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Effective network reconfiguration with distributed generation allocation in radial distribution networks using water cycle algorithm

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ABSTRACT

This paper presents a novel application of watercycle algorithm (WCA) for optimal distribution network reconfiguration (DNR) and distributed generation (DG) allocation in radial distribution network (RDN). WCA is proposed to simultaneously have the optimal topology of RDN and get the optimal DG size and placement. The objective is to minimize power losses and the voltage profile index. in addition, study the variation in both voltage magnitude and voltage stability profiles. Loss sensitivity factor index is utilized to crop the candidate buses for DG allocation aiming to narrow the search space for DG sizing. Moreover, the graph theory is presented to get the fundamental loops that used to reduce the search space for DNR by limiting the infeasible configurations during the optimization process, where the connection matrix of the radial network is used to check the radial constraint of each configuration. The proposed method has been applied on two different RDN with different scenarios. The obtained results verify the effectiveness of the proposed algorithm in comparison with previous works in literature.

1. Introduction

Electrical radial distribution network is the final stage in electric power delivery. It represents the junction between transmission system and consumers. Radial distribution systems usually suffer from high power losses and poor voltage profile due to its low voltage level and large drawn currents [1,2]. Moreover, voltage stability had the attention of many researchers due to the rapid expansion of distribution systems [3,4].Distributed generation allocation and network reconfiguration are among many different methodologies that have been used to improve the performance of radial networks [5]. Distribution network reconfiguration (DNR) means changing the network topology by changing the status of sectionalizing switches and tie switches (close / open), keeping the radiality constraint in such a way that the operator's objectives are optimized [6]. Recently, many researchers have applied new meta-heuristic approaches to get the optimum topology of the network. In [7], the enhanced genetic algorithm was proposed for DNR in order to reduce power losses and improve the network reliability. In [8], authors have employed DNR and capacitor placement simultaneously to minimize the system cost and improve the network performance. A binary gravitational search algorithm (BGSA) is used to optimize the fuzzy multi-objective problem. In [9], the minimum spacing tree (MST) algorithm is combined with heuristic rules to solve DNR

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problem so that the active power loss is minimized. Many other evolutionary algorithms have been utilized to solve DNR problems with various objectives such as: ant colony optimization (ACO) [10], particle swarm optimization (PSO) [11], honey bee mating optimization (HBMO) [12], enhanced gravitational search algorithm (EGSA) [13]. Distributed generation (DG) is an approach that employs small scale technologies (modular and renewable resources) to produce electricity close to load centre in capacities that range from a kilowatt to about 100 MW. Technical, environmental and economical benefits of DG allocation have attracted the attention of researchers. Analytical methods have been utilized for single and multi-DG allocation [14-16]. Various sensitivity indices have been applied such as novel power loss sensitivity [17], power stability index (PSI) [18] and voltage stability index [19]. Also, many new meta-heuristic approaches are applied for DG placement to optimize various objectives such as: genetic algorithm (GA) [20], PSO [21, 22], cat swarm optimization [23], krill herd approach (KHA) [24], modified teaching learning-based optimization (MTLBO) method [25], hybrid approach which combines harmony search algorithm (HSA) and particle artificial bee colony (PABC) [26] and bacterial foraging optimization algorithm (BFOA) [27]. Recently, the DNR and DG allocation issues have been integrated together in order to improve the network performance. In [28], HSA is proposed to simultaneously reconfigure and allocate DG in distribution network so that minimizing power losses and improving voltage profile. In [29], DNR is solved simultaneously with DG allocation using fireworks algorithm (FWA) in order to reduce power losses and improve voltage profile. In [30], the adaptive cuckoo search algorithm (ACSA) is presented to optimize network configuration in the presence of DG so that minimizing total power losses and enhancement of voltage stability. The authors in [31, 32] have taken the power loss as a single objective to be minimized when combining DNR and DG penetration. In [33], fuzzy-ACO approach is utilized to solve the problem considering power loss reduction, voltage profile enhancement and increasing of feeder loading balance. In [34], the problem is solved using a multi-objective based on bang-big crunch algorithm. The authors in [35] utilized an improved particle swarm optimization (IPSO) to solve DNR and DG allocation considering multi-objective function to be minimized. An optimization algorithm based on a discrete teaching-learning is illustrated in [36]. A multi-objective evolutionary algorithm is proposed in [37] based on the enhanced gravitational search algorithm considering power loss and operation cost minimization as well as transient stability improvement. In [38], uniform voltage distribution algorithm is proposed for simultaneous DNR and DG allocation and sizing so as to maximize the power loss reduction. In this paper, a novel approach based on WCA [39] is proposed to simultaneously solve DNR and DG allocation problems. The concept of WCA is inspired from nature by the observation of the streams and rivers moving to the sea [39, 40]. WCA mimics the water cycle process resulting in an efficient and reliable optimization algorithm compared to other optimization techniques. WCA has a simple structure and fewer insensitive parameters to tune so that it can be acclimatized to various optimization problems. WCA is able to explore global optima avoiding premature convergence to local optima and also has preferable convergence performance.all these merits encouraged the authors to apply WCA on radial system reconfiguration along with DG allocation. Graph theory [41] and loss sensitivity factor index [28] are used to reduce the search space for DNR and DG placement, respectively. The proposed algorithm is applied to a small scale 33-bus system and a large scale 118-bus network and results are compared with previous techniques in the literatures.

2. Problem Identification

The main objective of the paper is to reduce the total real power loss and the voltage deviationof RDN based on DG allocation and DNR . Also, bus voltage and stability profiles are studied with different optimization scenarios.

2.1. Power loss calculation

In this study forward-backward sweep load flow using Kirchhoff's laws is applied to solve the load flow of the distribution system under study. Referring to Fig. 1, active and reactive power received at bus j are deduced as:

$$\frac{V_i\angle\delta_i - V_j\angle\delta_j}{Z_{ij}\angle\theta_{ij}} \quad (1)$$

$$P_j + jQ_j = V_j\angle\delta_j \times I_j^* = \frac{V_i V_j}{Z_{ij}}\angle(\theta_{ij} - \delta_i + \delta_j) - \frac{V_j^2}{Z_{ij}}\angle\theta_{ij} \quad (2)$$

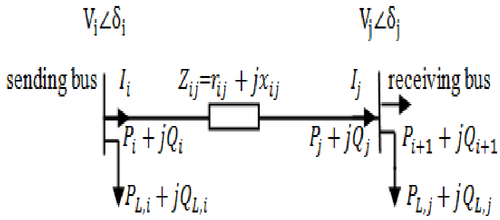

Fig. 1.Section of RDN of the ij bus

$$P_j=\frac{V_iV_j}{Z_{ij}}\cos(\theta_{ij}-\delta_i+\delta_j)-\frac{V_j^2}{Z_{ij}}\cos(\theta_{ij}) \quad (3)$$

$$Q_j=\frac{V_iV_j}{Z_{ij}}\sin(\theta_{ij}-\delta_i+\delta_j)-\frac{V_j^2}{Z_{ij}}\sin(\theta_{ij}) \quad (4)$$

where P_j and Q_j are the active and reactive power fed into receiving bus j, respectively; Z_{ij} and θ_{ij} are the impedance magnitude and angle of branch ij, respectively; V_i and V_j are voltage magnitude of bus i and bus j, respectively; and δ_i and δ_j are the angles of V_i and V_j, respectively.

Branch ij active power loss (P_{ij}^{loss})can be calculated using Equation 5.

$$P_{ij}^{loss}=|I_j|^2.r_{ij}=\frac{P_j^2+Q_j^2}{V_j^2}\,.\,r_{ij} \quad (5)$$

The total active power loss ($P_{T,Loss}$)is calculated using Equation 6.

$$P_{T,Loss}=\sum_{i=1}^{N_b-1}\sum_{j=2}^{N_b}P_{ij}^{loss}=\sum_{i=1}^{N_b-1}\sum_{j=2}^{N_b}\frac{P_j^2+Q_j^2}{V_j^2}\,.r_{ij}\,,\, j>i \quad (6)$$

whereN_b is the total number of network buses.

2.2. Voltage deviation and stability indices

The voltage deviation index (VDI) is considered as indicator for voltage profile improvement and may be calculated using Equation 7.

$$VDI=\max\left(\frac{V_1-V_j}{V_1}\right) j\in N_b \quad (7)$$

The voltage stability index (VSI) at each receiving bus can be obtained using Equation 8 [42].

$$VSI(j)=V_i^4-4.\left(P_j.r_{ij}+Q_j.x_{ij}\right).V_i^2-4.\left(P_j.x_{ij}-Q_j.r_{ij}\right)^2 \quad (8)$$

The bus with higher VSI is more stable with load increase and is not likely to collapse.

2.3. Objective function and constraints

This paper aims to minimize the total active power losses and the voltage deviation indexthen study the improvement in bus voltage profile and voltage stability profile. The objective function (F) will be calculated using Equation 9.

$$MinimizeF=min\left(\left(\frac{P_{T,Loss\,|R,DG}}{P_{T,Loss\,|base}}\right)+VDI\right) \quad (9)$$

where$P_{T,Loss\,|R,DG}$ is the total power loss with DNR including DG and $P_{T,Loss\,|base}$ is the total power loss of the base case RDN without reconfiguration or DG allocation.

The optimization process is subjected to the following constraints:
Power balance:

$$\left.\begin{array}{c} P_{slack}+\sum_{i=1}^{N_{DG}}P_{DG,i}=P_{Dt}+P_{T,Loss} \\ Q_{slack}=Q_{Dt}+Q_{T,Loss}\end{array}\right\}(10)$$

Bus voltage limits:

$$V_{Min}\le V_i\le V_{Max} \qquad i\in N_b \quad (11)$$

Line flow limits:

$$S_i\le S_i^{rated} \qquad i\in N_{br} \quad (12)$$

DG sizing limits:

$$P_{DG}^{Min}\le P_{DG,i}\le P_{DG}^{Max} \qquad i\in N_{DG} \quad (13)$$

DG penetration ratio:

$$\sum_{i=1}^{N_{DG}}P_{DG,i}\le\mu.P_{Dt} \quad (14)$$

where P_{Dt} andQ_{Dt} are the total load active and reactive demand respectively;N_{br} is the total number of branches under service; N_{DG} is the total number of DG; $P_{DG,i}$is the active power of DG unit i; V_{Min} and V_{Max} are floor and ceiling voltage limits; and S_i and S_i^{rated} are the actual and rated apparent power flow in branch i;P_{DG}^{Min} and P_{DG}^{Max} are the floor and ceiling limits of DG active power and μ represents the upper ratio of DG penetration as a percentage of total network load demand.

Radial configuration:

During the optimization process The new network configuration must be radial and there is not any isolated bus.

3. Search space for optimization

3.1. Graph theory and radiality check

This method is used to reduce the infeasible solutions which make the network not radial so that reducing the search space for DNR. For any distribution network with a number of branches $\boldsymbol{N_{br}}$ and a set of buses$\boldsymbol{N_b}$, a connection matrix (A) may be formulated with size ($\boldsymbol{N_{br}} \times \boldsymbol{N_b}$) [30] with elements identified in Equation 15.

$$A_{ij} = \begin{cases} 1 \quad if branch starts at bus j \\ -1 \quad if branch ends at bus j \\ \quad 0 \quad otherwise \end{cases} \qquad (15)$$

where$i$ = 1, 2, …., N_{br} and j = 1, 2, …., N_b

Fundamental loops (FL_s) which have the same number as tie lines [41, 43] are determined. Each configuration may be formed including a set of open switches from corresponding FL_s. However, some of lines are common in some loops so we must check the network radiality for each generated configuration as shown in Fig. 2.

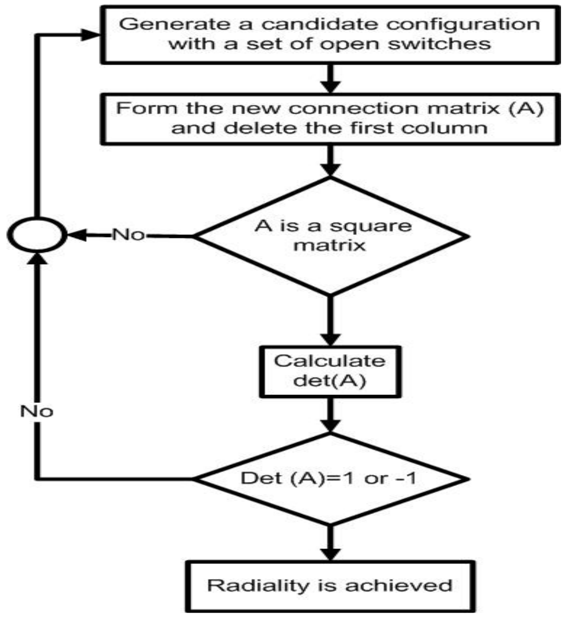

Fig. 2.Procedures to check system radiality

3.2. Sensitivity analysis for DG candidate buses

Sensitivity analysis is utilized to determine the candidate buses to allocate DG so that the search space for the WCA process is reduced. Loss sensitivity factor (LSF) is used which give index for the rate of loss reduction when real and reactive power are injected at each bus.

Referring to Equation 5, the LSF at each node j is obtained using Equation 16 then arranged in descending order.

$$LSF(j) = \frac{\partial P_{ij}^{loss}}{\partial P_j} . r_{ij} = \frac{2P_j}{V_j^2} . r_{ij} \qquad i \in \{1, \dots, N_b - 1\}, \ j \in \{2, \dots, N_b\} \qquad (16)$$

buses with the highest LSF index are chosen to be the candidate buses to allocate DG.

4. Overview of water cycle algorithm

The WCA is a recently developed simple and powerful evolutionary optimization algorithm inspired from nature [39] while the observation of the hydrological cycle. In water cycle process, solar heat causes water evaporation forming the clouds. Then, wind move clouds through colder atmosphere and water drops fall from clouds due to condensation process. Water flows above ground forming streams which flow to rivers and the rivers move towards the sea. Similar to other meta-heuristic optimizers, the WCA starts with an initial population represents the streams as shown in Equation 17.

$$X_{initial} = LB + rand.(UB - LB) \qquad (17)$$

where rand is a random uniform distributed number in [0,1]; LB and UB are the floor and ceiling boundaries of the WCA decision control variables.

For a (N_D) multi-dimension optimization problem, the stream represents an array of ($1 \times N_D$) as specified in Equation 18. A matrix of ($N_{pop} \times N_D$) is generated as an initial population to start the optimization process as shown in Equation 19.

$$stream = [x_i]_{1 \times N_D} \qquad i \in N_D \qquad (18)$$

$$Population = [x_{ij}]_{N_{pop} \times N_D} \quad i \in N_{pop}, j \in N_D \quad (19)$$

wherex_{ij} is the value of problem decision variable; N_{pop} is the population size; and N_D is the decision variables number.

A part (N_{sr}) of (N_{pop}) represents the first group which have better fitness values than the elements of the second group. The first group contains one sea (the best fitness value) plus a number of rivers (N_r) given by Equation 20 while the second group represents the number of streams (N_{stream}) as shown in Equation 21.

$$N_{sr} = 1 + N_r \quad (20)$$

$$N_{stream} = N_{pop} - N_{sr} \quad (21)$$

The number of streams which flows to the specific rivers and sea (NS_n) is obtained using Equation 22.

$$NS_n = round\left\{\left|\frac{Cost_n}{\sum_{i=1}^{N_{sr}} Cost_i}\right| . N_{stream}\right\} \quad n \in N_{sr} \quad (22)$$

where$Cost_i$ is the calculated objective function.

In the exploitation phase, streams and rivers update their new positions using Equations 23-25.

$$X_{stream}^{i+1} = X_{stream}^{i} + rand.C.(X_{river}^{i} - X_{stream}^{i}) \quad (23)$$

$$X_{river}^{i+1} = X_{river}^{i} + rand.C.(X_{sea}^{i} - X_{river}^{i}) \quad (24)$$

$$X_{stream}^{i+1} = X_{stream}^{i} + rand.C.(X_{sea}^{i} - X_{stream}^{i}) \quad (25)$$

where C is a number in the domain{1-2} and the best value of C may be chosen as 2 enabling rivers and streams to flow in different directions.

Each river exchange position with its connected stream which gives better solution (fitness) than the river. Such exchange is similarly done between the sea and its connected river or stream which give better solution than the sea.

Evaporation condition in Equation 26 is very important to prevent the algorithm from premature convergence to local optima.

$$|X_{sea}^{i} - X_{n}^{i}| < d_{max} \quad (26)$$
$$n \in \{river, directly\ connected\ streams\ to\ sea\}$$

whered_{max} is a small value (close to zero) which controls the intensity of search close to the sea.

If the evaporation condition is verified for a river flowing to the sea, the new precipitations (raining) will occur. So, a new position for that river and all of its connected streams will be obtained using Equation 27. The best among new streams is considered the river.

$$X_{new\ stream}^{i} = LB + rand.(UB - LB) \quad (27)$$

Also, a stream connected directly to the sea and verifying the evaporation condition will change to a new stream also connected to the sea as expressed in Equation 28.

$$X_{new\ stream}^{i} = X_{sea}^{i} + \sqrt{\mu}\,.randn(1, N_D) \quad (28)$$

where$\mu = 0.1$ as given in [40]; and $randn$ is a random vector has the same size of stream.

The value of (d_{max}) decreases adaptively with iteration number as shown in Equation 29.

$$d_{max}^{i+1} = d_{max}^{i} - \frac{d_{max}^{i}}{\max\_iteration} \quad (29)$$

Fig. 3 represent flow chart summarizing the procedures of the proposed WCA.

5. Numerical results and discussion

To demonstrate the efficiency and validation of the proposed algorithm in solving DNR and DG allocation simultaneously using WCA, a detailed performance analysis is applied on small scale 33-node and on a large scale 118-node **RDNs**comprising tie lines as shown in Figs. 4 and 5, respectively. Line and load data for the two test networks are given in [44, 45]. The proposed algorithm and associated distribution load flow are coded and performed using MATLAB [46]. The adopted WCA control parameters are carefully adjusted for each RDN and also the required inequality constraints are selected as shown in Table 1. DG of type 1is used (gives only active power) with a maximum number limited to three.In each network, five scenarios are studied to illustrate the efficiency of the proposed WCA.

Scenario 1: only DNR.

Scenario 2: only DG allocation on base case.

Scenario 3: DG allocation after DNR.

Scenario 4: DNR after DG allocation.

Scenario 5: simultaneous DNR and DG allocation.

5.1.33-node system

After obtaining the FL_s and calculation the top high ranking buses for DG placement according to LSF, the proposed algorithm is applied with different scenarios to find the optimal network topology and optimal DG placement (location and size). Optimal results (out of 50 independent runs) are listed in Table 2 for each scenario including the base case. In order to demonstrate the efficiency of the proposed technique, WCA performance is compared with techniques in the literature in Table 2. The comparison proves the ability of the proposed method to obtain the best results in terms of power loss reduction and voltage deviation minimization. Also, one can see that the simultaneous DNR and DG allocation (scenario 5) is the best way among other studied scenarios to give better optimal solutions. The bus voltage and VSI profiles for all studied scenarios including the base case are shown in Figs. 6 and 7. These figures show the improvement in voltage magnitude and VSIat all nodes for all studied scenarios as compared to the base case.

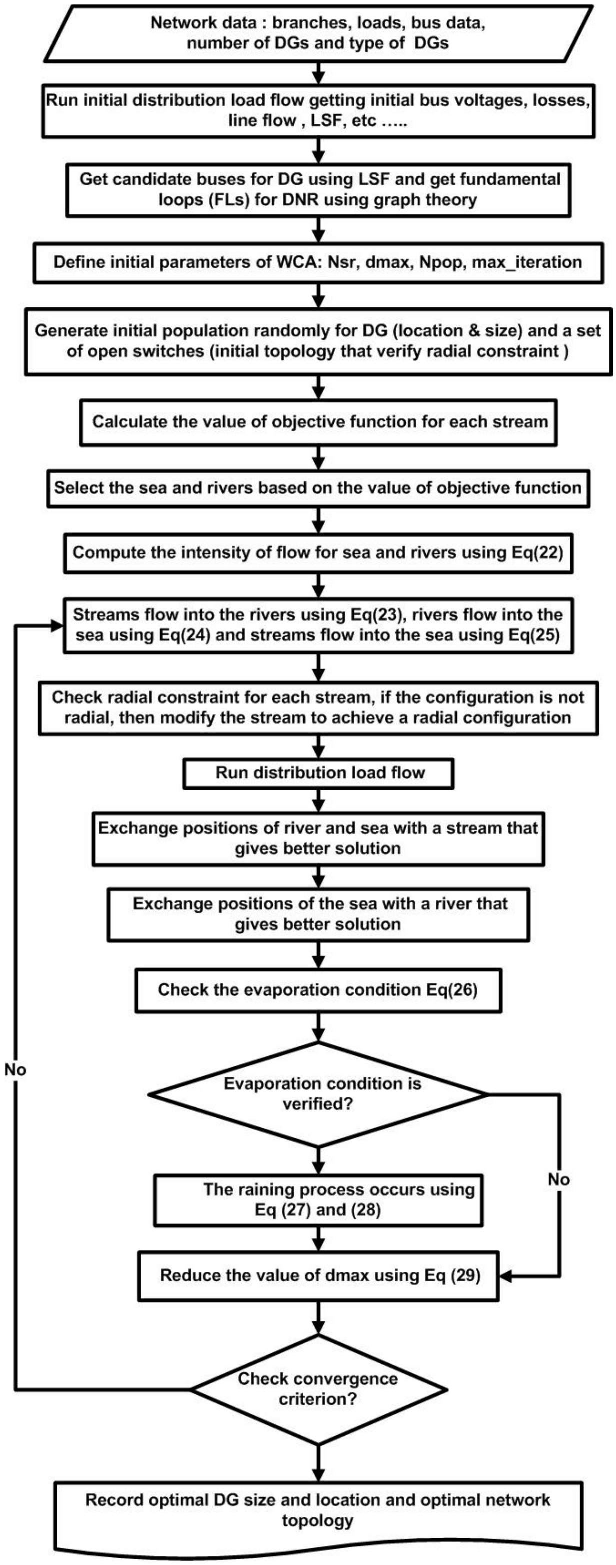

Fig. 3. Procedures for optimal DNR and DG allocation using the proposed WCA

Table 1. Parameters of WCA-based approach and the required inequality constraints

Parameter	Value	
	33-node	118-node
N_{pop}	50	100
N_{sr}	6	10
d_{max}	10^{-13}	10^{-13}
max_$iteration$	200	500
Voltage limits	$0.95 < V_j < 1.05$	$0.95 < V_j < 1.05$
$P_{DG}^{Min} \leq P_{DG,i} \leq P_{DG}^{Max}$	$0 \leq P_{DG,i} \leq 2\ MW$	$0 \leq P_{DG,i} \leq 5\ MW$

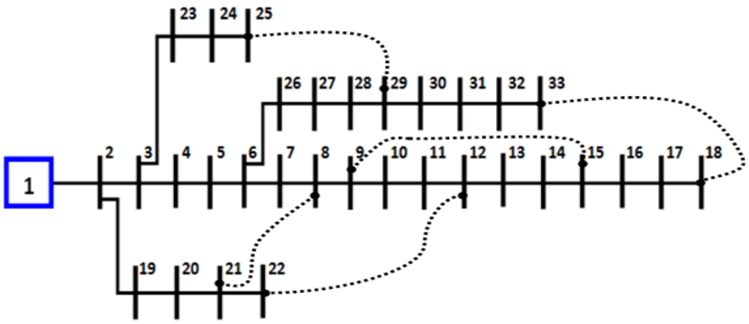

Fig. 4.33-node RDN (tie is represented by dotted line)

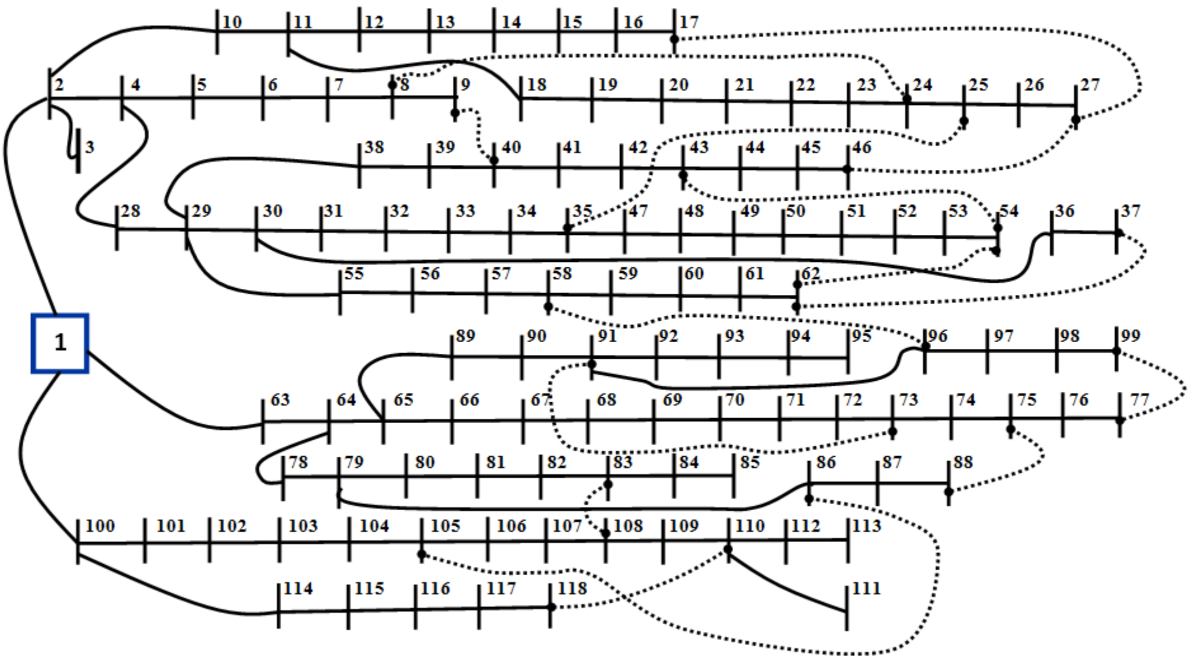

Fig. 5.118-node RDN (tie is represented by dotted line)

Table 2.optimal results on 33-node RDN

Study case	Parameter	Proposed WCA	FA [47][a]	HSA [28]	ACSA [30]
Base case	$P_{T,Loss}$ (KW) minimum V(p. u) @ bus minimum VSI @ bus Switches opened	202.67 0.9131 @ 18 0.6951 @ 18 33, 34, 35, 36, 37	202 - - -	- - - -	- - - -
Scenario 1	$P_{T,Loss}$ (KW) % loss reduction minimum V(p. u) @ bus minimum VSI @ bus Switches opened Average elapsed time(min)	139.98 30.93 0.9413 @ 32 0.7858 @ 32 7, 14, 9, 32, 28 3.68	139.4 31.2 - - 7, 14, 9, 32, 28 -	138.06 31.88 0.9342 - 7, 14, 9, 32, 37 -	139.98 30.93 0.9413 0.7878 7, 14, 9, 32,28 -
Scenario 2	$P_{T,Loss}$ (KW) % loss reduction minimum V(p. u) @ bus minimum VSI @ bus Switches opened DG(bus, size(MW)) Average elapsed time(min)	71.816 64.57 0.9718 @ 33 0.8924 @ 33 33, 34, 35, 36, 37 (13, 0.7892) (24, 1.0949) (30, 1.1557) 3.89	91.9 54.7 - - 33, 34, 35, 36, 37 (17, 0.6) (18, 0.1) (33, 0.9) -	96.76 52.26 0.967 - 33, 34, 35, 36, 37 (18, 0.107) (17, 0.5724) (33, 1.0462) -	74.26 63.26 0.9778 0.9118 33, 34, 35, 36, 37 (14, 0.7798) (24, 1.1251) (30, 1.3496) -
Scenario 3	$P_{T,Loss}$ (KW) % loss reduction minimum V(p. u) @ bus minimum VSI @ bus Switches opened DG(bus, size(MW)) Average elapsed time (min)	56.459 72.14 0.9741 @ 32 0.9011 @ 32 7, 14, 9, 32, 28 (12, 0.5358) (16, 0.5027) (25, 1.7168) 4	93.2 53.9 - - 7, 14, 9, 32, 28 (14, 0.35) (33, 0.7) (18, 0.1) -	97.13 52.07 0.9479 - 7, 14, 9, 32, 37 (32, 0.2686) (31, 0.1611) (30, 0.6612) -	58.79 71 0.9802 0.9264 7, 14, 9, 32, 28 (29, 1.7536) (12, 0.5397) (16, 0.5045) -
Scenario 4	$P_{T,Loss}$ (KW) % loss reduction minimum V(p. u) @ bus minimum VSI @ bus Switches opened DG(bus, size(MW)) Average elapsed time(min)	58.714 71.03 0.9775 @ 18 0.9135 @ 18 7, 34, 8, 36, 26 (13, 0.7892) (24, 1.0949) (30, 1.1557) 3.82	- - - - - - -	- - - - - - -	62.98 68.93 0.9826 0.9354 33, 9, 8, 36, 27 (14, 0.7798) (24, 1.1251) (30, 1.3496) -
Scenario 5	$P_{T,Loss}$ (KW) % loss reduction minimum V(p. u) @ bus minimum VSI @ bus Switches opened DG(bus, size(MW)) Average elapsed time (min)	51.464 74.61 0.9773 @ 14 0.9042 @ 17 33, 34, 11, 31, 28 (7, 0.96) (25, 1.2819) (33, 0.7649) 4.31	71 64.9 - - 7, 9, 13, 25, 31 (17, 0.4) (25, 0.8) (14, 0.4) -	73.05 63.95 0.97 - 7, 14, 10, 32, 28 (32, 0.5258) (31, 0.5586) (33, 0.5840) -	63.69 68.58 0.9786 0.9202 7, 10, 13, 32, 27 (32, 0.4263) (29, 1.2024) (18, 0.7127) -

(a) is firefly algorithm (FA)

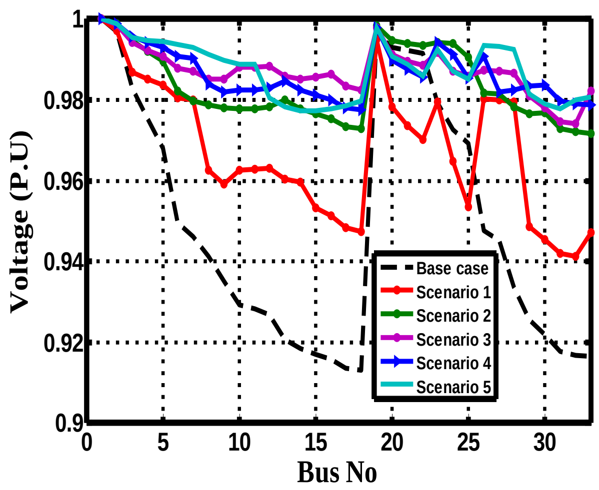

Fig. 6.Bus voltage profile of 33-bus network

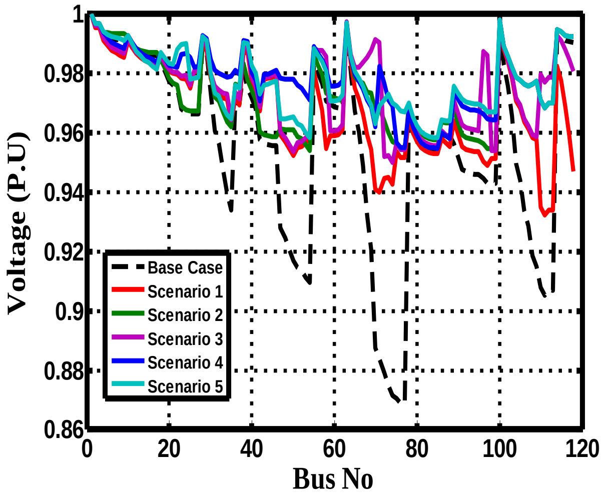

Fig. 8.Bus voltage profile of 118-bus network

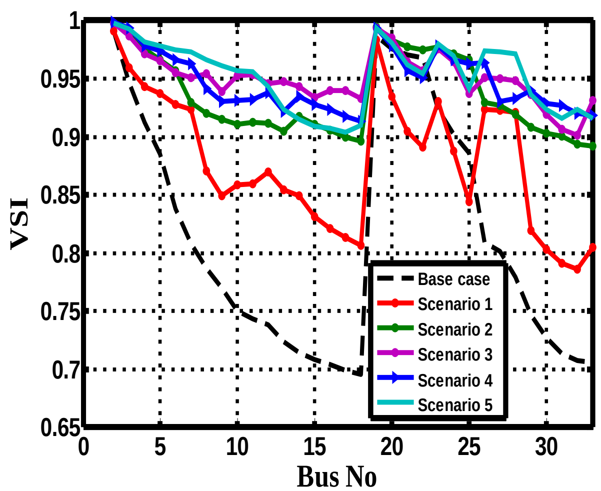

Fig. 7.Bus VSI profile of 33-bus network

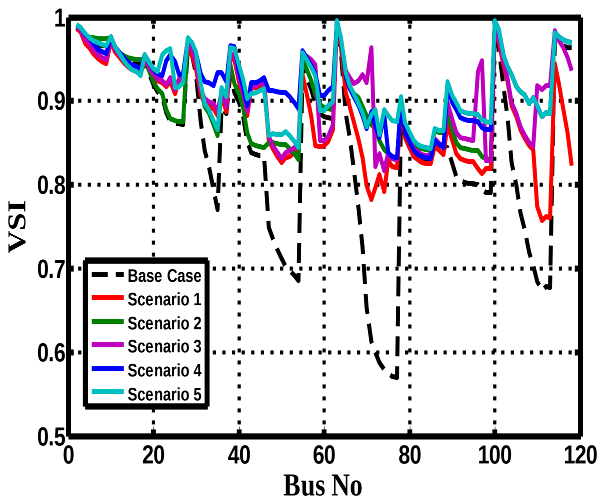

Fig. 9.Bus VSI profile of 118-bus network

5.2.118-node system

To demonstrate the strength and efficiency of the proposed technique using WCA in large scale network, it is applied on 118-node RDN. Similar to 33-node system, FL_s are obtained and LSF is utilized to get the top high ranking buses for DG placement. Optimal solutions (after 50 independent runs) are listed in Table 3 for each scenario including the base case. Figs. 8 and 9 show the improvement in bus voltage and VSIprofiles for all studied scenarios compared with the base case. The comparison with previous works in the literature is listed in Table 4 for scenario 1 and 2. This comparison proves the superiority of the proposed technique using WCA.

The convergence characteristics of WCA are shown in Fig. 10 and 11 when studying scenario 5 for 33-node and 118-node systems, respectively. It is clear that the WCA can obtain near global optimal solution smoothly and in steady convergence characteristics. Because of the randomness of the proposed approach, many trials have to be made in order to illustrate the robustness of the proposed method using WCA for each studied scenario. The obtained statistical measures (after 50 independent runs) are listed in Table 5 and the trend of fitness function over the 50 trials is shown in Fig. 12 for the two studied networks (Scenario 5).

Table 3.Optimal results of proposed algorithm on the 118-bus network

Study case	$P_{,Loss}$ (KW)	% loss reduction	minimum $\mathrm{V(p.u)}$ @ bus	minimu VSI @ bus	Switches opened	DG (bus, size(MW))	Average elapsed time (min)
Base case	1298.09	_	0.8688 @ 77	0.5698 @ 77	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132	–	-
Scenario 1	854.028	34.21	0.9323 @ 111	0.7577 @ 111	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	-	47.5
Scenario 2	667.29	48.59	0.9541 @ 54	0.830 @ 54	118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132	(50, 2.8833) (71, 2.9785) (109, 3.1199)	40.2
Scenario 3	634.98	51.08	0.95 @ 74	0.8172 @ 74	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	(70, 2.0403) (96, 1.7773) (110, 1.78)	41
Scenario 4	617.7	52.41	0.9549 @ 85	0.8315 @ 85	42, 25, 22, 121, 122, 58, 39, 125, 70, 74, 128, 129, 130, 131, 33	(50, 2.8833) (71, 2.9785) (109, 3.1199)	48
Scenario 5	598.65	53.88	0.9583 @ 85	0.8436 @ 85	42, 24, 21, 121, 122, 58, 39, 125, 70, 127, 98, 129, 130, 131, 132	(50, 3.1751) (73, 3.4582) (109, 3.1199)	48.5

Table 4. Comparison of 118-node RDN results

Scenario 1			
Method	Switches opened	$P_{T,Loss}$ (KW)	minimum $\mathrm{V(p.u)}$
Proposed WCA	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	854.028	0.9323
ITS [45][a]	42, 26, 23, 51, 122, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	867.4	0.9323
MTS [48][b]	42, 26, 23, 51, 122, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	867.4	0.9323
CSA [6][c]	42, 25, 23, 121, 50, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	855.04	0.9298
DE [49][d]	42, 26, 23, 51, 122, 58, 39, 95, 71, 74, 97, 129, 130, 109, 34	869.71	0.9323
Scenario 2			
Method	DG (bus , size (MW))	$P_{T,Loss}$ (KW)	minimum $\mathrm{V(p.u)}$
Proposed WCA	(50, 2.8833), (71, 2.9785), (109, 3.1199)	667.29	0.9541
MTLBO [25]	(58, 2.835841), (93, 2.871431), (115, 2.769435)	668.013	-
HSA-PABC [26]	(47, 3.25), (71, 2.95), (108, 3.2)	677.74	0.9474
SOS [50][e]	(68, 1.2591), (70, 2.3788), (104, 4.7958)	875.2687	-

(a) is improved tabu search algorithm (ITS)
(b) is modified tabu search (MTS) algorithm
(c) is cuckoo search algorithm (CSA)
(d) is differential evolution (DE) algorithm
(e) is symbiotic organism search (SOS) algorithm

Table 5.Statistical measures for the WCA after 50 runs

Statistical factor	Scenario 5	
	33-node	118-node
Minimum	0.2766	0.502878
Maximum	0.3141	0.54842
Mean	0.2934	0.516679
Median	0.2922	0.5101
Standard deviation	0.01253	0.013663
Variance	0.000157	0.0001867

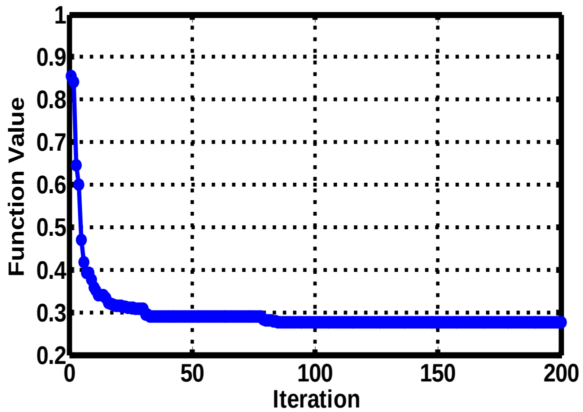

Fig. 10.convergence for 33-node (Scenario 5)

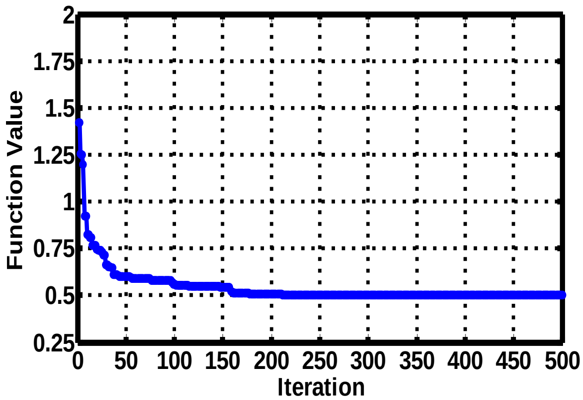

Fig. 11.convergence for 118-node (Scenario 5)

6. Conclusions

In this paper, WCA is applied to simultaneously have the optimal topology of RDN and get the

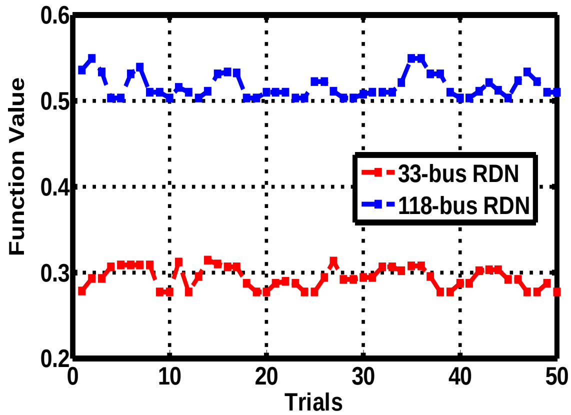

Fig. 12 Fitness function value vs. trials for scenario 5

optimal DG size and placement. The objective is to reduce the real total power loss and minimize the voltage deviation index with five different scenarios. Loss sensitivity factor index is used to get the candidate buses so that reducing the search space for DG allocation. The graph theory is presented to get the fundamental loops that used to reduce the search space for DNR by limiting the infeasible configurations during the optimization process. The proposed technique is applied on the small scale 33-node and the large scale 118-node systems with different scenarios. The best optimal results are obtained after 50 trials for each scenario and compared with previous results in the literature. The results prove that simultaneous DNR with DG allocation (Scenario 5) is the best scenario to obtain the maximum loss reduction and better voltage profile improvement. The comparison with previous works illustrate the strength and efficiency of the proposed WCA to get near global optimal results in smooth and steady convergence.

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