations to approach the optimal solution, while IGA needs 45 to 175 iterations. Comparing Figs 31 to 33 with Figs 27 to 29 shows better convergence performance of EGA compared to IGA in larger distribution systems.

H. SYSTEM 8: 59-BUS DISTRIBUTION NETWORK

Figure 34 shows a 33 kV real distribution network with radial feeder, lateral branches and substation bus. This system is a part of the distribution network of the city of Ahvaz in the southwest of Iran. The 59-bus system includes 58 normal branches (sectional switches) and five tie lines. Line and load data for this real distribution network are available in [38]. The active power losses of original network configuration are 178.66 kW. Tables 16 and 17 show the simulation results after applying EGA and IGA methods to this system. Convergence process of objective function is plotted in Figs 35 to 37 for both EGA and IGA methods.

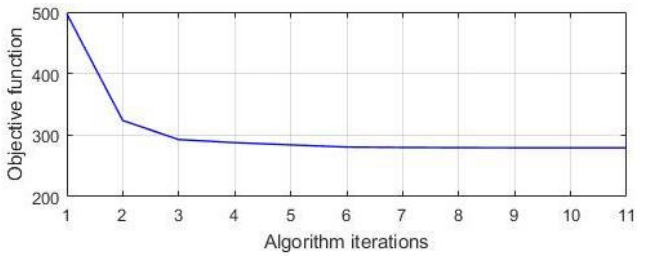

FIGURE 57. Best and worst convergence plot of EGA for system 13.

TABLE 28. Numerical results of EGA and IGA after 30 independent runs compared to TS method for system 14.

Items	Solutions	Methods		
		EGA	IGA	TS [116]
Best Open Switches		12,26,43,82, 118,131,133, 140,168,202, 203,208,212, 213,214	12,26,82,118, 131,133,168, 183,202, 203, 208,211,212, 213,214	29,66,74,83, 111,118,125, 131,135,136, 140,177,199, 202,208
Losses (kW)	Best	511.19	511.19	537.1
	Worst	511.19	512.85	537.2
	Mean	511.19	512.12	537.17
	SD	0	0.51	-
	Final	**511.19**	**512.63**	**537.17**
Time (s)	Minimum	29.44	524.28	-
	Maximum	35.16	1174.6	-
	Average	31.95	708.67	49.98
	SD	2.02	200.43	-
	Final	**33.97**	**909.1**	**49.98**

TABLE 29. Final solutions for system 14.

Methods	Open Switches	Losses (kW)	Time (s)
TS [116]	29,66,74,83,111,118,125,131,135, 136,140,177,199,202,208	537.17	49.98
IGA	12,26,43,82,118,131,133,168,202, 203,208,212,211,213,214	512.63	909.1
AMPL	12,26,43,82,118,131,133,140,168, 202,203,208,212,213,214	511.19	948.64
EGA	12,26,43,82,118,131,133,140,168, 202,203,208,212,213,214	511.19	33.97

TABLE 30. Parameters of CLONR for systems 6, 11, and 12 [34].

Parameters	Values
Initial amount of control parameter for hypermutation process (ρ_1)	0.1
Maximum amount of control parameter for hypermutation process (ρ_2)	0.2
Maximum generation	100
Control parameter for the cloning process	20

It can be seen that EGA method reaches the optimal configuration and minimum losses faster than TLBO and IGA methods. The results indicate that the IGA method finds the optimal solution between 47th and 201st iteration (Figs 35 and 36) after 2.85 seconds and before 14.13 s, while EGA algorithm finds the best solution in sixth iteration

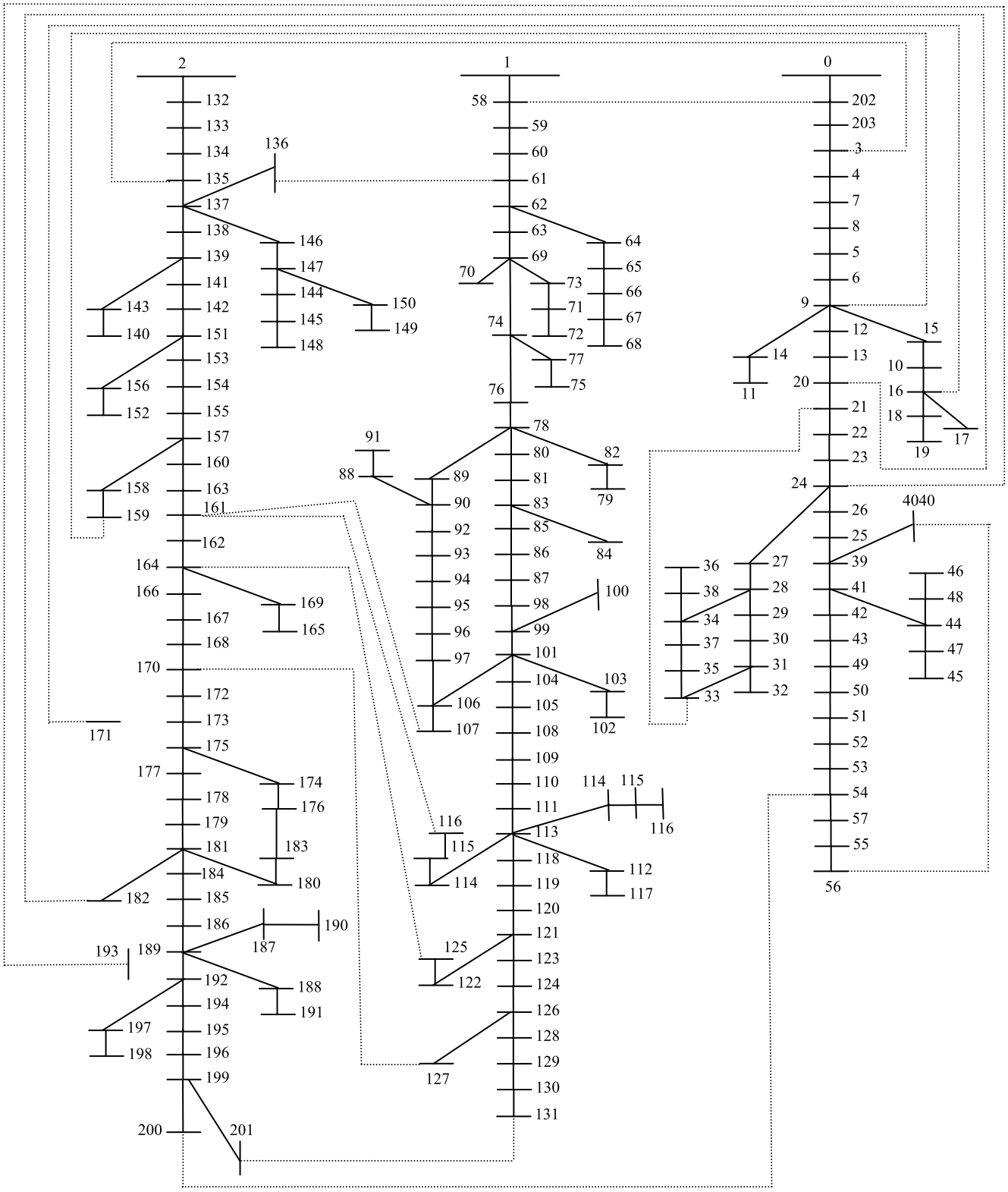

FIGURE 58. The 203-bus distribution system.

(Fig. 37) between 1. 7 s and 2.3 s. Each iteration of EGA algorithm takes more time than an iteration of IGA, because of using Prime's algorithm for creation of only radial solutions in EGA. However, the creation of only radial topologies (feasible solutions) in the whole evolutionary process helps the EGA to find optimal solution faster than IGA.

In some iterations of IGA method, non-radial solutions are created and that issue has increased number of

TABLE 31. Parameters of SA.

Parameters	Values													
	System 3							System 6			System 9	System 11		
	[14]	[78]	[29]	[63]	[67]	[88]	[78]	[14]	[88]	[78]	[14]	[21]	[29]	[67]
Acceptance ratio (r)	0.1	-	-	-	-	0.5	0.5	0.1	0.5	0.5	0.1	-	-	-
Cooling rate (a)	0.9	0.95	0.95	0.95	0.95	-	-	0.9	-	-	0.95	0.95	0.99	0.99
Initial temperature (T_0)	-	100	500	30	500	500	500	-	500	500	-	100	5000	5000
Final temperature (T_f)	-	25	-	6.4	-	0	0	-	0	0	-	25	-	-
Maximum iterations (k_{max})	-	10	200	300	200	220	220	-	220	220	-	1000	4000	4000
Temperature threshold (ε)	-	N	N	N	N	0.3	0.3	-	0.3	0.3	-	N	N	N
Markov chain length (L_M)	-	-	-	-	-	50	50	-	50	50	-	-	-	-
Distance parameter (δ)	-	-	-	-	-	2	2	-	2	2	-	-	-	-

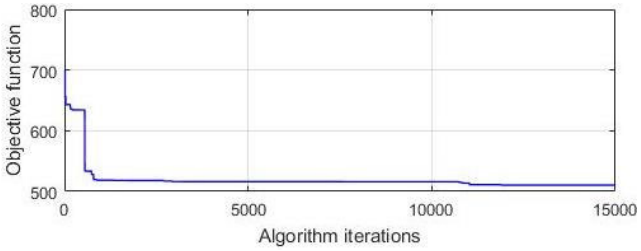

FIGURE 59. Worst convergence plot of IGA for system 14.

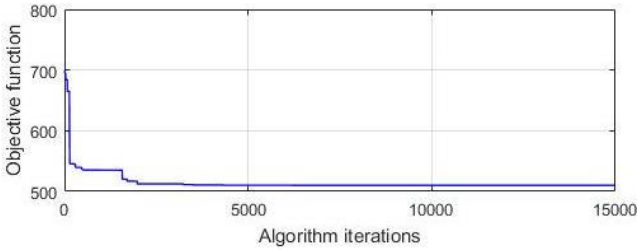

FIGURE 60. Best convergence plot of IGA for system 14.

iterations and therefore longer computational time of the IGA method to find the best radial topology, compared to the EGA method.

I. I.SYSTEM 9: 69-BUS DISTRIBUTION NETWORK

This system is a one-feeder 12.66 kV distribution network, including one substation bus, 68 load points and sectional switches, and five tie lines is shown in Fig. 38. Data for this system are available in [60]. Base values for this network are 12.66 kV and 1 MVA. The initial network losses are 225 kW and results are compared in Tables 18 and 19. The plots of objective function values versus iteration steps of EGA and IGA methods are shown in Figs 39 to 41.

Table 19 shows that different configurations may lead to the same power losses in the four optimal solutions for DSR problem in 69-bus test system. Accuracy of these optimal solutions for switching sequence was verified by EGA and IGA methods. The only difference of these configurations is the number of the second open switch. It means that opening

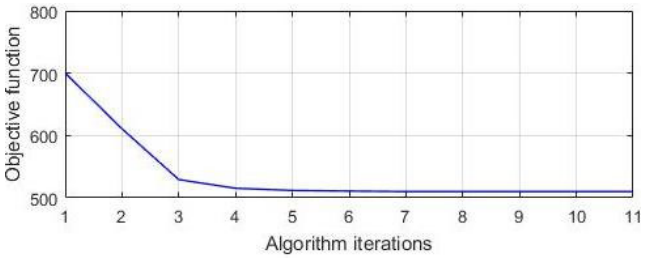

FIGURE 61. Best and worst convergence plot of EGA for system 14.

one of sectional switches 55 (between buses 55 and 56) to 58 (between buses 58 and 59) results in the same power losses, because buses 56 to 58 do not include any load and are connected with subsequent series branches in the network. The EGA method finds the configuration with minimum losses faster than heuristic, metaheuristic and all other GA methods in Table 19. Moreover, high processing time of DCGA presented in [92], as compared to the other reconfiguration algorithms, demonstrates that variable mutation probability used in the IGA can help to find accurate solution in much shorter computing time.

Figures 39 to 41 illustrate significantly better convergence characteristic of EGA algorithm, compared to IGA, because EGA has reached the optimal solution at least 44 and a maximum of 194 iterations before the IGA method.

J. SYSTEM 10: 70-BUS DISTRIBUTION NETWORK

This test system is an 11 kV radial distribution network with two substations, four feeders, 68 load buses, 11 tie lines, and 68 sectional switches, as shown in Fig. 42. Data for this system are available in [106]. The active power losses for initial network configuration are 227.5 kW with nominal power of 1 MVA. Table 20 and 21 show proposed optimal configurations, minimized power losses, and computing times for considered methods. Also, Figs 43 to 45 show convergence plots of the EGA and IGA methods. According to Table 21, standard GA could find more accurate solution in much higher computational time than GAMT method.

As mentioned earlier, GA in standard form is time-consuming method for network reconfiguration problem and

TABLE 32. Parameters of TS methods.

Parameters	Values									
	TS method			ITS method				MTS method		
	System 3	System 12		System 6		System 12		System 3	System 9	System 12
	[78]	[16]	[17]	[17]	[39]	[17]	[39]	[66]	[18]	[18]
Tabu length (L_T)	5	9	9	9	9	9	9	2	3	13
Neighborhood size (N)	5	-	-	-	-	-	-	3	5	15
Maximum iterations ($itr_{\max}$)	100	600	600	600	600	600	600	50	-	-
BE in each loop network (n_s)	-	3	3	3	3	3	3	-	-	-
Randomly selected tie switches (m_t)	-	1	1	1	1	1	1	-	-	-
Mutation rate ($\Pr_M$)	0	0	0	0.01	0.01	0.01	0.01	0	-	-
Crossover rate ($\Pr_C$)	0	0	0	0	0	0	0	0.5	-	-
Tolerance of population diversity (ε_1)	N	N	N	N	N	N	N	0.2	N	N
Tolerance of gene diversity (ε_2)	N	N	N	N	N	N	N	0.1	N	N
Value of scaling factor (F)	N	N	N	N	N	N	N	0.3	N	N
First parameter of scaling factor (c_d)	N	N	N	N	N	N	N	0.82	N	N
Second parameter of scaling factor (c_i)	N	N	N	N	N	N	N	1.2	N	N
Population size (d)	N	N	N	N	N	N	N	5	N	N
Iteration index (q)	N	N	N	N	N	N	N	10	N	N

TABLE 33. Parameters of RGA.

Parameters	Values												
	Syst. 3				Syst. 6					Syst. 9	Syst. 11	Syst. 12	
	[50]	[47]	[36]	[47]	[36]	[47]	[50]	[88]	[91]	[91]	[88]	[36]	[47]
$\Pr_C$	N	-	0.8	0.8	0.8	-	-	0.8	0.8	0.8	0.8	0.8	0.3
$\Pr_M$	N	$0.05 \le \Pr_M \le 1$	0.05	0.05	0.05	$0.05 \le \Pr_M \le 1$	-	0.05	0.05	0.05	0.05	0.05	50
Population size (d)	10	-	85	85	85	-	15	10	50	50	20	85	1
Max. generations (G_{max})	20	-	200	200	200	-	35	120	-	-	250	200	36
Fundamental loops (L_P)	3	-	-	-	-	-	5	-	-	-	-	-	-

TABLE 34. Parameters of GA.

Parameters	Values													
	Syst. 3					Syst. 6			Syst. 7	Syst. 9	Syst. 10	Syst. 11		Syst. 12
	[29]	[49]	[67]	[36]	[47]	[49]	[88]	[91]	[101]	[91]	[49]	[29]	[67]	[105]
$\Pr_C$	0.5	0.4	0.5	0.8	0.8	0.4	0.8	0.8	0.75	0.8	0.4	0.5	0.5	0.8
$\Pr_M$	0.03	0.1	0.03	0.05	0.05	0.1	0.05	0.05	0.09	0.05	0.1	0.03	0.03	0.05
d	5	30	5	85	85	40	10	50	50	50	70	10	10	20
G_{max}	50	40	50	200	200	50	120	-	2000	-	100	500	500	250

therefore other GA-based methods, such as GAMT, were proposed. However, GAMT method could not find the best configuration like some other GA approaches, even by creating radial solutions. This indicates that strategies considered to reduce computational time of reconfiguration algorithms should not affect method accuracy. This also highlights the strategy of computational time reduction used in the EGA method.

The EGA finds the optimal solution much faster than standard GA and GAMT and other reconfiguration methods that also find the same optimal configuration, such as IGA and AACO method presented in [31].

Figs 43 to 45 demonstrate better convergence of EGA compared to IGA, as EGA finds the best switching sequence after six iterations, in contrast to 175 iterations minimum and 4,362 iterations maximum of IGA.

K. TEST SYSTEM 11: 84-BUS DISTRIBUTION NETWORK

As shown in Fig. 46, this real 11.4 kV network consists of two substations on bus 84, 11 radial feeders, 83 sectionalizing switches, and 13 tie lines, with data presented in [21]. The current-carrying capacity of each line (I_{ij}^{max}) is 410 A. The power base value for this system is 1 MVA. The active power

TABLE 35. Parameters of ACO methods.

Parameters	Values											
	ACO method						AIS+ ACO method	AACO method				HACO method
	Syst. 3		Syst. 6	Syst. 11			Syst. 11	Syst. 10	Syst. 11	Syst. 12	Syst. 13	Syst. 13
	[29]	[67]	[88]	[29]	[67]	[88]	[109]	[31]	[31]	[31]	[31]	[32]
Population size (number of ants)	5	5	5	5	5	10	100	25	40	70	85	20
Maximum iterations (itr_{max})	30	30	120	500	500	250	100	100	100	100	100	100
Rate of pheromone evaporation (ρ)	0.6	0.6	0.6	0.9	0.9	0.9	0.25	0.1	0.1	0.1	0.1	0.1
Pheromone decay parameter (σ)	0.1	0.1	0.1	0.2	0.2	0.2	0.05	0.25	0.25	0.25	0.25	-
Parameter to determine the relative importance of pheromone versus distance (β)	0.1	0.1	0.1	0.15	0.15	0.15	-	0.5	0.5	0.5	0.5	-
Parameter to control the influence of amount of pheromone (α)	N	N	N	N	N	N	N	1	1	1	1	0.15
Number of loop vectors (L_V)	N	N	N	N	N	N	N	5	5	5	5	-
Constant ζ	N	N	N	N	N	N	N	0.05	0.05	0.05	0.05	-
Pheromone deposition constant (Q)	N	N	N	N	N	N	10	N	N	N	N	10

TABLE 36. Parameters of PSO methods.

Parameters	Values							
	PSO method			MPSO method			EICPSO method	HPSO method
	Syst. 3	Syst. 6	Syst. 9	Syst. 6		Syst. 9	Syst. 11	Syst. 10
	[25]	[28]	[25]	[27]	[28]	[27]	[28]	[65]
Velocity vector constants (C_1 and C_2)	2	2	2	2	2	2	1	2
Maximum inertia weight (ω_{max})	0.9	0.9	0.9	0.9	0.8	0.9	3	0.9
Minimum inertia weight (ω_{min})	0.4	0.4	0.4	0.2	-	0.2	-	0.4
Population size (Number of particles)	10	10	50	5	10	5	10	24
Maximum iterations	-	1000	-	25	1000	50	1000	-
Particle length	3	-	5	-		-	-	-
Escape rate	N	N	N	N	N	N	0.25	N
Control parameter for determining the weight of trail intensity (γ_1)	N	N	N	N	N	N	N	1
Control parameter for determining the weight of length of the path (γ_2)	N	N	N	N	N	N	N	1
Rate of pheromone evaporation (ρ)	N	N	N	N	N	N	N	0.99
Initial neighborhood radius (D_0)	N	N	N	N	N	N	N	10
Parameter for tuning the neighborhood radius	N	N	N	N	N	N	N	15

losses of initial network are 532 kW. Tables 22 and 23 as well as Figs 47 to 49 show the sets of results as in case of previously considered test system.

Table 23 confirms that the EGA method finds the same optimal configuration and same minimum power losses as some reconfiguration methods, but in shorter computation time. The genetic algorithm of SOReco also shows better performance (shorter computing time) than other GA methods in Table 23. As seen, its computation time is very close to EGA method, but this method could not find the same accurate solution as EGA for 70-bus test system. Figures 47 to 49 illustrate better convergence characteristic of EGA method compared to IGA, which solves the DSR problem after 11 iterations, compared to 971 and 4,363 iterations of IGA in the worst and best cases, respectively.

TABLE 37. Parameters of HSA.

Parameters	Values						
	System 6			System 9	System 11		System 12
	[39]	[88]	[91]	[91]	[88]	[112]	[39]
Harmony memory size (HMS)	10	10	20	20	20	10	25
Harmony memory considering rate (HMCR)	0.85	0.85	0.85	0.85	0.85	0.85	0.85
Pitch adjusting rate (PAR)	0.3	0.3	0.2	0.2	0.3	0.3	0.3
Maximum number of iterations	250	120	20	20	250	250	600

TABLE 38. Parameters of NSGA.

Parameters	Values				
	Syst. 3	Syst. 6	Syst. 9		Syst. 13
	[61]	[56]	[56]	[61]	[61]
Pr_C	1	0.09	0.09	1	1
Pr_M	-	0.01	0.01	-	-
d	20	30	30	30	50
G_{max}	3	50	250	10	20
L_P	3	40	40	5	21

TABLE 39. Parameters of FGA and FEA.

Parameters	Values			
	FGA method			FEA method
	Syst. 6		Syst. 9	Syst. 9
	[59]	[60]	[60]	[23]
Pr_C	0.8		0.9	-
Pr_M	0.05		0.01	-
G_{max}	200		100	103
d	85		20	5
Solution factor	N		N	0.75

TABLE 40. Parameters of GA+BE [88].

Parameters	Values	
	Syst. 6	Syst. 11
Pr_C	0.8	0.8
Pr_M	0.05	0.05
d	10	20
G_{max}	120	250

L. TEST SYSTEM 12: 118-BUS DISTRIBUTION NETWORK

This test system, as shown in Fig. 50, is an 11 kV distribution network with three radial feeders, one substation bus, 118 and 15 sectional and tie switches, respectively. The parameters and related data of the system can be found in [17]. Tables 24 and 25 show the relevant results.

The base MVA and initial power losses are 10 and 1,298 kW, respectively. Also, convergence plots of improved and efficient GA algorithms were depicted in Figs 51 to 53.

Although most methods listed in Table 25, including the proposed EGA approach could find optimal switching scenario (23,26,34,39,42,51,58,71,74,95,97,109,122,129, 130), the EGA method finds the optimal solution faster than other methods that find the same power losses as EGA. Figures 51 to 53 indicate substantially better convergence process of objective function of EGA, as compared to IGA method.

TABLE 41. Parameters of GAMT [49].

Parameters	Values		
	Syst. 3	Syst. 6	Syst. 10
d	10	15	40
G_{max}	15	30	50
Chromosome length (L_P)	3	5	11

TABLE 42. Parameters of NrGA [62].

Parameters	Values				
	Syst. 3	Syst. 6	Syst. 9	Syst. 11	Syst. 13
d	10	60	60	60	80
G_{max}	5	15	20	113	113
L_P	3	5	5	13	21
Elitism rate	≥ 0.2	0.5	0.6	0.5	0.5

TABLE 43. Parameters of DCGA.

Parameters	Values		
	Syst. 6	Syst. 9	Syst. 13
	[93]	[93]	[57]
Pr_C	0.8	0.8	$0.1 \leq Pr_C \leq 0.9$
Pr_M	0.02	0.02	$0.01 \leq Pr_M \leq 0.5$
G_{max}	200	500	30
d	-	-	200
Local elitism rate	N	N	0.3
Global elitism rate	N	N	0.4

TABLE 44. Parameters of SOReco [52].

Parameters	Values		
	Syst. 3	Syst. 10	Syst. 11
d	10	10	10
G_{max}	7	6	9
Selection	Ecological niche	Ecological niche	Ecological niche

M. SYSTEM 13: 136-BUS DISTRIBUTION NETWORK

Figure 54 shows this real network, which is part of the Tres Lagoas distribution system in Brazil, with data available in [115]. It has eight radial feeders, one substation bus, 135 sectionalizing switches and 21 tie lines, with nominal voltage and nominal power of 13.8 kV and 1MVA, respectively. The results for EGA and IGA methods are presented

TABLE 45. Parameters of DEA methods.

Parameters	Values		
	DEA method		VSDEA method
	Syst. 3	Syst. 11	Syst. 11
	[21]	[21]	[66]
Pr_M	0.1	0.1	-
Pr_C	0.5	0.5	0.5
d	5	5	5
G_{max}	40	1000	500
ε_1	0.3	0.3	0.1
ε_2	3	5	0.1
c_d	N	N	0.82
c_i	N	N	1.2
F	N	N	0.3
q	N	N	10

TABLE 46. Parameters of BB-BC for system 6 [39].

Parameters	Values
Population size	50
Maximum iterations	100
Adjustable factors for controlling the influence of the global best (β_1)	0.1
Adjustable factors for controlling the influence of the local best (β_2)	0.9

TABLE 47. Parameters of HBMO.

Parameters	Values			
	Syst. 6		Syst. 11	
	[71]	[88]	[71]	[88]
Speed reduction factor	0.93	0.93	0.93	0.93
Speed of queen at start of a mating flight (S_{min})	1	1	1	1
Speed of queen at the end of a mating flight (S_{max})	2	2	2	2
Number of drones (N_{Dreone})	20	10	20	20
Maximum iterations	-	250	-	250
Size of the queen's spermatheca (N_{Sperm})	20	-	20	-
Number of broods (N_{Brood})	20	-	20	-
Number of queens (N_{queen})	40	-	40	-

TABLE 48. Parameters of TLBO for systems 6, 8, and 9 [38].

Parameters	Values
Number of population	20
Maximum iteration	20
Number of loop vectors	5

in Table 26 and compared with available results for a number of other methods in Table 27. Figures 55 to 57 show the convergence characteristics of both applied genetic algorithms.

The results in Table 27 verify the solutions obtained by the EGA and IGA methods. However, the EGA method has better convergence performance than IGA and any other method. According to Figs 55 to 57, the EGA finds the optimal DSR solution after only nine iterations, compared to 5,509 and 9,965 iterations of the IGA method in the best and the worst cases, respectively. As seen in Table 27, EGA and the classic method of [117] propose the best configuration much faster than other methodologies.

TABLE 49. Parameters of BFOA for system 6 [35].

Parameters	Values
Dimension of the search space (Number of variables)	3
Number of bacteria in the population	20
Number of chemotactic steps	10
Length of a swim when it is on a gradient	4
Number of reproduction steps	4
Number of elimination/dispersal events	2
Probability that each bacterium will be eliminated/dispersed	0.75

TABLE 50. Parameters of dragonfly [72].

Parameters	Values	
	Syst. 3	Syst. 9
Number of search agents	40	40
Number of dimensions (variables)	3	5
Maximum number of iterations	100	100

TABLE 51. Parameters of SAPSO+ MSLFA [107].

Parameters	Values	
	Syst. 10	Syst. 11
Velocity vector constants (C_1 and C_2)	Variable	Variable
Population size	33	39
Number of neighborhoods	11	13

TABLE 52. Parameters of PSO+HBMO for system 10 [108].

Parameters	Values
Velocity vector constants (C_1 and C_2)	2
Maximum inertia weight (ω_{max})	0.9
Minimum inertia weight (ω_{min})	0.4
Population size	16
Speed reduction factor	0.93
Speed of queen at start of a mating flight (S_{min})	1
Speed of queen at the end of a mating flight (S_{max})	2
Number of workers (N_{Worker})	10
Number of drones (N_{Dreone})	16
Size of the queen's spermatheca (N_{Sperm})	15
Number of broods (N_{Brood})	15

N. SYSTEM 14: 203-BUS DISTRIBUTION NETWORK

In order to illustrate the effectiveness of the proposed methodology in much larger systems, both EGA and IGA methods are applied to 203-bus distribution network, with results listed in Tables 28 and 29. The initial configuration of this real 13.8 kV distribution network with three feeders, 201 sectional switches, 15 tie lines, and three substation nodes is shown in Fig. 58. The system data can be found in [116]. The convergence of EGA and IGA methods is plotted in Figs 59 to 61.

It can be observed that IGA and EGA methods find optimal configurations with lower power losses than configuration found by TS method. The EGA algorithm is much faster than IGA and TS methods.

It can be also seen in Table 29 that configuration proposed by the IGA is different from configuration proposed by the EGA method, but both result in the same minimum losses. For additional checking, optimal configuration of EGA is verified

by a classic optimization software package (A Mathematical Programing Language, AMPL) [118] (see Table 29).

According to Figs 59 to 61, EGA has a much better convergence characteristic than IGA, as it needs only seven iterations to converge to the optimal solution, while IGA method finds the same solution after minimum and maximum of 6,187 and 12,090 iterations, respectively. However, the IGA is more accurate than TS presented in [116].

V. CONCLUSION

After a comprehensive overview of existing metaheuristic methods, this paper presents a novel efficient genetic algorithm (EGA), which was developed to minimize active power losses via distribution system reconfiguration (DSR). The EGA method was applied to a number of test systems, representing different types and configurations of distribution networks of different sizes. The results obtained by EGA are in all cases compared with the results obtained by improved GA (IGA) and available results by classic, heuristic and some other metaheuristic and GA methods, in order to provide detailed evaluation of the efficiency and effectiveness of the proposed EGA method.

The presented simulation results show that both EGA and IGA methods are superior to all other considered/available methods for 7-bus, 12-bus, 30-bus, 49-bus, and 203-bus test systems. In all cases, EGA and IGA methods are better than classic methods of [73] and [74], GA algorithms of [86] and [101], and metaheuristic method of TS. However, IGA performance degrades in test Systems 3, 4, 6, and 9 to 14 compared to EGA and some classic, heuristic, and metaheuristic methods.

For all presented test systems, the EGA method finds the best DSR solution in shorter computational time than any other method, including IGA, as it has much better convergence characteristic.

The main reason why the EGA method exhibits significantly improved performance is that it creates only radial configurations during the search through the evolutionary process of GA, which effectively outperforms IGA and other GA-based methods, as well as classic, heuristic and other metaheuristic approaches.

Effectively, the presented and discussed features of the EGA method make it an efficient and powerful method for solving DSR problem in both offline (high accuracy) and online applications (short computation time).

APPENDIX

Available parameters of other algorithms used for comparison are presented in Tables 30 to 52.

REFERENCES

[1] M. Mahdavi, C. Sabillón, M. Ajalli, H. Monsef, and R. Romero, "A real test system for power system planning, operation, and reliability," *J. Control, Autom. Electr. Syst.*, vol. 29, no. 2, pp. 192–208, Apr. 2018.

[2] M. Mahdavi, L. H. Macedo, and R. Romero, "Transmission and generation expansion planning considering system reliability and line maintenance," in *Proc. Electr. Eng. (ICEE), Iranian Conf.*, May 2018, pp. 1005–1010.

[3] M. Mahdavi, C. Sabillon, A. Bagheri, and R. Romero, "Line maintenance within transmission expansion planning: A multistage framework," *IET Gener., Transmiss. Distrib.*, vol. 13, no. 14, pp. 3057–3065, Jul. 2019.

[4] M. Khodayari, M. Mahdavi, and H. Monsef, "Simultaneous scheduling of energy & spinning reserve considering customer and supplier choice on reliability," in *Proc. 19th Iranian Conf. Electr. Eng.*, Tehran, Iran, May 2011, pp. 491–496.

[5] O. Badran, S. Mekhilef, H. Mokhlis, and W. Dahalan, "Optimal reconfiguration of distribution system connected with distributed generations: A review of different methodologies," *Renew. Sustain. Energy Rev.*, vol. 73, pp. 854–867, Jun. 2017.

[6] Y.-Y. Fu and H.-D. Chiang, "Toward optimal multiperiod network reconfiguration for increasing the hosting capacity of distribution networks," *IEEE Trans. Power Del.*, vol. 33, no. 5, pp. 2294–2304, Oct. 2018.

[7] H. Hosseini, S. Jalilzadeh, V. Nabaei, G. R. Z. Govar, and M. Mahdavi, "Enhancing deregulated distribution network reliability for minimizing penalty cost based on reconfiguration using BPSO," in *Proc. IEEE 2nd Int. Power Energy Conf.*, Johor Bahru, Malaysia, Dec. 2008, pp. 983–987.

[8] S. Lei, Y. Hou, F. Qiu, and J. Yan, "Identification of critical switches for integrating renewable distributed generation by dynamic network reconfiguration," *IEEE Trans. Sustain. Energy*, vol. 9, no. 1, pp. 420–432, Jan. 2018.

[9] A. Kimiyaghalam, M. Mahdavi, A. Ashouri, and M. Bagherivand, "Optimal placement of PMUS for reliable observability of network under probabilistic events using BABC algorithm," in *Proc. 22nd Int. Conf. Exhib. Electr. Distrib. (CIRED)*, Stockholm, Sweden, Jun. 2013, pp. 1–4.

[10] A. Asrari, S. Lotfifard, and M. Ansari, "Reconfiguration of smart distribution systems with time varying loads using parallel computing," *IEEE Trans. Smart Grid*, vol. 7, no. 6, pp. 2713–2723, Nov. 2016.

[11] L. H. Macedo, J. F. Franco, M. Mahdavi, and R. Romero, "A contribution to the optimization of the reconfiguration problem in radial distribution systems," *J. Control, Autom. Electr. Syst.*, vol. 29, no. 6, pp. 756–768, Dec. 2018.

[12] A. Merlin and H. Back, "Search for a minimal-loss operating spanning tree configuration in an urban power distribution system," in *Proc. 5th Power Syst. Comput. Conf.*, London, U.K., 1975, pp. 1–18.

[13] H.-D. Chiang and R. Jean-Jumeau, "Optimal network reconfigurations in distribution systems: Part 2: Solution algorithms and numerical results," *IEEE Trans. Power Del.*, vol. 5, no. 3, pp. 1568–1574, Jul. 1990.

[14] H.-C. Chang and C.-C. Kuo, "Network reconfiguration in distribution systems using simulated annealing," *Electr. Power Syst. Res.*, vol. 29, no. 3, pp. 227–238, May 1994.

[15] Y.-J. Jeon, J.-C. Kim, J.-O. Kim, J.-R. Shin, and K. Y. Lee, "An efficient simulated annealing algorithm for network reconfiguration in large-scale distribution systems," *IEEE Trans. Power Del.*, vol. 17, no. 4, pp. 1070–1078, Oct. 2002.

[16] Y. Mishima, K. Nara, T. Satoh, T. Ito, and H. Kaneda, "Method for minimum-loss reconfiguration of distribution system by Tabu search," *Electr. Eng. Jpn.*, vol. 152, no. 2, pp. 18–25, Jul. 2005.

[17] D. Zhang, Z.-C. Fu, and L.-C. Zhang, "An improved TS algorithm for loss-minimum reconfiguration in large-scale distribution systems," *Electr. Power Syst. Res.*, vol. 77, nos. 5–6, pp. 685–694, Apr. 2007.

[18] A. Y. Abdelaziz, F. M. Mohamed, S. F. Mekhamer, and M. A. L. Badr, "Distribution system reconfiguration using a modified tabu search algorithm," *Electr. Power Syst. Res.*, vol. 80, no. 8, pp. 943–953, Aug. 2010.

[19] A. Kazemi, S. Jalilzadeh, M. Mahdavi, and H. Haddadian, "Genetic algorithm-based investigation of load growth factor effect on the network loss in TNEP," in *Proc. 3rd IEEE Conf. Ind. Electron. Appl.*, Singapore, Jun. 2008, pp. 764–769.

[20] A. C. B. Delbem, A. C. P. L. F. D. Carvalho, and N. G. Bretas, "Main chain representation for evolutionary algorithms applied to distribution system reconfiguration," *IEEE Trans. Power Syst.*, vol. 20, no. 1, pp. 425–436, Feb. 2005.

[21] C.-T. Su and C.-S. Lee, "Network reconfiguration of distribution systems using improved mixed-integer hybrid differential evolution," *IEEE Trans. Power Del.*, vol. 18, no. 3, pp. 1022–1027, Jul. 2003.

[22] G. Manikanta, A. Mani, H. P. Singh, and D. K. Chaturvedi, "Distribution network reconfiguration with different load models using adaptive quantum inspired evolutionary algorithm," in *Proc. Int. Conf. Sustain. Energy, Electron., Comput. Syst. (SEEMS)*, Oct. 2018, pp. 1–7.

[23] B. Venkatesh and R. Ranjan, "Optimal radial distribution system reconfiguration using fuzzy adaptation of evolutionary programming," *Int. J. Electr. Power Energy Syst.*, vol. 25, no. 10, pp. 775–780, Dec. 2003.
[24] M. S. Tsai and F. Y. Hsu, "Application of grey correlation analysis in evolutionary programming for distribution system feeder reconfiguration," *IEEE Trans. Power Syst.*, vol. 25, no. 2, pp. 1126–1133, May 2010.
[25] S. Sivanagaraju, J. V. Rao, and P. S. Raju, "Discrete particle swarm optimization to network reconfiguration for loss reduction and load balancing," *Electr. Power Compon. Syst.*, vol. 36, no. 5, pp. 513–524, Apr. 2008.
[26] M. Mahdavi, A. Bagheri, and E. Mahdavi, "Comparing efficiency of PSO with GA in transmission expansion planning considering network adequacy," *WSEAS Trans. Power Syst.*, vol. 7, no. 1, pp. 34–43, Jan. 2012.
[27] A. Y. Abdelaziz, F. M. Mohammed, S. F. Mekhamer, and M. A. L. Badr, "Distribution systems reconfiguration using a modified particle swarm optimization algorithm," *Electr. Power Syst. Res.*, vol. 79, no. 11, pp. 1521–1530, Nov. 2009.
[28] W.-C. Wu and M.-S. Tsai, "Application of enhanced integer coded particle swarm optimization for distribution system feeder reconfiguration," *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1591–1599, Aug. 2011.
[29] C. T. Su, C. F. Chang, and J. P. Chiou, "Distribution network reconfiguration for loss reduction by ant colony search algorithm," *Electr. Power Syst. Res.*, vol. 75, nos. 2–3, pp. 190–199, Aug. 2005.
[30] E. Carpaneto and G. Chicco, "Distribution system minimum loss reconfiguration in the hyper-cube ant colony optimization framework," *Electr. Power Syst. Res.*, vol. 78, no. 12, pp. 2037–2045, Dec. 2008.
[31] A. Swarnkar, N. Gupta, and K. R. Niazi, "Adapted ant colony optimization for efficient reconfiguration of balanced and unbalanced distribution systems for loss minimization," *Swarm Evol. Comput.*, vol. 1, no. 3, pp. 129–137, Sep. 2011.
[32] A. Ahuja, A. Pahwa, B. K. Panigrahi, and S. Das, "Pheromone-based crossover operator applied to distribution system reconfiguration," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 4144–4151, Nov. 2013.
[33] C. H. Lin, C. S. Chen, C. J. Wu, and M. S. Kang, "Application of immune algorithm to optimal switching operation for distribution loss minimisation and loading balance," *IEE Proc. Gener., Transm. Distrib.*, vol. 150, no. 2, pp. 183–189, Mar. 2003.
[34] L. W. de Oliveira, E. J. de Oliveira, F. V. Gomes, I. C. Silva, A. L. M. Marcato, and P. V. C. Resende, "Artificial immune systems applied to the reconfiguration of electrical power distribution networks for energy loss minimization," *Int. J. Electr. Power Energy Syst.*, vol. 56, pp. 64–74, Mar. 2014.
[35] K. S. Kumar and T. Jayabarathi, "Power system reconfiguration and loss minimization for an distribution systems using bacterial foraging optimization algorithm," *Int. J. Electr. Power Energy Syst.*, vol. 36, no. 1, pp. 13–17, Mar. 2012.
[36] R. S. Rao, S. V. L. Narasimham, M. R. Raju, and A. S. Rao, "Optimal network reconfiguration of large-scale distribution system using harmony search algorithm," *IEEE Trans. Power Syst.*, vol. 26, no. 3, pp. 1080–1088, Aug. 2011.
[37] A. Tyagi, A. Verma, and P. R. Bijwe, "Reconfiguration for loadability limit enhancement of distribution systems," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 1, pp. 88–93, Jan. 2018.
[38] A. Lotfipour and H. Afrakhte, "A discrete teaching–learning-based optimization algorithm to solve distribution system reconfiguration in presence of distributed generation," *Int. J. Electr. Power Energy Syst.*, vol. 82, pp. 264–273, Nov. 2016.
[39] M. Sedighizadeh, M. Esmaili, and M. Esmaeili, "Application of the hybrid big bang-big crunch algorithm to optimal reconfiguration and distributed generation power allocation in distribution systems," *Energy*, vol. 76, pp. 920–930, Nov. 2014.
[40] I. A. Quadri, S. Bhowmick, and D. Joshi, "Multi-objective approach to maximise loadability of distribution networks by simultaneous reconfiguration and allocation of distributed energy resources," *IET Gener., Transmiss. Distribution*, vol. 12, no. 21, pp. 5700–5712, Oct. 2018.
[41] N. G. Paterakis, A. Mazza, S. F. Santos, O. Erdinç, G. Chicco, A. G. Bakirtzis, and J. P. S. Catalão, "Multi-objective reconfiguration of radial distribution systems using reliability indices," *IEEE Trans. Power Syst.*, vol. 31, no. 2, pp. 1048–1062, Mar. 2016.
[42] J. Wang, W. Wang, Z. Yuan, H. Wang, and J. Wu, "A Chaos disturbed beetle antennae search algorithm for a multiobjective distribution network reconfiguration considering the variation of load and DG," *IEEE Access*, vol. 8, pp. 97392–97407, 2020.
[43] H. Wu, P. Dong, and M. Liu, "Distribution network reconfiguration for loss reduction and voltage stability with random fuzzy uncertainties of renewable energy generation and load," *IEEE Trans. Ind. Informat.*, vol. 16, no. 9, pp. 5655–5666, Sep. 2020.
[44] A. Abbasi, "Investigation of simultaneous effect of demand response and load uncertainty on distribution feeder reconfiguration," *IET Gener., Transmiss. Distrib.*, vol. 14, no. 8, pp. 1438–1449, Apr. 2020.
[45] M. Mahdavi, A. R. Kheirkhah, L. H. Macedo, and R. Romero, "A genetic algorithm for transmission network expansion planning considering line maintenance," in *Proc. IEEE Congr. Evol. Comput. (CEC)*, Jul. 2020, pp. 1–6.
[46] K. Nara, A. Shiose, M. Kitagawa, and T. Ishihara, "Implementation of genetic algorithm for distribution system loss minimum reconfiguration," *IEEE Trans. Power Syst.*, vol. 7, no. 3, pp. 1044–1051, Aug. 1992.
[47] J. Z. Zhu, "Optimal reconfiguration of electrical distribution network using the refined genetic algorithm," *Electr. Power Syst. Res.*, vol. 62, no. 1, pp. 37–42, May 2002.
[48] M. Mahdavi and H. Haddadian, "Evaluation of GA performance in TNEP considering voltage level, network losses and number of bundle lines," *Int. J. Discrete Math.*, vol. 3, no. 1, pp. 1–10, May 2018.
[49] B. Enacheanu, B. Raison, R. Caire, O. Devaux, W. Bienia, and N. HadjSaid, "Radial network reconfiguration using genetic algorithm based on the matroid theory," *IEEE Trans. Power Syst.*, vol. 23, no. 1, pp. 186–195, Feb. 2008.
[50] J. Mendoza, R. Lopez, D. Morales, E. Lopez, P. Dessante, and R. Moraga, "Minimal loss reconfiguration using genetic algorithms with restricted population and addressed operators: Real application," *IEEE Trans. Power Syst.*, vol. 21, no. 2, pp. 948–954, May 2006.
[51] M. A. N. Guimarães, C. A. Castro, and R. Romero, "Distribution systems operation optimisation through reconfiguration and capacitor allocation by a dedicated genetic algorithm," *IET Gener., Transm. Distrib.*, vol. 4, no. 11, pp. 1213–1222, Nov. 2010.
[52] B. Tomoiaga, M. Chindris, A. Sumper, R. Villafafila-Robles, and A. Sudria-Andreu, "Distribution system reconfiguration using genetic algorithm based on connected graphs," *Electr. Power Syst. Res.*, vol. 104, pp. 216–225, Nov. 2013.
[53] M. Mahdavi, A. R. Kheirkhah, and R. Romero, "Transmission expansion planning considering line failures and maintenance," in *Proc. 33rd Int. Power Syst. Conf.*, Tehran, Iran, Oct. 2018, pp. 1–7. [Online]. Available: http://psc-ir.com/cd/2018/papers/1038.pdf
[54] K. Prasad, R. Ranjan, N. C. Sahoo, and A. Chaturvedi, "Optimal reconfiguration of radial distribution systems using a fuzzy mutated genetic algorithm," *IEEE Trans. Power Del.*, vol. 20, no. 2, pp. 1211–1213, Apr. 2005.
[55] N. Gupta, A. Swarnkar, K. R. Niazi, and R. C. Bansal, "Multi-objective reconfiguration of distribution systems using adaptive genetic algorithm in fuzzy framework," *IET Gener., Transm. Distrib.*, vol. 4, no. 12, pp. 1288–1298, Dec. 2010.
[56] S. Chandramohan, N. Atturulu, R. P. K. Devi, and B. Venkatesh, "Operating cost minimization of a radial distribution system in a deregulated electricity market through reconfiguration using NSGA method," *Int. J. Electr. Power Energy Syst.*, vol. 32, no. 2, pp. 126–132, Feb. 2010.
[57] J. C. Cebrian and N. Kagan, "Reconfiguration of distribution networks to minimize loss and disruption costs using genetic algorithms," *Electr. Power Syst. Res.*, vol. 80, no. 1, pp. 53–62, Jan. 2010.
[58] J. M. Harris, J. L. Hirst, and M. J. Mossinghoff, *Combinatorics and Graph Theory*, 2nd ed. New York, NY, USA: Springer, Sep. 2008, pp. 1–396.
[59] Y.-Y. Hong and S.-Y. Ho, "Determination of network configuration considering multiobjective in distribution systems using genetic algorithms," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 1062–1069, May 2005.
[60] N. C. Sahoo and K. Prasad, "A fuzzy genetic approach for network reconfiguration to enhance voltage stability in radial distribution systems," *Energy Convers. Manage.*, vol. 47, nos. 18–19, pp. 3288–3306, Nov. 2006.
[61] A. M. Eldurssi and R. M. O'Connell, "A fast nondominated sorting guided genetic algorithm for multi-objective power distribution system reconfiguration problem," *IEEE Trans. Power Syst.*, vol. 30, no. 2, pp. 593–601, Mar. 2015.
[62] C. Wang and Y. Gao, "Determination of power distribution network configuration using non-revisiting genetic algorithm," *IEEE Trans. Power Syst.*, vol. 28, no. 4, pp. 3638–3648, Nov. 2013.
[63] C.-T. Su and C.-S. Lee, "Feeder reconfiguration and capacitor setting for loss reduction of distribution systems," *Electr. Power Syst. Res.*, vol. 58, no. 2, pp. 97–102, Jun. 2001.

[64] T. Niknam and E. A. Farsani, "A hybrid evolutionary algorithm for distribution feeder reconfiguration," *Sci. China Technol. Sci.*, vol. 53, no. 4, pp. 950–959, Apr. 2010.

[65] T. Niknam, "An efficient hybrid evolutionary algorithm based on PSO and ACO for distribution feeder reconfiguration," *Eur. Trans. Elect. Power*, vol. 20, no. 5, pp. 575–590, Jul. 2010.

[66] J. P. Chiou, C. F. Chung, and C. T. Su, "Variable scaling hybrid differential evolution for solving network reconfiguration of distribution systems," *IEEE Trans. Power Syst.*, vol. 20, no. 2, pp. 668–674, May 2005.

[67] C. F. Chang, "Reconfiguration and capacitor placement for loss reduction of distribution systems by ant colony search algorithm," *IEEE Trans. Power Syst.*, vol. 23, no. 4, pp. 1747–1755, Nov. 2008.

[68] A. Y. Abdelaziz, R. A. Osama, and S. M. El-Khodary, "Reconfiguration of distribution systems for loss reduction using the hyper-cube ant colony optimisation algorithm," *IET Gener., Transm. Distrib.*, vol. 12, no. 2, pp. 176–187, Feb. 2012.

[69] A. Saffar, R. Hooshmand, and A. Khodabakhshian, "A new fuzzy optimal reconfiguration of distribution systems for loss reduction and load balancing using ant colony search-based algorithm," *Appl. Soft Comput.*, vol. 11, no. 5, pp. 4021–4028, Jul. 2011.

[70] T. Niknam, "Application of honey bee mating optimization on distribution state estimation including distributed generators," *J. Zhejiang Univ. Sci. A*, vol. 9, no. 12, pp. 1753–1764, Dec. 2008.

[71] T. Niknam, "An efficient multi-objective HBMO algorithm for distribution feeder reconfiguration," *Expert Syst. Appl.*, vol. 38, no. 3, pp. 2878–2887, Mar. 2011.

[72] A. V. S. Reddy and M. D. Reddy, "Optimization of distribution network reconfiguration using dragonfly algorithm," *J. Elect. Eng.*, vol. 16, no. 4, pp. 1–10, 2016.

[73] K. Masteri and B. Venkatesh, "A new optimization method for distribution system reconfiguration," in *Proc. IEEE 27th Can. Conf. Electr. Comput. Eng. (CCECE)*, Toronto, ON, Canada, May 2014, pp. 1–4.

[74] J. AL-Sujada and O. Y. M. Al-Rawi, "Novel load flow algorithm for multi-phase balanced/unbalanced radial distribution systems," *Int. J. Adv. Res. Electr. Electron. Instrum. Eng.*, vol. 3, no. 7, pp. 10928–10942, Jul. 2014.

[75] S. Civanlar, J. J. Grainger, H. Yin, and S. S. H. Lee, "Distribution feeder reconfiguration for loss reduction," *IEEE Trans. Power Del.*, vol. 3, no. 3, pp. 1217–1223, Jul. 1988.

[76] C. A. Castro and A. A. Watanabe, "An efficient reconfiguration algorithm for loss reduction of distribution systems," *Electr. Power Syst. Res.*, vol. 19, no. 2, pp. 137–144, Aug. 1990.

[77] R. J. Sarfi, M. M. A. Salama, and A. Y. Chikhani, "Distribution system reconfiguration for loss reduction: An algorithm based on network partitioning theory," *IEEE Trans. Power Syst.*, vol. 11, no. 1, pp. 504–510, Feb. 1996.

[78] Y.-J. Jeon and J.-C. Kim, "Application of simulated annealing and Tabu search for loss minimization in distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 26, no. 1, pp. 9–18, Jan. 2004.

[79] F. V. Gomes, S. Carneiro, J. L. R. Pereira, M. P. Vinagre, P. A. N. Garcia, and L. R. Araujo, "A new heuristic reconfiguration algorithm for large distribution systems," *IEEE Trans. Power Syst.*, vol. 20, no. 3, pp. 1373–1378, Aug. 2005.

[80] F. V. Gomes, S. Carneiro, J. L. R. Pereira, M. P. Vinagre, P. A. N. Garcia, and L. R. D. Araujo, "A new distribution system reconfiguration approach using optimum power flow and sensitivity analysis for loss reduction," *IEEE Trans. Power Syst.*, vol. 21, no. 4, pp. 1616–1623, Nov. 2006.

[81] G. K. V. Raju and P. R. Bijwe, "Efficient reconfiguration of balanced and unbalanced distribution systems for loss minimisation," *IET Gener., Transmiss. Distrib.*, vol. 2, no. 1, pp. 7–12, Jan. 2008.

[82] A. K. Ferdavani, A. A. M. Zin, A. Khairuddin, and M. M. Naeini, "Reconfiguration of distribution system through two minimum-current neighbour-chain updating methods," *IET Gener., Transmiss. Distrib.*, vol. 7, no. 12, pp. 1492–1497, Dec. 2013.

[83] H. Ahmadi and J. R. Martí, "Linear current flow equations with application to distribution systems reconfiguration," *IEEE Trans. Power Syst.*, vol. 30, no. 4, pp. 2073–2080, Jul. 2015.

[84] H. Ahmadi and J. R. Martí, "Mathematical representation of radiality constraint in distribution system reconfiguration problem," *Int. J. Electr. Power Energy Syst.*, vol. 64, pp. 293–299, Jan. 2015.

[85] B. Novoselnik, M. Bolfek, M. Bošković, and M. Baotić, "Electrical power distribution system reconfiguration: Case study of a real-life grid in Croatia," *IFAC PapersOnLine*, vol. 50, no. 1, pp. 61–66, 2017.

[86] N. Kagan, "Configuração de redes de distribuição através de algoritmos genéticos e tomada de decisão fuzzy," M.S. thesis, Dep. Electr. Energy Autom. Eng., Univ. São Paulo, São Paulo, Brazil, 1999, pp. 1–187.

[87] M. E. Baran and F. F. Wu, "Network reconfiguration in distribution systems for loss reduction and load balancing," *IEEE Trans. Power Del.*, vol. 4, no. 2, pp. 1401–1407, Apr. 1989.

[88] H. R. Esmaeilian and R. Fadaeinedjad, "Energy loss minimization in distribution systems utilizing an enhanced reconfiguration method integrating distributed generation," *IEEE Syst. J.*, vol. 9, no. 4, pp. 1430–1439, Dec. 2015.

[89] M. A. Kashem, G. B. Jasmon, and V. Ganapathy, "A new approach of distribution system reconfiguration for loss minimization," *Int. J. Electr. Power Energy Syst.*, vol. 22, no. 4, pp. 269–276, May 2000.

[90] S. K. Goswami and S. K. Basu, "A new algorithm for the reconfiguration of distribution feeders for loss minimization," *IEEE Trans. Power Del.*, vol. 7, no. 3, pp. 1484–1491, Jul. 1992.

[91] R. S. Rao, K. Ravindra, K. Satish, and S. V. L. Narasimham, "Power loss minimization in distribution system using network reconfiguration in the presence of distributed generation," *IEEE Trans. Power Syst.*, vol. 28, no. 1, pp. 317–325, Feb. 2013.

[92] B. Khorshid-Ghazani, H. Seyedi, B. Mohammadi-Ivatloo, K. Zare, and S. Shargh, "Reconfiguration of distribution networks considering coordination of the protective devices," *IET Gener., Transmiss. Distrib.*, vol. 11, no. 1, pp. 82–92, Jan. 2017.

[93] S. A. Taher and M. H. Karimi, "Optimal reconfiguration and DG allocation in balanced and unbalanced distribution systems," *Ain Shams Eng. J.*, vol. 5, no. 3, pp. 735–749, Sep. 2014.

[94] A. B. Morton and I. M. Y. Mareels, "An efficient brute-force solution to the network reconfiguration problem," *IEEE Trans. Power Del.*, vol. 15, no. 3, pp. 996–1000, Jul. 2000.

[95] M. Lavorato, J. F. Franco, M. J. Rider, and R. Romero, "Imposing radiality constraints in distribution system optimization problems," *IEEE Trans. Power Syst.*, vol. 27, no. 1, pp. 172–179, Aug. 2012.

[96] J. A. Taylor and F. S. Hover, "Convex models of distribution system reconfiguration," *IEEE Trans. Power Syst.*, vol. 27, no. 3, pp. 1407–1413, Aug. 2012.

[97] T. Niknam, "A new hybrid algorithm for multiobjective distribution feeder reconfiguration," *Cybern. Syst.*, vol. 40, no. 6, pp. 508–527, Jul. 2009.

[98] K. Jasthi and D. Das, "Simultaneous distribution system reconfiguration and DG sizing algorithm without load flow solution," *IET Gener., Transmiss. Distrib.*, vol. 12, no. 6, pp. 1303–1313, Mar. 2018.

[99] H. Ahmadi and J. R. Martí, "Distribution system optimization based on a linear power-flow formulation," *IEEE Trans. Power Del.*, vol. 30, no. 1, pp. 25–33, Feb. 2015.

[100] T. E. McDermott, I. Drezga, and R. P. Broadwater, "A heuristic nonlinear constructive method for distribution system reconfiguration," *IEEE Trans. Power Syst.*, vol. 14, no. 2, pp. 478–483, May 1999.

[101] R. A. Abttan, "Electric distribution system reconfiguration for loss reduction using genetic algorithm," *J. Baghdad College Econ. Sci. Univ.*, vol. 2015, no. 43, pp. 457–478, 2015.

[102] A. A. Mohd Zin, A. K. Ferdavani, A. B. Khairuddin, and M. M. Naeini, "Reconfiguration of radial electrical distribution network through minimum-current circular-updating-mechanism method," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 968–974, May 2012.

[103] M. A. Kashem, V. Ganapathy, and G. B. Jasmon, "A geometrical approach for network reconfiguration based loss minimization in distribution systems," *Int. J. Electr. Power Energy Syst.*, vol. 23, no. 4, pp. 295–304, May 2001.

[104] G. K. V. Raju and P. R. Bijwe, "An efficient algorithm for minimum loss reconfiguration of distribution system based on sensitivity and heuristics," *IEEE Trans. Power Syst.*, vol. 23, no. 3, pp. 1280–1287, Aug. 2008.

[105] M. Arun and P. Aravindhababu, "A new reconfiguration scheme for voltage stability enhancement of radial distribution systems," *Energy Convers. Manage.*, vol. 50, no. 9, pp. 2148–2151, Sep. 2009.

[106] D. Das, "A fuzzy multiobjective approach for network reconfiguration of distribution systems," *IEEE Trans. Power Del.*, vol. 21, no. 1, pp. 202–209, Jan. 2006.

[107] T. Niknam and E. A. Farsani, "A hybrid self-adaptive particle swarm optimization and modified shuffled frog leaping algorithm for distribution feeder reconfiguration," *Eng. Appl. Artif. Intell.*, vol. 23, no. 8, pp. 1340–1349, Dec. 2010.

[108] T. Niknam, "An efficient hybrid evolutionary algorithm based on PSO and HBMO algorithms for multi-objective distribution feeder reconfiguration," *Energy Convers. Manage.*, vol. 50, no. 8, pp. 2074–2082, Aug. 2009.
[109] A. Ahuja, S. Das, and A. Pahwa, "An AIS-ACO hybrid approach for multi-objective distribution system reconfiguration," *IEEE Trans. Power Syst.*, vol. 22, no. 3, pp. 1101–1111, Aug. 2007.
[110] Y.-K. Wu, C.-Y. Lee, L.-C. Liu, and S.-H. Tsai, "Study of reconfiguration for the distribution system with distributed generators," *IEEE Trans. Power Del.*, vol. 25, no. 3, pp. 1678–1685, Jul. 2010.
[111] D. Shirmohammadi and W. H. Hong, "Reconfiguration of electric distribution networks for resistive line loss reduction," *IEEE Trans. Power Del.*, vol. 4, no. 2, pp. 1492–1498, Apr. 1989.
[112] P. Kumar, I. Ali, M. S. Thomas, and S. Singh, "Imposing voltage security and network radiality for reconfiguration of distribution systems using efficient heuristic and meta-heuristic approach," *IET Gener., Transmiss. Distrib.*, vol. 11, no. 10, pp. 2457–2467, Jul. 2017.
[113] R. A. Jabr, R. Singh, and B. C. Pal, "Minimum loss network reconfiguration using mixed-integer convex programming," *IEEE Trans. Power Syst.*, vol. 27, no. 2, pp. 1106–1115, May 2012.
[114] R. Tapia-Juárez and E. Espinosa-Juárez, "Reconfiguration of radial distribution networks by applying a multi-objective technique," in *Proc. Int. Conf. Artif. Intell.*, Athens, Greece, 2015, pp. 131–137.
[115] J. R. S. Mantovani, F. Casari, and R. A. Romero, "Reconfiguração de sistemas de distribuição radiais utilizando o critério de queda de tensão," *SBA Controle Automação*, vol. 11, no. 3, pp. 150–159, 2000.
[116] M. N. A. Guimarães and C. A. Castro, "Reconfiguration of distribution systems for loss reduction using Tabu Search," in *Proc. 15th Power Syst. Comput. Conf.*, Ghent, Belgium, 2005, pp. 1–6.
[117] H. Hijazi and S. Thiébaux, "Optimal distribution systems reconfiguration for radial and meshed grids," *Int. J. Electr. Power Energy Syst.*, vol. 72, pp. 136–143, Nov. 2015.
[118] R. Fourer, D. M. Gay, and B. W. Kernighan, "A modeling language for mathematical programming," *Manage. Sci.*, vol. 36, no. 5, pp. 519–554, May 1990.

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