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Optimal Switching Sequence using a Metaheuristic Algorithm for Feeder Reconfiguration

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Abstract

Electrical energy is continuously lost due to resistance in the power system networks. Distribution system experience enormous power losses as compared to the rest of the network. Solutions that reduce distribution power losses need to be planned for the purpose of lowering energy consumption, cost and balancing the generation to the load. Reduced power losses increase the life span of power equipment and reliability of the distribution network. One method of achieving improved power losses and voltage profile at no extra cost is by applying optimal switching sequence to the Radial Distribution System (RDS). The reconfiguration in network topology alters the current flowing through the lines hence minimizing power losses while maintaining the operating constraints. In this study, a metaheuristic nature inspired Modified Shark Smell Optimization (MSSO) algorithm was proposed to identify the optimal network reconfiguration in an IEEE 33-bus RDS. The results were evaluated and compared with other optimization algorithms to show the efficiency of the proposed algorithm.

Keywords – Modified Shark Smell Optimization (MSSO) algorithm, Network reconfiguration, Switching sequence, Radial distribution system.

I. INTRODUCTION

Electricity supply losses in the system mainly consist of technical losses which are mainly due to the power dissipation of electrical components. A major portion of power losses is experienced in the distribution network due to low voltage operations that ensure a smooth passage of the power supply to the end load users. Since power has to be transmitted at low voltage levels but still maintain high current, the distribution system experiences very highpower losses due to heat (I^2R), making it less efficient and susceptible to increased voltage drops and damage of components. A system which has high power losses will require more power generation to compensate for the power lost valued at the generation cost.

Optimization of technical losses in the distribution system is an issue that has been considered to solve the problem by effective planning and modeling of the power system. A reliable distribution system will transmit electric power to the consumer in an elastic manner which maintains protection of equipment and feeders in case of any contingencies [1]. Optimal switching of the network reconfiguration is one example of optimization technique applied to the system with no additional cost as compared to other methods such as capacitor placement, incorporation of FACTS devices and DG placement methods [2].

Feeder reconfiguration is not only limited to reducing power losses, but it also benefits in system security, improving the voltage profile, load balancing of the network and efficient use of DG systems. The topological arrangement of the distribution feeders is manipulated by varying the tie and sectionalizing switches while maintaining the constraints levels [3]-[4]. The reconfiguration of the network system ensures that all network operations are carried out in lucid and most favourable conditions while maintaining adequate levels that are reliable and secure for quality power supply. The tie switch and sectionalizing switch manipulation can enable the heavily loaded feeders to transfer load to less loaded ones thus minimizing power losses [5].

Different optimization algorithms have been applied in network reconfiguration to identify the optimum switching sequence that gives the overall minimum losses in the distribution systems to save on equipment, time and reduce cost. A review carried out in the network reconfiguration literature shows that each algorithm has a short fall in achieving maximum performance mostly of computational burden and in some cases not reaching the global optimum of the sequence which is meant to achieve the minimum losses in the system [6],[7]. However, some algorithms may prove to be more superior than other algorithms when benchmark testing them but perform poorly when applied to solve in a real-world problem [8],[9]. The approach, programming platform, software and technique used to apply optimization techniques greatly influences the performance depending on the problem being solved. In most systems nowadays, the goal is to achieve an optimization technique that can be applied in realtime [10].

This paper proposes a method to determine the optimal switching sequence of the distribution network reconfiguration using the Modified Shark Smell Optimization (MSSO) algorithm. The main objective of this work is to determine an optimal switching sequence of the distribution system that gives the least power losses and improve the voltage profile in real-time. The proposed method is examined on an IEEE 33-bus RDS and the results are evaluated and compared with other methods in the literature.

II. MATHEMATICAL FORMULATION AND CONSTRAINTS

The objective of the reconfiguration in the radial distribution network is to mitigate the real power losses subject to the constraints. Switch state changes will manipulate the distribution network's topography and allow for the distribution of loads to be balanced accordingly and avert the system from overloading. Power loss of any line between buses in a distribution system shown in Fig. 1 can be defined by [11]-[12]:

$$P_{loss} = \sum_{n=1}^{NL} r_n \left| I_n \right|^2 \tag{1}$$

P_{loss}: the total power loss in the network distribution.

NL: Set of branches.

r_n: the resistance in the branch n.

I_n: the current in the branch n.

The constraints considered for the optimization problem in (1) of network were [13]:

$$V_{n,\min} \leq V_n \leq V_{n,\max} \tag{2}$$

V_n is the voltage magnitude at *nth* bus.

The voltage limits must be retained within the allowed limits at the buses to maintain power quality.

Feeder's capability must have power limits in n branch [14];

$$k_n/P_n/ \leq P_{nmax} \quad n \in NL \tag{3}$$

$$k_n/Q_n/ \leq Q_{nmax} \quad n \in NL \tag{4}$$

$$k_n/I_n/ \leq I_{nmax} \quad n \in NL \tag{5}$$

Radial topology of the network must be maintained;

$$Tie_{sw} = (NL - N_{bus}) - 1 \tag{6}$$

$$NL = N_{bus} - 1 \tag{7}$$

where

R_n : Resistance in the nth branch.

Q_n : Reactive power in the nth branch.

P_n : Real power in the *n*th branch.

V_m : Voltage magnitude at node *m*.

k_n : Status topology of the branches (if branch n is closed $k_n = 1$ and if it is open it is 0).

NL: Set of branches in the network.

N_{bus}: The total number of buses.

When an optimization problem is constrained, it will mathematically determine optimal allocation of scarce resources subject to a set of constraints. In order to maintain a radial topology, each loop in the network must only have one switch open at all times. The topological radial structure constraints for each candidate is represented by (6) and (7). There must always be 5 tie switches and 32 sectionalizing switches in the network. There will be no isolated nodes and the final configuration must be radial with all loads connected.

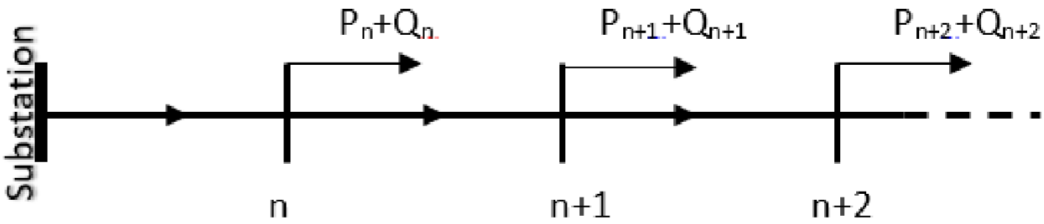

Fig. 1. Single line diagram of distribution system

III. OVERVIEW OF SHARK SMELL OPTIMIZATION ALGORITHM

3.1 Fundamental SSO Algorithm

In this section we first look briefly at the original SSO algorithm and then present the proposed MSSO algorithm which eliminates the gradient function and introduces the sigmoid transformation for smooth search ability. SSO algorithm is a meta-heuristic technique developed by Abedinia *et al*., based on the shark's ability to catch prey by its strong sense of smell [15],[16]. SSO is modelled based on the shark's behaviour to attack its prey once it picks up the blood odour in search space (sea). This inspired the optimization mechanism to be simulated with the aim of picking up the best solution in a given search space [17]. The following steps briefly explains the algorithm (for a minimization problem):

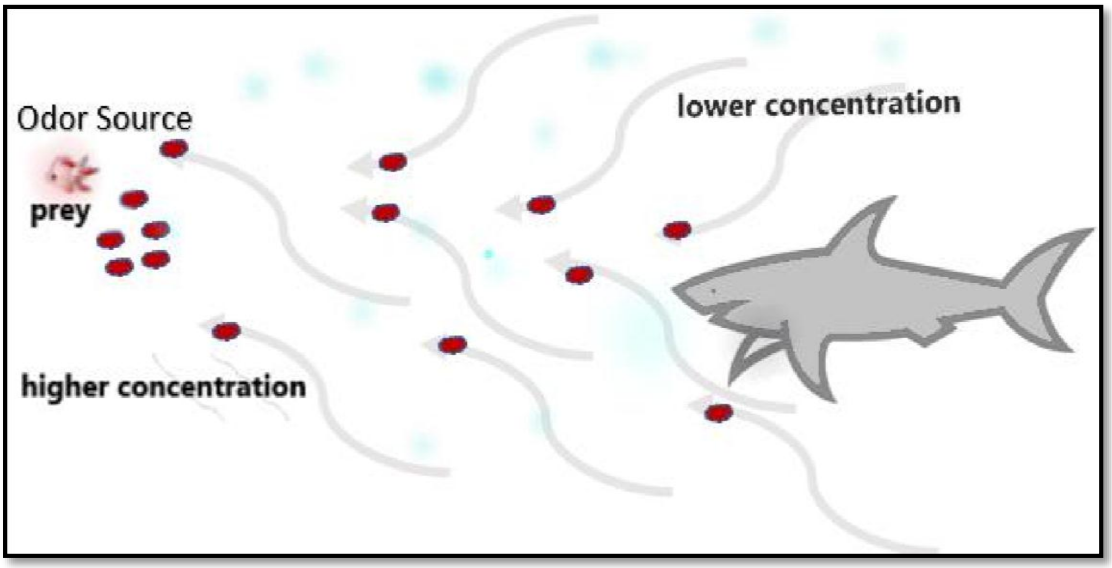

Fig. 2 Shark's movement towards the prey

Initialization

When modeling, a population of initial solutions is randomly generated for an optimization problem in a feasible search area (sea). A source (prey) represents the optimal solution whilst the quality of the solution is represented by the odour strength at a position. According to [16], the initial solution is given as follows;

$$x^1 = \left[x_i^1, x_2^1, x_3^1 \ldots, x_{np}^1 \right] \tag{8}$$

$i = 1,2,3\ldots,np$, (np is the size of the population).

x_i^k is the ith initial solution (population vector position).

$x_{i,j}^k$ represents jth dimension of the shark's ith position.

nv is the number of decision variables in an optimization problem.

Forward Movement

As the blood is discharged into the water, the shark will move towards the target with a velocity 'V', guided by the smell of the stronger odor particles, hence leading to a high-quality solution. In correspondence with the position vector, each velocity vector has a dimensional component element:

$$V_i^1 = \left[V_{i,1}^1, V_{i,2}^1, V_{i,3}^1, \ldots, V_{i,\mathrm{nv}}^1 \right] \tag{9}$$

The increase in shark's velocity is determined by the increase in the odor intensity. In each stage for magnitude of $V_{i,j}^k$, is given as follows;

$$\left|V_{i,j}^{k}\right| = \min\left[\left|\eta_k.R1.\nabla_{i,j}^{k} + \alpha_k.R2.V_{i,j}^{k-1}\right|, \left|\beta_k.V_{i,j}^{k-1}\right|\right] \quad (10)$$

i = 1, 2,…, np, j = 1, 2,…,nv, k = 1, 2,…, kmax

where

β_k is a velocity limiter ratio for stage *k*.

η_k is an element in [0,1].

α_k is the inertia coefficient.

$\nabla_{i,j}^{k}$ is the gradient of the objective function $\left(\left.\frac{\partial(OF)}{\partial x_j}\right|_{x_{i,j}^{k}}\right)$.

The rate of momentum α_k becomes constant for stage *k* (number of stages for shark's forward movement) and the velocity is dependent from its former state. *R1* and *R2* are random values, which gives a more random search when determining the velocity reached by the gradient function and to broaden the search in the algorithm. The considered sign for the value of $V_{i,j}^{k}$ depends on the direction of the selected term of the minimum operator. The velocity vector will determine the new position during the forward movement of the shark given by:

$$Y_i^{k+1} = x_1^k + V_1^k.\Delta t_k \quad (11)$$

$i = 1, 2, \ldots, np$, $k = 1, 2, \ldots, k\max$

Δt_k – time interval is assumed to be 1.

Rotational Movement

The rotational movement allows the shark to narrow down the stronger odour particles when moving forward and this process a local search carried out in the SSO algorithm modelled by the equation below:

$$Z_i^{k+1,m} = Y_i^{k+1} + R3.Y_i^{k+1} \quad (12)$$

To model the rotational movement of the shark, the number of points *M* in the local search are connected to form closed contour lines as shown in Fig. 3, whereby the position of point *m* of each stage in the local search is $Z_i^{k+1,m}$. As the operator implements a local search around Y_i^{k+1}, a random number *R3* is also generated.

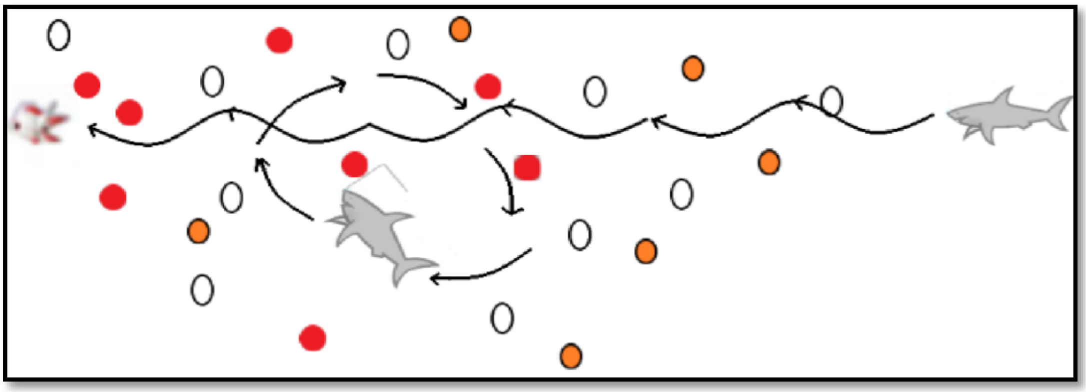

Fig. 3 Shark's rotational movement

Updating the Particle Position

The shark's search path will continue with the rotational movement as it moves closer to the point with a stronger odour sense as shown in (13);

$$X_i^{\,k+1} = \text{argmin}\{OF(Y_i^{\,k+1}), OF(Z_i^{\,k+1}), \ldots, OF(Z_i^{\,k+1,M})\} \quad (13)$$

$$i = 1, 2, \ldots, np$$

$X_i^{\,k+1}$ presents the next position of the shark or the candidate solution with the least objective function (*OF*) value. The *OF* should be minimized from the obtained forward movement and rotational movement. The cycle will continue until k reaches the minimum value (best individual) in the given population in a search space which will be chosen for the optimization problem.

3.2 Proposed MSSO Algorithm

In the MSSO algorithm there were two modifications made to the original algorithm which permits the exploration and exploitation capabilities to improve the global search performance in achieving the *OF* network reconfiguration problem. In the main loop of the algorithm the gradient of the *OF* in (10) was removed from the velocity movement operator for the shark. Instead of finding the minimum of the gradient function from the velocity equation, the *OF* was introduced in the fitness loop which compares the current best position of the shark with the previous best [12]. If the current fitness function is a better than the previous it will be updated until the iteration stops. The global minima from all the particles in a search space is selected as the global best. Since the shark's movement is non-linear in nature, this permits a sigmoid transformation [18] shown in (14) to be introduced in the forward movement operator when a new position is obtained soon after (11), for smooth search capability.

$$sigfun^{k+1} = \frac{ta}{1 + e^{-Y_i^{k+1}}} \quad (14)$$

where ta represents the branches in each loop.

The position value of the particles in each stage will settle at the nearest whole number among the given values in the loops created in the network. This will assist in getting a reasonable position towards the prey with the linearized part of the sigmoid moving the shark's non-linearity in a forward manner, thus returning a switch sequence which is identified with an objective function for each value of *k*.

IV. OPTIMAL NETWORK RECONFIGURATION USING THE PROPOSED MSSO ALGORITHM

The application of the MSSO algorithm to the network reconfiguration problem is discussed here. Fig. 4 shows the flow chart for the reconfiguration process with application of the algorithm to the network. The flow process of the proposed MSSO algorithm is as follows:

Step 1: The bus system data and MSSO algorithm parameters such as $np, nv, M, \eta, \alpha, \beta$ are generated.

Step 2: Initialization of the population vector for a given population size and $k = 1$. The initial open/closed switches of the network before configuration will present the solution vector, X^1 and the initial fitness (power loss).

Step 3: Each solution obtained per iteration (load flow) returns a fitness function (power losses) which is compared with the previous load flow and ensures that it is in the allowable limits of the system to operate.

Step 4: The new position of the shark is determined from the forward movement by moving vector solution X^1 to a new position Y_i^{k+1} using (11).

Step 5: A sigmoid function is introduced to the new position of the shark Y_i^{k+1} to linearize the shark's movement and obtains a new position from the tap switches given in the loops.

Step 6: Perform rotational movements to determine new position of the shark in a local search $Z_i^{k+1,m}$.

Step 7: The new position of the shark is determined from forward and rotational movements. The best switching sequence with the least power losses in the network will be identified and picked between the two movements. ***Step 8***: If k is not equal to k_{max}, go to *step 3*.

Step 9: The global minimum of the fitness function is chosen at the last best position $X^{K\max}$.

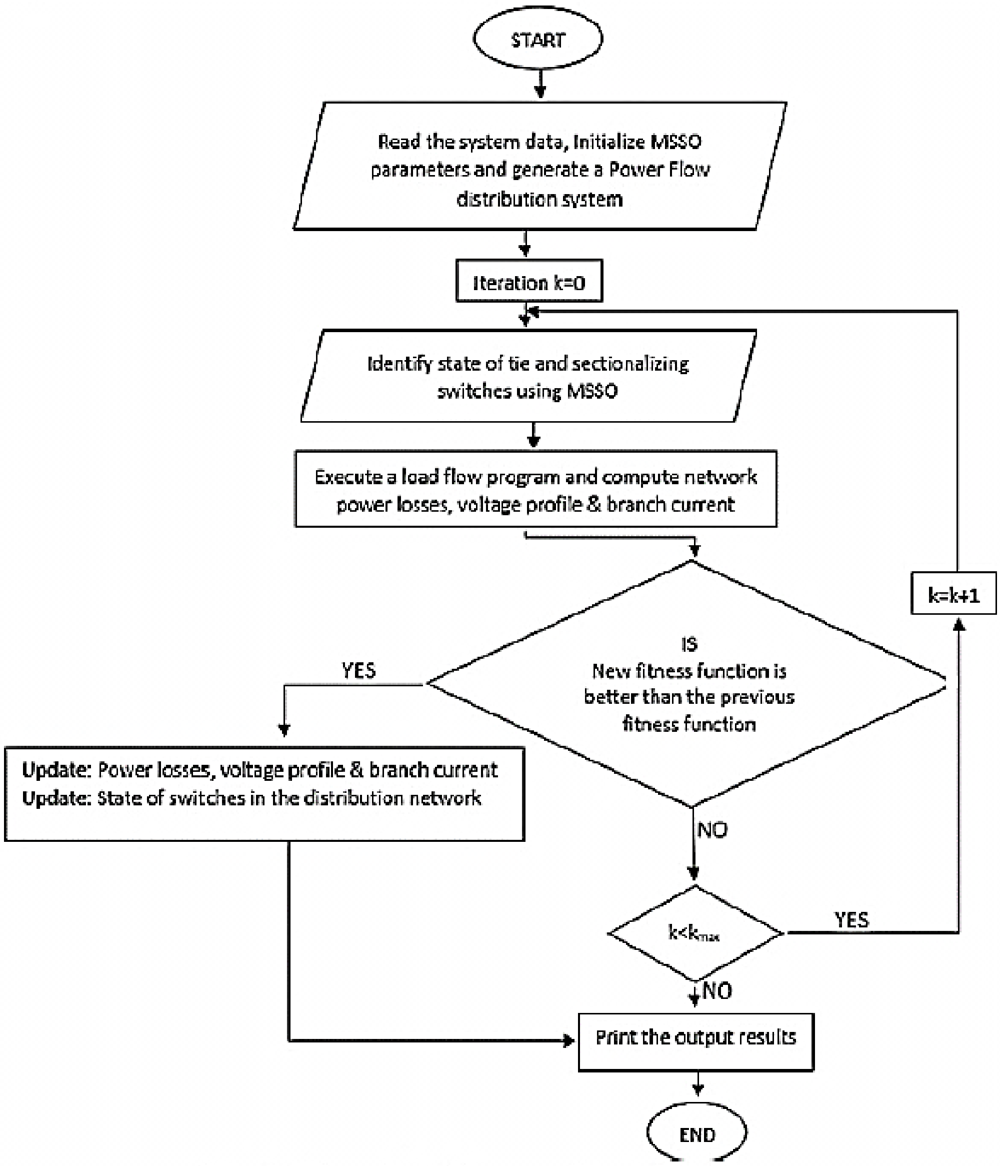

Fig. 4. Flowchart for reconfiguration process

Parameter settings: α = 0.5, β = 2, η = 0.9, M = 50, Population size (np) = 50.

Decision Variable (dimension) = 5.

Number of iterations (k) = 20.

The above defined parameters for the MSSO algorithm can be tuned depending on the size of the network or changes made to the system. The population of the problem evolves through the forward and rotational movement operators with a randomization to the parameter settings for each stage counter k.

V. RESULTS AND DISCUSSION

The proposed MSSO algorithm was implemented in Matlab software R2017a on a 2.5GHz, core i7 -6500 with 8.00 GB RAM. The load flow calculations were performed using Fast-decoupled method in MATPOWER package [19]. The load flow analysis was performed to obtain the parameters used in determining the performance of the network system. The data of the test system for a medium active and reactive power loading demand shown in Table A1. at the appendix, had the following characteristics;

- Normal system loading: Active power is 3,715 kW and Reactive power is 2300 kVAr.
- Base voltage: 12.66 kV and Base MVA: 100MVA.

5.1 Simulation Results of IEEE 33-bus System

Table 1: Load flow results of the 33-bus test system

Parameters	Case 1	Case 2
Tie-Switch	33 34 35 36 37	7 9 14 32 37
Real Power Loss (kW)	208.459	138.9276
Loss reduction (%)	-	33.36
Vmin (p.u)	0.91075	0.94234
Node	18	32

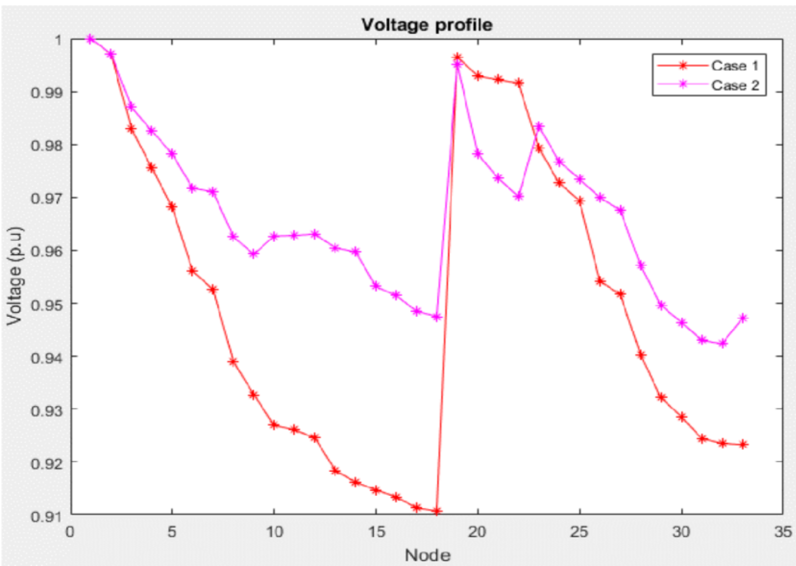

Fig. 5. Voltage profile before and after reconfiguration Case 1 and Case 2

Table 1 shows the summary of the load flow results for the 2 cases (before and after reconfiguration) used to analyze this study. The initial load flow simulation for case 1 was used as reference to show how the optimum network after reconfiguration had improved from the initial configuration of the system, shown in Fig. A1 at the appendix. It had total power losses of 208.459 kW. It is clear that after network reconfiguration in case 2 the total power losses had significantly reduced to 138.927 kW, amounting to 33.36% reduction than the initial network before reconfiguration. The optimal network had branches 7, 9, 14, 32 and 37 disconnected after the reconfiguration using the proposed MSSO algorithm in case 2. Fig. 5 shows the comparison of the voltage profile before and after network reconfiguration for case 1 and case 2, respectively. The voltage magnitude was set to operate between its minimum and maximum bounds of 0.9 and 1 p.u, respectively. The initial network for the first case had a minimum voltage of 0.91075 p.u at node 18, which improved to 0.94234 p.u in case 2 after network reconfiguration.

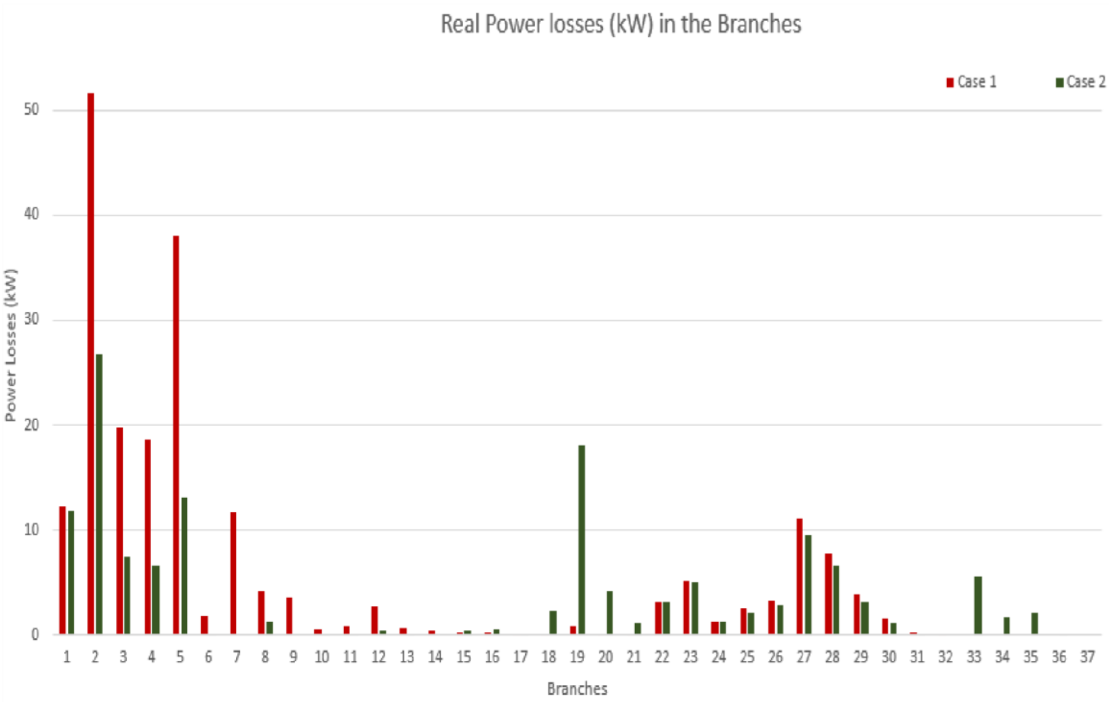

Fig. 6. Real power in 33-bus system before and after reconfiguration

The comparison for the real power losses in the branches are shown in Fig. 6 for initial configuration and after reconfiguration. The power losses in almost every branch reduced, except at 18, 19, 20, 21, 33, 34 and 35, where there was a small increase in losses due to load shifting of the feeders altered by the switching in case 2.

5.2 Comparative Study of Proposed MSSO Algorithm and Other Algorithms

The proposed approach obtained better values as compared to other algorithms, thus demonstrating the effectiveness of the MSSO algorithm in solving network reconfiguration problems. The results in Table 2 show the comparison of the proposed MSSO algorithm with different algorithms from the literature. The computational time for the proposed MSSO algorithm was 5.7s which was a short time-consuming process for the algorithm to converge to an optimum fitness function. The minimum voltage for the proposed MSSO algorithm and Hybrid Genetic Algorithm-Particle Swarm Optimization (HGAPSO) algorithm were the same with a small difference of 0.727 kW in power losses, making the proposed algorithm better. The proposed algorithm converged to a better fitness function (real power loss) with respect to other algorithms. The total minimum losses of the IEEE 33-bus system that can be obtained within permissible limits and without violating the constraints of the system was 138.928 kW. The proposed MSSO algorithm had the highest power loss reduction of 33.35% from the initial original network.

Table 2: Comparison of different algorithms for 33-bus test system

Parameters	**Proposed MSSO**	**HSA** [3]	**HGAPSO** [10]	**GA** [11]	**PSO** [11]
Tie switches	7 9 14 32 37	7 10 14 28 36	7 10 14 32 37	7 9 30 34 37	7 14 19 32 37
Best Ploss (kW)	138.928	146.39	139.655	140.282	139.982
Average Ploss (kW)	142.135	152.33	-	141.693	140.236
Worst Ploss(kW)	144.146	195.10	-	143.94	141.921
Loss reduction %	33.35	29.78	33.01	32.71	32.85
Vmin (p.u)	0.9423	0.9336	0.9423	-	-
Comp. Time (s)	5.7	7.2	-	27.43	18.32

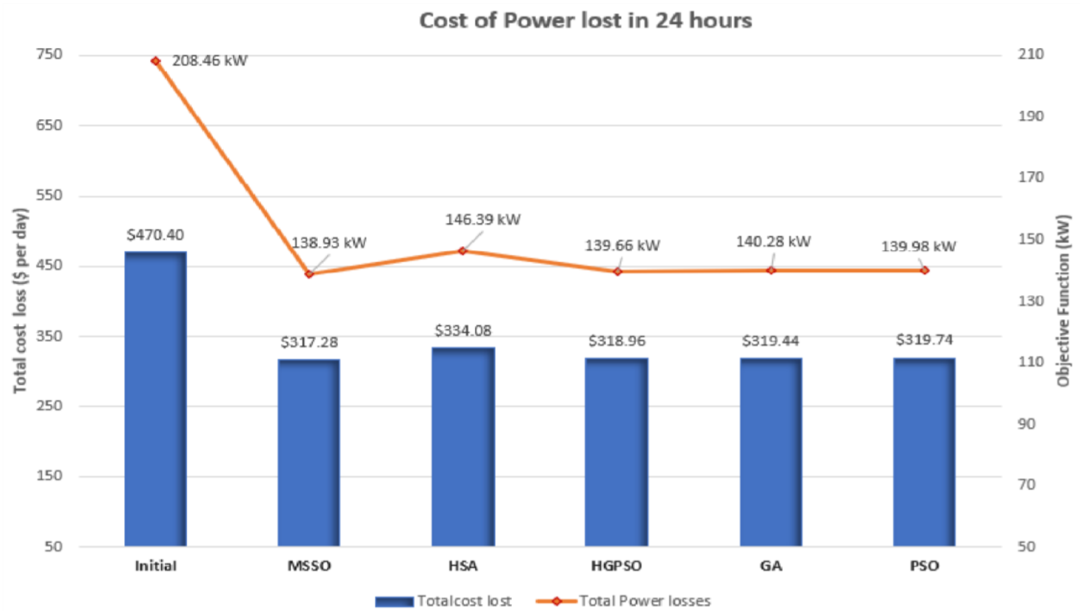

Fig. 7. Total Cost Lost Analysis of MSSO Algorithm with Other Algorithms

It can be evidently seen from Fig. 7 that the proposed MSSO algorithm serves better in reducing the power losses and cost saving as compared to the other methods despite the number of switches altered to open in the network. The operational cost of switching a single switch is taken to be 0.041$ from [20], and the cost of power per kWh is 0.094$/kWh using the Malawian energy prices. The total cost of power lost per day before network reconfiguration was $470.40. A cost reduction can be noticed in all the five algorithms applied in the IEEE 33-bus system for power loss reduction. The total cost of power lost when the proposed MSSO algorithm was applied was the lowest with $317.28 per day.

V. CONCLUSION

This paper demonstrates the effectiveness of the proposed algorithm when applied in network reconfiguration. The obtained results show that a fairly large amount of power losses reduced by 33.35% from the initial network when optimal network reconfiguration is applied using the proposed MSSO algorithm. There is generally a significant improvement in voltage profile from 0.91075 p.u to 0.9423 p.u with substantial reduction in power losses of the entire system. The proposed algorithm has a higher convergence rate which only takes 5.7s to converge to the optimum fitness function making it suitable for real time implementation. The algorithmic robustness and simplicity in coding made it easier to apply to the distribution system problem making it attractive as compared to other algorithms. The greedy search approach and heuristic information thoroughly guided and lead the search to a speedy discovery of good solutions.

APPENDIX

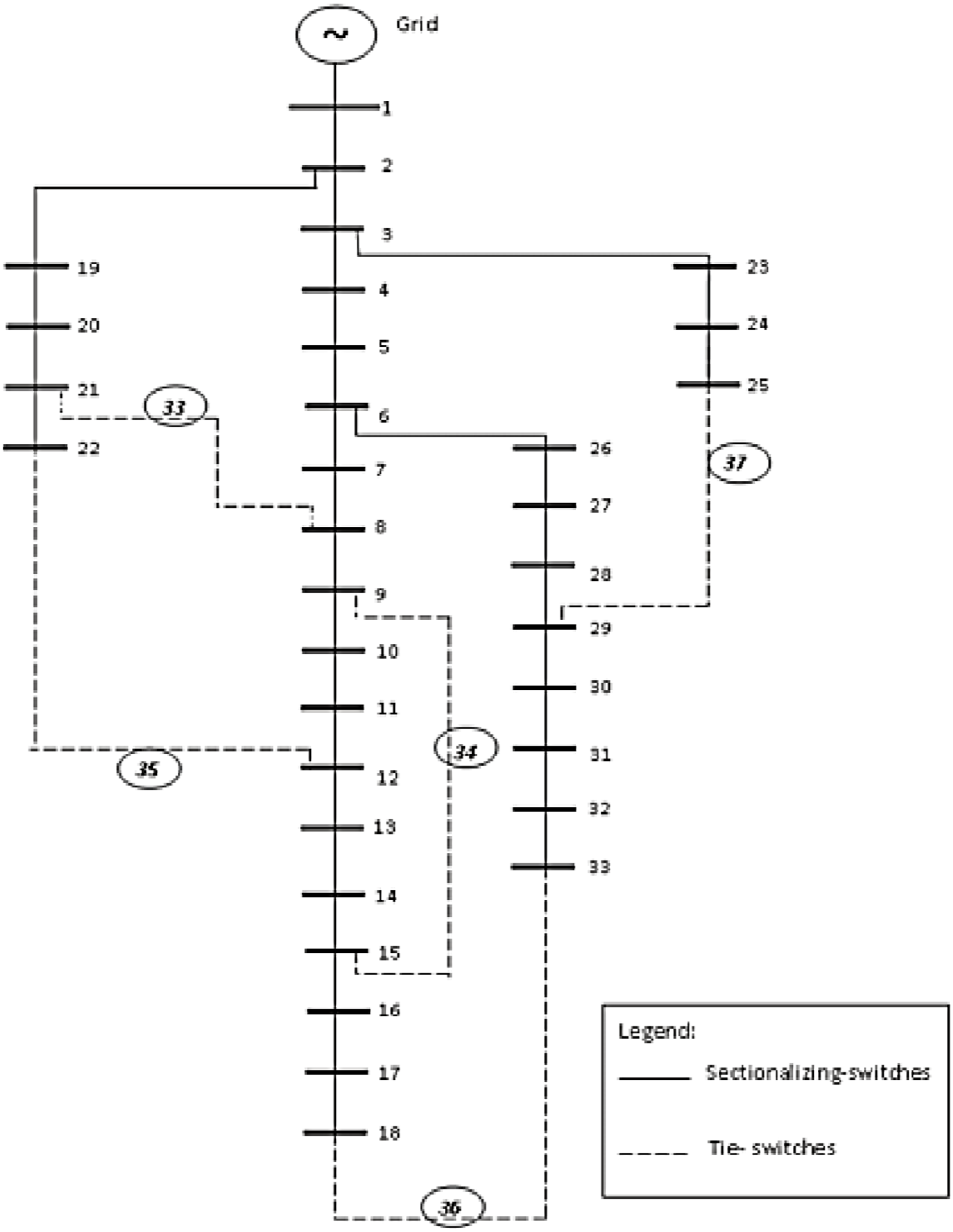

Fig. A1. Single line diagram of IEEE 33-bus RDS

Table A1: System data for 33-bus test Radial Distribution System

Serial Number	Sending Node	Receiving Node	P (kW)	Q (KVAr)	R (ohms)	X (ohms)
1	1	2	100	60	0.0922	0.047
2	2	3	90	40	0.4930	0.2511
3	3	4	120	80	0.3660	0.1864
4	4	5	60	30	0.3811	0.1941
5	5	6	60	20	0.8190	0.707
6	6	7	200	100	0.1872	0.6188
7	7	8	200	100	0.7114	0.2351
8	8	9	60	20	1.0300	0.74
9	9	10	60	20	1.0440	0.74
10	10	11	45	30	0.1966	0.065
11	11	12	60	35	0.3744	0.1238
12	12	13	60	35	1.4680	1.155
13	13	14	120	80	0.5416	0.7219
14	14	15	60	10	0.5910	0.526
15	15	16	60	20	0.7463	0.545
16	16	17	60	20	1.2890	1.721
17	17	18	90	40	0.7320	0.574
18	18	19	90	40	0.1640	0.1565
19	19	20	90	40	1.5042	1.3554
20	20	21	90	40	0.4095	0.4784

Serial Number	**Sending Node**	**Receiving Node**	**P (kW)**	**Q (KVAr)**	**R (ohms)**	**X (ohms)**
21	21	22	90	40	0.7089	0.9373
22	22	23	90	50	0.4512	0.3083
23	23	24	420	200	0.8980	0.7091
24	24	25	420	200	0.8960	0.7011
25	25	26	60	25	0.2030	0.1034
26	26	27	60	25	0.2842	0.1447
27	27	28	60	20	1.0590	0.9337
28	28	29	120	70	0.8042	0.7006
29	29	30	200	600	0.5075	0.2585
30	30	31	150	70	0.9744	0.963
31	31	32	210	100	0.3105	0.3619
32	32	33	60	40	0.3410	0.5302
33	21	8	-	-	2.0000	2.0000
34	9	15	-	-	2.0000	2.0000
35	12	22	-	-	2.0000	2.0000
36	18	33	-	-	0.5000	0.5000
37	25	29	-	-	0.5000	0.5000
Total Loading			**3715**	**2300**		
Substation voltage kV base = 12.66kV and MVA base = 100MVA (per unit calculations)						

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