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Application of Neuro-Swarm Intelligence Technique ToLoad Flow Analysis

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ABSTRACT :*Load flow analysis (LFA) is essential when planning design or stretching of a new or existing power station. Neuro-Swarm Intelligence is an optimally automated Artificial Intelligence (AI) solution technique which combines Artificial Neural Network (ANN) and Artificial Bee Colony (ABC) algorithms for power flow analysis. The ABC algorithm is used to evolve the solution space and train the ANN for optimal power flow solution. The ANN learning from the ABC, memorizes and registers the best initial data (parameter) setting which yields the best solution and sets the maximum cycle (maxCycle) for optimal load flow analysis (OLFA). Results from test conducted on the Diobu PHEDC 4-bus system using Neuro-Swarm algorithm showed good performance with less computational time and divergence mostly in heavy loading conditions. The results were validated by comparing them with that of Particle Swarm Optimization (PSO). The results showed better performance of Neuro-Swarm Intelligence in terms of flexibility, number of control parameters, computational time and number of iteration.*

KEYWORDS *-Artificial Intelligence, Load Flow Analysis, Neuro-Swarm Intelligence, Particle Swarm Optimization*

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I. INTRODUCTION

Load flow analysis (LFA) is a very important part of power system analysis that has received considerable attention for over several decades. It is needed for voltage stability analysis, power system reliability and control. Especially in the event of a fault situation in the chosen power network, be it a transmission or a distribution system. Fundamentally, load flow analysis involves determination or solution of the power network where the bus voltages, angles or power flows (real and reactive powers) are unknown or presumed to be unknown. Load flow solution is a solution of the network under steady state condition subject to certain inequality constraints under which the system operates such as, load nodal voltages, reactive power generation of the generators, tap setting of a tap changing transformer under load transformer [1].According to convention, such solutions have generally been investigated in the network (static) domain, with the use of popular analytic tools such as Gauss-Seidel, Newton-Raphson and fast decoupled methods of solutions. When the goal is to ensure a power balance by minimizing the mismatch in real/reactive power, LFA becomes an optimization problem and is termed optimal power flow (OPF).However, the solution using the conventional method such as Newton-Raphson may sometimes become intractable due to convergence issues particularly during heavy loading condition further caused by high R/X ratio of the system and singularity in the Jacobian matrix [2].Thus, the urgent need to address LFA in the time (dynamic) domain becomes necessary as well [3].

The primary purpose of this research is to develop a competent neuro-swarm intelligence model for load flow analysis in a distribution system. Neuro-Swarm is a neuro-evolutionary type of artificial intelligence (AI) which employs evolutionary algorithms to produce artificial neural network (ANN), parameters and rules applicable in artificial life, computer games and evolutionary robotics.

The distribution system under investigation is the Port Harcourt electricity distribution company (PHEDC) system, with a primary focus on Diobu distribution zone. The advantage of the conventionally adopted numerical method of Newton-Raphson is in its high level of accuracy and effectiveness during lightly loaded connection; however, a switch must be made where necessary to the neuro-swarm computer-based method during heavy loading. The importance of the swarm technique is to intelligently evolve an optimal solution space during network dynamics while the neural part is used to learn and memorize the best set of swarm settings that give the desired fitness or convergence to the load flow. This results to a very robust and efficient LFA scheme.

The current challenge of maintaining load stability, heavy loading of PHEDC network and the high cost of processing network data using conventional methods makes it a mandatory task to develop more effective solutions. The conventional numerical method of Newton-Raphson can become computational expensive for large distribution network due to its quadratic convergence. Thus, it is important that newer and more reliable techniques be developed. This work addressed this problem by evaluating the potential of a promising hybrid Artificial Intelligence (AI) technique based on neuro-swarm intelligence for optimal load flow predictions and identifying the most suitable one to use.

II. RELATED WORK

Many scholars are moving away from the numerical methods of solution and recent research shows focus on the trending artificial intelligence (AI) technique. Nevertheless, AI techniques as a solution method to load flow problems have attracted a lot of attention and research in recent time. [4] proposed a dynamic radial basis function artificial neural network while [5] proposed an improved continuation power flow (CPF) model integrated with an evolutionary mechanism-based particle swarm optimization (PSO) method via coordinate transformation.

References [6] and [7] proposed guaranteed convergence particle swarm optimization with Gaussian mutation (GPSO-GM). Reference [8] proposed a hybrid particle swarm optimization-based method (HPSOBM) for optimal power flow solution. References [9] and [10] proposed an interval type-2 fuzzy logic controlled (IT2FLC). Reference [11] proposed genetic algorithm (GA) while reference [12] proposed a real-coded genetic algorithm (RCGA) for load flow solution in electrical power systems. Reference [13] utilized bat algorithm based on weight sum method (WSM) while references [14] and [15] proposed artificial bee colony (ABC). Reference [16] proposed modified artificial bee colony (MABC) while reference [17] proposed hybrid artificial bee colony.

In spite of the numerous advantages inherent in the proposed methods there is room for exploration in other to develop a novel approach for better or similar performance.

III. METHODOLOGY

The method employed in this researchis a combination of two Artificial Intelligence Techniques - ANN and ABC, known as Neuro-Swarm Intelligence. This technique was compared with PSOas a popular state-of-the-art algorithm for validation. See reference [18] and [19] for the implementation of the PSO algorithm.

3.1. Fundamental Equations for Load Flow Analysis on N-bus System

A typical power system comprises of buses and these buses are connected to each other transmission lines having impedances, admittances and other line parameters. Consider an n-bus system comprising of voltages, angles, admittances and line (MW and MVAR) flows between pairs of buses indexed at say i, k; then the real and reactive power can be deduced by taking into consideration the current flowing into bus i for an N-bus network.

The current received at bus i from the generator or power grid is given as;

$$I_i = Y_{i1}V_1 + Y_{i2}V_2 + .. + Y_{ik}V_K = \sum_{i,k=1}^{n} Y_{ik}\, V_k \qquad (1)$$

Considering magnitude and phase angle, the voltage and admittance will be given as;

$$V_k = V_K \angle \delta_k \quad \text{(voltage at the bus k)} \qquad (2)$$

$$Y_{ik} = Y_{ik} \angle \theta_{ik} \text{(admittance between bus i and bus k)} \qquad (3)$$

Substitute equations (2) and (3) into equation (1)

$$I_i = \sum_{i,k=1}^{n} Y_{ik} \angle \theta_{ik} V_k \angle \delta_k \qquad (4)$$

$\delta_i, \delta_k are phase angles of$ bus i and k, while δ_{ik} is the angular difference between bus i and k.

Conjugate of the injected current at bus i will be;

$$I_i^* = \sum_{i,k=1}^{n} Y_{ik} \angle -\theta_{ik} V_k \angle - \delta_k \qquad (5)$$

Apparent power available at bus i will be;

$$S_i = V_i I_i^* = P_i + jQ_i \qquad (6)$$

Substitute equation (5) into equation (6), considering the magnitude and angle of V_i, we have:

$$P_i + jQ_i = V_i \angle \delta_i \sum_{i,k=1}^{n} Y_{ik} \angle -\theta_{ik} V_k \angle -\delta_k \qquad (7)$$

Rearranging equation (7) gives;

$$P_i + jQ_i = \sum_{i,k=1}^{n} Y_{ik} V_i V_k \angle (-\theta_{ik} + \delta_i - \delta_k) \qquad (8)$$

But,

$$\delta_{ik} = \delta_i - \delta_k \qquad (9)$$

$$-\theta_{ik} = \theta_{ki} \qquad (10)$$

Substituting the relations in equations (9) and (10) into equation (8)

$P_i + jQ_i = \sum_{i,k=1}^{n} Y_{ik} V_i V_k \angle (\theta_{ki} + \delta_{ik})$ (11)

From the equation (11), the active real and imaginary power will be;

$P_i = \sum_{i,k=1}^{n} Y_{ik} V_i V_k \cos(\theta_{ki} + \delta_{ik})$ (12)

$Q_i = \sum_{i,k=1}^{n} Y_{ik} V_i V_k \sin(\theta_{ki} + \delta_{ik})$ (13)

Equations (12) and (13) are used to obtain calculated values of real and reactive power.Note that when the bus generates electrical power, it is termed a generator bus otherwise it is a load-bus; a slack bus is also often necessary to accommodate (suck-up) the excess power flows.

The line flows may further be expressed as changes in the computed real bus/or generator powers with respect to pre-specified real bus/or generator values and is expressed as:

$\Delta P_i = \left| P_i^{sp} - P_i^{cal} \right|$ (14)

Where:

P_i^{sp} = the specified real bus powers at power exchange sequence i,

P_i^{cal} = the computed real bus powers at power exchange sequence i, using equation (12)

Similarly, the reactive power changes may be expressed as:

$\Delta Q_i = \left| Q_i^{sp} - Q_i^{cal} \right|$ (15)

Where:

Q_i^{sp} = the specified reactive bus powers at power exchange sequence i,

Q_i^{cal} = the computed reactive bus powers at power exchange sequence i, using equation (13).

Typically, the admittances, line power demand and generations are given while the bus voltages and angles are obtained by making an initial guess and solving using a load-flow program.

The net power balance is then expressed as the sum over all bus power sequence exchanges as:

$\Delta P_{net} = \sum_i^n \Delta P_i^2$ (16)

and,

$\Delta Q_{net} = \sum_i^n \Delta Q_i^2$ (17)

Working data was obtained for the three feeders considered from transmission company of Nigeria (TCN) and PHEDC as regards transformer and feeder parameters which is contained in Tables 1 and 2 in Appendix 2.Based on the acquired data, calculations were done using per unit system to get the MVAsc for easy representation of the system schematic diagram. Let the base MVA be 90 for a per unit voltage of unity, knowing that:

$Z_{p.u(new)} = Z_{p.u(old)} \times \frac{MVAnew}{MVAold}$ (18)

$$Z_{1new} = 0.1217 \times \frac{90}{30} = 0.3651 p.u$$

$$Z_{2new} = 0.1028 \times \frac{90}{60} = 0.1542 p.u$$

T1 and T2 are connected in parallel and as such their equivalent impedance will be gotten using equation (8).

$Z_{p.uequi.} = \frac{Z_{1p.u} \times Z_{2p.u}}{Z_{1p.u} + Z_{2p.u}}$ (19)

$$Z_{p.uequi.} = \frac{0.3651 \times 0.1542}{0.3651 + 0.1542} = 0.1084 p.u$$

The maximum short-circuit MVA can be calculated using equation (20)

$MVA_{sc} = \frac{MVA \times V_{PU}}{Z_{pu.equi.}}$ (20)

$$MVA_{SC} = \frac{90 \times 1}{0.1084} = 830.165$$

$$MVA_{SC} \approx 830.2$$

From the length parameters of the lines acquired, it is observed that all three lines are short lines and as thus, sending-end current (I_s) is equal to receiving-end current (I_r) and the line will be analyzed using equation (11). The proceeds from substituting values into equations (18), (19) and (20) is used for the network schematic shown in Figure 1, a 4-bus system comprising of a grid, transmission lines, high voltage circuit breakers and lumped loads representing feeder loads.

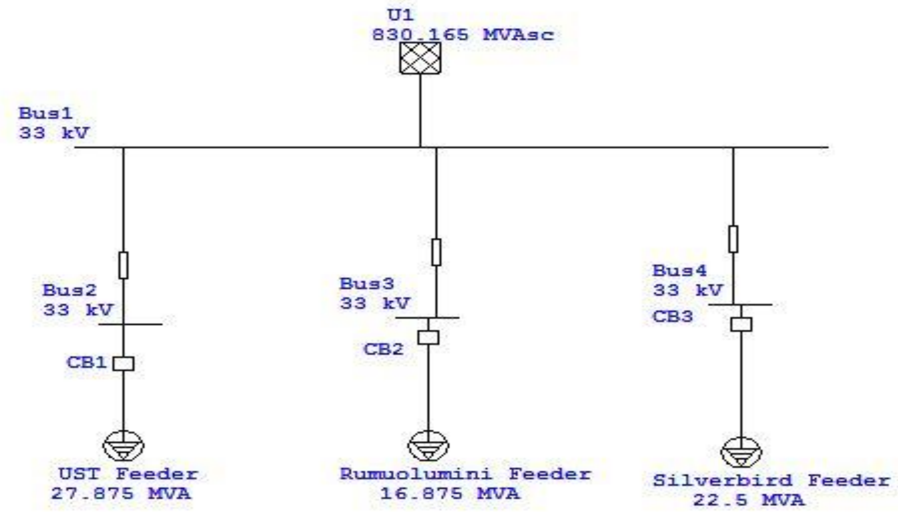

Figure 1 - Etap Presentation of PHEDC 33KV Network Schematic for Diobu Zone

3.2. Analysis of the Neuro-Swarm Technique

The neuro-swarm technique employs two forms of AI. First, it uses the ABC algorithm to evolve a solution space after tuning over several parameter settings, and then uses an ANN to learn the best settings for each variation in specified bus powers. ABC is an optimization swarm intelligence technique based on the foraging behaviour of self-organized and decentralized honey bees whereas ANN is a complex adaptive system or parallel data processing or computing system used for actualizing faster computational solution than conventional solution technique. The honey bee colony is basically made up of three classes of bees namely; employed, onlookers and scout bees. These three classes are further divided into two groups known as employed and onlooker bees due to the like-features of the scout and employed bees. In the honey bee colony, the employed bees leave the hive in search of food source initialized by the scout bees, on seeing the food source they go back to the hive to initiated the waggle dance to disclose the position and amount of nectar contained in the various sources to the onlooker bees based on a greedy selection process.

The onlookers getting the needed information based on the waggle dance initiated by the employed bees move out from the hive to explore the best food source. Exhausted food sources are abandoned by the onlookers and the employed bee whose food source is exhausted becomes a scout bee by going out to search for new food sources. These steps are repeated and the best food source corresponding to the best solution is memorized and registered until the termination or stopping criteria is met [20 and 21]. The neural part of this model aims at learning and memorizing the best initial settings that produces the best solution after several trials so as to determine the maximum cycle of the ABC algorithm. The idea behind this technique is to build a system that lends itself to automation. The flow diagram of a typical hybrid ABC routine for optimal load flow analysis (OLFA) is shown in Figure 2. It shows how the ABC finds the best solution to the LFA problem i.e. at what set of ABC tuning parameters does the system solve the OLFA problem.

The OLFA problem specifically looks for the bus voltages and angles which are unknown at the start of the simulation but are constrained to expectation boundary point (upper and lower limit).

3.2.1 Tuning ABC Parameters for Optimal Load Flow Analysis

The ABC parameters are constrained parameters i.e. there is a typical (limited) range of values that give optimum performance. In order to perform load flow optimization with the ABC, a fitness (objective) function has to be defined for the OLFA problem. The magnitude and angles of the voltages are scheduled in the range $-1 \leq V \geq 1 \; and -1 \leq \partial \geq 1$.

This is obtained from equations (16) and (17) and is expressed as:

$$f_{obj} = \sqrt{\Delta P_{net} + \Delta Q_{net}} \qquad (21)$$

The optimization process will be achieved by producing working values of bus voltages and angles at a minimum objective function.

Initial setting of basic ABC parameters like number of food source (solution) are required for kick-starting an ABC optimization process.

Values of fitness function (f_{obj}) must be close to zero or attain very small values including convergence after a setting number of trial observations have been made.
Relating the ABC parameters to LFA, the food source corresponds to the possible solution while the fitness function describes the solution quality.

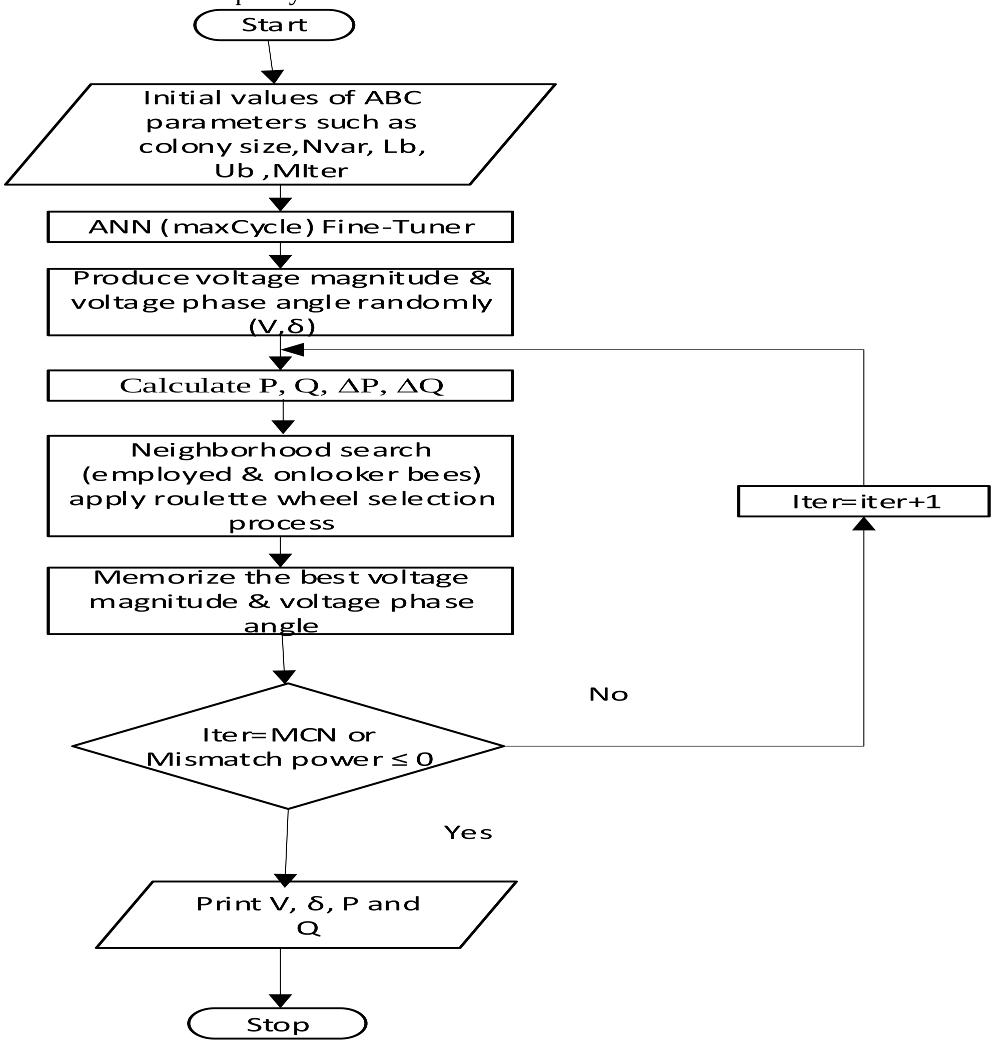

Figure 2 - Scheme for Automated Load Flow using Neuro- Swarm Technique

3.2.2 Training ABC Parameters for Optimal Load Flow Analysis

In order to automate the process for OLFA, a training scheme based on artificial neural network is used. The parameters of the ABC such as colony size, limit trials are studied and memorized by a feed-forward artificial neural network (FF-ANN) trained via the back-propagation algorithm; after a number of optimal training patterns are synthesized by the ABC and memorized by the FF-ANN, the system now learns to automatically predict the best set of ABC parameters for optimal load flow and further tuning of parameters is not necessary.

IV. RESULTS AND DISCUSSION

Tables 1 and 2 clearly show results for bus voltages and angles for normal and heavy loading conditions using Neuro-Swarm and PSO while Tables 3, 4. 5 and 6 show results for the line flows including losses for Neuro-Swarm and PSO for both cases of loading. For the heavy loading condition, a load factor of 20 is applied and results obtained were promising.

Table 1: Bus Voltage-Angle Response under Normal Loading Conditions

Bus ID	Neuro-Swarm Bus Voltage (pu)	Result Bus Angle (rad)	PSO Bus Voltage (pu)	Result Bus Angle (rad)
1	0.6682	0.0000	0.6682	0.0000
2	1.0309	0.7382	1.0309	0.7382
3	1.0309	0.7553	1.0309	0.7553
4	0.5000	0.7429	0.5000	0.7429

Table 2: Bus Voltage-Angle Response under Heavy Loading Conditions

Bus ID	Neuro-Swarm Bus Voltage (pu)	Result Bus Angle (rad)	PSO Bus Voltage (pu)	Result Bus Angle (rad)
1	1.0000	0.0000	1.0000	0.0000
2	0.8729	0.7149	0.8729	0.7149
3	1.0309	0.7571	1.0309	0.7571
4	0.5000	0.7462	0.5000	0.7462

Table 3: Neuro-Swarm Power Flow Result for Normal Loading Condition

Bus ij	P_{ij} (pu)	Q_{ij} (pu)	Bus j i	P_{ji} (pu)	Q_{ji} (pu)
1 2	0.0022	0.0017	2 1	−0.0019	−0.0013
1 3	0.0013	0.0010	3 1	−0.0011	−0.0008
1 4	0.0015	0.0011	4 1	−0.0014	−0.0010

Table 4: PSO Power Flow Result for Normal Loading Condition

Bus i j	P_{ij} (pu)	Q_{ij} (pu)	Bus j i	P_{ji} (pu)	Q_{ji} (pu)
1 2	0.0022	0.0017	2 1	−0.0019	−0.0013
1 3	0.0013	0.0010	3 1	−0.0011	−0.0008
1 4	0.0015	0.0011	4 1	−0.0014	−0.0010

Table 5: Neuro-Swarm Power Flow Result for Heavy Loading Condition

Bus i j	P_{ij} (pu)	Q_{ij} (pu)	Bus j i	P_{ji} (pu)	Q_{ji} (pu)
1 2	0.0416	0.0357	2 1	−0.0413	−0.0353
1 3	0.0200	0.0216	3 1	−0.0198	−0.0214
1 4	0.0360	0.0240	4 1	−0.0359	−0.0239

Table 6: PSO Power Flow Result for Heavy Loading Condition

Bus i j	P_{ij} (pu)	Q_{ij} (pu)	Bus j i	P_{ji} (pu)	Q_{ji} (pu)
1 2	0.0416	0.0357	2 1	−0.0413	−0.0353
1 3	0.0200	0.0216	3 1	−0.0198	−0.0214
1 4	0.0360	0.0240	4 1	−0.0359	−0.0239

V. CONCLUSION

Load Flow Analysis (LFA) has been performed in this research using a swarm technique(Neuro-Swarm optimization), Artificial Bee Colony (ABC) optimization fine-tuned by an Artificial Neural Network, with promising results. Another very popular swarm technique, the Particle Swarm Optimization (PSO) has also been investigated in the light of validating the Neuro-Swarm technique for load flow optimization (LFO). The results of using the PSO have been reported and are indeed promisingas well. Graphical results provided in Appendix1 shows that the proposed algorithm outperformed PSO with fast computational time due to the self-automation properties of the neuro-swarm.

VI. RECOMMENDATION

The algorithm should be applied to systems with long and medium feeder lines in transmission and distribution networks. Additionally, large data sets should be used to train the ANN for better accuracy.

Finally, future research should be conducted in the light of comparing the implemented method with other hybrid AI solution methods.

APPENDICES

Appendix 1: Graphical Results

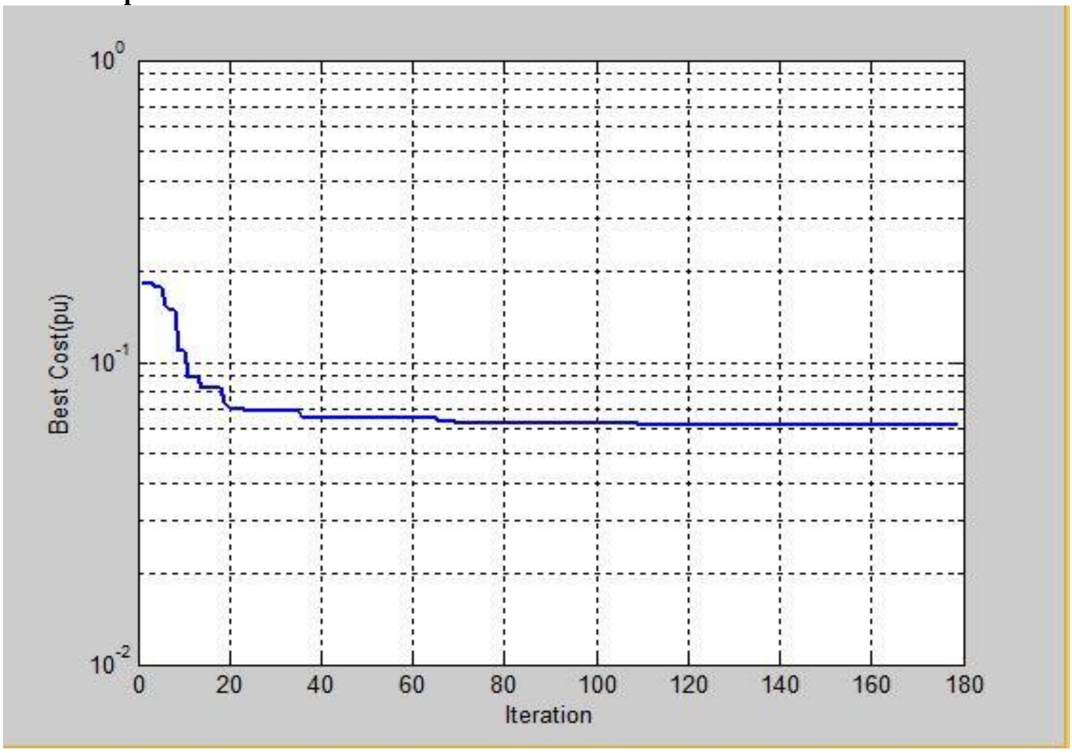

Figure 3 - Neuro-Swarm Fitness Performance under Normal Bus Loading

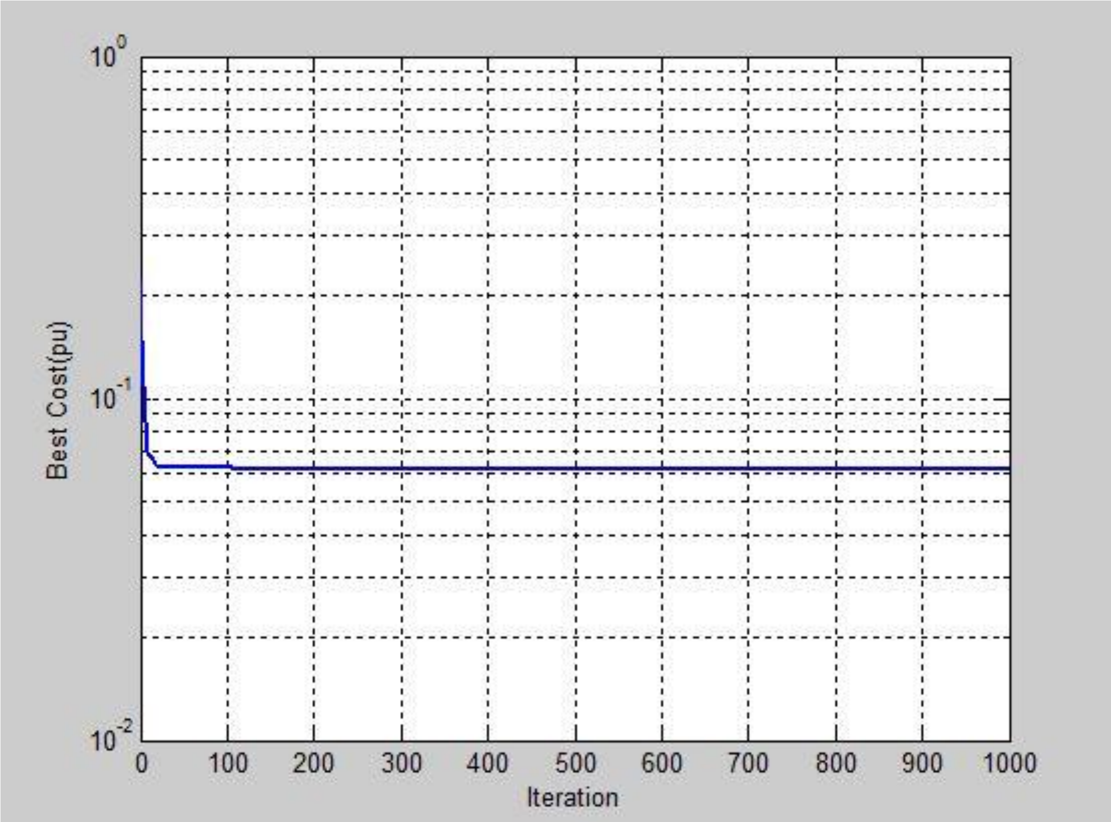

Figure 4 - PSO Fitness Performance under Normal Bus Loading

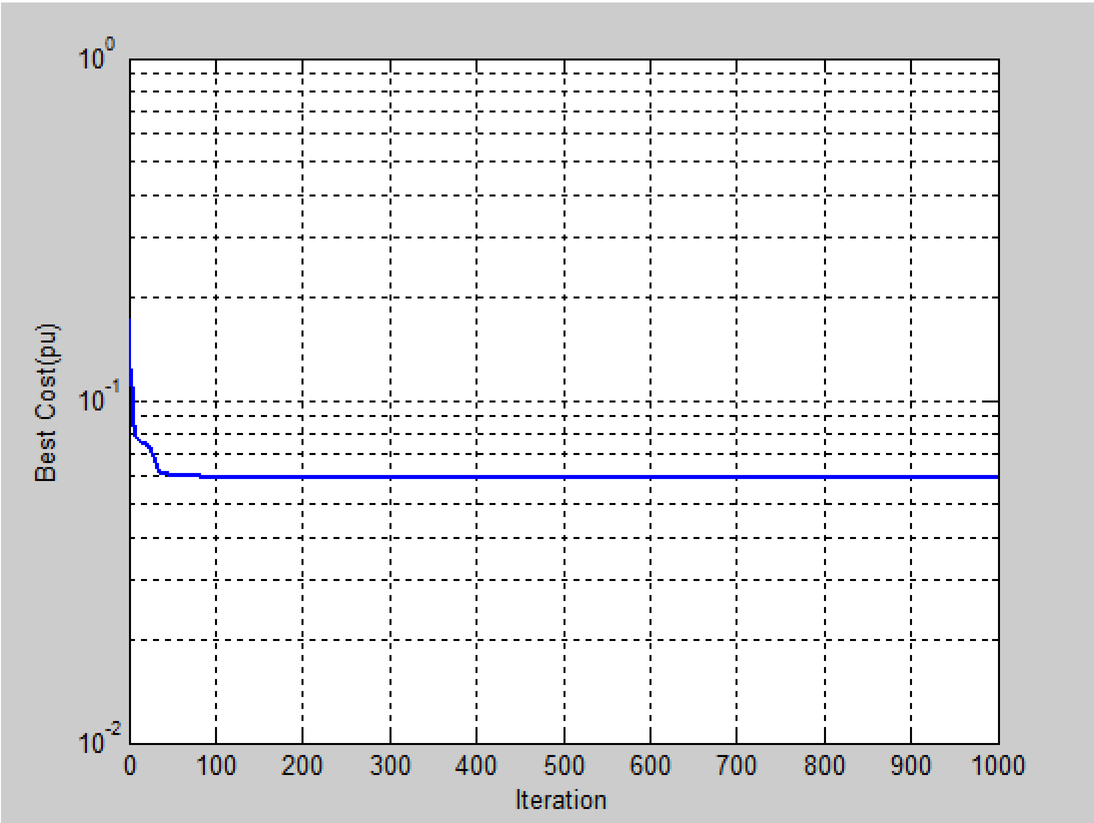

Figure 5 - Neuro-Swarm Fitness Performance under Heavy Bus Loading

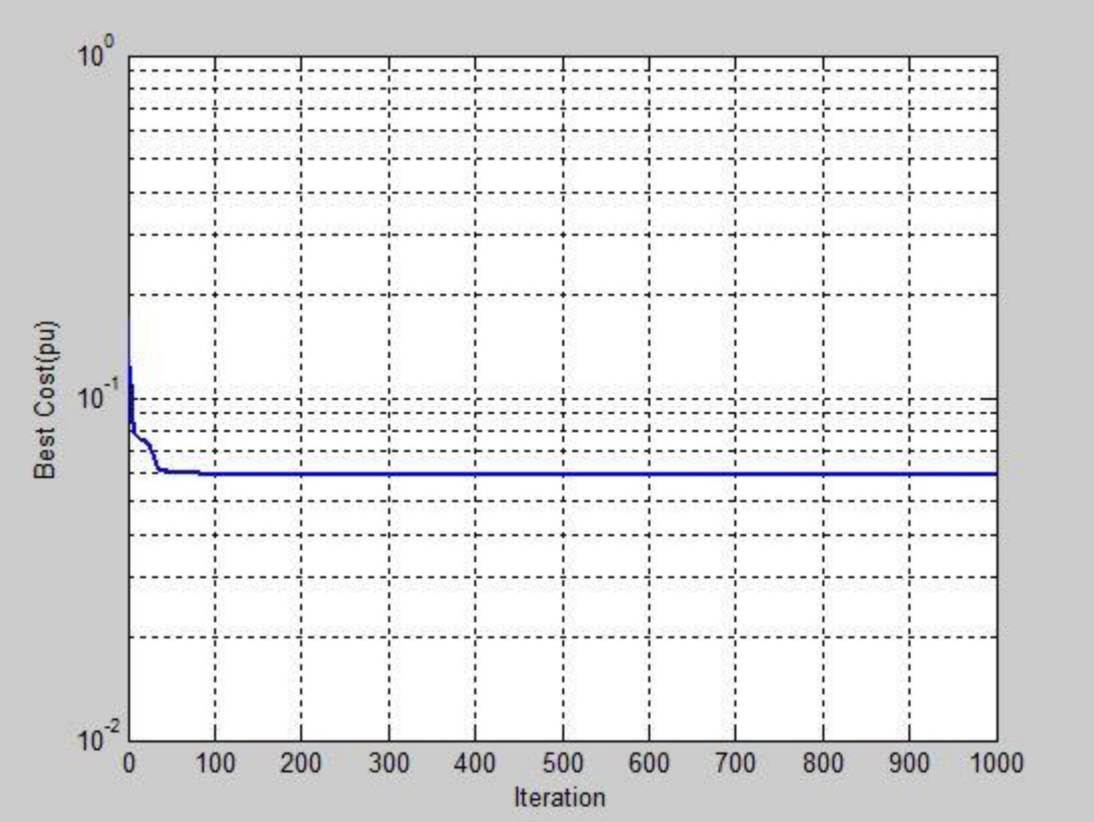

Figure 6 - Fitness Performance of the PSO under Heavy Bus Loading

Appendix 2: Parameter Tables

Table 7: Key ABC Parameters

PARAMETER/UNIT	DEFAULT VALUE
Colony Size	200
Employed bees limit trials	5000
Maximum forage cycle	4500
Parameter size	16

Table 8: Key Neural Network Parameters

PARAMETER/UNIT	DEFAULT VALUE
Neuron Size	6
Number of Training Epochs	10000
Training parameter tolerance goal	10^{-50}
Training rule	Levenberg-Marquardt
Learning rule	Gradient descent with momentum
Transfer Function (Hidden Layer)	Tan-sigmoid

Table 9:132/33kv Transformer Rating

Source: TCN, (2017).

S/N	Name	S (MVA)	Z (%)
1	T1	30	12.27
2	T2	60	10.28

Table 10: Feeder Data at 80% Power Factor

Source: PHEDC, (2017).

S/N	Feeder Name	Pmin. (MW)	Pmax. (MW)	Length (KM)
1	UST	20.8	22.3	14.2

2	Rumuolumini	10.0	13.5	22.78
3	Silverbird	15.0	18.0	4.5

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