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Analysis of Distribution System Reconfiguration under Different Load Demand in AL-KUT City by using PSO Algorithm

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K E Y W O R D S

Network reconfiguration, Particle Swarm Optimization (PSO), power loss reduction, voltage profile improvement.

A B S T R A C T

Network reconfiguration is the best way to inquisitive a flexible, reliable and effective distribution network. An efficient optimization technique that uses Particle Swarm Optimization (PSO) is described and analyzed with the goal of reducing power losses and enhancing the voltage profile in the distribution network by reconfiguring the network, taking into account the branch current limit, branch capacity limit, bus voltage limits and radial structure constraint (no meshed loop). The approach is applied to the part of AL-KUT city distribution system (TAMOZE region system) to attain an optimum network configuration in connection with power loss. Two dissimilar load situations are regarded, and the performance of the suggested approach is also proved by increasing the decrease in power loss by using MATLAB under steady-state conditions.

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1. INTRODUCTION

Network reconfiguration of distribution systems is a very significant energy-saving strategy. As well, due to its characteristics, it is inherently an optimization issue. Distribution systems are an important connection between the utility and the consumer, where sectionalizing switches are used for both security and configuration administration. New studies have shown that up to 13% of the overall power generated is lost in the form of line losses at the distribution level. The investigation of approaches for the reconfiguration of the network is therefore of huge advantage. The goal of network reconfiguration is to decrease power loss and enhances the network voltage profile by altering the status of present sectionalizing and tie switches. [1]

Consumer requirements fluctuate with the time of day, the day of the week, and the season; thus, the reconfiguration of the feeder allows to transport loads from high to low loaded areas. Network reconfiguration can also be utilized in planning studies, to calculate the optimum structure of the network throughout the total planning process. [2]

Since the distribution system comprises of numerous switches and the number of switching operations available is enormous. Network reconfiguration is therefore a very complicated decision-making issue. On the other hand, the radial and discrete nature of the switch values prevent the use of classical optimization approaches to resolve the reconfiguration issue. Most approaches are therefore dependent on heuristic search methods, using either analytical or knowledge-based engines [3], which they search for a close to – optimum solution for large power systems in a rational time.

Over the last two decades, several researchers have solved the issue of network reconfiguration using various approaches aimed at reducing the loss of power and/or improving the voltage profile of power distribution networks [4].

Merlin and Back in 1975, suggested a heuristic branch and bound form approach for evaluating network configuration for minimal line losses. In the first step, the solution scheme begins with a meshed network by closing all network switches. The switches are then opened one at a time until reaching a new radial configuration. In this method, the switch to be opened at each level is selected to reduce the loss of the resulting network line [5]. Shirmomohammadi and Hong in 1989, improved the Merlin and Back methods. As a result, it shares the two key benefits of that approach, convergence to the optimum or near optimum solution and independence from the initial status of the network switches from the final solution. At the same time, this approach removes all of Merlin and Back's key disadvantages [6]. Nara in 1992, proposed the Genetic Algorithm (GA). The basic design of GA makes it ideal for various multi-objective optimization problems. The key issue when using GA is the effective chromosome coding and decoding process that describes the distribution network and the structure of the fitness function [7]. Li and Chen in 2003, developed an effective and reliable approach based on the Tabu Search (TS) technique; TS is a heuristic optimization technique that offers an optimal solution to solve the problem of network reconfiguration in the distribution system in order to minimize line losses under normal operating conditions [8]. Charles and Khan in 2005, suggested a new technique for network reconfiguration, based on an ant colony system algorithm. In the presence of constraints, the approach is highly versatile and globally optimal. It has some good features, such as positive feedback, distributed computing and greedy heuristics, which make it the best method of network reconfiguration [9]. Salazar and Gallego in 2006, proposed an algorithm based on artificial neural network theory and they also present a clustering technique to determine the best training set for a single neural network with the generalization ability [10]. Gupta and Niazi in 2011, present a new method for reconfiguration of radial distribution systems for minimization of real power loss using adaptive particle swarm optimization without involving any additional cost for the installation of tap changing transformers, capacitors, and concerned switching equipment. The initial population for particle swarm optimization is created using a heuristic approach and the particles are adapted with the help of graph theory to generate feasible individuals [11]. The available research on network reconfiguration to minimize power loss commonly considers a scenario of constant load demand and less attention was paid to the representation of the variable load demand in the reconfiguration of the network. These approaches, therefore, consist of disadvantages with regard to the demand for a practical load. Ignoring variations in load demand causes a lack of certainty in the distribution network to minimize power losses.

This work proposes a Particle Swarm Optimization (PSO) technique for good analysis since it describes the impact of loading patterns on the performance of the distribution system for active and passive networks. The suggested method seeks to detect the real loss of power under different load characteristics. Thus, the likely advantage of this method is the involvement in offering more flexibility for power companies in terms of distribution network operation, as well as opening up new prospects for the automation of smart distribution networks.

The suggested technique is checked on the part of AL-KUT distribution system with the goal of minimizing the real power losses. The system was programmed and implemented using a MATLAB environment. The key objective of this work is to analyze the reconfiguration of the network from a diverse viewpoint with respect to loading models. This method allows the exchange of a pre-defined set of different reconfigurations; thus, it is essential for an automated modern distribution system for planning and operation.

The content in this article is structured as follows: The distribution system reconfiguration problem formulation is given in Section 2. Section 3 explains the algorithm that was suggested here. The test system is described in section 4. The results of the simulation are presented and discussed in Section 5. This article ends with some conclusions.

2. DISTRIBUTION SYSTEM RECONFIGURATION PROBLEM FORMULATION

I. Load Flow Calculations using Backward / Forward Sweep

Load flow is fundamental for the analysis of the distribution systems, for the investigation of design, planning, control and operation issues. The network load flow is iteratively resolved from two sets of recursive equations. The first set of equations to determine the power flow through the branches beginning with the last branch and continuing backward towards the root bus. The second set of equations was used to calculate the magnitude and voltage angle of each bus beginning from the root bus and continuing in the forward direction towards the last bus. These equations can be derived as follows, and Figure 1 illustrates the representation of two buses in a distribution line. Consider that the ‘j’ branch is linked between the ‘i’ and ‘i+1’ buses. [12]

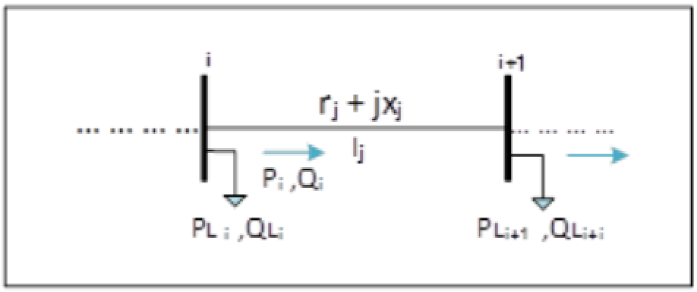

Figure 1:The representation of two buses in a distribution line

The efficient active (P_i) and reactive (Q_i) powers that flow from bus ‘i' to the bus ‘i+1’ through branch ‘j’ can be computed backwards from the last bus and are given as in Eq. (1) and (2) respectively:

$$P_i = P'_{i+1} + r_j \frac{(P'_{i+1}+Q'_{i+1})}{V_{i+1}^2} \quad (1)$$

$$Q_i = Q'_{i+1} + x_j \frac{(P'_{i+1}+Q'_{i+1})}{V_{i+1}^2} \quad (2)$$

Where:
$P'_{i+1} = P_{i+1} + P_{Li+1}$ and $Q'_{i+1} = Q_{i+1} + Q_{Li+1}$
P_{Li+1} and Q_{Li+1} : the connected load at bus ‘i+1’.
P_{i+1} and Q_{i+1}: the effective active and reactive power flows from node ‘i+1’.

The voltage magnitude and angle at each bus are computed in the forward direction. Consider a voltage $V_i \angle \delta_i$ at the bus ‘i’ and $V_{i+1} \angle \delta_{i+1}$ at bus ‘i+1’, then the current that flows through the branch ‘j’ having an impedance, $z_j = r_j + jx_j$ connected between ‘i’ and ‘i+1’is given as in Eq. (3):

$$I_j = \frac{V_i \angle \delta_i - V_{i+1} \angle \delta_{i+1}}{r_j + jx_j} \quad (3)$$

The overall active and reactive power loss of the radial distribution system can be computed as in Eq. (4) and (5) respectively:

$$TPL = \sum_{j=1}^{N_b} r_j \frac{(P_i^2+Q_i^2)}{V_i^2} \quad (4)$$

$$TQL = \sum_{j=1}^{N_b} x_j \ \frac{(P_i^2+Q_i^2)}{V_i^2} \quad (5)$$

Initially, a flat voltage profile is presumed at all nodes i.e., 1.0 pu. The branch powers are evaluated iteratively by the updated voltages at each node. [12]

II. The Objective Function

The primary aim of the reconfiguration of the feeder is to achieve optimum operation of the distribution system, by re-configuring the distribution lines in such a way that the specified objective function is fulfilled. Subsequent goals are accomplished through the network reconfiguration, for example:

1) Actual power loss reduction.
2) Balancing feeder loads and helping to handle network overload situations by transporting loads from extremely loaded feeders to low-loaded feeders.
3) Bus voltage profile improvement.
4) Restoration of service under faulty conditions, thus enhancing system protection, reliability and improving power efficiency.
5) Planning outages for maintenance service restoration under faulty conditions.

These research goals that can be satisfied by network reconfiguration are the decrease of power loss and enhancing the voltage profile, taking into account limitations and dissimilar scenarios of load variations. The objective function used to calculate the smallest value of the overall active power losses is illustrated in Eq. (6) [13].

$$F\,(x) = min\,(TPL) \quad (6)$$

$$x = [Tie_1; Tie_2; \ldots\ldots; Tie_{Ntie}; Sw_1; Sw_2; \ldots\ldots Sw_{Ntie}]$$

Where

x: control variable vector; Tie_i: ith tie switch state; Sw_i: ith switch.

The objective function is subjected to the subsequent limitations:

1) Radiality means that no loops are permitted on the network.
2) The voltage of each bus must be within the top and minimum limitations as illustrated in Eq. (7).

$$v_i^{min} \le |v_i| \le v_i^{max} \qquad i = 1,2,\ldots,N_n \quad (7)$$

Where: v_i is the ith bus voltage magnitude, v_i^{min} and v_i^{max} are the minimum and maximum voltage magnitude limitations of the ith bus.

1) Branch power limit: Power flow at each branch must be always below or equal to its maximum capacity, as illustrated in Eq. (8)

$$S_j \le S_j^{max} \quad (8)$$

2) Branch current limit:

$$|I_j| \le I_{max} \quad (9)$$

Where: $|I_j|$ is the current magnitude flowing in the branch j, I_{max} is the maximum permissible current limit.

3. PARTICLE SWARM OPTIMIZATION (PSO) ALGORITHM

In the year 1995, a novel evolutionary computation method called Particle Swarm Optimization (PSO) was suggested by Kennedy (social-psychologist) and Eberhart (electrical engineer) [14]. PSO is one of the heuristic approaches employed by researchers to overcome several issues associated with power systems. The main principle of PSO is depending on the social actions (foraging) of creatures for example, birds (flocking) and fish (schooling). The birds or the fish will travel to the food at a specific position or speed. Their motion will be based on their own experiences and on the experiences of other 'friends' in the group ($pbest$ and $gbest$). PSO has a kind of specific language and terminology, Table I summarizes these terminologies [15].

TABLE I: Some keywords used to describe the PSO algorithm

Particle or Agent	One single individual in the swarm.
Swarm	The entire collection of agents.
Fitness	A single number representing the quality of a given solution.
pbest	The location of the best fitness returned for a specific agent.
gbest	The location of the best fitness returned for the entire swarm.
Maximum velocity	The maximum allowed velocity in a given direction.

The main appealing characteristic of PSO is its simplicity since it includes only two models of equations. In PSO, the coordinates of any particle symbolize a potential solution related to two vectors, the position (x_i) and velocity (v_i) vectors. The size of vectors x_i and v_i is like the number of particles. A swarm comprises a number of particles "or probable solutions" that move thru a feasible solution space to discover optimum solutions. Any particle updates its position on the basis of its own finest exploration (finest swarm total experience) and its previous velocity vector according to the following Equations [16].

$$v_i^{k+1} = w\, v_i^k + c_1 \times rand \times \left(\frac{Pbest_i - x_i^k}{\Delta t}\right) + c_2 \times rand \times \left(\frac{gbest_i - x_i^k}{\Delta t}\right) \quad (10)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} * \Delta t \quad (11)$$

Where:

v_i^{k+1} : is the new velocity of ith particle; v_i^k : is the original velocity of ith particle; w: is the inertia weight and is generally set to 1 or is changing with time; $rand$: is a random number between 0 and 1; x_i^k: is the present position in the ith dimension; c_1, c_2: are the acceleration coefficients; $pbest_i$: is the personal best position in the ith dimension; $gbest_i$: is the global best position in the ith dimension; Δt:is the time step.

The flow chart of the proposed PSO method presented here is seen in Figure 2. The following steps provide clarification to the flow chart:

1) Initialize a population of particles with arbitrary positions and velocities on dimensions in the space.
2) Read the distribution system load and line data and perform load flow.
3) Set maximum iterations = max_ite.
4) Calculate fitness function (power loss) for Pbest.
5) Max_ite = max_ite -1.
6) Update the velocity and the position using Equations (10) and (11) respectively.
7) Calculate the fitness function (power loss) for each particle.
8) If satisfying all the restrictions; If the particle fitness is better than the $pbest$, the value is set to $pbest$. If the best fitness better than the $gbest$, the value is set to $gbest$.
9) If Max_ite = 0 prints the results.
10) Stop.

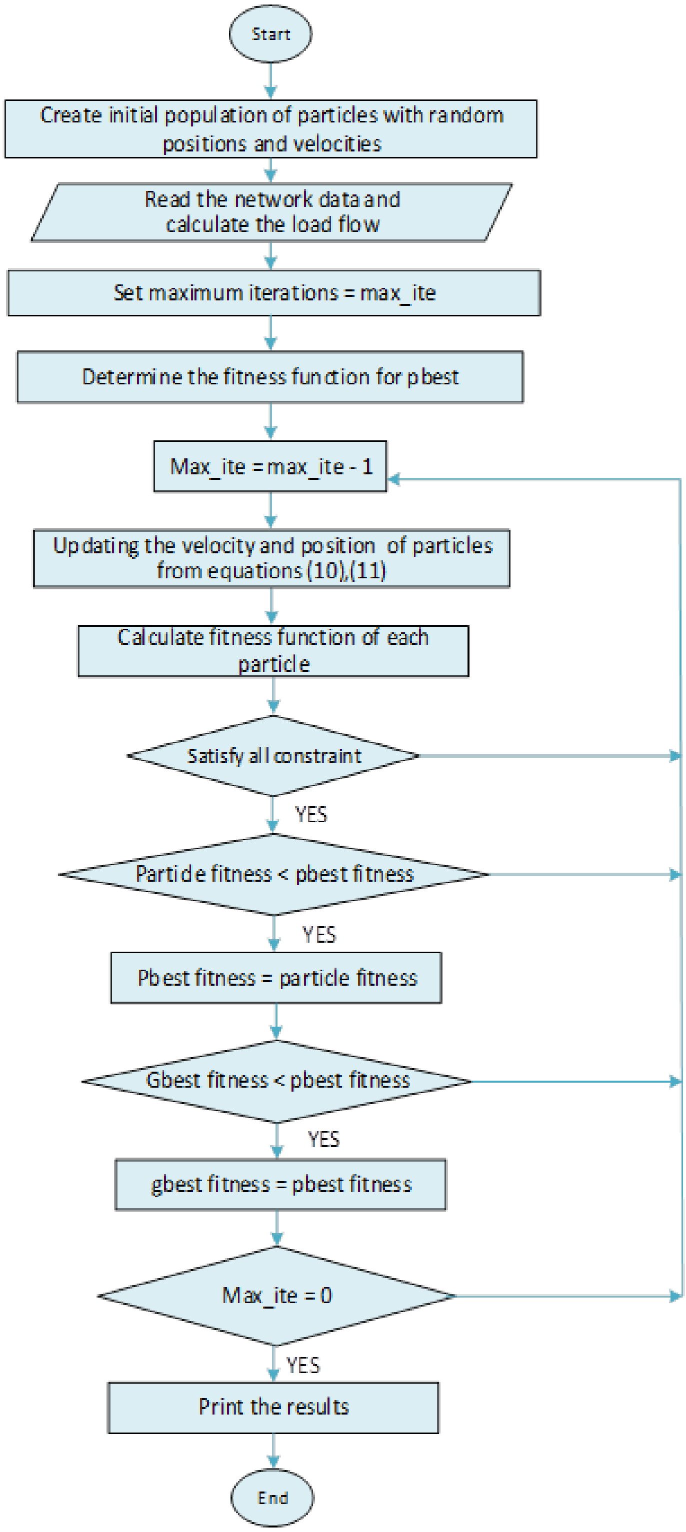

Figure 2: Flow Chart of the load flow and Particle Swarm Optimization (PSO) Algorithm

The load flow and Particle Swarm Optimization (PSO) algorithm were tested on the standard IEEE 33-bus test system and compared to other approaches in our paper [17].

4. TEST DISTRIBUTION SYSTEM AND SIMULATION STUDIED CASES

I. TAMOZE Region 35-Bus System

The TAMOZE region system is part of the AL-KUT city distribution system, the schematic diagram of this system can be seen in Figure 3, its line and load data are given in appendix A Table A.1 and Table A.2 respectively. This system consists of two feeders, 35 buses, five usually opened switches (tie switches) are Sw-36 to Sw-40, recognized by dotted lines and 35 usually closed switches (sectionalizing switches) are Sw-01 to Sw-35, recognized by solid lines. The base network voltage is 12.66 kV, the $Sbase$ is 100 MVA and the overall network loads are 6186.511 kW and 4639.876 $kVar$.

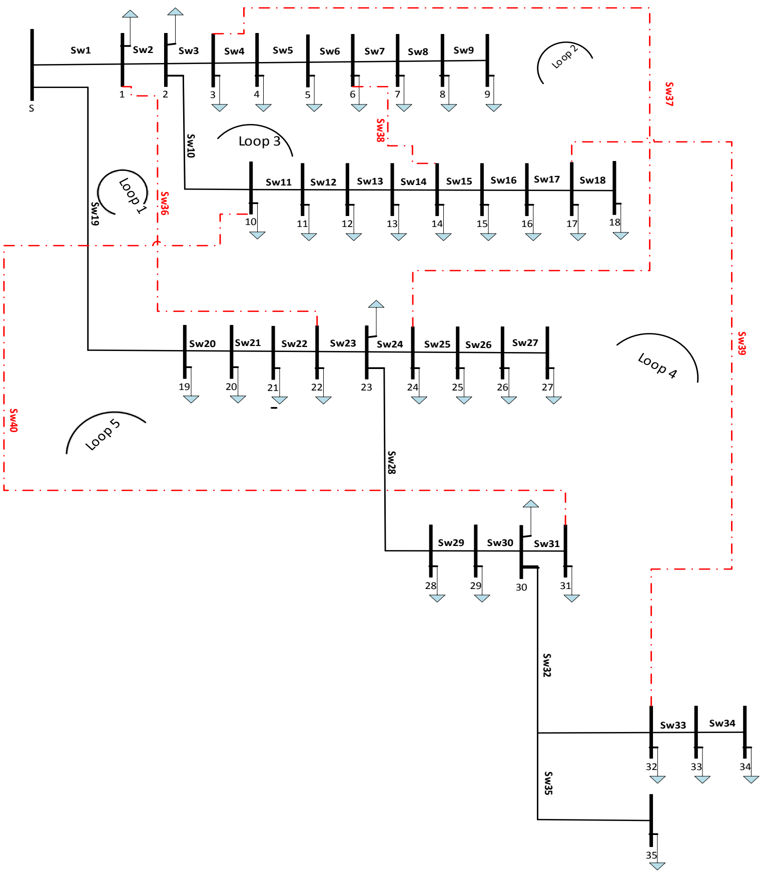

Figure 3:TAMOZE region (in AL-KUT city) system before reconfiguration

In this paper, the efficiency of the proposed method evaluated in two separate cases; constant load case study and different load patterns case study.

II. Different Load Patterns Case Study

Modern electrical networks are a complicated blend of dynamic and static components that work in a variety of configurations [18]. A constant load model may be defined as a polynomial load representing the power relationship to voltage magnitude and frequency [19]. As shown in Eq. (12) and (13), the general structure of a load model comprising of actual and reactive power reliance on voltage (V) and frequency (f) is:

$$PL_i = f_{PL}(V,f) \tag{12}$$

$$QL_i = f_{QL}(V,f) \tag{13}$$

Where:

(PL_i), (QL_i): real and reactive load demand; f_{PL}, f_{QL}: are the functions of system actual and reactive load demand.

The load that depends on frequency is frequently ignored, as voltage variations are often extra recurrent and observable than system frequency variations [20]. In this study, the main network connection maintains the frequency constant; thus Eq. (14) and (15) act as the load model based on the variations in the bus voltages. Load demands have been updated to depend on voltage, and the system reconfiguration was varied to the voltage profile of the system buses. As a result, demand action has altered with the reconfiguration of the system. In order to implement the real and reactive load, this load was defined as voltage-dependent as indicated in Eq. (14) and (15).

$$PL_i = PL_{i0}\left[p_1\left(\frac{V_i}{V_{i0}}\right)^2 + p_2 \ + p_3\left(\frac{V_i}{V_{i0}}\right)^0\right] \tag{14}$$

$$QL_i = QL_{i0}\left[q_1\left(\frac{V_i}{V_{i0}}\right)^2 + q_2 + q_3\left(\frac{V_i}{V_{i0}}\right)^0\right] \tag{15}$$

$$p_1 + p_2 + p_3 = 1 \tag{16}$$

$$q_1 + q_2 + q_3 = 1 \tag{17}$$

In addition, Eq. (14) and (15) represent the ZIP model, where Z, I and P denote the load component of constant impedance, constant current and constant power, respectively. The parameters (p_1 and q_1), (p_2 and q_2), and (p_3 and q_3) in Eq. (16) and (17) indicate the relative involvement of constant impedance load, constant current load, and constant power for active and reactive loads, respectively. PL_{i0} and QL_{i0} are the references of real and reactive power of the ith customer at rated voltage V_{i0} = 1 per unit. V_i is the per-unit delivering voltage of the ith customer. Equations (14) and (15) can be modified as Eq. (18) and (19), respectively, for the voltage-exponential load.

$$PL_i = PL_{i0}\left[\ \left(\frac{V_0}{V_{i0}}\right)^\sigma\right] \tag{18}$$

$$QL_i = QL_{i0}\left[\left(\frac{V_i}{V_{i0}}\right)^\tau\ \right] \tag{19}$$

Where

$$\sigma \cong \frac{p_1\times 2+p_2\times 1+p_3\times 0}{p_1+p_2+p_3} \tag{20}$$

$$\tau \cong \frac{q_1\times 2+q_2\times 1+q_3\times 0}{q_1+q_2+q_3} \tag{21}$$

Equations (18) and (19), σ and τ denote the voltage-exposing features of the actual (PL_i) and reactive (QL_i) load requirements, respectively; σ , τ can be computed from Eq. (20) and (21) respectively. The actual and reactive power exponent values used here are illustrated in Table II.

TABLE II: Type of loads and the exponent values [21]

Load Type	condition	σ	τ
Residential Consumer	Summer and Spring /at day time	0.72	2.96
	Summer and Spring /at night	0.92	4.04
	Winter and Autumn /at day time	1.04	4.19
	Winter and Autumn /at night	1.30	4.38
Commercial Consumer	Summer and Spring /at day time	1.25	3.50
	Summer and Spring /at night	0.99	3.95
	Winter and Autumn /at day time	1.50	3.15
	Winter and Autumn /at night	1.51	3.40

5. SIMULATION RESULTS AND DISCUSSION

For the two different load scenarios of the TAMOZE region (in AL-KUT city) system and when the PSO method is applied, a group of 200 particles is generated to construct the viable solution of the system in each iteration; where the maximum number of iterations is 60. The parameters of PSO methods which they selected by the trial and error approach are illustrated in Table III below:

TABLE III: The parameters of PSO algorithm

	w	c_1	c_2
Constant load Case study	0.9	1.2	0.12
Different load patterns Case study	0.9	1.1	0.12

I. Best Reconfiguration Results for Constant Load Case Study

The system active and reactive load demands of every bus in March 2020 shall be used without any change. Network reconfiguration, depending on the constant load demand is implemented by using the proposed PSO algorithms. The results of this analysis are listed in Table IV.

TABLE IV: Simulation results of TAMOZE region system (in KUT city) with constant load demand $(\sigma = 0, \tau = 0)$

Approach	Open State	TPL (kW)	TQL $(kVar)$	TSL (kVA)	V_{min} $(p.u.)$
Initial configuration	Sw36, Sw37, Sw38, Sw39, Sw40	96.4865	46.6438	107.1694	0.9727
(PSO)	Sw29, Sw36, Sw37, Sw38, Sw39	50.4638	28.3375	58.3661	0.9844

Table IV illustrates that the finest reconfiguration obtained from the switches set (Sw-29, Sw-36, Sw-37, Sw-38, Sw-39) for the TAMOZE region system with constant feeder load demand, due to the minimum TPL, TQL and TSL for the optimum switch set. The real loss of power of the best reconfiguration compared to the initial system configuration showed a significant decrease in a real power loss of 47.69 % from 96.4865 kW to 50.4638 kW with a total reduction in a real power loss of 46.0227 kW. The minimum voltage was also enhanced by 1.17 % from 0.9727 $p.u.$ to 0.9844 $p.u.$

It has been shown that the voltage profile for all buses was enhanced after reconfiguration. When applying the PSO technique, the voltage profile of the original and ideal system configurations with constant load demand is shown in Figures 4.

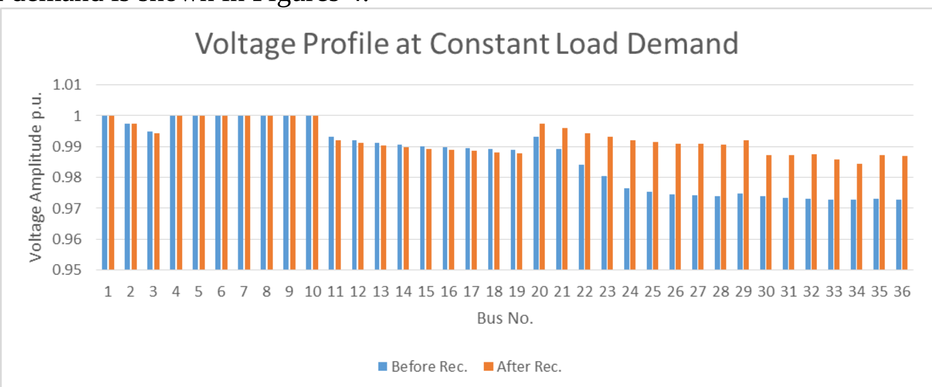

Figure 4: The voltage profile (pre- and post the reconfiguration) for TAMOZE region system (in KUT city), using the PSO algorithm, with constant load demand when $(\sigma = 0, \tau = 0)$

II. Best Reconfiguration Results for Different Load Patterns Case Study

Tables V–XII show the results of the reconfiguration when PSO techniques are applied to the TAMOZE region (in AL-KUT city) system for various load patterns (for all seasons). From these tables, it was observed that the reconfiguration pattern with switch sets (Sw-29, Sw-36, Sw-37, Sw-38, Sw-39) had the minimum TPL, TQL and TSL. When applying the PSO algorithm, the voltage profiles of the original and ideal system configurations, with different values of actual and reactive power exponents (σ, τ) are shown below.

TABLE V: Simulation results of TAMOZE region (in KUT city) system when $\sigma = 0.72$, $\tau = 2.96$

Approach	Open State	TPL (kW)	TQL $(kVar)$	TSL (kVA)	V_{min} $(p.u.)$
Initial configuration	Sw36, Sw37, Sw38, Sw39, Sw40	90.4577	43.7295	100.4732	0.9735
(PSO)	Sw29, Sw36, Sw37, Sw38, Sw39	48.9241	27.4241	56.5566	0.9847

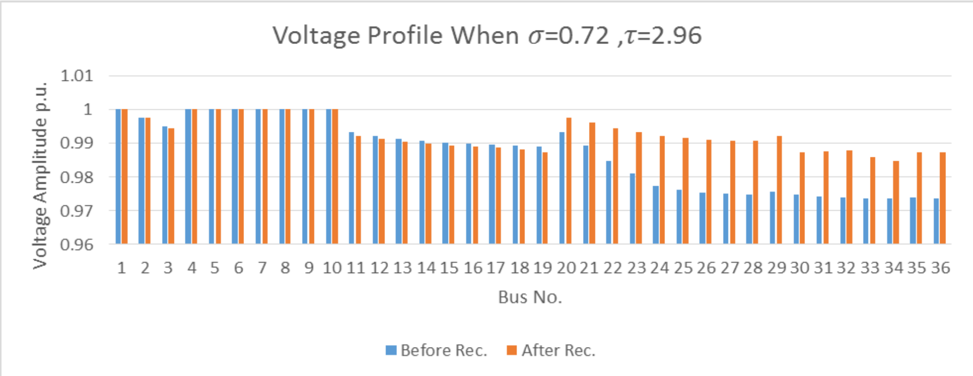

Figure 5: The voltage profile (pre- and post the reconfiguration) for TAMOZE region system (in KUT city), using the PSO algorithm when $\sigma = 0.72$, $\tau = 2.96$

TABLE VI: Simulation results of TAMOZE region (in KUT city) system when $\sigma = 0.92$, $\tau = 4.04$

Approach	Open State	TPL (kW)	TQL $(kVar)$	TSL (kVA)	V_{min} $(p.u.)$
Initial configuration	Sw36, Sw37, Sw38, Sw39, Sw40	88.5754	42.8196	98.3825	0.9738
(PSO)	Sw29, Sw36, Sw37, Sw38, Sw39	48.4236	27.1277	55.9687	0.9848

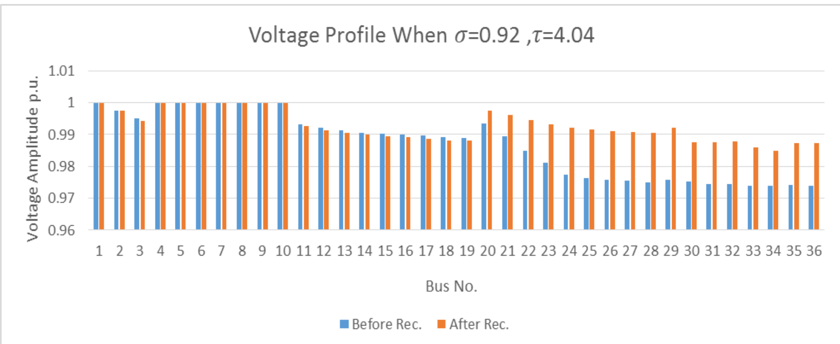

Figure 6: The voltage profile (pre- and post the reconfiguration) for TAMOZE region system (in KUT city), using the PSO algorithm when $\sigma = 0.92$, $\tau = 4.04$

TABLE VII: Simulation results of TAMOZE region (in KUT city) system when $\sigma = 1.04, \tau = 4.19$

Approach	Open State	TPL (kW)	TQL $(kVar)$	TSL (kVA)	V_{min} $(p.u.)$
Initial configuration	Sw36, Sw37, Sw38, Sw39, Sw40	88.0832	42.5816	97.8358	0.9739
(PSO)	Sw29, Sw36, Sw37, Sw38, Sw39	48.2936	27.0508	55.8161	0.9848

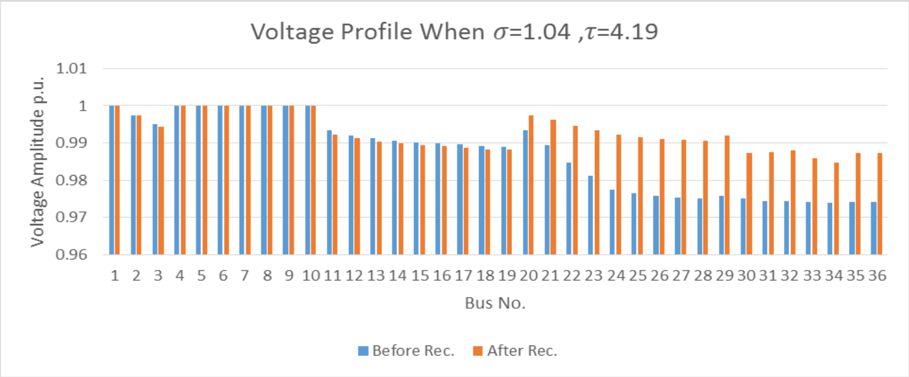

Figure 7: The voltage profile (pre- and post the reconfiguration) for TAMOZE region system (in KUT city), using the PSO algorithm when $\sigma = 1.04, \tau = 4.19$

TABLE VIII: Simulation results of TAMOZE region (in KUT city) system when $\sigma = 1.30, \tau = 4.38$

Approach	Open State	TPL (kW)	TQL $(kVar)$	TSL (kVA)	V_{min} $(p.u.)$
Initial configuration	Sw36, Sw37, Sw38, Sw39, Sw40	87.1903	42.1500	96.8441	0.9740
(PSO)	Sw29, Sw36, Sw37, Sw38, Sw39	48.0583	26.9118	55.5399	0.9848

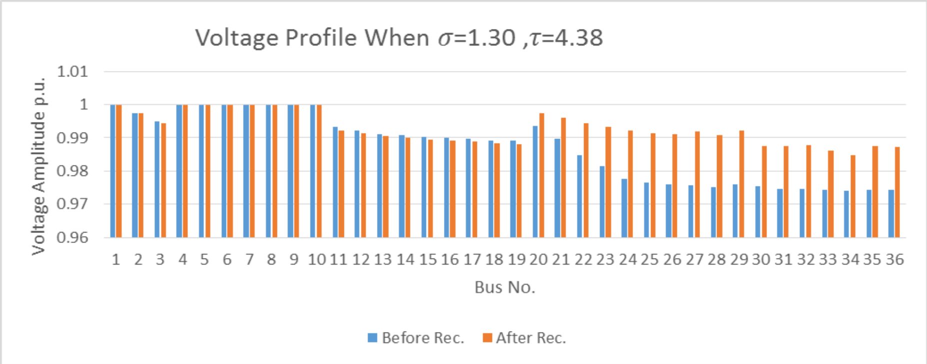

Figure 8: The voltage profile (pre- and post the reconfiguration) for TAMOZE region system (in KUT city), using the PSO algorithm when $\sigma = 1.30, \tau = 4.38$

TABLE IX: Simulation results of TAMOZE region (in KUT city) system when $\sigma = 1.25$, $\tau = 3.50$

Approach	Open State	TPL (kW)	TQL $(kVar)$	TSL (kVA)	V_{min} $(p.u.)$
Initial configuration	Sw36, Sw37, Sw38, Sw39, Sw40	88.4052	42.7373	98.1935	0.9739
(PSO)	Sw29, Sw36, Sw37, Sw38, Sw39	48.3875	27.1067	55.9265	0.9848

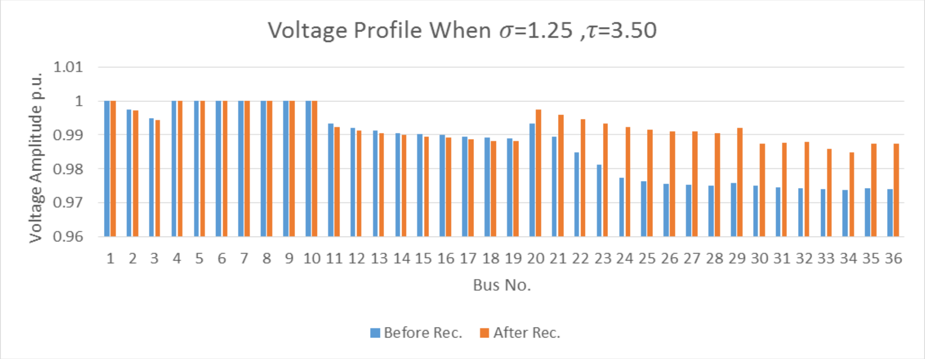

Figure 9: The voltage profile (pre- and post the reconfiguration) for TAMOZE region system (in KUT city), using the PSO algorithm when $\sigma = 1.25$, $\tau = 3.50$

TABLE X: Simulation results of TAMOZE region (in KUT city) system when $\sigma = 0.99$, $\tau = 3.95$

Approach	Open State	TPL (kW)	TQL $(kVar)$	TSL (kVA)	V_{min} $(p.u.)$
Initial configuration	Sw36, Sw37, Sw38, Sw39, Sw40	88.5064	42.7862	98.3059	0.9738
(PSO)	Sw29, Sw36, Sw37, Sw38, Sw39	48.4073	27.1181	55.9496	0.9848

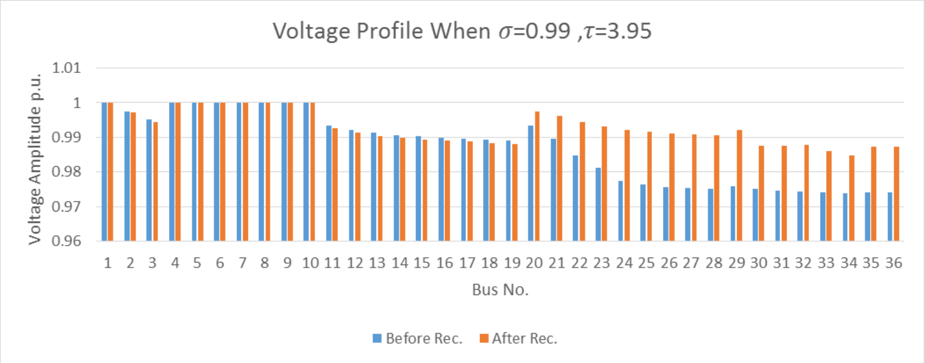

Figure 10: The voltage profile (pre- and post the reconfiguration) for TAMOZE region system (in KUT city), using the PSO algorithm when $\sigma = 0.99$, $\tau = 3.95$

TABLE XI: Simulation results of TAMOZE region (in KUT city) system when $\sigma = 1.50$, $\tau = 3.15$

Approach	Open State	TPL (kW)	TQL $(kVar)$	TSL (kVA)	V_{min} $(p.u.)$

Initial configuration	Sw36, Sw37, Sw38, Sw39, Sw40	88.2203	42.6479	97.9881	0.9739
(PSO)	Sw29, Sw36, Sw37, Sw38, Sw39	48.3424	27.0805	55.8739	0.9848

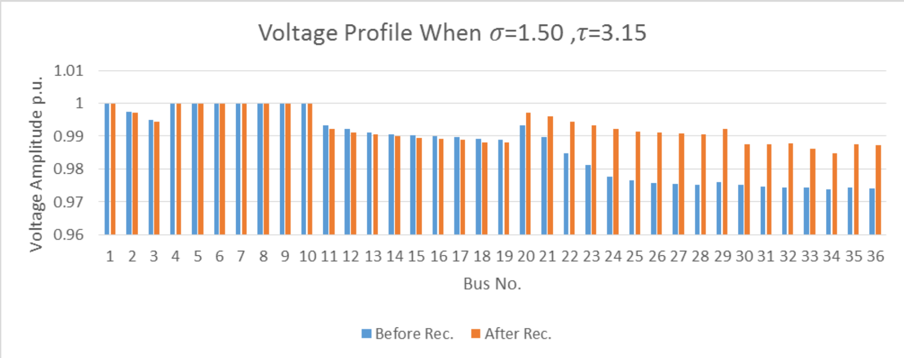

Figure 11: The voltage profile (pre- and post the reconfiguration) for TAMOZE region system (in KUT city), using the PSO algorithm when $\sigma = 1.50$, $\tau = 3.15$

TABLE XII: Simulation results of TAMOZE region (in KUT city) system when $\sigma = 1.51$, $\tau = 3.40$

Approach	Open State	TPL (kW)	TQL $(kVar)$	TSL (kVA)	V_{min} $(p.u.)$
Initial configuration	Sw36, Sw37, Sw38, Sw39, Sw40	87.8764	42.4817	97.6061	0.9740
(PSO)	Sw29, Sw36, Sw37, Sw38, Sw39	48.2505	27.0259	55.7658	0.9848

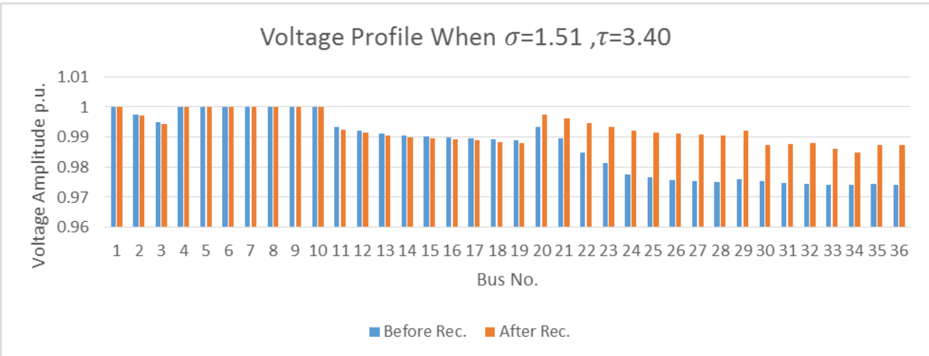

Figure 12: The voltage profile (pre- and post the reconfiguration) for TAMOZE region system (in KUT city), using the PSO algorithm when $\sigma = 1.51$, $\tau = 3.40$

Tables V-XII illustrate that the real loss of power of the best reconfiguration compared to the initial system configuration, showed a significant decrease in the real power loss and the minimum voltage was also enhanced when the values of σ and τ are increased and vice versa. Also Figures 5-12 show the voltage profile improvement, post the system reconfiguration for different values of σ and τ.

6. CONCLUSION

The primary aim of this work is to analyze the reconfiguration of power distribution systems under different load demands using the PSO method, in order to reduce system power losses and enhance the voltage profile. This work, therefore, forms the foundation for electrical companies to use it in the reconfiguration of distribution systems to minimize the operating costs and improving the efficiency of their systems. PSO reaches the optimal solution for the TAMOZE region system (which is a part of AL-KUT city distribution system) after 72.6 sec. and the results were obtained showed a decrease of real power loss by 47.69 % after the system reconfiguration at constant demand and the minimum voltage of the system improved by 1.29%. Extensive series of test cases pertain to the practical system for different loading conditions show that for minimum loss, two tie switches should be closed. Also, the voltage profile all over the system is also improved. There are no tie lines in the network in practice, so to implement the reconfiguration process the tie lines are assumed. This work can be conducted into the means of increasing the PSO convergence, which may lead to a fine search for starting and initializing the algorithm. Extra work is required for dynamic parameter refinements so as to speed up the convergence process.

7. APPENDIX A

TABLE A.1: Line data of TAMOZE region (in AL-KUT city) system

Line No.	From Bus	To Bus	R (Ω)	X (Ω)
1	S	1	0.1149	0.0556
2	1	2	0.1226	0.0593
3	2	3	0.1252	0.0605
4	3	4	0.1539	0.0744
5	4	5	0.0632	0.0306
6	5	6	0.0498	0.0241
7	6	7	0.0344	0.0167
8	7	8	0.0517	0.0250
9	8	9	0.0613	0.0296
10	2	10	0.0926	0.0448
11	10	11	0.0811	0.0392
12	11	12	0.0671	0.0324
13	12	13	0.0511	0.0247
14	13	14	0.0485	0.0235
15	14	15	0.0383	0.0185
16	15	16	0.0575	0.0278
17	16	17	0.0843	0.0408
18	17	18	0.0958	0.0463
19	S	19	0.1693	0.0818
20	19	20	0.1054	0.0509
21	20	21	0.1379	0.0667
22	21	22	0.1117	0.0540
23	22	23	0.1316	0.0636
24	23	24	0.1214	0.0587
25	24	25	0.1214	0.0587
26	25	26	0.0735	0.0355
27	26	27	0.1852	0.0895
28	23	28	0.0849	0.0412
29	28	29	0.0479	0.0232
30	29	30	0.0447	0.0216
31	30	31	0.0575	0.0278
32	30	32	0.0798	0.0386
33	32	33	0.0779	0.0377
34	33	34	0.0722	0.0349
35	30	35	0.0626	0.0303

36*	2	23	2.0000	2.0000
37*	4	25	2.0000	2.0000
38*	7	15	2.0000	2.0000
39*	18	33	0.5000	0.5000
40*	11	32	0.5000	0.5000
		*tie switch		

TABLE A.2: Load data of TAMOZE region (in AL-KUT city) system

Bus No.	Real Power Load (kW)	Reactive Power Load (Kvar)
1	143.683	107.762
2	141.046	105.784
3	193.451	145.088
4	256.814	192.610
5	165.465	124.098
6	183.222	137.416
7	222.856	167.142
8	206.598	154.948
9	198.340	148.755
10	225.267	168.950
11	153.467	115.100
12	157.583	118.187
13	144.447	108.335
14	139.394	104.546
15	131.239	98.4290
16	122.615	91.9610
17	134.183	100.637
18	188.453	88.8390
19	160.286	120.214
20	195.176	146.382
21	190.485	142.864
22	193.258	144.944
23	182.620	136.965
24	215.669	161.751
25	109.865	82.3980
26	161.159	120.869
27	161.825	121.369
28	180.489	135.367
29	175.206	131.404
30	157.479	118.109
31	169.146	126.860
32	199.583	149.687
33	208.304	156.228
34	159.000	119.250
35	162.221	121.665

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