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Power Loss Optimization Using Distribution System Reconfiguration in Presence of DG

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Abstract: Distributed Generation sources (DG) penetration in power system has seen phenomenal increase in recent times. Distribution system performance improves if DG's are placed at optimal locations. As distribution network configuration greatly affect its operating conditions, network configuration and optimal location for DG needs to be analyzed concurrently. This research presents a recent meta-heuristic Biogeography Based Optimization (BBO) to minimize the power loss and improve voltage profile by identifying optimal switching combinations and DG allocation. Loss sensitivity analysis is performed to find the optimal locations for DG allocation. Load flow is carried out using backward forward sweep method. The objective is evaluated subject to operating limitations of the system. The proposed method has been tested on IEEE-33 bus radial distribution system under different operating conditions of DG placement and configuration. The results demonstrate the efficacy of the proposed method.

Key words: Power loss, BBO, DG, reconfiguration, radial distribution system, placement, configration

INTRODUCTION

Distributed Generation (DG) penetration in distribution system world over has shown significant growth in recent years. Distribution systems with DG units benefit in reduction of expansion cost, reduction in power loss, relieving of overloads and improved reliability if DG units are allocated at best locations in the system. The distribution systems typically have radial configuration and consists of tie switches which are normally open and sectionalizing switches which are normally closed (Esmaeilian and Fadaeinedjad, 2015). The conventional distribution systems have unidirectional flows. Power loss minimization in a distribution system has been a critical issue for distribution companies. One of the possible solutions to deal with this problem is network reconfiguration which alters close and open status of the network switches. Since, configuration of the network can affect optimal location of DG placement, a combined approach which will integrate DG placement in reconfiguration is required (Wu *et al*., 2010).

Network reconfiguration is a discrete, non-differentiable, combinatorial optimization problem. Additionally, if DG placement is integrated then identifying optimal solution becomes more complex to be solved by deterministic methods. In the literature, many techniques have been proposed using meta-heuristic algorithms which effectively identify network configuration with least power loss with or without DG placement. By Esmaeilian and Fadaeinedjad (2015), network reconfiguration is performed integrating DG placement using a hybrid technique of meta-heuristic and heuristic algorithms to achieve minimum energy loss with reduced computational time. Different types of loads are considered for study. The method is applied to unbalanced distribution network to verify its robustness. Ant colony algorithm (Wu *et al*., 2010) simultaneously implements configuration and placement of DG to achieve minimum energy loss and incremental load balance factor of distribution network with DG integrated. By Ing *et al*. (2016) network reconfiguration is performed simultaneously with DG and tap change setting using imperialist competitive optimization algorithm. This study analyzes the effect of different Distributed Generation (DG) operating modes. A multiobjective approach is implemented by Tuladhar *et al*. (2016) using DG unit reactive power to identify minimum loss configuration of distribution system. Various parameters like system power loss minimization, solar energy wastage and voltage profile improvement is proposed using non-dominated sorting particle swarm optimization. Rao *et al*. (2013) used Harmony Search Algorithm (HSA) to optimize the

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objective of power loss minimization and improving voltage profile by configuring network with DG placement. Sensitivity analysis is employed to find optimal location of DG units. Different operating conditions of DG placement and reconfiguration of network are considered to study the performance of proposed method.

The heuristic algorithms find solutions to reconfiguration problem which are close to the best and they find it fast and hence used for real time distribution automation purpose. However, being approximate in nature these algorithms generally converge to local optimal solutions. By contrast, the meta-heuristic algorithms achieve global optima but due to its structure of selecting solutions randomly and probabilistically computational time is very high which is unsuitable for real time operations (Braz and Souza, 2011).

In this research, a new meta-heuristic algorithm, Biogeography Based Optimisation (BBO) has been proposed to reduce energy loss and improve voltage profile of the buses by concurrently configuring the network with DG integrated at optimal location. Biogeography is the branch of Biology which deals with the topographical distribution of biological species and BBO has features common to other meta-heuristic methods like GA, PSO or DE thus making BBO a suitable technique which can be applied to power system optimization problems (Simon, 2008). Migration of species is a feature which is exclusive to BBO and directly affects the selection pressure. By Simon *et al*. (2011), it has been shown that improved results for benchmark problems are obtained due to selection pressure of BBO. Therefore, it can be concluded that BBO is a technique which can be employed for network reconfiguration of distribution system for reduction in losses integrated with DG at optimal location in the distribution system.

In this study, BBO searches for global optimal solution of switching combinations representing configured network simultaneously with optimal location of DG placement which will give minimum energy losses and bus voltage improved profile. Sensitivity analysis is used to locate best bus location for DG placement. Optimisation is performed subject to various constraints and load flow is performed using backward forward sweep method. The study is arranged as: problem formulation along with constraints and loss sensitivity factor, backward forward sweep load flow method, BBO technique and its application to the problem, simulation results of IEEE-33 bus radial distribution test system, conclusion and discussion on the results is presented at the last.

Problem formulation

Problem statement: The key objective is to identify the effective sizes of DG allocation in distribution system which will minimize the system power loss while satisfying operating constraints. The Objective function is given as:

$$\text{Minimise}\, f = \min(P_{T,loss}) \tag{1}$$

The objective function Eq. 1 is subjected to the following constraints. Power flow balance:

$$P_{ss} = P_{loss} + P_D \tag{2}$$

Voltage magnitude to be maintained within limits:

$$V_{min} \leq |V_k| \leq V_{max} \tag{3}$$

- Radial configuration must be maintained
- Load bus should not be interrupted
- Currents to be maintained within limits

Radial topology of distribution network: For determination of Radial nature of network, a branch bus incident matrix approach is used. Here, A is the incidence matrix having one row for every branch and one column for every node and entry in row "i" and column as per following "j" rules:

- A_{ij} = 0, if branch i is not connected to node j
- A_{ij} = -1, if branch i is directed toward node j
- A_{ij} = 1, if branch i is in direction away from node j

The matrix has row-column dimension for any network with branches and nodes excluding the reference node. If the determinant of A is either 1 or -1, then the system is radial and if the determinant is zero, then the system is not radial or some loads are disconnected from distribution system.

Problem formulation: Power flow in distribution system can be expressed using set of algebraic equations as shown in Fig. 1:

$$P_{k+1} = P_k - P_{loss,k} - P_{Lk+1} \tag{4}$$

$$= P_k - \frac{R_k}{|V_k|^2}\left\{P_k^2 + (Q_k + Y_k|V_k|^2)^2\right\} - P_{Lk+1} \tag{5}$$

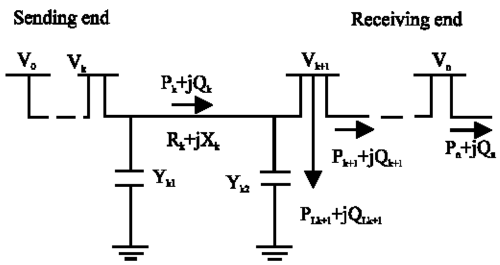

Fig. 1: Single line diagram of distribution system

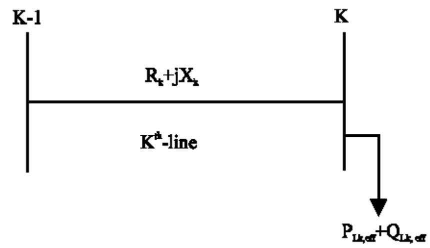

Fig. 2: Line section of power system

$$Q_{k+1} = Q_k - Q_{Loss,k} - Q_{LK+1} = Q_k - \frac{X_k}{|V_k|^2}\left\{P_k^2 + (Q_k + Y_{k1}|V_k|^2)^2\right\} - Y_{k1}|V_k|^2 \quad (6)$$

$$Y_{k2}|V_{k+1}|^2 - Q_{L,\,k+1} \quad (7)$$

$$|V_{k+1}|^2 = |V_k|^2 + \frac{(R_k^2+X_k^2)}{|V_k|^2}(P_k^2+Q_k^2) - 2(R_k P_k + X_k Q_k) \quad (8)$$

The power loss between section from bus to is calculated as:

$$P_{loss}(k,\, k+1) = R_k \frac{P_k^2+Q_k^2}{|V_k|^2} \quad (9)$$

The total energy loss in the system is determined by adding up line losses of all sections which is given as:

$$P_{r,\,Loss} = \sum_{k=1}^{n} P_{Loss}(k,\, k+1)$$

Loss sensitivity factor: Loss sensitivity factor is calculated to locate the buses for installation of DG units. Consider a line section consisting of impedance and load R_k+jX_k and $P_{Lk,\,eff}+jQ_{Lk,\,eff}$, respectively connected between and K-1 buses as shown in Fig. 2:

$$P_{section\ loss} = R_k \frac{(P_{Lk,\,eff}^2 + Q_{Lk,\,eff}^2)R_k}{V_j^2} \quad (11)$$

LSF, the loss sensitivity factor is calculated using following expression:

$$\frac{\partial P_{section\ loss}}{\partial P_{Lk,\,eff}} = \frac{2 * P_{Lk,\,eff} * R_k}{V_k^2} \quad (12)$$

From Eq. 12 LSF is calculated from load flows. These factors are used to decide upon the order in which buses to be considered for installation of DG units. This is done by arranging LSF in descending order.

MATERIALS AND METHODS

Backward forward sweep method

Power flow: In a radial network, the backward/forward sweep method for the load-flow computation is an iterative method in which at each iteration, two computational stages are performed. The load flow is solved iteratively from two sets of equations. The first set of equations calculates the power flow in the branches starting from the last branch and then proceeding in the direction towards the root node. This is backward sweep. The second set of equations calculates the voltage magnitude and angle of each node starting from the base or root node and proceeding in direction towards the last node. This is forward sweep.

Forward sweep: The forward sweep is mainly a voltage drop calculation with current or power flow updates. In forward sweep, voltages and angles at nodes are updated from branches in the first level to last level in distribution system. Thus, forward sweep propagates in a direction starting from feeder source node and calculates the voltages at each node. The feeder substation voltage is maintained at actual value. During the forward propagation, the net power in each branch is held constant to the value evaluated in backward sweep.

Backward sweep: The backward sweep is mainly a current or power flow solution with possible voltage updates. The calculations done for the branches in the last layer and it propagates in the direction of branches connected to the source node. The updated net power flows in every branch are evaluated in the backward sweep using the node voltages of previous iteration. The voltages computed in the forward path are kept constant during the backward propagation and updated power flow in every branch is used in backward walk along the feeder in backward sweep. Backward propagation thus originates at the extreme end node and propagates in the direction of source node.

By comparing the calculated voltages in previous and present iterations, the successive iteration is obtained. The convergence is achieved if the voltage mismatch is less than specified tolerance; otherwise new updated power flows in every branch are calculated using backward sweep with the current values of voltages and the procedure is repeated until the solution is converged.

The backward/forward sweep technique is now reformulated in a way suitable for the analysis of the convergence of the iterative process. Consider Fig. 1, a branch is connected between the node k and k+1. The effective active P_k and reactive Q_k powers that are flowing through branch from node k to node k+1 can be calculated backwards from last node and is given as:

$$P_k = P'_{P'k+1} + R_k \frac{(P'^2_{k+1} + Q'^2_{k+1})}{V^2_{k+1}} \quad (13)$$

$$Q_k = Q'_{P'k+1} + R_k \frac{(P'^2_{k+1} + Q'^2_{k+1})}{V^2_{k+1}} \quad (14)$$

$$P'_{k+1} = P_{k+1} + P_{Lk+1} \quad (15)$$

$$Q'_{k+1} = Q_{k+1} + Q_{Lk+1} \quad (16)$$

$$P_{k+1} = P_k - P_{k+Loss,k} - P_{Lk+1} \quad (17)$$

$$Q_{k+1} = Q_k - Q_{Loss,k} - Q_{Lk+1} \quad (18)$$

Biogeography based optimization: Biogeography based optimization is a new nature inspired algorithm proposed by Simon (2008). Biogeography defines how different species move from one island (or habitat) to another and how the islands are upgraded with better species. A habitat is any area, geographically separated from other islands. Habitats suitable for residences of biological species are assigned high Habitat Suitability Index (HSI), a variable equivalent to fitness function. Habitat suitability can be evaluated through variables, e.g., weather, rain, etc. and are called Suitability Index Variables (SIVs). SIVs are the independent variables of the habitat and are used to calculate HSI.

By Simon *et al.* (2011), performance of BBO is compared with GA for different parameters. It has been pointed out analytically and substantiated by simulation results on benchmarks problems that retention of optimum value is better in BBO compared to GA once it is found. BBO performs, relatively better for large population size. In case of mutation rate if it decreases, performance of BBO improves, i.e., the chances of obtaining optimal population increases. A large population and generation size will increase the search space and computation burden will increase. Therefore, a trade-off is made regarding results obtained with GA by Simon *et al.* (2011) and results of economic dispatch by Bhattacharya and Chattopadhyay (2010) while initializing parameters in the proposed study. Population size or number of members of habitat H is set at 50, habitat modification probability P_{mod} is 1, mutation probability = 0.005, maximum immigration rate E = 1, maximum emigration rate = 1 assuming linear curve, number of iterations orgeneration $Iter_{max}$ is set at 100 and elite habitat P = 2. However, different set of initial parameters may give different results which are not considered in this study.

Mathematically a probabilistic model is used to represent emigration and immigration. Let P_S is the probability of S_{max} having species at t time in habitat. Then P_S gets modified from time t to t+Δt as per following:

$$\begin{aligned} P_S(t+\Delta t) &= (1-\lambda_S \Delta t-\mu_S \Delta t)P_S(t) \\ &+ P_S-\Delta t-\lambda_S+P_S+\mu_S+\Delta t \end{aligned} \quad (19)$$

Immigration and emigration rates are represented by λ_s and μ_s, respectively. At time (t+Δt) number of species is S and one of the following conditions is true:

- No emigration or immigration occurred from time t to (t+Δt) and number of species are S at t
- One species emigrated if count of species was S+1 at time t
- One species immigrated if count of species was S-1 at time t

For k species, equations of λ_k and μ_k are written as:

$$\mu_k = \frac{Ek}{n}$$

$$\lambda_k = 1(1-\frac{k}{n}) \quad (20)$$

$$\lambda_k + \mu = E$$

Two important process of BBO, migration and mutation are explained as:

Migration: In proposed BBO approach, probable solutions are considered as real number vectors. An individual real number in vector represents a single SIV. Habitat suitability index, HSI which is fitness of solution under consideration is estimated using SIV's in the vector. High HSI solutions signify high fitness value of the objective function or better quality solution. Information of the solutions is probabilistically shared between habitats using emigration and immigration rates evaluated for each solution. Habitat modification probability P_{mod} decides which solutions S_i will undergo modification. If given candidate solution is chosen for modification, then immigration rate λ probabilistically decides the number of SIV which will get modified in the solution. Once SIV's are selected for modification, emigration rate μ of other solutions in the set decide which solutions of the habitat will undergo migration. Randomly selected SIV_S now migrate to previously selected solution. To prevent deterioration of the solutions due to immigration process, elitism is employed to retain the better solutions through iterations. Habitats with best HSI move to next iteration and are not subjected to the migration.

Mutation: Because of natural calamities or some unforeseen events, sometimes HSI of given habitat undergoes sudden changes. BBO treats such events by mutation of SIV. Probabilities for every species count are evaluated and then mutation rates are decided using species count probabilities. Every candidate solution has its probability which acts as an indicator of survival of the solution. Solutions having low probability most likely will mutate into another solution while solutions with high probability have less chances of getting mutated. It can therefore be inferred that solutions with medium HSI values stand good chances of forming better solutions post mutation.

The main steps of BBO are as follows: First, initialize the BBO parameters like habitat modification probability P_{mod}, mutation probability, maximum rate of mutation m_{max}. Population size, number of iterations or generation, etc. Initialize several candidate solutions within feasible region of habitats based on the habitat size. It can be represented in matrix form and is independent variable:

$$[H] = \begin{bmatrix} x_{11} & x_{12} & ,\dots, & x_{1m} \\ x_{21} & x_{22} & ,\dots, & x_{2m} \\ ,\dots, & ,\dots, & ,\dots, & ,\dots, \\ x_{n1} & x_{n2} & ,\dots, & x_{nm} \end{bmatrix}$$

Estimate the HSI for every habitat of the population set for specified emigration rate μ_s, immigration rate λ_s, the HSI of all SIV sets is calculated where individual habitat is represented as $H_1 = [x_{11}, x_{12}, ..., x_{1m}]$ calculate the number of valid species of all habitats using their HSI values. The habitats, whose fitness or HSI values are finite are considered as valid species S

Elite habitats based on better HSI values are identified. Modify the habitat as per migration and mutation operation. HSI is now recomputed for all those non-elite habitats which have undergone modification in migration operation. Once every habitat is modified, its viability as a probable solution should be verified (go to step 3) for the next iteration. This loop can be terminated after predefined numbers of iterations. Robustness of the algorithm is verified by conducting 20 trials of the simulation.

RESULTS AND DISCUSSION

BBO algorithm is tested on standard IEEE 33 bus Radial Distribution System (RDS) shown in Fig. 3 using MATLAB 2012 programming environment on PC with Intel core i5, 2.40 GHz and 1 GB RAM.

Test system: The test system is IEEE standard 33 bus radial distribution system which is base case. The test system has radial structure with 33 buses and supply of 12.66 kV. It comprises of 5 tie-lines (looping branches) and 32 sectionalizing switches. The normally open switches are 33-37 and the normally closed switches are 1-32. The line data and load data is taken from Rao *et al*. (2013) and total real and reactive power loads on the system are 3715 kW and 2300 kVAr, respectively. In the simulation, following operating scenarios are considered for analysis.

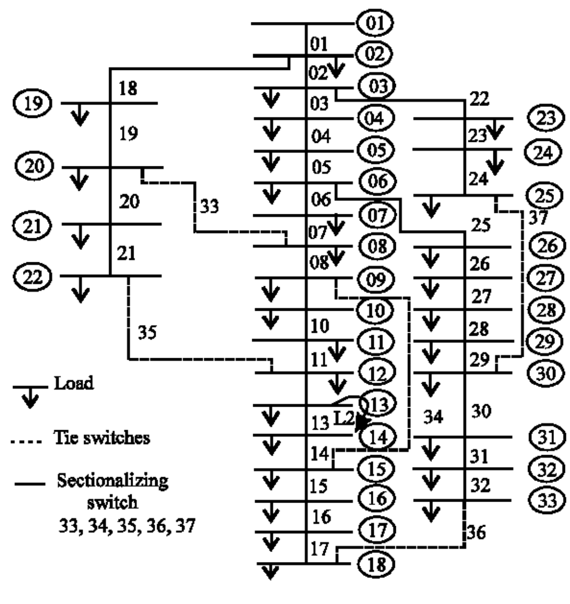

Fig. 3: IEEE 33 bus system (base case)

Table 1: Different conditions (case) for analysis

Networks	Conditions
1	System as base case (without reconfiguration and DG)
2	Only reconfigured system
3	System as Base case with DG units
4	System reconfigured and DG units allocated
5	System with simultaneous reconfiguration and DG allocation

Table 2: Loss and DG location for 33 bus system

Cases	Switches opened	Power loss (kW)	Min voltage (p.u)	Loss reduction (%)	DG, MW (Bus No.)
1	33, 34, 35, 36, 37	208.0	0.910	-	-
2	7, 9, 14, 32, 37	138.9	0.942	33.21	-
3	33, 34, 35, 36, 37	94.51	0.958	54.56	1.12 (3), 1.42(6), 0.78(8)
4	7, 9, 14, 32, 37	73.07	0.968	64.87	1.60 (3), 1.36(6), 0.81(8)
5	7, 11, 14, 32, 37	71.89	0.963	65.43	1.02(3), 0.92(6), 1.31 (8)

Table 3: Comparison of results

Methods	Operation	Case 2	Case 3	Case 4	Case 5
BBO	Switches Open	7, 9, 14, 32, 37	-	7, 9, 14, 32, 37	7, 11, 14, 32, 37
	Loss (kW)	138.9	94.5	73.07	71.89
	Min. voltage (p.u.)	0.942	0.95	0.968	0.963
	Loss reduction (%)	33.21	54.5	64.87	65.43
HSA	Switches Open	7, 9, 14, 32, 37	-	7, 9, 14, 32, 37	7, 10, 14, 28, 32
	Loss (kW)	138.0	96.7	97.13	73.05
	Min. voltage (pu)	0.970	0.96	0.947	0.970
	Loss reduction (%)	31.88	52.2	52.07	63.95
GA	Switches Open	9, 28, 33, 34, 36	-	9, 28, 33, 34, 36	7, 10, 28, 32, 34
	Loss (kW)	202	100.1	98.36	75.13
	Min. voltage (pu)	0.931	0.96	0.950	0.976
	Loss reduction (%)	30.15	50.6	51.46	62.92

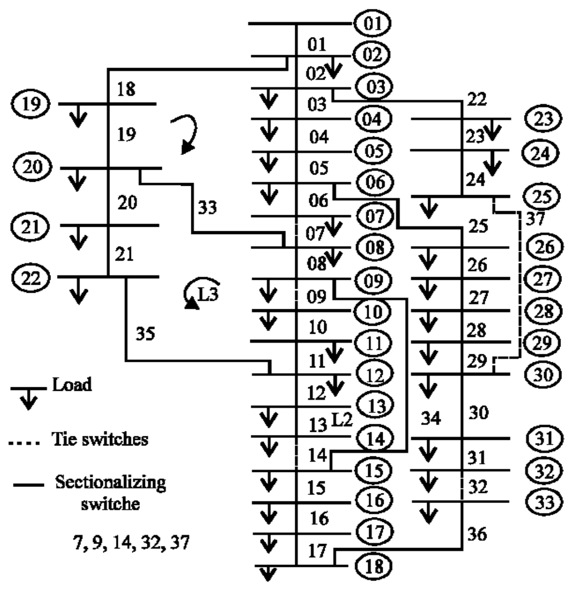

Fig. 4: IEEE 33 bus system (reconfigured case)

Optimization by BBO for different scenarios as shown in Table 1, yields combination of switches to be kept open for optimal losses and voltage profile. One such combination has been shown in Fig. 4.

Using sensitivity analysis (Rao *et al*., 2013), Loss Sensitivity Factors (LSF) are computed for installing the DG units at candidate bus locations. After computing sensitivity factors at all buses, these factors are sorted and ranked in ascending order. Top three locations are identified to install DG units in the system and their sizes for installation at candidate buses are in the range of 0-2 MW Fig. 4 and 5. The network is simulated for nominal load. It is observed from Table 2 that base case power loss (in kW) is 208 which reduce to 138.92, 94.51, 73.07 and 71.89 in network scenarios 2-5, respectively. Similarly, the percentage loss reduction for network 2-5 is 33.21, 54.56, 64.87 and 65.43, respectively. It shows that power loss reduction in network V is highest. The voltage profiles of all network cases are shown in Fig. 5 which shows improvement of voltages from scenario 1-5. Table 3 provides the comparison of the performance of BBO with results from literature.

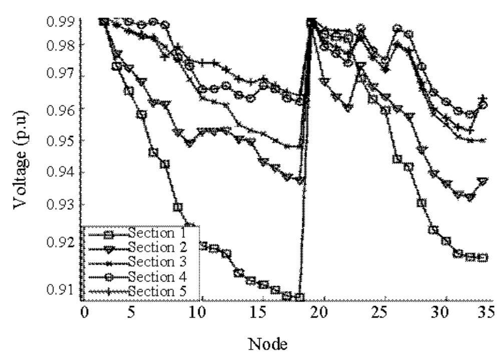

Fig. 5: Voltage profiles of 33 bus system

CONCLUSION

Although, BBO could find switching combination with power loss nearly same as other methods in scenario 2, significant improvement is seen for other cases wherein BBO has converged to a better optimal solution than other methods. Power loss has reduced considerably owing to installation of matching DG unit at the buses.

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