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Optimal Switching Sequence using an Improved Metaheuristic Technique in a Distribution Network System with Fixed DG Units

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***Abstract*— Integration of renewable DGs in distributed networks has become a critical issue in meeting the increasing electricity demand while considering economic and environmental impacts. DGs integrated into the electric distribution network assist with voltage improvement and power loss mitigation. However, it may also come with other technical challenges such as stability, reliability and power quality issues if poorly designed. This would lead to worsening the performance of the power system and the degradation of network components. Optimal network reconfiguration has proven to be very beneficial in effective reduction of power system losses when simultaneously employed with DG units. This research reports on the development and valuation of a proposed metaheuristic optimum network reconfiguration method for total real power loss decrease in radial distribution schemes with fixed DG units. The proposed method was designed in MATLAB and the IEEE 33-bus radial distribution system was employed in assessing its performance.**

Keywords*— Distributed generation, MATLAB, Metaheuristic, Network reconfiguration, Radial distribution system

I. Introduction

The rate of the distributed generation's incursion into the grid comes with several challenges which may affect the quality of power rendered in the distribution system. Since there is already a significant amount of power loss in distribution systems due to low voltage operation and high current flow, the feeder system becomes more susceptible to high voltage drops and damage of components. Reduction of system power losses can improve the quality of power provided, hence boosting the lifespan of key electrical components [1]. A reliable distribution system distributes electric power to the customer in an adaptable manner, maintaining the protection of equipment and feeders from any contingencies [2]–[6].

Recently, there has been a trend with emphasis on increasing energy market with a mix of various renewable energies to the electrical grid [7], [8]. According to [9], conventional power plants can benefit from Renewable Energy Technologies (RETs) and other ancillary services for succesful supply to the nearby loads and grid during low and peak demand periods. Introduction of DG units to the distribution networks (DNs) provide crucial auxiliary services due to their optimization nature [10], [11]. Nevertheless, reliability of the system becomes of great concern for durable solutions in terms of maintenance costs, availability and readiness when in operation as discussed in [12], [13]. In a power system set up, electrical energy supply to the consumers must not have any interruptions and should maintain acceptable tolerance margins for the voltage and frequency. The source of generation must ensure that the quality of power supplied does not compromise the system and ensure effective maximization of technical and fiscal profits. Some of the negative circumstances that accompany DG penetration in electrical networks are, incorrect installation in terms of size and location, that leads to instability issues [14], [15], back feeding of power, relay malfunctioning and grid system blackouts which may damage non-islanded DG units [16]–[18].

An ideal radial distribution system (RDS) network reconfiguration (NR) refers to the exercise through which the topological structure of the radial DN is optimally modified in order to accomplish the set objectives [19],[20]. The objectives may include reduction of the overall real and reactive power losses, improvement of voltage profiles, economic operations and the reduction of overloads happening in the system as the operating requirements change [5]-[7],[21]–[24]. Adjusting the structural layout of the system for radial distribution systems is attained through the opening and closing of tie switches and sectionalizing branches. Use of NR ensures network processes are achieved in lucid and satisfactory settings whilst maintaining sufficient levels of reliability and secure supply when DG units are connected as discussed in [25], [26].

This research work was aimed at introducing an improved metaheuristic approach for carrying out optimal NR in a RDS while assuming that there was manual placement of fixed DG

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units due to technical or economic reasons influenced by the geographical topology. The simulation results give evidence of the expected behavior to maintain a reliable system in addition to the benefits of total power loss lessening and voltage profile improvement. Evaluation of the proposed optimization algorithm was compared with two other algorithms. The work is arranged as follows; the adopted methodology is outlined in Section II, while Section III presents an overview of the simulation results and lastly, Section IV gives an outline of the conclusions.

II. METHODOLOGY

The outcome of this study was centered on the computational simulations undertaken on MATLAB platform utilizing an IEEE 33-bus RDS.

A. Problem Formulation and Controls

Distributed power flow is calculated using equations in references [27],[28]. The injected current at bus *n* is shown in (1);

$$I_n = \left(\frac{P_n + jQ_n}{V_n} \right) \tag{1}$$

To obtain branch current between buses *n* and *n+1,* Kirchhoff's Current Law is applied.

$$I_{n,n+1} = I_{n+1} + I_{n+2} \tag{2}$$

Assuming constant loads without interruption at load point. Kirchhoff's Voltage Law is used at bus *n+1*.

$$V_{n+1} = V_n - I_{n,n+2}\left(r_{n,n+2} + jx_{n,n+2}\right) \tag{3}$$

Equation (4) and (5) are used to compute complex load flow.

$$P_n = \sum_{n=1}^{NL} \left|Z_{n.n+1} V_n V_{n+1}\right| \cos\left(\theta_{n\,n+} + \delta_n - \delta_{n+1}\right) \tag{4}$$

$$Q_n = -\sum_{n=1}^{NL} \left|Z_{n.n+1} V_n V_{n+1}\right| \sin\left(\theta_{n\,n+} + \delta_n - \delta_{n+1}\right) \tag{5}$$

Equation (6) and (7) are used to find the line power losses between buses.

$$P_{loss(n,n+1)} = r_{n,n+1} \left(\frac{P_{n,n+1}^2 + Q_{n,n+1}^2}{\left|V_{n+1}\right|^2} \right) \tag{6}$$

$$P_{Tloss} = \sum_{n=1}^{NL} P_{loss(n,n+1)} \tag{7}$$

After NR, the power loss is obtained as.

$$P'_{loss(n,n+1)} = r_{n,n+1} \left(\frac{P'^2_{n,n+1} + Q'^2_{n,n+1}}{\left|V'_{n+1}\right|^2} \right) \tag{8}$$

$$P'_{Tloss} = \sum_{n=1}^{NL} P'_{loss(n,n+1)} \tag{9}$$

Before and after reconfiguration, the power loss difference gives a total power loss reduction.

$$\Delta P_{Tloss} = \sum_{n=1}^{NL} P_{Tloss(n,n+1)} - \sum_{n=1}^{NL} P'_{Tloss(n,n+1)} \tag{10}$$

B. Mathematical Model of the Distribution NR

In this study, the objective function used is as shown in (11) and it is subjected to constraints shown in (12)-(18).

$$\min f = \sum_{n=1}^{NL} k_n R_n \left(\frac{P_n^2 + Q_n^2}{V_n^2} \right) \quad n \in NL \tag{11}$$

The bus voltage magnitudes must be located within the acceptable range [27].

$$V_{m,\min} \le V_m \le V_{m,\max} \tag{12}$$

DG unit capacity;

$$P_{nmin} \le P_{DG,n} \le P_{nmax} \quad n \in NL \tag{13}$$

The DG output is operated within the acceptable limits. Feeder's capability power is limited in the *n*th branch.

$$k_n/P_n/ \le P_{nmax} \quad n \in NL \tag{14}$$

$$k_n/Q_n/ \le Q_{nmax} \quad n \in NL \tag{15}$$

$$k_n/I_n/ \le I_{nmax} \quad n \in NL \tag{16}$$

Maintain radial topology structure of the network;

$$Tie_{sw} = (NL - N_{bus}) + 1 \tag{17}$$

$$Sec_{sw} = N_{bus} - 1 \tag{18}$$

where P_n: Real power in the *n*th branch,
Q_n : Reactive power in the *n*th branch,
V_m: magnitude voltage at node *m,*
R_n: *n*th branch resistance,
k_n: Topology status of open /closed branches,
NL: Set of network branches,
N_{bus}: Total number of buses.

Individual network loop switches must be open at any time to maintain a radial topology, expressed in Eqn. (17) and (18). All nodes are connected, and the final arrangement will still be radial, with all loads actively connected.

C. Formulation of the Proposed Algorithm

The Shark Smell Optimization (SSO) algorithm is based on the shark's strong sense of smell and its subsequent behaviour when a prey is within a search space that is close or miles away. The biological behaviour of a shark instigated the optimisation process to be modelled with a goal of finding the most suitable solution or results in a specified search space. In the Modified SSO algorithm [28], the gradient function from the velocity movement operator is eliminated and the sigmoid transformation function, which improved in the smooth search of the shark, is introduced. Improvements in modifying the SSO Algorithm [29][30], permitted for the exploration and exploitation aptitude to make the global search operation better in attaining the *Objective Function* (*OF)* of the NR problem. Comparison between the present best and the previous best position of the shark in the fitness loop is done with the introduced *OF* [31].

Whenever the present fitness function surpasses the preceding, it would be updated right through to the last iteration. The particles within the search space that gives the least or minimum *OF* value are considered to be the global best. For a fluid search, the shark's non-linear movement permits for a sigmoid transformation [32] to be put in the forward movement operator when a new position is found just after the rotational movement.

D. Pseudo Code for Modified SSO Algorithm

Begin

Initialize

Set the parameters $np, k_{max}, \eta_k, \alpha_k$ and $\beta_k (k = 1, 2, \ldots, k_{max})$

Initial population is generated with all individuals

Generates the decisions randomly within an acceptable range

Stage counter to k = 1 is initialized.

For k = 1:k_{max}

For every single odor particle

Determine the fitness value

If **new** fitness value < previous Local best value

Set the **new** Local best

End

Select odor particles with the most suitable fitness value from all possible particles as the Global best

Forward movement

Determine each element of the velocity vector, $V_{i,j}$ $(i = 1, \ldots, np, j = 1, \ldots, nd)$

Find the next position of the shark in the forward direction, Y_i^{k+1} $(i = 1, \ldots, np)$

Include a sigmoid transformation to the newly realized position, $sigfun^{k+1}$

Rotational movement

Determine the location of the shark due to its rotational motion, $Z_i^{k+1,m} (m = 1, \ldots, M)$

Select the new location of the shark relative to both its movements, X_i^{k+1}

End *for k*

Fix k = k + 1

Select the best position of the shark in the final phase which has the most suitable fitness function.

End

E. Network Reconfiguration using Modified SSO Algorithm

Table I shows the parameters used in solving the optimal network reconfiguration problem using MSSO [28]. The size or modifications made to the system network influence how the parameters' flow process is fine-tuned. The most effective technique in this process relied on the dynamic mechanism in which the parameters are modified during the evolution process. There is evolution in population for the defined problem through the movement operators, with parameter setting randomization at each stage of counter *k*. The particles' position at each stage settles to the nearest set of a whole number, from the values given in the formed network loops, thus assisting in obtaining a reasonably accurate status towards the prey. The shark's zig-zag movement in the forward direction is modelled by the linearized section of the sigmoid which ensures the return switch sequence identifies with an *OF* for each value of *k*. A random search was made by the MSSO algorithm because of its stochastic nature. This implies that the variables initially set have no adverse impact on the search for the best solutions.

TABLE I.
DEFINED PARAMETERS FOR MSSO ALGORITHM

Parameter	Description	Value
α	inertia coefficient	0.5
β	velocity limiter ratio [0.1-4]	2
η	element [0-1]	0.9
M	local search stages	50
nv	dimension decision variables	5
np	population size	50
k	number of iterations	20
Δt_k	Time interval	1
ta	branches in each loop	-

F. IEEE 33 Bus Test System

The IEEE 33-bus RDS is composed of 33 buses, 32 lines, and 5 tie switches which were considered in this study. It has a single substation bus that provides power to the rest of the buses connected to permanent loads as shown in Fig. 1. Fast Decoupled technique was employed in the load flow analysis in checking the performance of the system with the suggested algorithm. The total system power loss drops and the voltage profile improvement were analysed for the following cases:

Case 1: Before NR with DG units,
Case 2: After NR with MSSO with DG units.

Each updated configuration from the loop identified by MSSO algorithm had to perform a load flow analysis and determine its optimum operating point. The IEEE 33-bus radial distribution structure has five loops which were used in the creation of the search space. From the generated search space, the best arrangement of tie branches and sectionalising switches that are to be opened and closed were obtained.

The RDS has 37 branches and 33 buses. 32 branches have sectionalizing switches that are usually closed while the tie switches of 5 branches are usually open. A solid black line is used to depict the branches with sectionalizing switches. While a broken or dotted red line is used to depict the branches with tie switches. The result of five loops is as shown in Fig.1, when all the tie and sectionalizing switches are shut, with 3,715 kW and 2,300 kVAr total real and reactive power loads, respectively. The stipulated line voltage for the system is 12.66 kV while the data for the load and line are as in [33].

Each DG unit of same size was placed on four fixed buses and locations shown in Table II [33]. The DG positions were assumed to be in fixed locations explicitly designed for the chosen energy generation, in the event optimal location is not possible due to geographical positioning of the network.

TABLE II. DG DATA

Location (Bus#)	6, 12, 16, 31
Size (kW)	499.5
Total size (kW)	1998

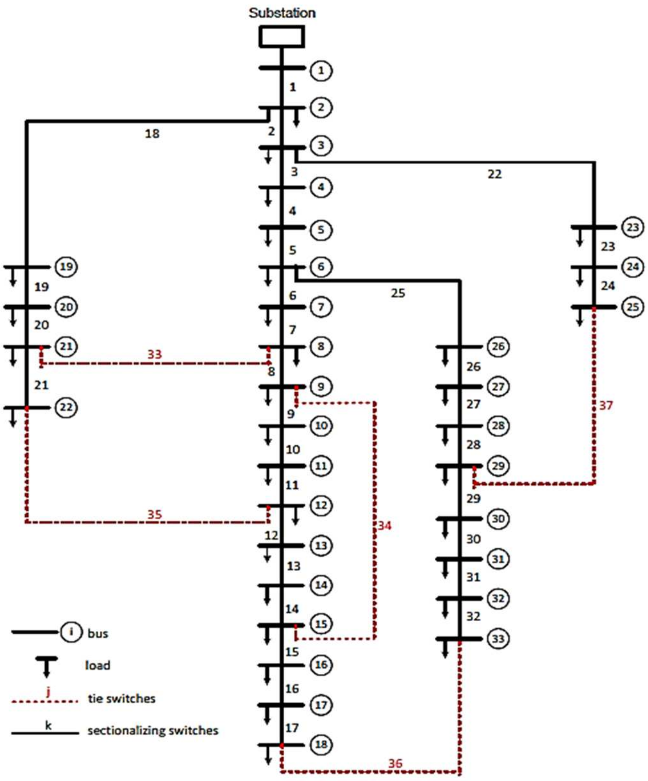

Fig. 1. One-line diagram of the IEEE 33-bus RDS feeder

III. Simulation Results And Discussion

Table III gives statistical results with regards to the performance of the proposed optimal NR approach after 20 independent runs. The initial simulated load flow of the original network was used as reference to show the significant performance compared with the other two cases. A substantial power loss reduction was noted for *case 1* compared to the base network, with *case 2* giving a further reduction in power loss to 64.9211kW.

A small increase in power loss was experienced in some branches due to the load feeder switching experienced in *case 2*, as depicted in Fig. 2. The rest of the branches in the network had power loss reduction. Two feeder connections in buses two and three carried most of the power to all the branches. The bulk power flow from the substation was in the second branch, which experienced the major losses in the network. The feeder line power loss decreases as it moves further away from the substation. A reconfiguration process is used to minimize losses through manipulation of the power flow. This leads to reduced power loss in most of the branches of the optimized tie switches. The second branch of the network had substantial apparent power loss reduction in both cases compared to the original base case (Table IV). To relieve the distribution power lines from overloading through the substation grid power supply, the DG units boosted the power supply in the distribution system. This promotes an optimized power flow in an unstrained manner during operation.

TABLE III.
Load Flow Analysis for Different Cases in the Network

Parameters	Original Network	Case 1 DG Units only	Case 2- MSSO (Reconfiguration) + DG units
Open-Switches	33, 34, 35, 36, 37	33, 34, 35, 36, 37	7 9 14 32 37
Real Power Loss (kW)	208.46	83.76	64.92
Loss reduction (%)	-	59.82	68.86
V_{min} (p.u)	0.9107	0.9657	0.9700
Node	18	33	32

TABLE IV.
Experienced power losses in second branch of the Network

Case	P (kW)	Q (kVAr)	S (kVA)	Loss reduction %	Comments
Original	51.60	26.28	57.91	-	No Investment
Case 1	19.42	9.89	21.79	62.37	DG units only
Case 2	14.31	7.29	16.06	72.27	NR & DG units

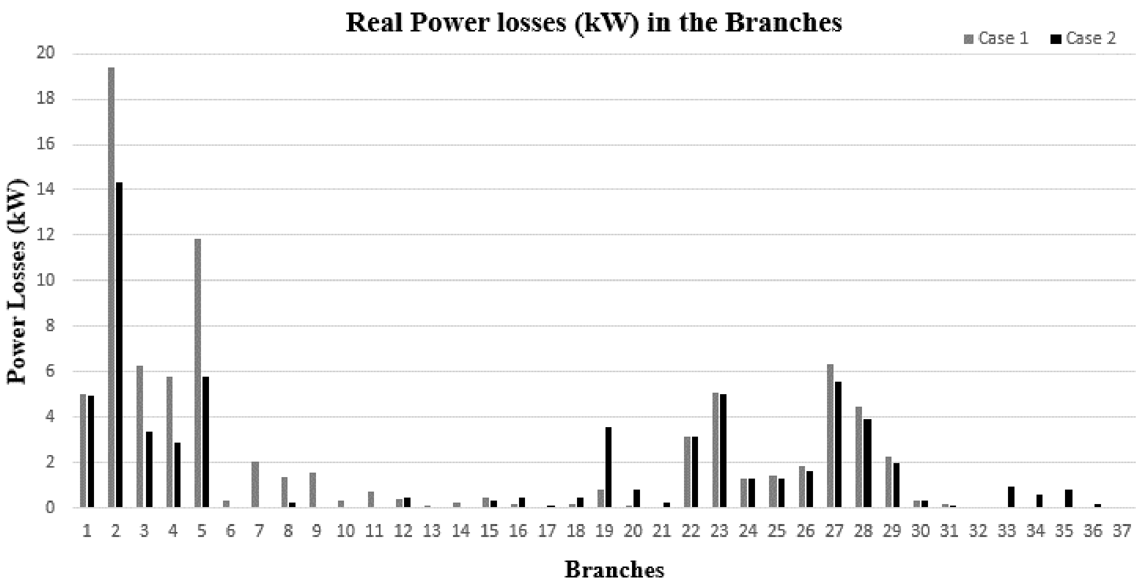

Fig. 2. Comparison of Branch Power Losses before and after NR with DGs

A. Comparative analysis with other Algorithms considering DGs

Fig. 3 and Table V gives an illustrative comparison of the various parameters obtained using two other approaches to appreciate the merits of the MSSO algorithm. It should be noted that the parameters in Table II were considered in the analysis. It can be observed that the MSSO outperformed the other optimal NR approaches based on convergence rate, best power loss and loss reduction. There was minimum voltage drop in buses 20 to 22 due to the network topological changes. The random nature of the approach permitted a minimum of 20 permutation runs to identify an optimal fitness with less iterations and convergence rate as depicted in Fig. 4.

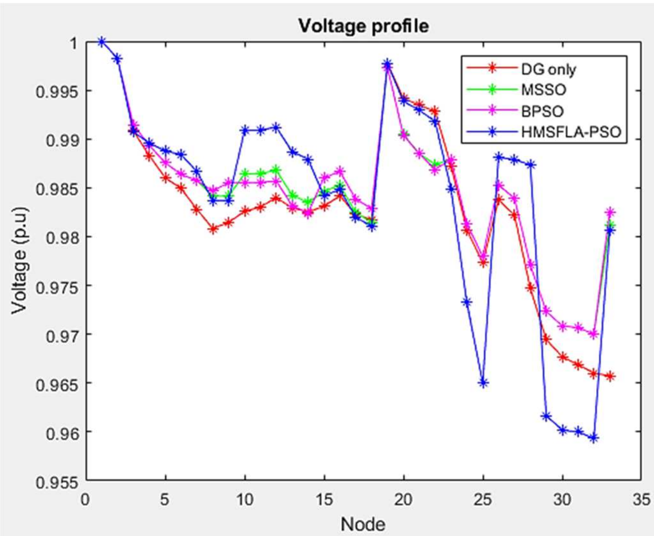

Fig. 3. Comparison of bus voltage profiles

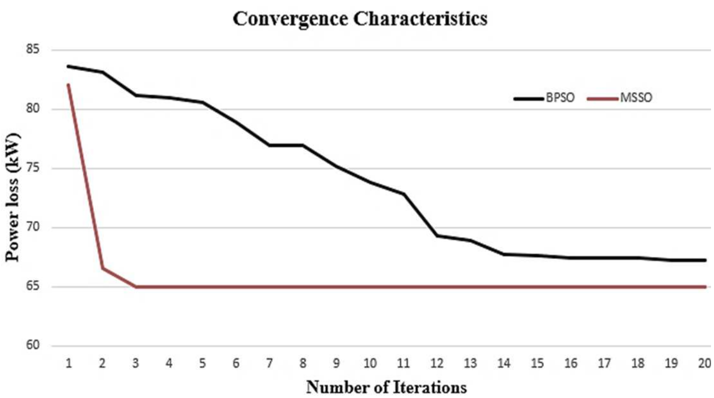

Fig. 4. Convergence characteristics

TABLE V.
COMPARISON RESULTS WITH OTHER ALGORITHMS

Parameters	MSSO	BPSO	HMSFLA-PSO [33]
Optimal Tie switches	7, 9, 14, 32, 37	7, 8, 14, 32, 37	9, 14, 28, 32, 33
Best P_{loss} (kW)	64.921	67.182	69.396
Average P_{loss} (kW)	66.573	68.082	70.326
Worst P_{loss} (kW)	68.925	80.211	70.963
Loss reduction %	68.86	67.00	66.71
Comp. Time (s)	5.10	29.29	-
V_{min} (p.u)	0.9700	0.9700	0.9593

IV. CONCLUSION

This study establishes the effectiveness of an improved MSSO algorithm when NR is applied in the presence of fixed DG units. Integration of DGs to the RDN play a vital role in improving the losses, as substantial amount of power loss reduction was experienced supported by the study and in the literature. DG unit placement before NR had a significant improvement in voltage profile. However, there was a further loss reduction observed when MSSO algorithm was introduced in the network. Minimum computational burden in settling to an optimal solution was experienced as compared to the other approaches. The positive DG contributions in power loss *OF* was emphasized in the obtained results. There was also a tremendous relief on overloaded feeders in the network after the bus voltage profile improvement. Future works will consider looking at the applicability of the proposed solution in other types of distribution networks and real-life systems.

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