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# A Comparative Study of Swarm Intelligence Techniques for Load Flow Optimization of the Nigerian 132kV Power Transmission Network

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## ABSTRACT
*This paper presents three swarm intelligence (SI) algorithms: Particle Swarm Optimisation (PSO), Bee Colony Optimisation (BCO) and Ant Colony Optimisation (ACO) as Load Flow Optimizers (LFO) for the solution of a power systems network. Studies were performed considering the number of sample iterations while the settings of other SI systemic parameters are held constant. Experiments were conducted by applying the SI-LFO to a section of the Nigerian 132kV Power Transmission Network (Port-Harcourt region). Results show that the PSO gave the best fitness performance overall after three simulation runs and iteration values of 500, 600, 700 and 1000; with a power mismatch of $7.105*10^{-15}$, $7.354*10^{-6}$ and 0.078 respectively for PSO, BCO and ACO after 1000 iterations. This suggests that particle swarming approach of the PSO is a more reliable swarm-optimizer for load flow studies in this application.*

**KEYWORDS:** Load flow, Optimization, Power system, Swarm intelligence, Transmission network.

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## 1. INTRODUCTION

The power system network is a very important part of the modern society as it provides the basic infrastructure for heating, cooling and lighting among so many other essential functions to an ever teeming populace. In order to meet the demands of consumers, proper planning of power system networks is essential. One essential tool or technique in this regard is the Load Flow Analysis (LFA) (Keyhani, 2016; Tostado *et al.*, 2019). Some of the immediate benefits of the LFA include the economic dispatch management and in transient stability studies.

This paper aims to perform a comparative study of the three SI techniques - PSO, BCO and ACO, for the load flow optimization of the Nigerian 132kV power transmission network. In realizing the above aim, the following objectives were pursued: Evaluating the transient and steady state stabilities of 132KV transmission line, solving the load flow problem of 132kV transmission line using the three SI techniques, evaluating and comparing simulation results of the three techniques in term of their power mismatch.

Typically, the LFA requires the solution of a set of equality and inequality constraints needed to determine the power network system states and hence solve the power systems network (Tostado *et al.*, 2019). Traditional LFA tools such as the Newton-Raphson and Gauss-Seidel are very useful for some kinds of problems but when the power system network becomes more demanding, these techniques face high line R/X loading and convergence issues (Keyhani, 2016; Tostado *et al.*, 2019; Al-Anbarri & Naief, 2017). In recent times, there has been a renewed interest in the use of meta-heuristics algorithms based on swarm intelligence for power flow problems (Ahiakwo et al., 2018; Acharjee & Goswami, 2009a; Acharjee & Goswami, 2009b; Acharjee & Goswami, 2009c; Gnanambal *et al.*, 2010; Gnanambal *et al.*, 2011; Jain *et al*., 2016). Three popular techniques are the Particle Swarm Optimization (PSO), Bee Colony Optimization (BCO) and Ant Colony Optimization (ACO). These algorithms have been successfully used in the solution of many other power system problems.

In this paper, we present a comparative analysis of the aforementioned swarm intelligence (SI) algorithms used as Load Flow Optimizers. These classes of algorithms (PSO, BCO and ACO) are compared on the basis of their fitness scores for a given number of parameter-specific iteration steps and for a given number of simulation trial runs. SI algorithms are applied to the solution of a section of the Nigerian 132-kV power network (Port-Harcourt region).

Particle Swarm Optimization (PSO), Bee Colony Optimization (BCO) and Ant Colony Optimization (ACO) are swarm meta-heuristics for constrained optimization of the Load Flow Optimisation (LFO) in a power system network. PSO is a well-known social cognitive and meta-heuristic Artificial Intelligence (AI) approach that builds on the collective behavior of groups of particles which include flock of birds or fish schools (Kennedy & Eberhart, 1995). The key parameters of the PSO are its population size and the maximum number of iterations required to attain a solution objective. Some important parameters that have been added to PSO are the Constriction coefficient which controls the convergence rate of PSO and the Inertia damping weight ratio which is used to control the velocity of a swarming particle. In a PSO-LFO, particles (individuals) represent candidate load flow parameter solutions (Solaiman & Sheta, 2016). These solutions are bounded using an exploitative/explorative global best search procedure in which positions and hence speed of the particles is changed to obtain an optimal or best-fitting candidate.

BCO is an emerging swarm intelligence technique inspired by the beautiful organizational and foraging ability of honey bee swarms while combining the global optimum capabilities of evolutionary computers with a fitness-based model (Anireh & Osegi, 2019). It was developed by Karaboga (2005), and has been widely applied by power system researchers. In the BCO-LFO simulation, an evolutionary process comprising an exploitative and explorative procedure is used to evolve foods (candidate load flow power system parameter solutions) in order to determine the best possible solution candidate. This typically results in a set of sub-optimal solutions through simulation time. The exploitative functions are handled by two sub-routines referred to as the employed and onlooker bees while the explorative functions are performed by the scout-bees sub-routine (Bansal *et al*., 2013; Ekinci & Demirören, 2016). The key parameters of the BCO are its food number and the maximum number of iterations required to attain a solution objective. An important parameter also widely included is its limit trial which defines the number of food quality (solution) searches that will be performed by an employed bee; if the food presents no good solution after the specified number of searches it is discarded. Preliminary results of LFO for transient stability studies of Nigerian 132kV power transmission network using BCO are presented in Oko *et al.* (2019).

ACO is a popular metaheuristic approach that uses the intelligent foraging behaviour of ants to find good solutions to combinatorial problems. It was first introduced by Dorigo (1992). In an ACO-LFO, the ants always seek for the shortest path to food source(s) from their nest; these short paths represent the optimal or best fitting load flow parameters.

## 2. MATERIALS AND METHODS

Load Flow Optimization for Power System Network. In a load flow optimization (LFO), a power system network is solved in order to determine performance indicators such as the bus voltages and angles, real and reactive power flows under certain system parameter configurations including the line admittances, bus and generator power requirements. In modelling a LFO, the active and reactive power mismatches are usually considered, represented as:

$$\Delta P_i = P^{inj} - \sum_{j=1}^{n} |V_i||V_j||Y_{ij}|\cos(\delta_i - \delta_j - \theta_{ij}) \quad (1)$$

$$\Delta Q_i = Q^{inj} - \sum_{j=1}^{n} |V_i||V_j||Y_{ij}|\sin(\delta_i - \delta_j - \theta_{ij}) \quad (2)$$

Where:
$\Delta P_i$ = active power mismatches at bus $i$
$\Delta Q_i$ = reactive power mismatches at bus $i$
$P^{inj}$ = injected active power at bus $i$
$Q^{inj}$ = injected reactive power at bus $i$
$|V_i|$ = absolute value of the voltage at bus $i$
$|V_j|$ = absolute value of the voltage at bus $j$
$|Y_{ij}|$ = absolute value of the admittance matrix of the $ij^{th}$ *element*
$\theta_{ij}$ = admittance angle at bus $i, j$
$\delta_i$ = voltage angle of the bus $i$
$\delta_j$ = voltage angle of the bus $j$

The unknown vector of the LFO problem can also be further represented as a union set as in (3):

$$x_{LF} = \{\delta_{PV} \cup \delta_{PQ} \cup V_{PQ}\} \quad (3)$$

Where:
$\delta_{PV}$ = voltage angle vector of the PV buses
$\delta_{PQ}$ = voltage angle vector of the PQ buses
$V_{PQ}$ = voltage magnitude vector of the PQ buses
The size of $x_{LF}$ is computed using:

$$n_s = n_{PV} + 2n_{PQ} \quad (4)$$

Where:
$n_{PV}$ = number of the PV buses
$n_{PQ}$ = number of the PQ buses

Typically, a tolerance measure is used to stop the simulation run and reduce the computational expense. This is determined by the convergence rule in (5) and after repeating (1) to (4).

$$\max\{|\Delta P_i| \cup |\Delta Q_i|\} \leq \varepsilon \ \ \forall\ i \quad (5)$$

The generalized LFO procedure is as follows:
*Step 1*: Define Power Network Initial Parameter Conditions including the bus data and line data values; these values are needed later on for defining the LFO boundary constraints.
*Step 2*: Compute the Line Admittance of the power network buses and the corresponding angles.
*Step 3*: Define the LFO constraints (upper and lower bounds) basing on the power system optimization parameters: Bus Voltage, Bus Angle, Bus and Generator Real and Reactive Powers and Power Injections.
*Step 4*: Define the fitness (objective) function of the LFO; this function computes the load flow, power mismatches and the net power mismatches using the aforementioned constraints defined in the previous step (Step 3).
*Step 5*: Solve the power network by finding the best foods in accordance to the LFO algorithm routine and the fitness function defined in Step 4.

## 2.1 LFO using PSO

The solution operations detailing the PSO technique are presented as follows:
A population of individuals (particles) representing possible solutions are randomly created; these individual particles are bounded within a dimension, $j$ and an explorative/exploitative search is performed by the PSO for a global best (*gb*) position.
Each particle in the population changes position within a search space until an optimal solution is attained; each particle is characterized by its position, best position and velocity in the considered search space.
Each particle in the population exchange information within the neighborhood of other particles, memorize the best positions reached by a swarm of the population of particles while updating their positions for a given maximum number of iterations; the position update is modeled as:

$$v_{ij}^{new} = v_{ij}^{old} + c_1 \times r_{ij} \times (bp_{ij} - x_{ij}) + c_2 \times r_{2j} \times (gp_j - x_{ij}) \quad (6)$$

$$x_{ij}^{new} = x_{ij} + v_{ij}^{new} \quad (7)$$

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Where:
$v_{ij}$ = velocity of particle *i* in dimension *j*
$x_{ij}$ = position of particle *i* in dimension *j*
$c_1, c_2$ = positive constants
$r_{1j}, r_{2j}$ = random numbers
$bp_{1j}$ = best position reached so far by the particle
$gp_{1j}$ = global best position reached by the neighborhood.

## 2.2 LFO using BCO

In BCO, there are three classes of foraging bees (Bansal *et al.*, 2013):

i. Employed bees
ii. Onlooker bees
iii. Scout bees

Employed bees (EBs) scout for food sources. Onlooker bees (OBs) minimize the objective by probabilistically selecting food sources with the best qualities. EBs set forth as Scout bees (SBs) once their food sources are completely exploited, which then forage for new sources of food. EBs and OBs perform exploitative duties while SBs perform explorative duties. The solution operations detailing the BCO technique are presented as follows:
A sequence of food sources (position or points of real values) are generated randomly according to the following formula:

$$x_{ij} = x_{\min j} + rand[0,\ 1](x_{\max j} - x_{\min j}) \qquad (8)$$

This is called the initialization phase.
An EB updates her position by replacing the fitness (nectar information) or simply the fitness value (FV) of an old solution with a new one if the new solution FV is better; the update equation for all EBs is defined as:

$$x_{ij}^{j} = x_{ij} + \phi_{ij}\left(x_{ij} - x_{kj}\right) \qquad (9)$$

An OB analyzes all the solutions of FVs obtained from the EBs and selects a solution based on a fitness-related-probability as:

$$prob_i = \frac{fitness_i}{\sum_{i=1}^{SN} fitness_i} \qquad (10)$$

An SB replaces an abandoned food source (i.e. a food source that is not updated) with a randomly chosen food source within the search space after a predetermined number of limit trials:

$$x_{ij} = x_{\min j} + rand[0,\ 1](x_{\max j} - x_{\min j}), \quad for\ j \in \{1, 2, \ldots, D\} \qquad (11)$$

Where:
$x_{ij}$ = position of food source *i* in direction *j*
$x_{\min j}$ = lower bound of $x_i$ in direction *j*
$x_{\max j}$ = upper bound of $x_i$ in direction *j*
*SN* = food source number
*D* = dimension of the problem
$\phi_{ij}$ = a random number between -1 and +1
$fitness_i$ = fitness value of solution *i*

## 2.3 LFO using ACO

ACO basically comprises of two key steps:

1) A solution construction or representation.
2) A pheromone update.

Step 1 is usually constructed from a finite set of solution values which is a subset of an empty partial solution (Socha & Dorigo, 2008).

Step 2 uses the idea of ant pheromone trails to update the good solutions by increasing its fitness values. For continuous domains, the following equations model the primary operations of the first step while a Monte Carlo operation takes care of important steps. Sampling a Gaussian function at construction step *i*, in accordance to the following probability:

$$p_i = \frac{\omega_l}{\sum_{r=1}^{k} \omega_r} \qquad (12)$$

Where:
$\omega_l$ = a computed weight of a chosen solution
$\omega_r$ = a computed weight of other solutions

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Computing a weighted standard deviation:

$$\sigma_l^i = \xi \sum_{e=1}^{k} \frac{\left|s_e^i - s_l^i\right|}{k-1} \qquad (13)$$

Where:
$k$ = size of solution archive
$s_l$ = chosen solution
$s_e$ = other solutions
$\xi$ = a convergence intensification factor

**Tables 1 to 3 give the key system parameters used to simulate the three LFOs in this work.**

**Table 1: PSO System Parameters**

| Parameters | Default Values |
|---|---|
| Maximum Iteration | 1000 |
| Population Size | 50 |
| Constriction coefficients | 2.05 |
| Inertia Damping Weight Ratio | 1.00 |
| No. of runs | 10 |

**Table 2: BCO System Parameters**

| Parameters | Default Values |
|---|---|
| Maximum Iteration | 1000 |
| Food Number | 50 |
| Limit trials | 500 |
| No. of runs | 10 |

**Table 3: ACO System Parameters**

| Parameters | Default Values |
|---|---|
| Maximum Iteration | 1000 |
| Population Size | 50 |
| Sample size | 10.00 |
| Intensification factor | 0.40 |
| Deviation distance ratio | 1.00 |
| No. of runs | 10 |

Small signal voltage stability experiments in the context of load flow of a section of the Nigerian 132kV power transmission network (Port-Harcourt region) are conducted on an Intel i-core-2 PC using a 2.3GHz processor. The considered Nigerian sub-transmission network is a 1-machine, 14-bus system with most interconnecting lines of the double circuit type.

All simulations are performed using MATLAB. Data for the NPHC-132 1-machine, 14-bus power system is obtained from the Transmission Company of Nigeria (TCN).

## 3. RESULTS AND DISCUSSION

The fitness plots of applying PSO, BCO AND ACO LFO approaches to the Nigerian 132-kV power transmission network (Port-Harcourt region), 1-machine 14-bus system are as shown in Figures 1 to 3.

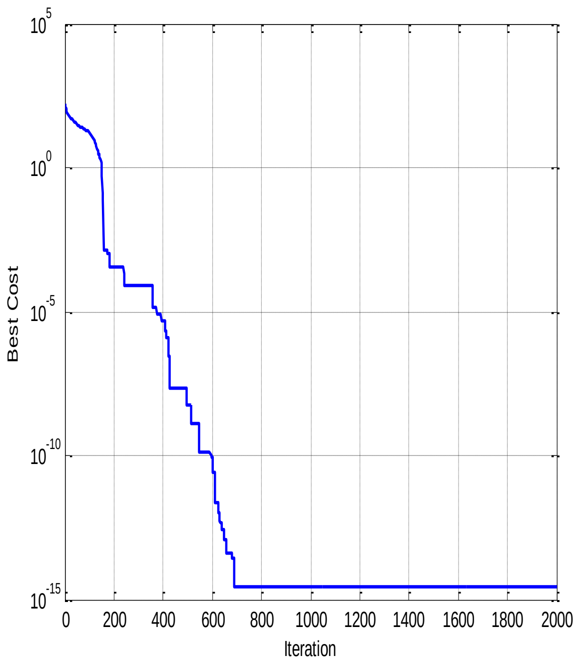


**Figure 1 PSO-LFA Fitness Plot**

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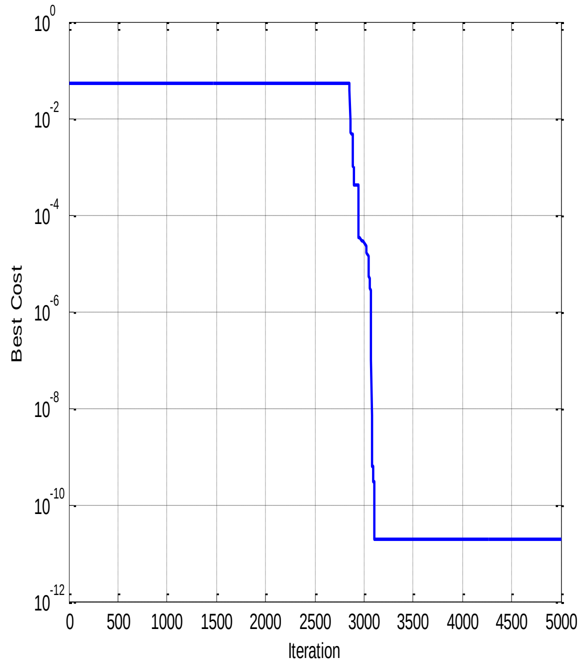


**Figure 2 BCO-LFA Fitness Plot**

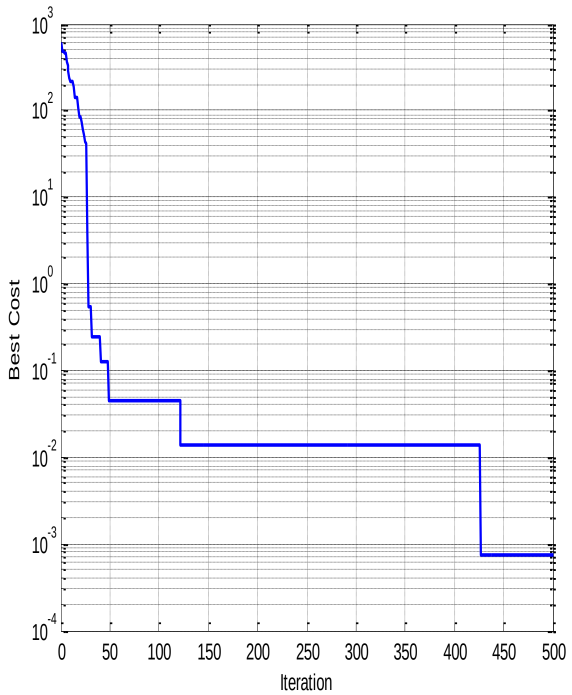


**Figure 3 ACO-LFA Fitness Plot**

The power mismatches (fitness scores) as computed by the three LFO algorithms are shown in Table 4, and the solved bus voltages (mean voltages) at maximum set iteration values. The results are obtained after three simulation runs and iteration values of 500, 600, 700 and 1000. For the power mismatch test, only the results of the best simulation run (from the three simulated cases) are considered.

**Table 4: LFO Power Mismatch Performance**

| Iteration Values | PSO-LFO Power Mismatch | BCO-LFO Power Mismatch | ACO-LFO Power Mismatch |
|---|---|---|---|
| 500 | $3.197*10^{-14}$ | 61.655 | 0.583 |
| 600 | 0.000 | 30.496 | 0.171 |
| 700 | 0.000 | 8.520 | 0.655 |
| 1000 | $7.105*10^{-15}$ | $7.354*10^{-06}$ | 0.078 |

A performance optimization study of three swarm intelligence techniques, the PSO, BCO and ACO load flow optimization (LFO) was presented. The study investigated the influence of one of the LFO optimization parameters called the "iteration" or "maxcycle" parameter on the power mismatch value and voltage response during a load flow optimization. The study bus considered is the Nigerian 132kV sub-transmission Port-Harcourt region. The results indicate that higher value of the iteration parameter improves the power mismatch value and hence stabilizes the voltage response. The PSO and BCO showed close correlation and gave realistic load flow solutions, but however, PSO has comparatively lower values in terms of best fitness and power mismatch as shown in Figs. 1-3 and Table 4. This makes the PSO algorithm a better approach for solving the current problem.

## 4. CONCLUSION

This work investigated new ways of approaching the power system stability studies based on predictive optimization through the use of the following three swarm intelligence algorithms: the Bee Colony Optimization (BCO) which is

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based on the Artificial Bee Colony (ABC) algorithm, Ant Colony Optimization (ACO) and the Particle Swarm Optimisation (PSO) algorithm for optimizing the load flow part of a power system network prior to stability studies.

Power mismatch results also show that stability is reasonably guaranteed at a certain iteration value (for instance an iteration of 1000 is just sufficient for the power network using the PSO-LFO and BCO-LFO. Also, the power mismatch reduces as the iteration value increases.

Future studies will explore the potential of the various swarm-based LFOs in power system load flow studies for various power system networks and in transient/steady state stability studies. These studies will be conducted in comparison with other alternative and promising swarm intelligence techniques including algorithmic variants of the considered techniques.

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