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OPTIMAL RECONFIGURATION OF DISTRIBUTION NETWORKS FOR POWER LOSS REDUCTION USING POLITICAL OPTIMIZER ALGORITHM

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Network Reconfiguration (NR) is the process of altering the status of the switches in a Distribution Network (DN), in a bid to minimize power loss and improve the overall performance of the network. Problems such as load imbalances, power losses and equipment overloading which could potentially arise during NR can adequately be solved using appropriate optimization algorithms which factor in, the non-linearity of the electric power system. A recent meta-heuristic optimization algorithm, namely Political Optimizer (PO) was employed to optimally reconfigure DNs in this study. Backward-Forward (BF) sweep algorithm, a load flow analysis method was used to determine the initial state of the network. A PO model based on power loss reduction and voltage stability index was developed in MATLAB. The optimization model was applied to a standard IEEE 33-bus system and Ayepe 11 kVA 34-bus feeder of Ibadan Electricity Distribution Company (IBEDC) of Nigeria and implemented using MATLAB. Simulation results showed that for the IEEE 33-bus system, there was a 45.42 % reduction in the total power loss in the network, while for the Ayepe 11 kVA 34-bus DNs, there was a 12.86 % reduction in the total power loss after reconfiguring the network using PO. The results demonstrated the effectiveness of the PO algorithm for optimal reconfiguration of DNs.

Index terms- Distribution Network, Network Reconfiguration, Optimization, Political Optimizer, Backward-Forward Algorithm, Power Loss

1. INTRODUCTION

Distribution Networks (DNs) are often operated under overload conditions due to the daily growth of energy consumers and available limitations of generation and transmission of energy in many developing countries. Overloading the network subsequently results in issues such as power losses and voltage instabilities [1]. The attention of utility companies has been drawn to power loss reduction and voltage profile improvements so as to maximize the economic benefit that comes with the distribution of electrical energy and address the need for better quality of service to consumers through efficient utilization of available energy and minimization of high-power losses in the network [2]. All these and more can be achieved by reconfiguring the network through a technique generally referred to as Network Reconfiguration (NR) [1].

The process of NR looks into the re-arrangement of the feeder topology by changing the open/close status of sectionalizing and tie switches in the network. [3]. The primary aim of reconfiguring the network is to find a radial operating structure that has significant effect on the network power losses and improves the voltage profile under normal operating conditions [4]. Generally, DNs are built by connecting one substation to the other in a single network. The operation of DNs is usually radial in nature and looks like a tree structure [5]. A radial DNs consists of a combination of sectionalizing (Normally Closed) and tie (Normally Opened) switches which determine the configuration of the network. By performing switching actions, the topology of the system can be altered to obtain the best possible configuration [6][7].

As a result of the non-linearity of the DNs, NR is a complicated, combinatorial, non-differentiable and constrained optimization problem. The optimization problem of NR has been addressed in many literatures via several conventional algorithms. However, many of the problems associated with an electric power system are very difficult to solve using conventional optimization techniques such as branch and bound, analytic approach, expert system and linear programming only. It has been observed that most of these techniques find it hard to determine the optimal configuration of the switches in the network [8].

Recently, optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Ant Colony Search Algorithm (ACSA), Artificial Bee Colony (ABC), Simulated Annealing (SA), Tabu Search and many others have been used to provide adequate reconfiguration of DNs. These meta-heuristic optimization algorithms give good enough solutions in reasonable time due to their stochastic nature when compared to the traditional methods [9][10]. This study therefore focused on using a

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weighted multi-objective Political Optimizer (PO) algorithm to optimally reconfigure DNs to minimize power loss and improve voltage stability.

In [6], a Particle Swarm Optimization (PSO) approach for the reconfiguration of a radial distribution network to achieve minimal loss was presented. The work considered the local best particle point as well as its nearby particle value before arriving at the best particle. The work adopted the use of socio-cognitive learning, where each particle uses the experience of nearby particles to produce a better result. Optimal reconfiguration of a DNs using a multi-objective technique based on reliability index was developed by [11]. The work adopted both a decoding process based on random spanning tree strategy to minimize the chances of an unfeasible solution and a network reduction technique to simplify the problem and reduce the computation time.

In [12], a multi-objective Genetic Algorithm (GA) to reconfiguration which considered power loss and system interruption frequency index using binary string for each branch of a power distribution system was developed. An approach for Distribution Feeder Reconfiguration (DFR) considering distribution generators (DGs) using cuckoo search algorithm (CSA) was presented by [13]. The primary aim of the study was to minimize the total active power generated by the DGs and voltage deviation of the network buses

Reconfiguration of 33-node, 69-node and 119-node DNs based on CSA resulted in satisfactory power loss minimization and voltage profile maximization in [14]. A Harmonic Search Algorithm (HSA) for the sole aim of reducing real power loss was presented in [15]. The radial structure of the network was incorporated as a constraint in a bid to achieve the main goal of the optimization process. The proposed method was tested on 33-bus and 69-bus systems. Integration of cycle-break algorithm into GA for DFR was presented by [10]. The main aim of the study was the minimization of power loss and computational time. The proposed approach was tested on three different test systems namely 70-bus, 136-bus and 880-bus systems.

2. PROBLEMS AND OVERVIEW OF ELECTRICAL DISTRIBUTION NETWORKS

Radial DNs are commonly used in developing countries. The primary objective of a DN is to convey the transmitted energy to the end users. However, there are several problems associated with this type of DN. One of such is power losses which connotes revenue loss to utility companies [12][16][17][18]. One of the primary sources of power losses in a DN is the line connecting the substation to the consumer loads; these losses are larger at high voltage levels than they are at lower levels [7].

It is estimated that distribution systems account for a loss of about 5–13 % of the total power generated. Some of the problems associated with a DN include but are not limited to imbalance of the radial structure, establishing load balancing, equipment over-loading, losses, among others [7][19]. Some of the solutions include the placement of capacitors, incorporation of Distributed Generation (DG) and Network Reconfiguration (NR) [19][20][21][22].

3. MATERIALS AND/OR METHODS

The objective functions considered in this study were the active power loss and voltage stability index for the two test systems. A multi-objective solution method was employed to find the optimal reconfiguration of the DNs which minimizes the network power losses and improves voltage stability using PO. A backward/forward (BF) sweep algorithm was employed for the load flow analysis of the two test systems to determine the steady state of the network.

The backward/forward sweep technique was selected due to the radial nature and high resistance to reactance ratio of the distribution network. An optimization model based on power loss reduction and voltage stability index was formulated using PO. The resulting model was implemented using MATLAB. In order to study the net effects of network reconfiguration using PO in a DN, the developed model was applied to the two test systems - a standard IEEE 33-bus system and Ayepe 11 kVA 34-bus feeder of Ibadan Electricity Distribution Company (IBEDC) of Nigeria - to demonstrate its effectiveness.

3.1 LOAD FLOW ANALYSIS USING BACKWARD-FORWARD ALGORITHM

Load flow analysis of the two test systems was carried out using the BF algorithm to evaluate the initial arrangement/configuration of the switches and the total power loss of the network. The various equations and steps for the BF algorithm given in [23] was used in this study.

3.2 OPTIMIZATION MODEL

Since NR has an optimization problem, it is subject to several operational constraints which are used to determine the most appropriate configuration of the network for power loss reduction. The objective function of interest is power loss reduction and voltage stability index improvement. Hence, the following relation represents the optimization model;

$$OF = \mu_1 f_1 + \mu_2 f_2 \quad (1)$$

where: $OF$is the objective function, f_1 is the total active power loss reduction index while f_2 is the voltage stability index (VSI). μ_1 and μ_2 are the weighing co-efficients demonstrating the relative importance of the objectives. It is assumed for the purposes of this work that;

$$\mu_1 + \mu_2 = 1 \quad for \quad 0 < \mu \leq 1 \quad (2)$$

$$f_1 = P_{Loss}^{Re\,c} = \sum_{ni=1}^{N} I_{ni}^2 R_{ni} \quad (3)$$

$$f_2 = VSI_{(ni+1)} = |V_{ni}|^4 - 4[P_{ni+1}X_{ni} - Q_{ni+1}R_{ni}]^2 - 4[P_{ni+1}R_{ni} - Q_{ni+1}X_{ni}]|V_{ni}|^2 \quad (4)$$

The most important objective being the reduction of the total power loss in the network was allocated 70 % of the total weighing average and the other 30% was allocated to the VSI; where P_{loss}^{Rec} denotes the total power loss in the network after reconfiguration, I_{ni} is the current magnitude after reconfiguration, $I_{ni(ini)}$ is the current magnitude for the base case (before reconfiguration) and R_{ni} is the resistance of the line 'ni'. $V_{ni},\ P_{ni+1},\ Q_{ni+1},\ R_{ni}\ and\ X_{ni}$ are the sending end voltage; real power, reactive power, resistance, and impedance respectively.

Several equality and inequality constraints were used to guide the objective function. These constraints are

The load flow constraint:

$$P_{Gi} - P_{Di} - \sum_{i=1}^{N} V_i V_j Y_{ij} \cos\theta_i - \delta_i + \delta_j = 0 \quad (5)$$

$$Q_{Gi} - Q_{Di} - \sum_{i=1}^{N} V_i V_j Y_{ij} \sin\theta_i - \delta_i + \delta_j = 0 \quad (6)$$

where; P_{Gi} and P_{Di} are the real power generation and demand at the i^{t} bus; Q_{Gi} and Q_{Di} are the reactive power generation and demand at the i^{th} bus; V_i and V_j are the voltage magnitudes at the i^{th} and j^{th} bus; θ_i is the angle between buses i and $j$in the admittance matrix; δ_i and δ_j are the voltage angle at the i^{th} and j^{th} bus.

The limit on bus voltages:

$$V_i^{min} \leq V_i \leq V_i^{max} \quad (7)$$

The limit of the feeders:

$$I_i^{min} \leq I_i \leq I_i^{max} \quad (8)$$

Radial Configuration constraint:

$$N_{tie} = N_{br} - (N_b - N_{ss}) \quad (9)$$

where; N_{br}, N_{tie}, N_b and N_{ss} are the number of branches, the number of tie switches, the number of buses, and the number of substations in the network respectively.

4. IMPLEMENTATION OF POLITICAL OPTIMIZER

The PO algorithm is a novel optimization algorithm inspired through the process of a political system of a country, society or an organization, to provide optimal solution to optimization problems. [24][25]. In its application to an optimization problem, the algorithm is divided into six major categories, which are in no particular order: formation of political parties, allocation of constituencies, campaign for election, party swapping, election process within the party, and setting up the parliament/government [25]. These key phases are mathematically mapped to meet the main goal of optimal network reconfiguration.

The following equation describes the mathematical model of the PO algorithm in solving the NR problem [26].

$$P = \{P_1, P_2, P_3, \ldots\ldots\ldots P_n\} \quad (10)$$

$$P_i = \{p_i^1, p_i^2, p_i^3, \ldots\ldots p_i^n\} \quad (11)$$

$$P_{i,k}^j = \{P_{i,1}^j, P_{i,2}^j, P_{i,3}^j, \ldots\ldots P_{i,d}^j\} \quad (12)$$

The population P is divided into 'n' parties, P_i with each party having n number of members representing the objective function to the optimization problem. Moreover, each j^{th} member of the population in the search space is noted as P_i^j and denoted using a d-dimensional vector; where d is the dimension of the search space which includes the voltage limit on the buses, the radial nature of the network and the status of the switches. $P_{i,k}^j$ is k^{th} dimension of P_i^j. The fitness of each party member is then evaluated using the objective function expressed in equation (1). Once the fitness of all the party members has been computed, the party leader is randomly identified and denoted as P_i^*, while the collection of all the party leaders in the population is denoted as P^*.

After the inter-party election, the winner of each constituency forms the new possible solutions to the optimal reconfiguration problem and are denoted as C^*, thereby reducing the search space; where C_j^* denotes the

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winner of j^{th} constituency as described using equation (13) to (16)

$$C = \{C_1, C_2, C_3, \ldots\ldots\ldots C_N\} \quad (13)$$

$$C_{j,} = \{P_1^j, P_2^j, P_3^j, \ldots\ldots P_n^j\} \quad (14)$$

$$P^* = \{P_1^*, P_2^*, P_3^*, \ldots\ldots\ldots P_n^*\} \quad (15)$$

$$C_j^* = \{C_1^*, C_2^*, C_3^*, \ldots\ldots\ldots\ldots C_n^*\} \quad (16)$$

At the election campaign phase, each member of the population tries to enhance their chances in the election by changing their positions using the expressions described by [26][27] in equations (17) and (18).

$$P_{i,k}^j(t+1) = \begin{cases} m^* + r\left(m^* - P_{i,k}^j(t)\right), \\ m^*(2r-1)\left|m^* - P_{i,k}^j(t)\right|, & \text{if;} \\ m^*(2r-1)\left|m^* - P_{i,k}^j(t-1)\right|, \end{cases}$$

$$\begin{aligned} P_{i,k}^j(t-1) \le P_{i,k}^j(t) \le m^* \\ P_{i,k}^j(t-1) \le m^* \le P_{i,k}^j(t) \\ m^* \le P_{i,k}^j(t-1) \le P_{i,k}^j(t) \end{aligned} \quad (17)$$

$$P_{i,k}^j(t+1) = \begin{cases} m^* + r\left(m^* - P_{i,k}^j(t)\right), \\ P_{i,k}^j(t-1) + r\left(P_{i,k}^j(t) - P_{i,k}^j(t-1)\right), & \text{if;} \\ m^*(2r-1)\left|m^* - P_{i,k}^j(t-1)\right|, \end{cases}$$

$$\begin{aligned} P_{i,k}^j(t-1) \le P_{i,k}^j(t) \le m^* \\ P_{i,k}^j(t-1) \le m^* \le P_{i,k}^j(t) \\ m^* \le P_{i,k}^j(t-1) \le P_{i,k}^j(t) \end{aligned} \quad (18)$$

Secondly, the position of each party member representing a possible solution to the reconfiguration problem is updated using the position of the party leader. Lastly, the positions of every possible solution are then updated relative to the position of successful electorates. Moreover, an adaptive parameter, λ known as party switching rate is then used to achieve the balance between exploration and exploitation during the search process. This is necessary to ensure convergence is achieved in a minimal time. The members of the population P_i^j, are then selected and switched to some randomly chosen party P_r.

Subsequently, the position of the party leaders and successful electorates at the party level are updated using expression (19) below [26].

$$C_j^* = P_q^i \quad (19)$$

where $q = argmin\, f\left(P_i^j\right)$; for $1 \le i \le n$ and $P_j^* = P_q^i$.

The party leaders and successful electorates represent the optimal solution to the optimization problem and are responsible for running the parliament. In order to achieve an optimal solution, each of the electorate is made to mimic the interaction and collaboration of the winning candidate to be considered for a position in the government when the elections are over. Finally, the position of each parliamentarian C_j^* is updated relative to a randomly chosen parliamentarian C_r^*.

The optimal solution to the reconfiguration problem is the parliamentarian with most enhanced performance relative to the randomly chosen parliamentarian. The most enhanced parliamentarian gives the minimized power loss and the optimal position of the switches in the network.

5. RESULTS AND DISCUSSIONS

Load flow analysis was performed using BF sweep algorithm to determine the initial condition of the test systems. The developed optimization model was first applied to the standard IEEE 33-bus and the effects were examined. The steady state results obtained showed that the line between bus 5 and 6 had the highest power loss with a value of 52.97 kW; the total power loss in the network was 205.36 kW. The result obtained after reconfiguration showed that the highest power loss occurred on the line between bus 5 and 6 with a value of 32.47 kW. The total power loss in the network after optimal reconfiguration was reduced to 112.08 kW. The results of voltage profile and total power loss comparison for the standard IEEE 33-bus system before and after optimal reconfiguration are shown in Fig. 1 and 2 respectively.

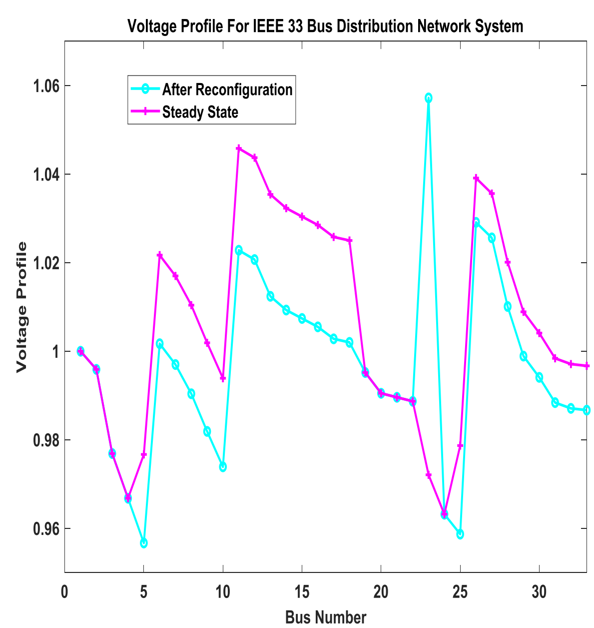

Fig. 1. Voltage Profile Comparison of IEEE 33-Bus Network before and after Reconfiguration

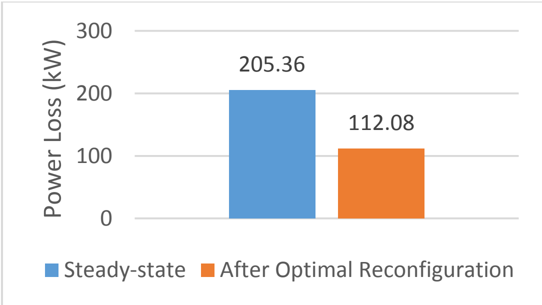

Fig. 2. Power Loss Comparison of IEEE 33-Bus Network before and after Reconfiguration

Similarly, for the Ayepe 11 kVA 34-Bus network, simulation results before the optimal reconfiguration of the network showed that the line with the highest power loss was the line connecting buses 1 and 2 with a power loss value of 120.15 kW. The total real power loss in the network was 237.06 kW. The developed optimization model was also applied on Ayepe 34-bus DNs and the effects were examined. The results showed that the highest power loss occurred on the line between 1 and 2 with a value of 112.65 kW. The total power loss in the network after optimal reconfiguration was reduced to 206.58 kW. The changes can be attributed to the alteration in the topology of the network switches. The results of voltage profile and total power loss comparison for the Ayepe 11 kVA 34-bus network before and after optimal reconfiguration are shown in Fig. 3 and 4 respectively.

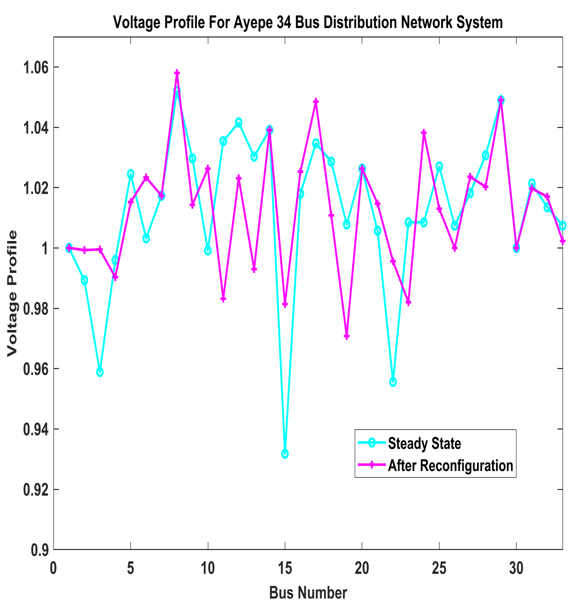

Fig. 3. Voltage Profile Comparison of Ayepe 11 kVA 34-Bus Network Before and After Reconfiguration

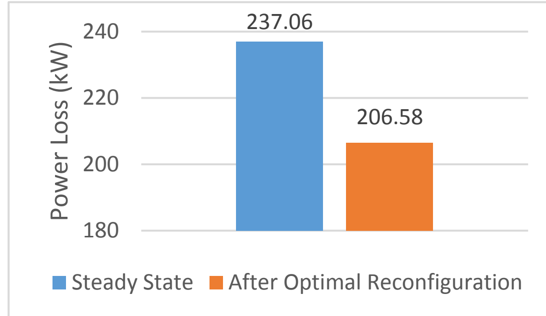

Fig. 4. Power Loss Comparison of Ayepe 11 kVA 34-Bus Network before and after Reconfiguration

Power loss reductions of 93.28 kW and 30.48 kW were therefore obtained for the standard IEEE 33-Bus DN and the Ayepe 11kVA 34-Bus DN respectively. Equivalently, a respective 45.42% and 12.86% reduction in power losses on the standard IEEE 33-Bus and Ayepe 34-Bus DNs was achieved after the optimal reconfiguration of the networks using a political optimizer.

Table 1 depicts the comparison of the power loss results obtained for the optimal network reconfiguration of IEEE 33-bus system using PO with that of the modified Selective Particle Swarm Optimization (SPSO) technique used in [28]. The active power loss reduction and computational time obtained using PO and modified SPSO are (45.42% and 0.398) and (44.37% and 0.490) respectively. It is clear that the PO outperforms SPSO in terms of power loss reduction and computational time respectively.

TABLE 1: SUMMARY OF THE COMPARED RESULTS FOR IEEE 33-BUS DISTRIBUTION SYSTEM

PERFORMANCE PARAMETERS	*OPTIMIZATION TECHNIQUES*	
	POLITICAL OPTIMIZER	*MODIFIED SELECTIVE PARTICLE SWARM OPTIMIZATION*
Power Loss Reduction (%)	**45.42**	**44.37**
Computational Time (sec.)	**0.398**	**0.490**

6. CONCLUSION

This study has investigated the application of PO for optimal reconfiguration of both a standard DN and a practical DN for power loss reduction and voltage profile

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improvement. The steady state operating condition of the network was determined using BF sweep algorithm for load flow analysis. An optimization model using PO was developed and implemented using MATLAB. The developed model was applied to standard IEEE 33-bus and Ayepe 11 kVA 34-bus DNs using power loss as the performance metric.

Simulation results of the IEEE 33-bus network showed that there was a reduction in power loss of 93.28 kW (45.42%) after reconfiguring the system using PO. While, a power loss reduction of 30.48 kW (12.86%) was obtained for the Ayepe 11 kVA 34-bus network after reconfiguring the system using PO. The obtained results demonstrated the efficacy of the political optimizer algorithm for optimal distribution network reconfigurations.

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