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An Improvement of Load Flow Solution for Power System Networks using Evolutionary-Swarm Intelligence Optimizers

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Abstract:
Load flow report which reveals the existing state of the power system network under steady operating conditions, subject to certain constraints is being bedeviled by issues of accuracy and convergence. In this research, five AI-based load flow solutions classified under evolutionary-swarm intelligence optimizers are deployed for power flow studies in the 330kV, 34-bus, 38-branch section of the Nigerian transmission grid. The evolutionary-swarm optimizers used in this research consist of one evolutionary algorithm and four swarm intelligence algorithms namely; biogeography-based optimization (BBO), particle swarm optimization (PSO), spider monkey optimization (SMO), artificial bee colony optimization (ABCO) and ant colony optimization (ACO). BBO as a sole evolutionary algorithm is being configured alongside four swarm intelligence optimizers for an optimal power flow solution with the aim of performance evaluation through physical and statistical means. Assessment report upon application of these standalone algorithms on the 330kV Nigerian grid under two (accuracy and convergence) metrics produced PSO and ACO as the best-performed algorithms. Three test cases (scenarios) were adopted based on the number of iterations (100, 500, and 1000) for proper assessment of the algorithms and the results produced were validated using mean average percentage error (MAPE) with values of voltage profile created by each solution algorithm in line with the IEEE voltage regulatory standards. All algorithms proved to be good load flow solvers with distinct levels of precision and speed. While PSO and SMO produced the best and worse results for accuracy with MAPE values of 3.11% and 36.62%, ACO and PSO produced the best and worse results for convergence (computational speed) after 65 and 530 average number of iterations. Since accuracy supersedes speed from scientific considerations, PSO is the overall winner and should be cascaded with ACO for an automated hybrid swarm intelligence load flow model in future studies. Future research should consider hybridizing ACO and PSO for a more computationally efficient solution model.

Keywords: Evolutionary-Swarm, Intelligence, Power, Optimizers, Accuracy, Convergence, Comparative, Analysis

1. INTRODUCTION

Power flow studies (PFS) are a crucial component of power system analysis that have attracted a lot of interest for many years. Analysis of voltage stability, regulation, and the dependability of the power system all need it. especially in the case of a transmission or distribution system fault in the specified power network. In its most basic form, load flow analysis is figuring out or solving the power network in cases where the bus voltages, angles, or power flows (real and reactive powers) are unknown or assumed to be unknown.

Ahiakwo et al. [1] In order to construct a power system and extend an existing power system to meet rising load demand, load flow solutions provide the load nodal voltages, phase angles, power injection at all buses, and power flows across interconnecting power channels. As usual, these kinds of solutions have been looked at in the network (static) domain using well-known analytical methods like Newton-Raphson, Gauss-Seidel, and fast-decoupled methods of solutions. Power flow analysis turns into an optimization issue when the aim is to maintain a power balance by decreasing the discrepancy between actual and reactive power [2]. However, when there is heavy loading, the system's high R/X ratio and a singularity in the Jacobian matrix could make it hard for the solution found using a standard method, like Newton-Raphson [3]. Therefore, to get around the problems with the old Newton-Raphson (NR), Gauss Siedel (GS), Fast Decouple, and other non-linear solution methods, many researchers have come up with different artificial intelligence (AI) designs that work better without sacrificing accuracy.

In this study, we will focus on AI-based evolutionary techniques that are part of swarm intelligence. The goal is to use a statistical tool for a comparative analysis to find out how significant the proposed methods are at different levels of confidence. The power system under investigation is the Nigerian power grid, with a primary focus on the 330 kV transmission network. An evolutionary algorithm (EA) and four swarm intelligent (SI) optimizers will be used to diagnose the power system under study. The goal is to find out what the current state of the Nigerian grid is by looking at bus voltage magnitudes, angles, real power, reactive power, and real and reactive power losses.

The performance of the traditional load flow methods and GS was evaluated in [4], and NR performed better compared to the GS solution method, especially as bus and network complexity increased. Ghiasi did a study to compare the load flow on Tehran Metro Line 2 Newton Raphson, fast decoupling (FD), and accelerated Gauss Siedel (AGS) from ETAP 12 in order to find out how well the proposed method works. The results obtained show that NR is superior in terms of computational speed, while accelerated Guass Siedel performs best in terms of accuracy with an acceleration factor of 1.45 [5]. This researcher recommended that future researchers develop more sophisticated power flow algorithms.

Araujo et al. [6] conducted a comparative study between the Newton-Raphson-based method and the backward sweep method for tide studies. These two of his methods were compared in terms of changes in X/R ratio, load ramps up to the convergence limit, impact on the load model, and impact on voltage regulator modeling. Both methods were tested on 34- and 134-bus systems, and the results showed that the Newton-Raphson-based model converged strongly and increased the number of iterations minimally. In contrast, the backward-forward sweep (BFS) led to a significant increase in the number of iterations. It increases the number of iterations and computation time. The NR-based method showed better computational quality in handling voltage regulators with a shorter computational time. Nevertheless, the BFS performed better than the NR-based model at high loads. Considering network complexity and size, NR provided a better solution than solving highly meshed networks.

Djalal et al. [7] in the presence of renewable power plants in the Sulselrabar system, NR was deployed on the ETAP premise for power flow studies and power system analysis to solve the lingering power issues in the region. Zdiri et al. [8] surveyed to find solutions to the radial distribution networks' wide range of resistance and reactance ratios-related bottlenecks with traditional NR and GS methods. The authors deployed an AI-based iterative method for power flow analysis and impact assessment of a photovoltaic system in a radial grid.

Tostado-veliz et al. [9] proposed and implemented a new Runge-Kutta method for tide studies. The explicit Heun method and the embedded Heun-Euler method that were suggested were used, and the simulation results that were looked at showed that they were robust and converged quickly. In their paper, they recommended that future work be directed toward verifying their claims by comparing the effectiveness of the proposed method with other optimal power flow algorithms. Guevara et al. [10] modeled a microgrid and performed a power flow analysis with ETAP to determine the system state. Power flows were run on a microgrid modeled using adaptive NR, and the results were compared with real-time figures.

Rulivanta et al. [11] explored capacitor placement as a tool to control voltage profiles and reduce power losses in ETAP using one of the traditional load flow solver methods to determine the existing and improved conditions of the distribution network.

Also, Hussain et al. [12] explored power flow analysis in the smart grid domain as an alternative to conventional power grids. Abirami and Ravi [13] looked at load flow in a 10-bus loop distribution network with and without automatic voltage regulators (AVRs) and power system stabilizers (PSS) to determine voltage stability. Hussain et al. [14] in an attempt to improve the voltage profile and reliability of a 132/11 kV substation power system, authors used one of ETAP's load flow solvers and evaluated the performance of the system with and without capacitors.

Hiwarkar et al. [15] used the IEEE 14 bus network as a test case to test the effectiveness of the Newton Raphson (NR) method to relax the Guass Siedel (GS) limitation. All algorithms modeled and evaluated in MATLAB confirmed the success of NR and GS in large-scale systems. Chowdhury et al. [16] used ETAP load flow analysis software's adaptive NR to redesign a 2500 kVA, 11/0.4 kV substation. The goal was to make the voltage profile and power flow in the network better.

Sharma et al. [17] performed a power flow analysis in a static radial distribution network using graphic theory. The results obtained after testing on two different static, radially distributed networks showed faster computation with minimal complexity. Egoigwe et al. [18] as part of their research on improving power flow control using phase-shifting transformers, to determine the state of his IEEE 5 bus network before and after the improvement, they gave a power flow study in a MATLAB environment to NR. Hawas et al. [19] simulated and analyzed distributed photovoltaic systems with DigSILENT.

Samuel et al. [20] conducted a study using his 330-kV power grid in Nigeria with IEEE 14 and 28 buses as a test case. In their study, an artificial neural network (ANN) was used for tide studies, and the results were validated using conventional NR techniques. The performance is efficient with minimal error compared to the results obtained with NR. Remha et al. [21] employed the weight sum method-based bat algorithm (BA) to handle multi-objective optimization issues. The suggested method may optimize the voltage stability index and reduce total active power loss, according to test findings on common IEEE 12-bus, 33-bus, 69-bus, and 85-bus power feeds.

To find the stress-stable loading range, Dong et al. [22] suggested using a better continuous power flow (CPF) model connected through coordinate transformation with a particle swarm optimization (PSO) method based on evolutionary mechanisms. In order to attain high performance, parallel processing is also employed in programming. The suggested approach may provide values for the load margin problem with excellent accuracy and reliability, according to tests on an IEEE 14 bus test system. An artificial neural network with a dynamic radial basis function was presented in [23]. The findings show that both radial and poorly-conditioned networks with high R/X ratio values may be successfully applied using the suggested strategy. Additionally, using it to test a variety of power and distribution systems and comparing the results with those of other load flow techniques helped to confirm this method's dependability, accuracy, robustness, and efficiency.

Sa'ed et al. [24] proposed and implemented analytical tools for optimal sizing, mapping, and dissemination of distribution generation (DG) using 12, 33, and 69 buses as test cases. The results obtained were judged satisfactory in a validation report using the improved analysis (IA) and PSO methods. Sur et al. [25] used a modified set theory-centric approach to the analysis of unbalanced tidal currents. The proposed method has been tested using standard 10-bus, IEEE 13 and 123 three-phase single-ended radial networks, and IEEE 28-bus balanced radial systems. The performance of the algorithms used showed superior computational speed and convergence compared to traditional BFS and BIS.

Artale et al. [26] proposed a virtual tool for tide research in microgrid systems. The made-up algorithm is based on a reverse forward sweep load flow analysis method and was proven to work by measuring voltage and current at the start of a medium voltage (MV) injection. To improve computational efficiency by identifying and eliminating irrelevant iterative loops, Verma and Sarkar [27] proposed a forward-backward sweep for distribution network power flow analysis by integrating distributed generation and transformers.

Veerasamy et al. [28] developed a generalized Hopfield neural network (HNN) for power flow analysis in a MATLAB environment. The proposed algorithm was tested using 3-bus and 5-bus networks, and the results after evaluation were judged to be superior to conventional NR in terms of computation time and accuracy.

Abdullah et al. [29] In their work, they describe four optimization algorithms inspired by nature, namely the genetic algorithm (GA), differential evolution (DE), flower pollination algorithm (FPA), locust optimization algorithm (GOA), and cascaded imperial competition algorithm (ICA). To achieve the goal of achieving the optimal tidal flow solution for the island microgrid through statistical evaluation by SPSS software, we used about four hybrid algorithms and performed F- and T-tests to select the most important solution algorithm. The imperialistic competitive differential extension works better with fewer iterations and faster computation times, as shown by the test results for the 6-bus and IEEE 37-bus.

Fikri et al. [30] compared the results of deterministic methods and artificial intelligence-based neural networks for load flow calculation. The results obtained after the simulation showed a higher accuracy of NR compared to GS and ANN. ANN outperformed GS and NR in terms of computational speed. Ahiakwo et al. [1] used artificial swarm intelligence technology for honeybee colonies developed by Karaboga [31] to provide an optimized load current solution for the Zone 4 distribution network of Port Harcourt Electricity Distribution Company (PHEDC) in the Port Harcourt section of his 132-kV transmission network in Nigeria, Jagun et al. [32] employed a similar strategy.

Huynh et al. [33] proposed and implemented a probabilistic approach for power flow studies in IEEE 118 bus networks. The hybrid solution used in this study combined principal component analysis and differential expansion (DE), and the results were compared with Monte Carlo simulations. Alanazi et al. [34] proposed a new adaptive Gaussian taught-learning-based optimization method (AGTLPO) for solving non-convexity-related power flow problems. Twelve different scenarios were created from three IEEE standard 30, 57, and 118 test bus systems. The results obtained with the proposed method proved to be more efficient than the usual TLPO algorithm in all 12 scenarios.

Khunkitti et al. [35] In their research, they proposed the Multi-Objective Marine Predator Algorithm (MaMPA) as a solution for solving single-, multiple-, and multi-objective optimal power flow problems. In their study, they defined multi-objectives as two to three research objectives, and multi-objectives as three or more research objectives. Objectives to consider include cost, emissions, voltage stability index, transmission losses, and more. The algorithms were tested on IEEE 30 and 118 test bus systems to see how well they worked. Compared to the algorithms in the review, they did the best on single, multiple, and multiple target problems.

Previously, Khunkitti et al. [36] surveyed optimal power flow studies. In their research, they combined the advantages of two swarm intelligence techniques to arrive at an optimal solution to the flow problem. To get the best power flow over IEEE 30 and 57 bus networks, the Dragon Fly algorithm (DA) and particle swarm optimization (PSO) were put together to make a hybrid solution. Test results after the successful application of the proposed hybrid solution yielded higher accuracy with longer computation time compared to standalone attributes of DA and PSO.

Taher et al. [37] considered an improved Moth Flame Optimization (IMFO) algorithm as a possible solution to the optimal power flow problem. The IMFO algorithm is inspired by mimicking the motion of moths toward the moon and has been implemented in single and multi-target power flow solutions using 30, 57, and 118 test bus systems.

The results obtained after simulation confirm that IMFO is a robust and efficient power flow-solving algorithm. EMFO is better than other standalone power flow algorithms they looked at in their study, as shown by the fact that it converges quickly. Riaz et al. [38] used the Hybrid Particle Swarm Gray Wolf Optimizer (HPS-GWO) algorithm for optimal power flow through the integration of renewable energy sources. The algorithm was tested on a modified IEEE 30 bus system with the goal of improving the convergence rate, minimizing generation costs and emissions, and optimizing the power flow. Simulation results highlight the success of HPS-GWO in all three goals compared to the separate performances of the PSO and GWO algorithms. Nusair and Alhmoud [39] developed and implemented a balanced optimization algorithm to optimize energy flow with the integration of renewable energy sources. The test results of the simulation report show the superiority of the proposed algorithm compared to other independent solutions.

Calasan et al. [40] in their study found an optimized current solution through the application of the CONOPT solver in the General Algebraic Modeling System (GAMS) software. Conventional and improved IEEE 30 bus systems are used to evaluate the test performance, and the results show that the proposed algorithms are optimally effective in solving current problems, minimizing losses. transmission loss and improve the profile and stability index. Nadimi-Shahraki et al. [41] used IEEE standard 14, 30, 39, 57, and 118 test bus systems to do single- and multi-objective optimal power flow analysis on standard 14, 30, 39, 57, and 118 test bus systems. hybrid moth flame optimization algorithm (WMFOA) of the algorithm. The performance results of the twin algorithm and some hybrid and independent methods confirm the superiority of the proposed algorithm. The combination of the two algorithms solved the problem of early convergence, leading to a high-quality solution. Maru and Padma [42] evaluated the performance of three current analysis algorithms with and without a STATCOM device. Teaching-learning-based optimization (TLBO) and the Jaya algorithm were used to validate the power of the proposed multi-population-based variable Jaya algorithm (MPMJ). The proposed algorithm has good and impressive computational performance, outperforming the TLBO and Jaya algorithms after simulation. Moreover, the algorithm provides a fast convergence solution and optimal power flow.

Sayed et al. [43] show how well the Moth Swarm Algorithm (MSA) works by using it on the IEEE 30 bus network to look at current, lower load, and find the best way to assign generated devices. by Thyristor Controlled Series Capacitors (TCSC). Validate the robustness of the algorithm based on comparison with other optimization algorithms such as Gray Wolf Optimization (GWO), Whale Optimization (WO), Particle Swarm Optimization (PSO), teach-and-learn based optimization (TLBO), and Butterfly Flame Optimizer (MFO).

Nusair et al. [44] used four nature-inspired automatic optimization algorithms for power flow resolution and FACT device allocation. Slime Mold Algorithm (SMA), Marine Predator Algorithm (MPA), Artificial Ecosystem-Based Optimization (AEO), and Jellyfish Search (JS) were used to obtain the solution energy throughput method using the IEEE 30 bus test system. The results obtained by comparing the proposed methods with particle swarm optimization (PSO) gave optimal results. The value of the voltage drops obtained with the AEO will be at least 27% of the value obtained with the PSO. Sallam et al. [45] conducted a study to evaluate the computing power of a modified version of the Differential Evolution (DE) algorithm called the Multi-Operator Differential Evolution algorithm. (MODE). This algorithm has been tested using IEEE 30 and 118 bus systems to support single-target and multi-target current problems. The comparative results claimed by the authors place the proposed algorithm ahead of its contemporaries due to the degree of optimization results produced in the presence of renewable energy sources.

Abdi et al. [46] looked at how well four hybrid metadata algorithms solved the problems of finding the best power flow and reactive power distribution in the network. IEEE 30 and 57 buses. Differential Evolution with Orthogonal Interference (OECD), Hybrid Gray Wolf Particle Swarm Optimization (HGWPSO), the Cosine Sine Algorithm (SCA), and the Hybrid PSO and GA (HPSO-GA) are the four algorithms that were looked at in this study. Based on simulation results, SCA is computationally inefficient for large and complex networks, while efficient and accurate hybrid methods are based on benchmark reports.

Muppidi et al. [47] presented the effectiveness of Fast Voltage Stability Index optimization techniques and the Gray Wolf Algorithm (GWA) to improve current solutions through cost optimization. fuel cost, and line load capacity. The test of the proposed algorithm by simulation on the IEEE 30 bus network is performed in a MATLAB environment.

Saddique et al. [48] conducted a comparative analysis of four meta-methods based on evolution to achieve optimal power current and optimal reactive power distribution. IEEE 14, 30, and 57 bus networks were used as case studies to test the proposed algorithms. The algorithms considered by the authors are the sine-cosine algorithm (SCA), differential evolution (DE), particle swarm optimization (PSO), and whale optimization (WO). The simulation results on MATLAB show that the performance of SCA is superior to that of other algorithms in all scenarios.

Abdo et al. [49] implemented a modified gray wolf optimizer (GWO) called gray wolf optimizer, developed to solve the problem of nonlinear currents. Using a 30-bus network, the proposed algorithm was implemented and compared with other metadata algorithms, especially GWO, to evaluate the performance and appearance of the optimized current solution.

Layth et al. [50] considered the need to apply an improved model of the differential algorithm for optimal energy solutions. In their study, an improved Differential Evolution (IDE) algorithm was developed and tested on an IEEE 30 bus network to evaluate its performance. The investigative report derived from the 1EEE 30 bus simulation using the developed algorithm shows high convergence characteristics compared with other algorithms considered in the literature.

Pandya and Jariwala [51] solved optimal current problems in hybrid power systems using Weibull probability distribution and butterfly flame optimization (MFO). The IEEE 30 bus network, which is a combination of traditional power plants and renewable energy sources, is used as a case study for algorithm simulation and performance evaluation.

Mezhoud et al. [52] proposed and implemented a wind turbine optimization algorithm (WDO) to solve optimal current problems. The proposed algorithm, compared with other optimization algorithms in this study, is effective with high convergence and reliability. The validation report was generated using IEEE 30 and 57 bus networks as case studies. The fractional order particle swarm optimization (FO-PSO) method was suggested by Khan et al. [53] as the best way to coordinate the current and reactive power. Standard IEEE 30 and 57 buses were used as test cases to see how well single-target and multi-objective FO-PSO algorithms worked. The results reported by the authors demonstrate the effectiveness of FIFO-PSO in providing a solution to the optimal reactive power distribution problem.

Also, Jamal et al. [54] implemented a nature-inspired meta-empirical algorithm called Gray Wolf Optimization (GWO) as a solution to power distribution problems related to reactance and optimal current. In addition, using a 30-bus test system as a case study, the proposed algorithm was tested for performance analysis and evaluation. The results, as inferred from the simulation scenarios, confirm the robustness and efficiency of the GWO algorithm.

Shaheen et al. [55] By solving the nonlinear optimal current problem with emission, we proposed a modified crow search optimization (MCSO) algorithm. This modification is a combination of the crow search optimizer (CSO) and the new bat algorithm (NBA) to improve current solutions for one or more targets. IEEE 30 bus, I18 bus, and West Delta grid were used to test the performance of the algorithm, and the results were very promising and confirmed the effectiveness of MCS.

Sarhan et al. [56] have implemented an improved version of teaching-learning-based optimization (TLBO) for single- and multi-objective optimal current problems.

Nadimi-Shahraki et al. [57] used a combination of super-experience combining the efficient whale optimization algorithm (EWOA) and particle swarm optimization (PSO) to solve the flow problems. electricity. The EWOA-PSO super experience has been applied to solve current problems in small, medium, and large power system networks contained in the IEEE standard library. The analytical results of the simulation show the success of the hybrid algorithm in providing solutions to functional problems with one or more objectives.

Jumani et al. [58] provided a solution to current problems by implementing an AI-based optimizer called the Grasshopper Optimization Algorithm (GOA). GOA has been used in the grid-tied microgrid system to optimize the current controller, and the results obtained using the proposed algorithm are consistent with the PSO results.

Attia et al. [59] to propose the optimal power flow solution, proposed using a modified sine cosine algorithm (MSCA). The result of applying the proposed method to IEEE standard and medium-bus systems corresponds to the solutions of other algorithms in the document. MSCA is said to be simple and powerful to solve optimal power flow (OPFP) problems with high computational speed compared to SCA.

Sarhan et al. [60] suggested a new way to look at the economic and technical problems that arise when water flows are changed, which they called perturbation-based optimization (TOWBO). The robustness and efficiency of the algorithm have been tested on 30 and 57 buses, considering the convergence speed and quality of the solution compared to other optimization algorithms included in the literature. Ezeruigbo et al. [61] and Abdulkareem et al. [62] misrepresented the 330 kV Nigerian grid in their separate research publications in reputable journals. In their submission, generators were designed to operate on 330 kV in the Nigerian grid, which is wrong and misleading.

In this paper, the efficacy of five standalone evolutionary-swarm intelligence algorithms will be compared on the basis of speed and accuracy for improved power flow study and to correctly remodel the 330 kV, 34-bus transmission network.

II. METHODOLOGY

Materials used for executing this research are single line diagram, transmission line data, MATLAB, ETAP etc. All materials used were duly collated in compliance with relevant IEEE standards from [61-63] and Transmission Company of Nigeria (TCN). The corrected single-line diagram of the 34 bus, 38 branches, 330kV Nigerian grid network is contained in Figure 1, with the replacement of generators with power grids rated in MVA_{SC}.

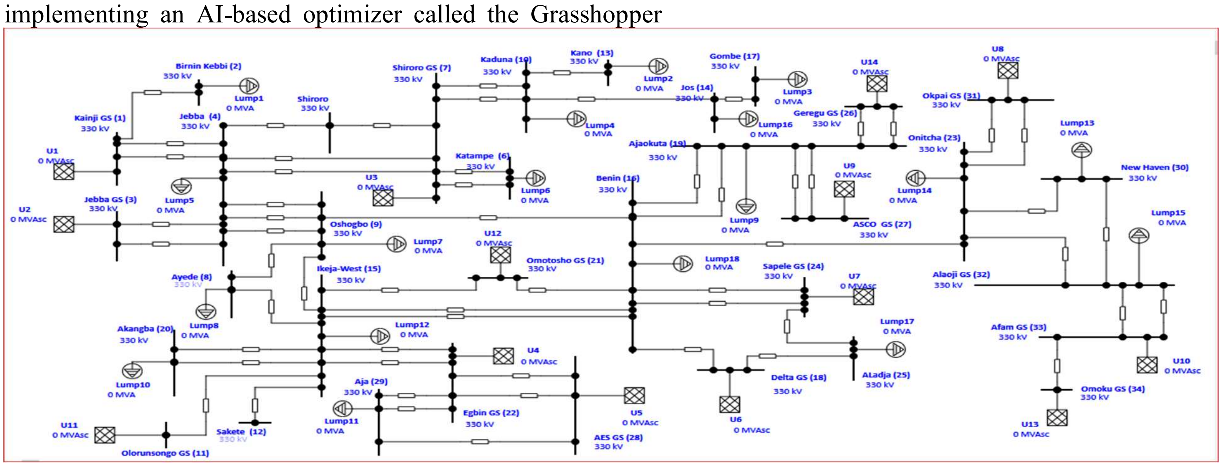

Figure 1: Single Line Diagram of the 34-Bus Section of the Nigerian Grid [61-63]

Methods

Nodal Voltage Analysis

The power grid's input current at bus i is represented as;
$I_i = Y_{i1}V_1 + Y_{i2}V_2 + .. + Y_{ik}V_K = \sum_{i,k=1}^{n} Y_{ik} V_k$ (1)
The voltage and admittance will be given as follows, taking magnitude and phase angle into account:
$V_k = V_K \angle \delta_k$ (2)
$Y_{ik} = Y_{ik} \angle \theta_{ik}$ (3)
Substitute equations (2) and (3) into equation (1)
$I_i = \sum_{i,k=1}^{n} Y_{ik} \angle \theta_{ik} V_k \angle \delta_k$ (4)
δ_i, δ_k are the phase angles of buses i and k, and θ_{ik} is the angle separating buses i and k.
the current injection at bus i's conjugate will be;
$I_i^* = \sum_{i,k=1}^{n} Y_{ik} \angle -\theta_{ik} V_k \angle -\delta_k$ (5)
Apparent power available at bus i will be;
$S_i = V_i I_i^* = P_i + jQ_i$ (6)
Substitute equation (5) into equation (6), considering the magnitude and angle of V_i
we have;
$P_i + jQ_i = V_i \angle \delta_i \sum_{i,k=1}^{n} Y_{ik} \angle -\theta_{ik} V_k \angle -\delta_k$ (7)
Rearranging equation (7) gives;
$P_i + jQ_i = \sum_{i,k=1}^{n} Y_{ik} V_i V_k \angle (-\theta_{ik} + \delta_i - \delta_k)$ (8)
But,
$\delta_{ik} = \delta_i - \delta_k$ (9)
$-\theta_{ik} = \theta_{ki}$ (10)
Substitute 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)
From equations (12) and (13) the mismatch power equation is deduced as contained in equations (14) and (15).
$\Delta P_i = \left| P_i^{sp} - P_i^{cal} \right|$ (14)
where,
P_i^{sp}= the actual active power at bus i
P_i^{cal}= the predicted active power at bus i
Similarly, the reactive power mismatch 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, and
Q_i^{sp}= the computed reactive bus powers at power
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)
Optimization in this research is to minimize voltage drop and power loss using the objective function expressed in equation 18 as a product of equations 16 and 17.
$F_{min.\ objective} = \sqrt{\Delta P_{net} + \Delta Q_{net}}$ (18)

Evolutionary Algorithm (EA)

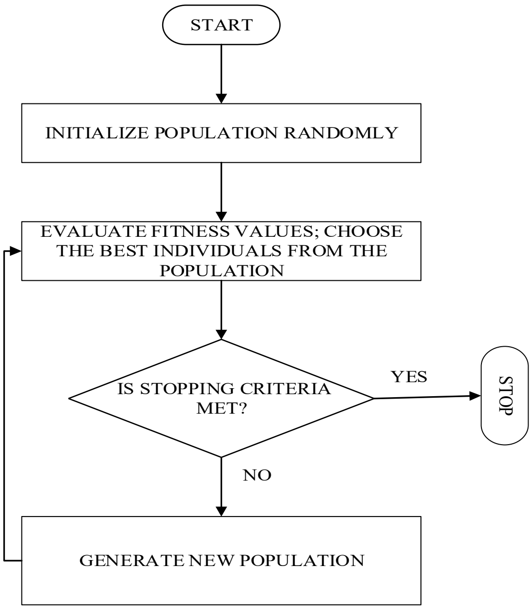

Figure 2: Procedural Framework of Evolutionary Algorithms (EA) [64]

Swarm Intelligence Optimizers (SIO)

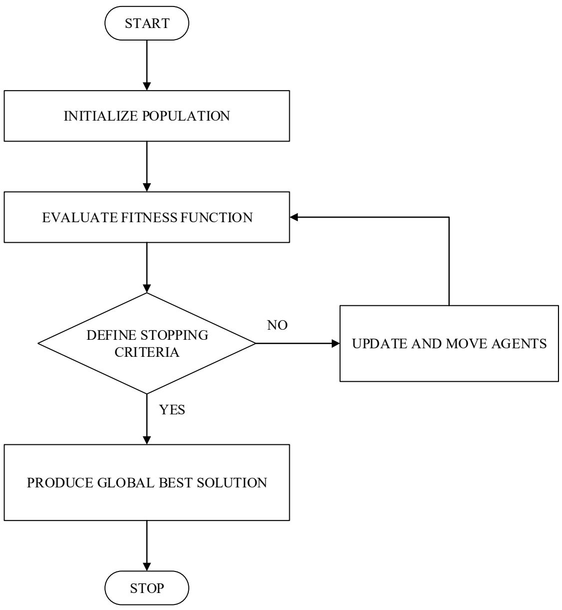

Figure 3: Procedural Framework of Swarm Intelligence Algorithm [65]

Mean Absolute Percentage Error (MAPE)

As a means of validation, MAPE is used for confirmation of results using the voltage magnitude result as reference. Mathematically, the statistical error or accuracy measurement tool can be modified to accommodate power flow parameters as;

$$MAPE = \log_{10} 10^{\frac{1}{N}} \sum_{i=1}^{N} \frac{|V_A - V_C|}{V_A} \times 100 \quad (19)$$

Where;
N is the total number of buses or busbars
V_A is the actual voltage magnitude at each bus in pu
V_C is the calculated or computed voltage magnitude at each bus in pu

III. RESULTS AND DISCUSSION

Simulation results emanating from the 34-bus, 38-branch section of the Nigerian 330kV power grid are presented and discussed in this section. All results presented for the various load flow parameters for the five swarm and evolutionary-based algorithms are done using histograms and graphs. All load flow solution algorithms were simulated in incremental steps of 5, starting from 100 to 1000 iterations for effective comparison.

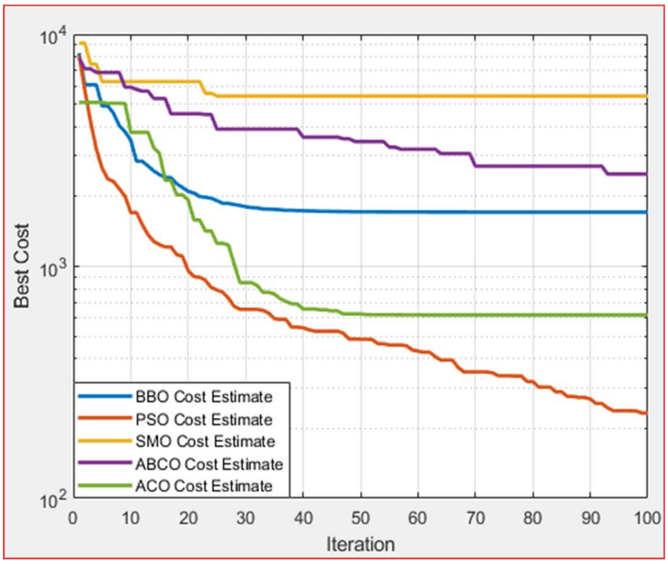

Figure 4: Best Cost (Fitness) of Algorithms in 100 Iterations

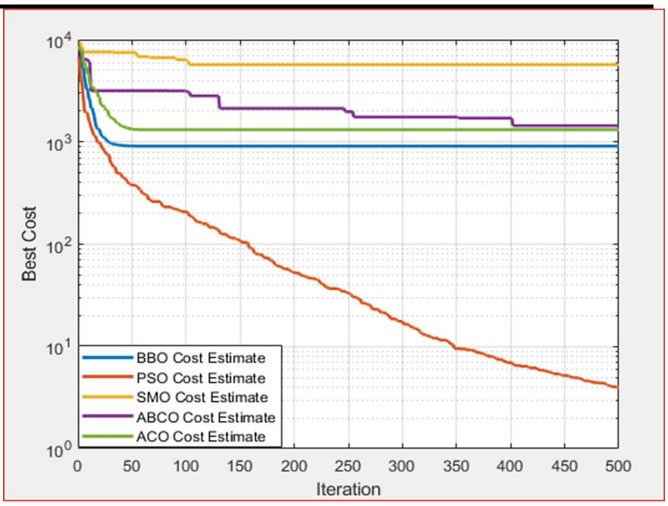

Figure 5: Best Cost (Fitness) of Algorithms in 500 Iterations

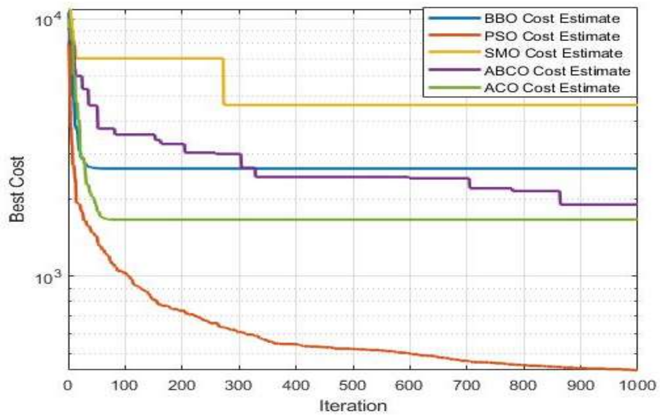

Figure 6: Best Cost (Fitness) of Algorithms in 1000 Iterations

From the results in figures 4, 5, and 6, the best cost estimate, which can be translated to the minimum cost or minimum power mismatch between the real and reactive power, is produced by PSO in all test cases. For all three sets of iterations, PSO and SMO were consistent in their positions, with PSO coming out on top and SMO maintaining the least position. The results produced by PSO were recorded as 124.39, 3.72, and 11.80 kVA for 100, 500, and 1000 iterations as best, while results produced by SMO in similar conditions were recorded as 5965.95, 5490.00 and 4779.29 kVA as worse.

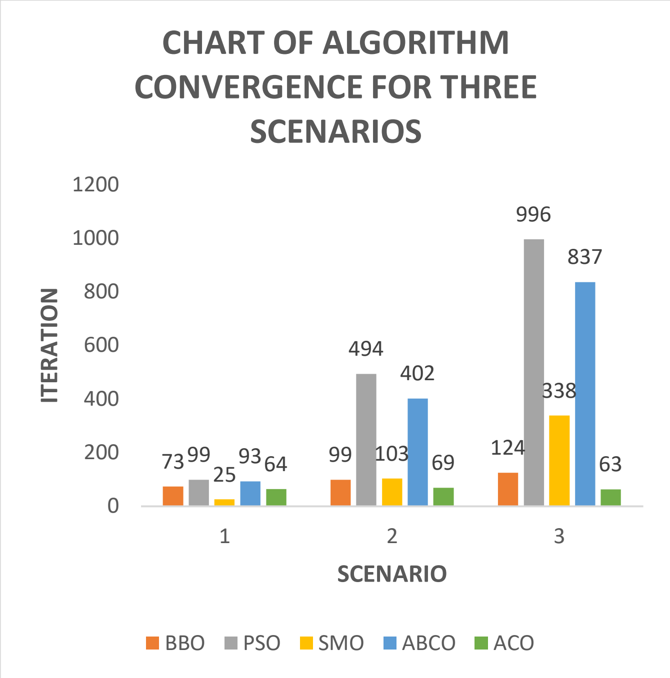

Figure 7: Algorithm Convergence Index for Three Test Cases

In Figure 7, for 100 iterations, SMO converged after 25 iterations followed by ACO, BBO, ABCO and PSO with the following number of iterations; 64, 73, 93 and 99. For 500 iterations, ACO converged after 69 iterations followed by BBO, SMO, ABCO and PSO with the following number of iterations; 99,103, 402 and 494. Finally, for 1000 iterations, ACO maintained its lead with an early convergence after 63 iterations followed by BBO, SMO, ABCO and PSO with the following number of iterations; 124, 338, 837 and 996.

Summarily, from the convergence result in all three scenarios, ACO produced the best result twice making it computationally faster than the other algorithms. The other algorithms queued behind ACO repeating their positions in test case 2 (500 iterations) and 3 (1000 iterations).

4.1 Validation

Table 3: MAPE Result from Bus Voltage Magnitude Evaluation

Iter.	BBO (%)	PSO (%)	SMO (%)	ABCO (%)	ACO (%)
100	24.11	10.58	29.97	24.95	18.07
500	22.27	3.11	36.62	16.87	21.67
1000	24.54	3.12	26.05	15.21	24.39

Based on the simulation results shown in Table 3 for 100 iterations, PSO came out on top with the least mean absolute percentage error (power mismatch) value of 10.58%. ACO, BBO, ABCO, and SMO came in second through fourth with the following MAPE values: 18.07%, 24.11%, 24.95%, and 29.97%, respectively. In test case two, for a maximum iteration of 500, PSO still maintained its lead in the top spot with a better MAPE value compared to the former produced under 100 iterations. In this test case, the performance of three out of five algorithms improved.

The result of the algorithms based on the performance or credibility of the solution are arranged in order of relevance from first to last as PSO, ABCO, ACO, BBO, and SMO with the following MAPE values; 3.11%, 16.87%, 21.67%, 22.27%, and 36.62% respectively. For 1000 iterations, two out of the five algorithms proved better in performance compared to the results obtained in the last test scenario. From the data in Table 3, PSO and SMO maintained their top and last spots with MAPE values of 3.12% and 26.05% respectively.

Summarily, the best and worst MAPE values for BBO were derived from 500 and 1000 iterations, while PSO and ABCO produced their best and worst results at 500 and 1000 iterations. SMO's best and worst result was produced in 1000 and 500 iterations, while ACO produced its best and worst in 100 and 1000 iterations.

From the results of success and failures in the last paragraph, the best test case for all algorithms should be pegged at 500 iterations as its probability of producing a worse result is 1/5 compared to 100 and 1000 iterative test cases having probabilities of 2/5 respectively. With PSO and SMO being the overall winner and loser in all three test cases, these positions remained unchanged as the best test case result is presented graphically in Figure 8.

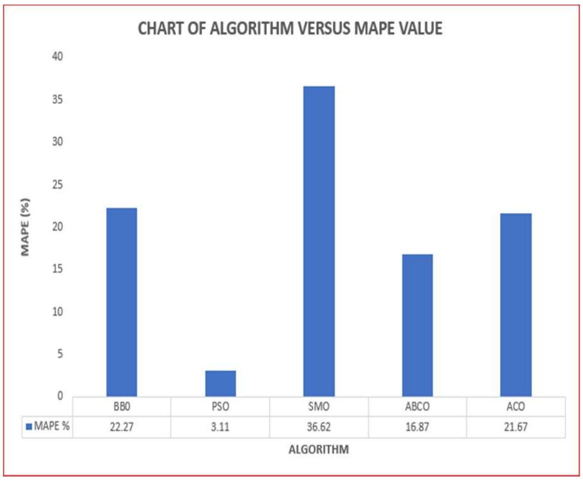

Figure 8: MAPE Result for Best Test Case (500 Iteration)

For convergence, the computational speed of the algorithms is evaluated by taking the mean result from the three test cases. The algorithm with the least and highest mean value will be considered the quickest and slowest algorithm, as contained in Figure 9. From the chart in Figure 9, considering an average number of iterations as a tool for performance validation, ACO converged earliest with the least average number of iterations, followed by BBO, SMO, ABCO, and PSO.

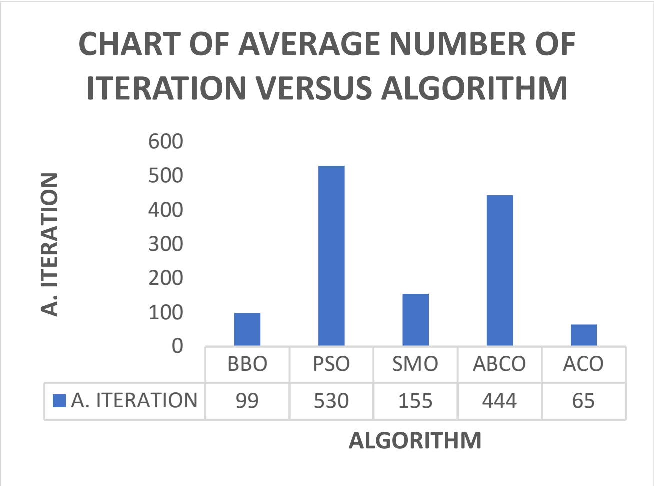

Figure 9: Algorithm Convergence Report for Performance Validation

IV. CONCLUSION

Five evolutionary-swarm intelligence algorithms are being used to diagnose the 34-bus, 38-branch, 330kV Nigerian transmission grid. The goal is to find the best algorithm based on accuracy and convergence rate (speed). Among the five AI-based computational metaheuristics applied to solve the non-linear power flow equation are BBO, PSO, SMO, ABCO, and ACO. Pre- and post-validation results after simulation using three test case iterative (100, 500, and 1000) scenarios identified PSO and ACO as the best-performed algorithms, with the former being the best in accuracy and the latter being the best in speed. On the contrary, analytical and statistical results spotted SMO and PSO as the worse-performed algorithms in terms of accuracy and speed. Though all algorithms provided good load flow solutions, the accuracy of the PSO, as validated by the MAPE value, is enormous and incomparable with the speed offered by ACO; hence, the PSO is the overall winner amongst the five algorithms.

Declaration of Competing Interest

All authors declare that there is no conflict of interest

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