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Network Reconfiguration of Distribution System for Loss Reduction Using GWO Algorithm

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ABSTRACT

This manuscript presents a feeder reconfiguration in primary distribution networks with an objective of minimizing the real power loss or maximization of power loss reduction. An optimal switching for the network reconfiguration problem is introduced in this article based on step by step switching and simultaneous switching. This paper proposes a Grey Wolf Optimization (GWO) algorithm to solve the feeder reconfiguration problem through fitness function corresponding to optimum combination of switches in power distribution systems. The objective function is formulated to solve the reconfiguration problem which includes minimization of real power loss. A nature inspired Grey Wolf Optimization Algorithm is utilized to restructure the power distribution system and identify the optimal switches corresponding minimum power loss in the distribution network. The GWO technique has tested on standard IEEE 33-bus and 69-bus systems and the results are presented.

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1. INTRODUCTION

The Modern power systems are complex networks with multiple generating stations and load centers are interconnected through long transmission lines and distribution networks. The aim of the power system is to generate energy and deliver this energy to the consumers at a rated value of voltage and minimum loss. Under heavy loaded conditions, the reactive power flow causes significant losses and also causes reduction in voltage levels. So that we should minimize the real power losses and improve the voltages in the distribution system. Finally, network configuration may be varied with switching operations to transfer load flows among the feeders. There are two kinds of switches in the distribution systems are normally closed switches that connect two line sections and normally open switches on the tie lines that connect two primary feeders or loop type laterals.

Optimal network reconfiguration (RCG) is the topological structure of feeders by shifting the open or closed status of sectionalizing and tie switches with minimum loss while maintaining radial structure in distribution systems. There are different methods were used for optimal reconfiguration. Generally, network reconfiguration is essential to provide service to as many consumers as possible during a fault condition or for maintenance purposes and reduces real power losses and balance the loads to avoid overload of network branches. Baran [1] described as reconfiguration problem realized by modifying the status of sectional and tie switches by the branch exchanging algorithm for real power loss reduction and load balancing. Venkatesh [2], explained a fuzzy adoption of evolutionary programming and considering optimization of multiple objectives based on power losses and maximum node voltage deviations. Sivanagaraju [3] presented a scheme to resolve the voltage stability of radial distribution systems by network reconfiguration. Das [4]-[5] described the network reconfiguration and the impacts of radial structures using a multi-objective approach. Damodar Reddy [6] described a fuzzy multi-objective algorithm was used for the network reconfiguration to loss reduction, while reconfiguration also improves auxiliary operational parameters. Gupta [7], described a new adaptive particle swarm optimization (PSO) for network reconfiguration of radial distribution systems for minimization of real power loss. R S Rao [8]-[9] presents HSA, ITS algorithms for reconfiguration of large scale distribution systems to reduce the losses. Mostafa [10], proposed an efficient method is called improved binary PSO is presented simultaneous reconfiguration is solved to attain the lowest losses with constraints node voltages, branch currents and radial nature of the system.

Mirjalili [11] developed a new meta-heuristic algorithm is called Grey Wolf Optimizer (GWO) motivated by grey wolves.In GWO, gray wolves are divided into four categories of such as alpha; beta, delta, and omega are engaged in recommending the headship hierarchy. Sudhakara Reddy [12] proposed PSO algorithm with an objective of reducing power losses by using Network reconfiguration. Diego [13] described a forward-backward sweep load flow method using fixed point conceptions and the contraction mapping theorem. Reza [14] proposed an adaptive modified firefly algorithm by considering a few Wind Turbines (WTs) with an objective of reducing the total cost of active power losses. This method was suggested to increase the convergence speed of the algorithm and avoid premature convergence.

Suyanto [15] proposed a power flow based Modified Backward Forward method was used to capture the complexities of unbalanced 3-phase distribution system for improvement of voltage profile. Archana [16] described a modified Teaching-learning based optimization (MTLBO) algorithm for network reconfiguration of the distribution system with an intention of minimization of operational cost and maximization of system reliability. Sudhakara Reddy [17] proposed the dragonfly algorithm (DFA) is exclusively applied to the network reconfiguration problem. Alonso [18] presented the artificial immune algorithm for reduce the power losses and improve the reliability index using graph theory. Dorostkar [19] described an hourly reconfiguration in the presence of renewable energy sources to reduce network losses.

This paper proposes (i) Switching loops using step by step switching (ii) Switching loops using simultaneous switching (iii) The GWO algorithm is used to network reconfiguration to reduce the losses while maintaining the radial structure. The proposed GWO algorithm has been tested on a standard IEEE 33-bus and 69-bus test systems to reduce the total real power loss, while maintaining radial structure. To find real power loss, a suitable load flow method is required. In this paper, backward-forward load flow method is employed.

2. LOAD FLOW METHOD

Up to now, a number of researchers proposed backward-forward sweep method for balanced radial distribution systems power flow analysis. In the backward state, Kirchhoff's Current Law (KCL) is applied to calculate the branch currents from load currents and Kirchhoff's Voltage Law (KVL) is applied to find the voltages of each node for each upstream bus of a line i.e., in forward stream.

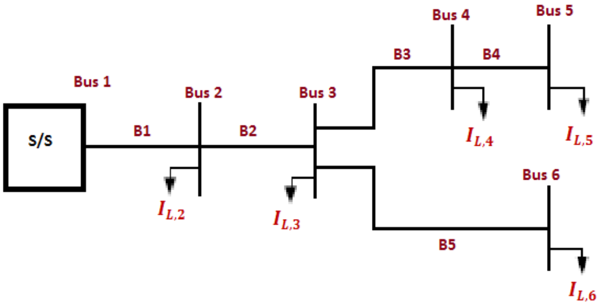

Figure 1. A Simple 6-bus radial distribution system

The complex power injected into the bus n is given by

$$S_{L,n} = P_{L,n} + j*Q_{L,n} = V_n.I_{L,n}^{\ *} = V_n.\left(\frac{P_{L,n} + j*Q_{L,n}}{V_n}\right)^* = V_n.\frac{P_{L,n} - jQ_{L,n}}{V_n^*} \quad (1)$$

2.1. Formation of BIBC Matrix

The relation between load currents and branch currents can be found by using KCL equations [14] as follows.

$$I_{B5} = I_{L6} \tag{2}$$

$$I_{B4} = I_{L5} \tag{3}$$

$$I_{B3} = I_{L4} + I_{L5} \tag{4}$$

$$I_{B2} = I_{L3} + I_{L4} + I_{L5} + I_{L6} \tag{5}$$

$$I_{B1} = I_{L2} + I_{L3} + I_{L4} + I_{L5} + I_{L6} \tag{6}$$

Thus, the relationship between load currents and branch currents can be expressed in matrix form is given by

$$\left[I_B\right] = \left[BIBC\right].\left[I_L\right] \tag{7}$$

2.2. Branch-Current to Bus-Voltage Matrix (BCBV)

The receiving end voltages can be calculated by forward sweeping across the line by subtracting the line section drop from the sending end voltages of the line section. The relation between the branch currents and bus voltages can be obtained by following equations [14].

$$V_2 - V_1 = I_{B1}.Z_{12}$$

$$V_3 - V_2 = I_{B2}.Z_{23}$$

$$V_4 - V_3 = I_{B3}.Z_{34}$$

$$V_5 - V_4 = I_{B4}.Z_{45}$$

$$V_6 - V_5 = I_{B5}.Z_{36}$$

The above equations represented in the reduced matrix form [14] is given by

In general form, $$\left[\Delta V\right] = \left[B \quad C \quad B \quad V\right]\left[I_B\right] \tag{8}$$

2.3. Forward sweep

The receiving end voltages can be calculated by forward sweeping across the line by subtracting the line section drop from the sending end voltages of the line section.

$$V_q(k) = V_p(k) - I_B(k) * Z_B(k) \tag{9}$$

2.4. Power losses

The power losses in the distribution systems are real power loss and reactive power loss. The total real power loss in a balanced radial distribution system consisting of B branches can be written as

$$P_{LT} = \sum_{k=1}^{B} I_k^2.R_k \tag{10}$$

3. NETWORK RECONFIGURATION

Network Reconfiguration (RCG) is defined as the topological structure of feeders by shifting the open or closed status of sectional and tie switches while maintaining radial structure in power distribution systems.

3.1. Radiality constraint

Any distribution network with 'n' number of nodes and 'b' number of branches are said to be a radial network if it satisfies the following two constraints:

❖ The total number of branches 'b' is given by

$$b=n-1 \tag{11}$$

❖ The network should satisfy the conservation of power flow constraint, i.e. every load node should be linked to the substation bus by an exclusive path such that every load at each node is energized.

❖ The network should not contain any closed paths for the reconfigured data during switching.

3.2. Objective Function

The objective function of Network Reconfiguration is formulated to exploit the power loss in the radial distributed system, which is given by

$$Fitness\_Function = \min\left\{P_{Loss}\right\} \tag{12}$$

The network reconfiguration can be solved by the following two approaches.

- Step by step switching
- Simultaneous switching

In the present work, we are designed and implemented the Switching corresponding to each Loop i.e., L_{SW} for network reconfiguration by using step by step switching [6],[7], which is shown in Table 1. From step by step switching, we are designed and implemented the best switching for the network reconfiguration by using simultaneous switching [7],[17]. Here, L_{SW} is used to find optimal switching corresponding to minimum loss while maintaining the radial structure in the distribution systems.

Table 1. Switching Loops corresponding to Network Reconfiguration

Test System	Step by Step Switching					Simultaneous Switching												
33-Bus	33	6	7			33	6	7	--	--	--	--	--					
	35	8	11			35	8	9	10	11	--	--	--					
	36	31	32			36	15	16	17	29	30	31	32					
	37	28	--			37	22	23	24	25	26	27	28					
	34	14	--			34	12	13	14	--	--	--	--					
69-Bus	72	55	56	57	58	72	46	47	48	49	52	53	54	55	56	57	58	--
	71	11	12	--	--	71	11	12	13	14	--	--	--	--	--	--	--	--
	73	61	--	--	--	73	21	22	23	24	25	26	59	60	61	62	63	64
	69	--	--	--	--	69	9	10	--	--	--	--	--	--	--	--	--	--
	70	--	--	--	--	70	15	16	17	18	19	20	--	--	--	--	--	--

4. GREY WOLF OPTIMIZATION ALGORITHM

4.1. Introduction

Grey Wolf optimization is a new Swarm Intelligence algorithm inspired by grey wolves proposed by Mirjalili [11]. The behaviour of the grey wolves is characterized by social hierarchy and hunting. These two phases are involved in the GWO. The social hierarchy is a phenomenon in which the most powerful wolf guides the other wolves. The most powerful wolves are alpha, beta and delta in decreasing order.

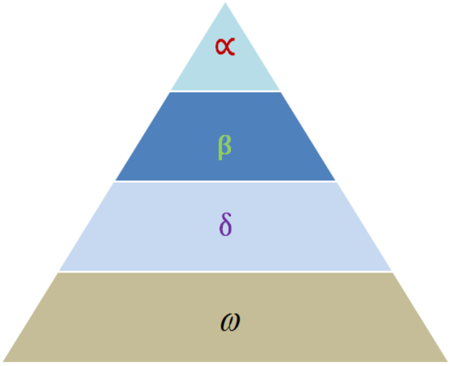

Figure 2. Hierarchical representation of grey wolves

GWO is a new meta-heuristic algorithm is inspired by grey wolves. The nature inspired GWO technique imitates the headship hierarchy and hunting mechanism of grey wolves in nature or the environment. In this algorithm, grey wolves are categorized as four types as alpha, beta, delta, and omega are employed for simulating the leadership hierarchy. Additionally, the three major actions of hunting, penetrating for prey, encircling prey, and attacking prey, are implemented.

The three solutions corresponding to alpha, beta and delta wolves are selected as the best solutions. The rest of the aspirant solution is supposed to be omega ω. In the GWO algorithm, the hunting (Optimization Process) is supervised by α, β and δ. The ω wolves simply follow these three wolves. The first best solution corresponds to X and so on. The hunting behaviour of grey wolves is characterized by locating the prey and encircling it. This phase is incorporated in the optimization as follows:

$$\begin{aligned} A &= 2*a*r_1 - a \\ C &= 2*r_2 \end{aligned} \tag{13}$$

$$a = 2 - 1*\left({(2)}/{Max\_iter} \right) \tag{14}$$

Grey wolves have the ability to identify the location of prey and encircle them. The hunt is frequently guided by the alpha. The beta and delta might also participate in hunting intermittently. However, in a search space we have no initiative concerning the position of the optimum (prey). In order to simulate the hunting behaviour of grey wolves, we suppose that the alpha (best candidate solution), beta and delta have better information about the potential position of the prey. Therefore, we save the first three best results obtained so far and need the other search agents, together with the omegas to revise their positions according to the situation of the best search agents. The position of the prey is determined from the following equations:

$$\left. \begin{aligned} P_\alpha &= (C_1 * X_\alpha) - X \\ P_\beta &= (C_2 * X_\beta) - X \\ P_\delta &= (C_3 * X_\delta) - X \end{aligned} \right\} \tag{15}$$

$P_\alpha, P_\beta, P_\delta -$ Position vectors of the wolves in the population with respect to alpha, beta and delta wolves. Where $C_1, C_2, C_3 -$ are generate random numbers within range of [0, 2]; X-search agents, (population); $X_\alpha, X_\beta, X_\delta -$ Best search agents corresponding to the best solutions, i.e., alpha, beta and delta. The encircling behaviour is mimicked to find the new positions of the wolves as follows:

$$X(t+1) = \frac{(X_1 + X_2 + X_3)}{3} \tag{16}$$

$$X_1 = X_\alpha - (A_1 * P_\alpha)$$
$$X_2 = X_\beta - (A_2 * P_\beta)$$
Where, $X_3 = X_\delta - (A_3 * P_\delta)$

Where A_1, A_2, A_3 are random numbers dependent on the parameter a, defined in equation (13). The solution convergence in space space is dependent on the parameters A and C.

$$Solution = \begin{cases} Converge, & if \quad A < 1 \\ Diverges, & if \quad A > 1 \end{cases} \tag{17}$$

If $|A| < 1$ shows forces the wolves to attack towards the prey. Otherwise, wolves are searching for new prey.

4.2. Algorithm of Proposed GWO Method

Step 1 : Initialize the population, number of variables, limits of the variables.
Step 2 : Initialize the positions of Alpha Beta and Delta with a dimension of $zeros(1x\dim)$
Step 3 : Initialize the positions of switches by using the basic load flow with LSW from Table 1
Step 4 : Set the termination condition and start iteration count.
Step 5 : Initialize the optimization parameter a, where the elements of are linearly decrease.
Step 6 : The network reconfiguration, load flow algorithm changes in power flows at the respective switching which are randomly selected based on LSW.
Step 7 : Update the position of wolves by using eq. (15).
Step 8 : Update the new fitness by the following equation

$$Solution = \begin{cases} \alpha - score = Fitness, \; if & fitness < \alpha - score \\ \beta - score = Fitness, \; if & fitness < \beta - score \\ \delta - score = Fitness, \; if & fitness < \delta - score \end{cases} \tag{18}$$

Step 9 : Repeat the same procedure, until the solution converges by eq. (17)
Step 10 : If solution converges or a convergence criterion is met, then stop the objective search in the searching process. The $\alpha - score$ is assigned to best score corresponding to the best position.

5. RESULTS AND DISCUSSIONS

In this proposed GWO algorithm, the control parameters are shown in Table 2.

Table 2. The control parameters for GWO algorithm

Parameters	GWO
Number of search agents	30
Maximum iteration	100
Dimension	5
Best_score	Alpha_score
Best_pos	Destination_position

5.1. IEEE 33-bus test system

The configuration of 12.66KV, 100MVA, 33-bus test system with 37 branches, 32 sectionalizing switches and 5 tie switches. The total substation load of (4715+j*2300) kVA [6]. The Single line diagram of 33-bus system after reconfiguration is shown in Figure 3. The MATLAB results for original network and reconfigured network are shown in Table 3.

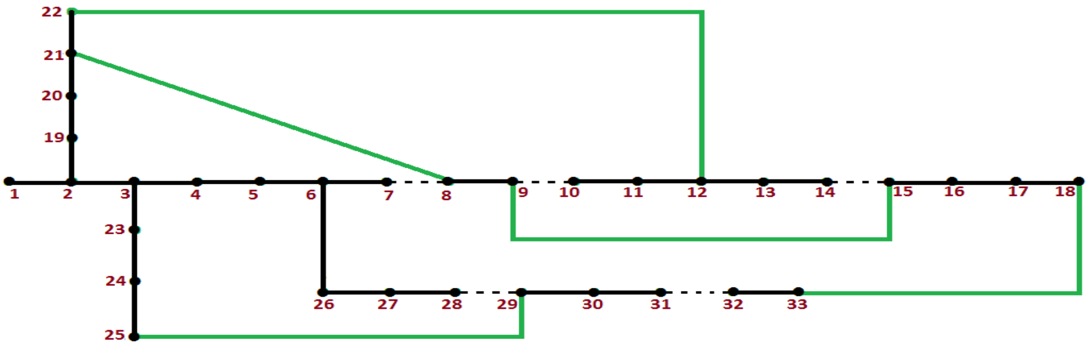

Figure 3. Single line diagram of 33-bus after network reconfiguration

Table 3. Network Reconfiguration for 33-bus system

1	Initial switching for the original network	33, 34, 35, 36, 37
2	Total real power loss for the original network	369.2558 kW
3	Final switching by using step by step reconfiguration	7, 11, 31, 28, 14
4	Total real power loss of the reconfigured network	241.4075 kW
5	Optimal switching by using simultaneous reconfiguration	7, 9, 31, 28, 14
6	Total real power loss of the reconfigured network	238.2888 kW

5.2. IEEE 69-bus test system

The 69-bus system of 100MVA, 12.66KV, IEEE 33-bus test system with 73 branches, 68 sectionalizing switches and 5 tie switches. The total substation load of (3802.2+j*2694.6) kVA [6]. The Single line diagram of the 69-bus system after reconfiguration is shown in Figure 4. The MATLAB results for original network and reconfigured network results are shown in Table 4.

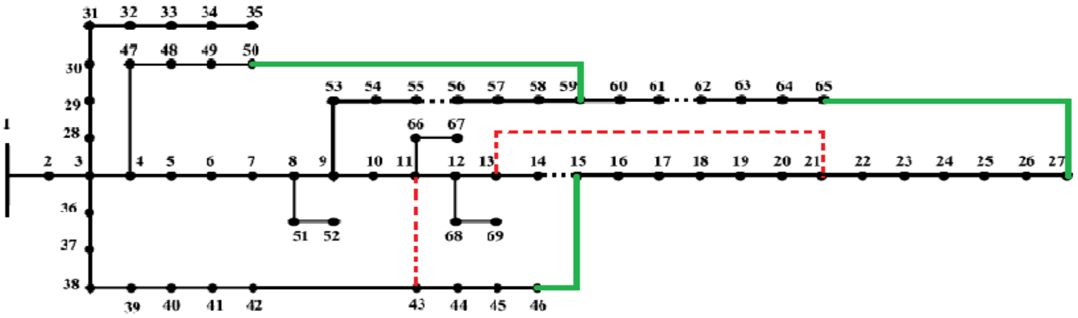

Figure 4. Single line diagram of 69-bus after network reconfiguration

Table 4. Network Reconfiguration for 69-bus system

1	Initial switching for the original network	69, 70, 71, 72, 73
2	Total real power loss for the original network	225.0044 kW
3	Final switching by using step by step reconfiguration	58, 12, 61, 69, 70
4	Total real power loss of the reconfigured network	99.8206 kW
5	Optimal switching by using simultaneous reconfiguration	56, 14, 61, 69, 70
6	Total real power loss of the reconfigured network	99.6216 kW

From Table 3, the power loss reduction is 34.62% using step by step switching and 35.47% using simultaneous switching for 33-bus system. From Table 4, the power loss reduction is 55.64% using step by step switching and 55.72% using simultaneous switching for 69-bus system. The optimal switches after network reconfiguration are highlighted in Table 1, indicated as dotted lines, shown in Figure 3 and Figure 4. The maximum possible switching operations (N) are 5 (Five) for 33-bus and 3 (Three) for 69-bus systems respectively. The voltage profiles of initial network and after reconfiguration network for IEEE 33-bus and

69-bus test systems are shown in Figure 5 and Figure 6 respectively. The results of the 33-bus and 69-bus test systems are compared with the previously published articles shown in Table 5.

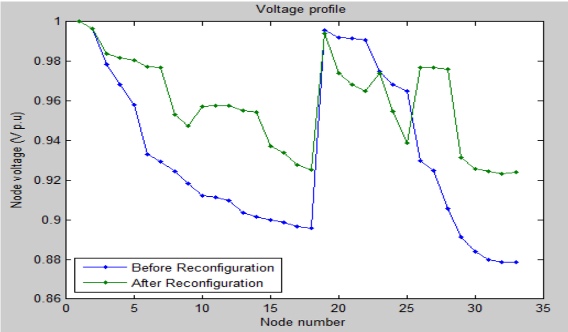

Figure 5. Comparison of voltage profile for IEEE 33-bus system

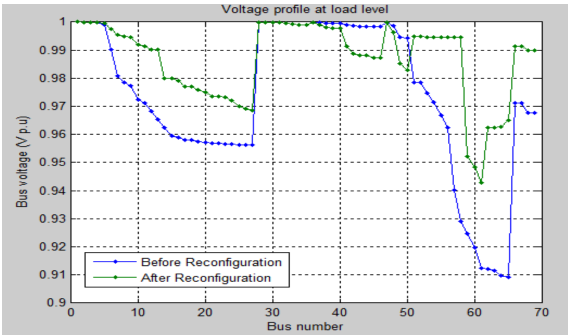

Figure 6. Comparison of voltage profile for IEEE 69-bus system

Table 5. Comparative Results for Network Reconfiguration

33-Bus System				69-Bus System			
Method	Open Switches	N	Loss Reduction	Method	Open Switches	N	Loss Reduction
B-EX [1]	6,34,11,31,28	4	29.08 %	B-EX [1]	69,70,14,58,61	3	55.72 %
EP[2]	7,14,9,32,37	4	33.76 %	Analytical [6]	69,70,14,55,62	3	55.64 %
Analytical [6]	11,14,7,31,28	5	34.62 %	GA [9]	69,70,14,53,61	3	54.08 %
APSO [7]	7,9,14,32,37	4	31.15 %	RGA [9]	69,17,13,55,61	4	55.42 %
HSA [8]	7,14,10,36,37	3	31.89 %	PSO [13]	69,70,12,58,61	3	55.64 %
BPSO [10]	7,9,14,32,37	4	31.15 %	DFA [17]	69,70,12,58,61	3	55.64 %
MTLBO [16]	7,11,14,36,37	3	30.10 %	Proposed GWO	69,70,12,58,61	3	55.64 %
DFA [17]	11,14,7,31,28	5	34.62 %		69,70,14,56,61	3	55.72 %
Proposed GWO	11,14,7,31,28	5	34.62 %	Here, N represents the maximum possible switching operations are done during optimization process			
	9,14,7,28,31	5	35.47 %				

6. CONCLUSION

In this paper, The Grey Wolf Optimization (GWO) Algorithm is successively implemented for network reconfiguration of the primary distribution system to achieve the least amount loss with respect to the optimal combination of switches. The network reconfiguration problem is solved by using step by step switching and simultaneous switching. The final configuration is attained with respect to lowest loss. The maximum loss reduction is 127.8483 kW for 33-bus and 125.1838 kW for 69-bus test systems respectively. The minimum voltage before RCG is 0.8785p.u at node 33 and after RCG it is raised to 0.9232p.u at node 32 for 33-bus system. The minimum voltage before RCG is 0.9092p.u at node 65 and after RCG it is raised to 0.9428p.u at node 61 for 69-bus system. The results show that better performance and effectiveness of the proposed GWO algorithm. The results reveal that a significant reduction in real power losses and improvement in the voltage profile with simultaneous reconfiguration as compared to step by step switching.

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