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Application of Swarm Intelligence Approach for Improved Power System Diagnosis

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ABSTRACT

This paper seeks to proffer an optimal power flow solution to the non-linear Euler-based load flow equations. Three Swarm intelligence (SI) optimization algorithms, namely, spider monkey (SM), artificial bee colony (ABC) and ant colony (AC) are used for optimal power flow diagnosis of the 330kV Nigerian transmission grid network. All algorithms are modeled and simulated in MATLAB environment. The results after simulation for 100 iterations revealed the strengths and weaknesses of the three algorithms. The power mismatch (error) value produced by SMO, ABCO, and ACO are 5420.94, 2499.35 and 616.72kVA, respectively, after 25, 93 and 64 iterations. Evidently, the results have shown the superiority of ACO over ABCO and SMO in accurately solving the non-linear load flow equations with a minimal error value. Future researchers should consider leveraging the strengths of ACO and SMO for an automated power flow solution.

KEYWORDS: Accuracy, AI-based, Convergence, Speed, Traditional.

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1.0 INTRODUCTION

Power system diagnosis is a vital study prior to any other study conducted on the power system, as it reveals the current state of the power network under normal and abnormal conditions. Certain parameters, such as bus voltage and angular magnitudes, are key when observing the behavior of a power system, as they largely influence the behavioral patterns of other network parameters. Load flow analysis has garnered significant attention in both historical and contemporary contexts. This attention stems from its application in several areas, such as power system design, expansion, and fault analysis and mitigation. Both conventional and artificial intelligence (AI) methodologies have been utilized to address the non-linear load flow equations, with the primary objective of enhancing both accuracy and computational efficiency. The study conducted by Cheruku *et al.* (2017) utilized the SMO-based rule mining approach to attain a diabetes prediction accuracy of 87%.

Again, Irshad *et al.* (2023) introduced a hybrid model by cascading rain forest and spider monkey optimization for patient monitoring and diagnosis through health care data collection and pattern prediction. The performance of the proposed hybrid model shows higher accuracy when compared with traditional statistically inclined methods.

The study conducted by Kumar *et al.* (2022) employed an autonomic resource provision and scheduling (ARPS) approach in conjunction with the Sequential Minimal Optimization (SMO) algorithm to optimize performance and energy usage inside a cloudSim framework. The speed outcome demonstrated the efficacy of the Sequential Minimal Optimization (SMO) algorithm in comparison to other algorithms examined in the study. Otuom *et al.* (2019) combined a deep-stacked polynomial network with SMO for intrusion detection. Again, the computational speed of SMO was adjudged to be better than other algorithms compared in the research. Kaushal *et al.* (2022) proposed a combination of the kernel homophone two-fish encryption algorithm (KHTEA) and exponential Boolean spider monkey optimization (EBSMO) for improving the security of an IoT (internet of things) network.

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The speed of SMO was leveraged with KHTEA for an optimized security network system.

Abu-Mouti and El-Hawary (2011) used the ABCO technique for distributed generation sizing and placement in an IEEE 69-bus network. In their findings, the robustness of ABCO for prediction and allotment was showcased. The studies conducted by Sumpavakup *et al.* (2010) and Ahgajan *et al.* (2021) utilized the ABCO algorithm in conjunction with other artificial intelligence (AI) algorithms to achieve optimal power flow solutions in various power networks. The findings of the study demonstrated the superior computing capabilities of ABCO in comparison to other AI-based algorithms examined in their research. Subramanian *et al.* (2013) conducted a comparative analysis of the ABCO technique and a modified firefly algorithm to effectively tackle the challenges associated with economic dispatch inside power networks. ABCO exhibited a higher level of precision in comparison to the Firefly algorithm, as indicated by the findings of their study.

Mouassa and Bouktir (2015) used ABCO for discrete optimal reactive power flow problems in IEEE 14, 30, and 57 bus test systems. Again, Mouassa and Bouktir (2017) used ABCO for solving economic dispatch problems with non-convex cost functions. The outcomes of both studies show a high level of accuracy and average computational speed for ABCO. Doung *et al.* (2019) deployed biogeography-based optimization (BBO) and compared its outcome with ABCO for optimal placement and sizing of photovoltaic generating units in distribution networks. Results obtained using both algorithms highlight the strength of ABCO in terms of accuracy compared to BBO.

Bingul and Karahan (2018) used PSO and ABCO for tuning different controllers for integrating systems with time delays. The strengths of both algorithms were revealed, with PSO being better in accuracy and ABCO being better in computational speed. Abdillah *et al.* (2020) employed the Artificial Bee Colony Optimization (ABCO) method in conjunction with Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) to achieve optimal sizing and positioning of static capacitor banks. The objective of this approach was to enhance the voltage profile. The findings of their study demonstrated the superior speed efficiency of the genetic algorithm (GA) in comparison to the artificial bee colony optimization (ABCO) and particle swarm optimization (PSO) techniques. Amin *et al.* (2021) deployed a modified ABCO for power loss minimization in an IEEE 30-bus test system. Results obtained using the modified ABCO show better accuracy and speed compared to ABCO.

Again, Agrawal *et al.* (2019) deployed ABC for optimal location and sizing of static var compensators (SVC) in IEEE 14 and 30-bus systems. Results obtained using the proposed algorithm were compared with results from other metaheuristics like PSO and teaching learning-based optimization (TLBO). Karakonstantis and Vlachos (2015) considered ACO as a tool for solving economic dispatch problems. Simulation results highlight the speed and accuracy level of ACO in providing numerical problems. Abderrahmani *et al.* (2023), in their findings, suggested a hybridized model comprising ACO and GA for solving optimal real power dispatch problems. Raviprabakaran and Subramanian (2016) deployed an enhanced ACO to solve optimal power flow problems amid ecological emissions. Again, Sen and Mathur (2016) proposed a modified algorithm comprising ACO, ABC, and harmonic search (HS) for solving economic load dispatch problems. The proficiency of ACO for optimal numerical solution was reported in their separate findings. After a critical look at the literature, the selected algorithms in this paper have not been compared on a standalone basis, especially as applicable to the 330-kV transmission grid.

This study utilizes a swarm-based computational technique with artificial

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intelligence to investigate the best power flow in the 330 kV Nigerian transmission grid network. The research compares the efficiency and precision of three optimization algorithms. Three swarm optimizers have been selected for the purpose of power system diagnosis: spider monkey optimization (SMO), artificial bee colony optimization (ABCO), and ant colony optimization (ACO). The efficacy of the three selected metaheuristics will be considered in terms of speed (number of iterations before convergence) and error (power mismatch) associated with each solution. The research objectives are as follows:

(i) Collect relevant network data from Transmission Company of Nigeria (TCN) on the 330kV national grid network.
(ii) Redesign of the single-line diagram of the 330kV National Grid Network in ETAP
(iii) Configure three swarm intelligence optimization algorithms in a MATLAB environment for an improved power flow solution.
(iv) Apply the developed tools in analyzing power flow studies in the 330kV transmission network.
(v) Compare the results of the algorithms in terms of accuracy and speed (convergence rate).

2.0 MATERIALS AND METHODS

2.1 Materials

The single line diagram of the 34-bus, 330kV network is remodeled from data collated from transmission company of Nigeria retrieved from Akwukwaegbu *et al.* (2017), Ezeruigbo *et al.* (2021) and Abdulkareem *et al.* (2021).

2.2 Methods

2.2.1 Nodal Voltage Analysis

The nodal voltage analysis method is used to derive the fundamental load flow equations as shown in equation 1.

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

Deduced from equation (1) is the active real and imaginary power as contained in equation 1 and 2.

$$P_i = \sum_{i,k=1}^{n} Y_{ik} V_i V_k \cos (\theta_{ki} + \delta_{ik}) \quad (2)$$

$$Q_i = \sum_{i,k=1}^{n} Y_{ik} V_i V_k \sin (\theta_{ki} + \delta_{ik}) \quad (3)$$

The objective function of this research is premised upon the difference between the actual and predicted power mismatch values deduced from equations 2 and 3 as.

$$F_{Obj.}^{min.} = \sqrt{\Delta P_{net} + \Delta Q_{net}} \quad (4)$$

Three swarm intelligent optimizers are considered in this research to proffer optimal solution to the load flow objective equation.

2.2.2 Swarm Intelligence Approach

The approach to swarm intelligence is outlined in Figure 2.

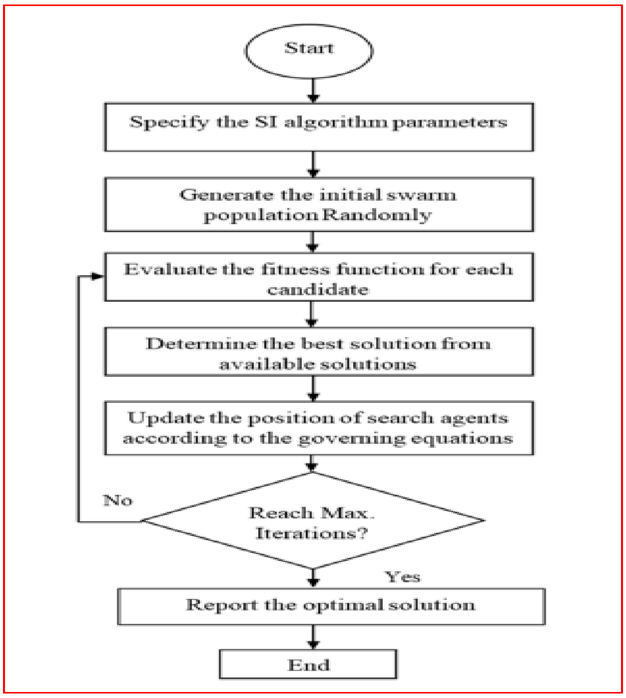

Fig. 2: SI Procedural Flowchart

Source: Jumani *et al.,* (2020)

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3.0 RESULTS AND DISCUSSION

The power flow result for the 34-bus, 38-branched Nigerian transmission grid is displayed for analysis in Figures 3, 4, and 5.

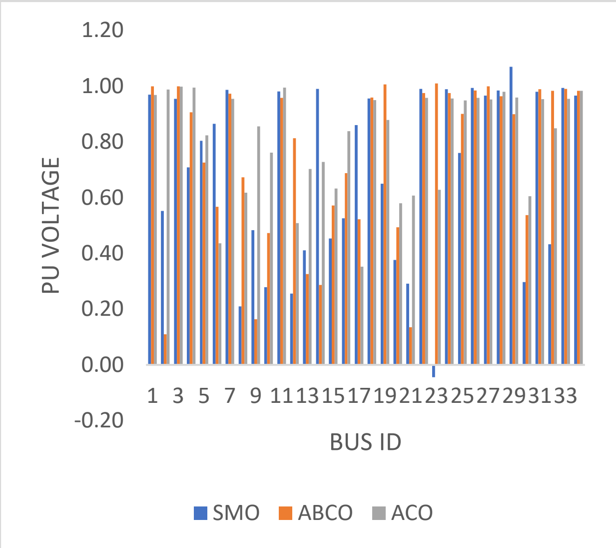

Fig. 3: Busbar Voltage Magnitude Result in PU

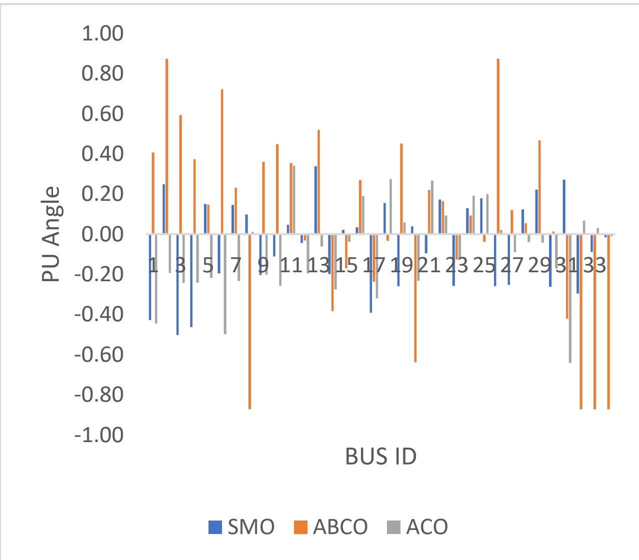

Fig. 4: Busbar Voltage-Angular Magnitude in PU

Figures 3 and 4 clearly show the voltage profile results produced by SMO, ABCO and ACO. The magnitude of voltage and its corresponding angles at each bus has been represented in Figure 3 and 4 for 100 iterations. As shown in both Figures 3 and 4, the least and highest voltage for SMO was recorded at buses 23 and 29, as 0.04pu and 1.07pu respectively. Similarly, the least voltage for ABCO was produced at bus 2, as 0.11pu, while the highest voltage was recorded at buses 19 and 23 as 1.01pu respectively.

Lastly, at buses 17 and 3, ACO produced its least and highest voltages as 0.35pu and 1.00pu respectively. A critical look at the voltage profile results contained in Figures 3 and 4, shows that bulk of the system buses are bedeviled by critical under voltage issues. Also, the accuracy of the ACO proved to be better compared to SMO and ABCO but this will be validated using the fitness curve.

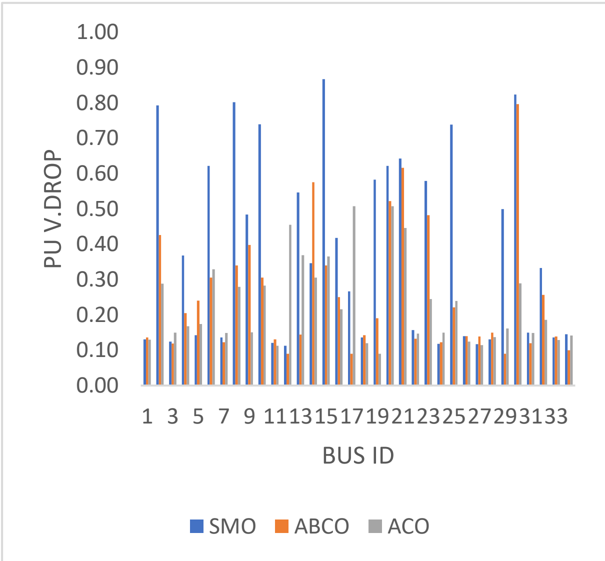

Fig. 5: Busbar Voltage Drop in PU

Figure 5 shows the voltage drops at each bus for evaluation of the proposed algorithms in line with the permissible voltage drop as mandated by IEEE. Application of SMO show that eight (8) out of 34 buses are in violation of the ±5% voltage drop requirement in the under-voltage region. The violating buses are buses 8, 10, 13, 15, 19, 20, 21, 23, 25 and 30 respectively.

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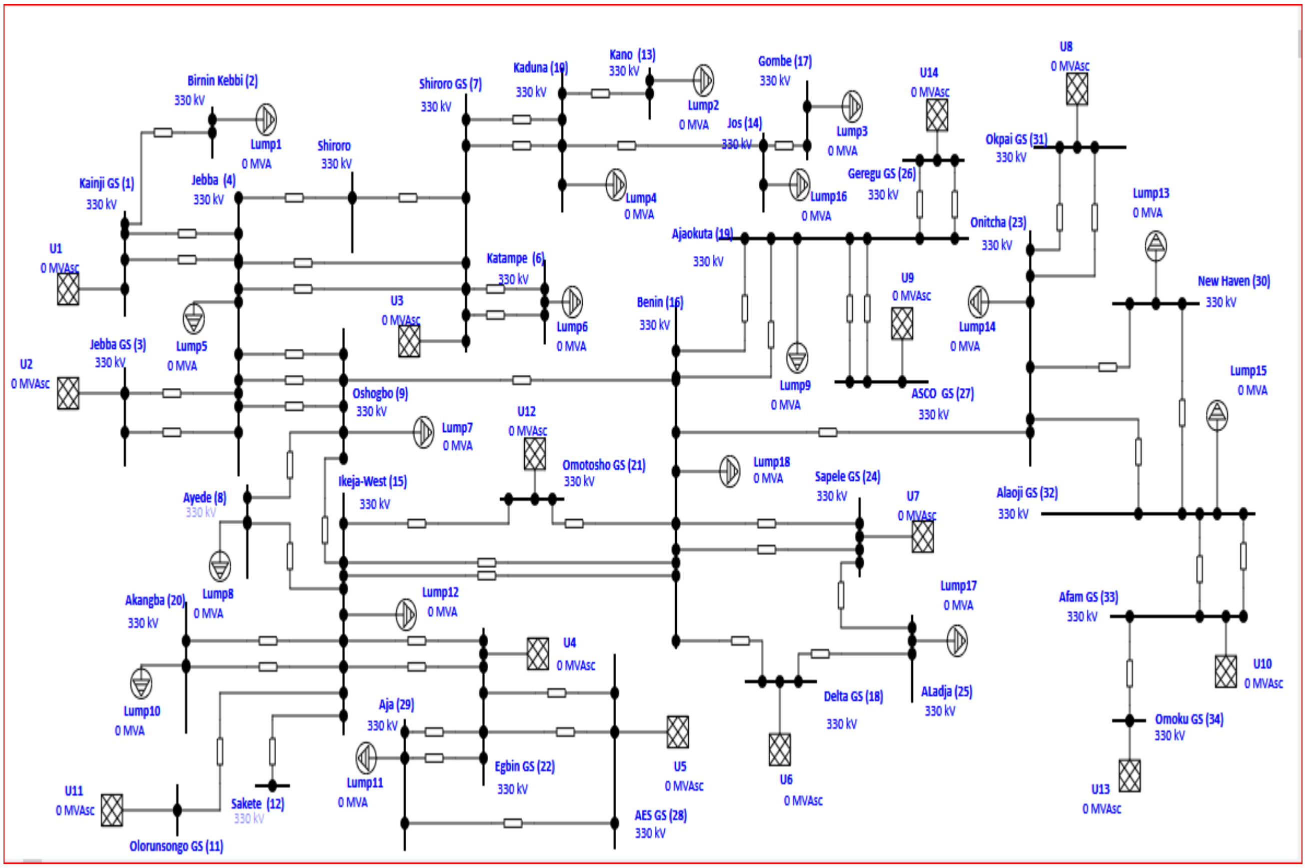

Fig. 1: Single Line Diagram of the 34-Bus Section of the Nigerian Grid

Application of ABCO show that four (4) out of 34 buses are in violation of the ±5% voltage drop requirement in the under-voltage region. The violating buses are buses 14, 20, 21 and 30 respectively. This result tends to agree with results produced by SMO to an extent, as buses 20, 21 and 30 are consistent with the results produced by SMO.

Application of ACO reveals that one (1) out of thirty-four (34) buses is in violation of the IEEE statutory voltage regulation of ±5%. The violating bus as per the results produced by ACO is bus 20. The consistent appearance of bus 20 in all three results justifies the algorithms robustness for voltage profile prediction. Cumulatively, the per unit voltage drop produced by SMO, ABCO and ACO are 13.07, 8.58 and 7.81 respectively. By the above result, ACO is more accurate and followed by ABCO.

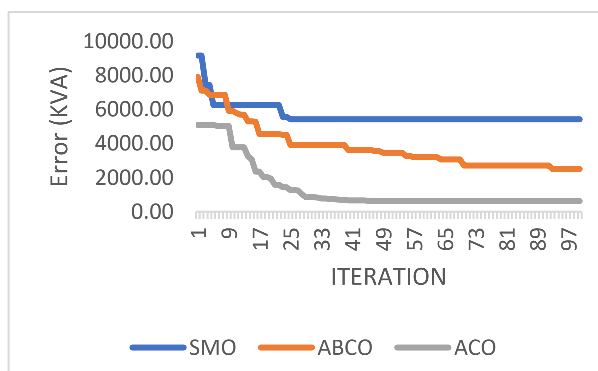

Fig. 6: Algorithm Fitness Report showing Accuracy and Convergence

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The accuracy of the algorithms as a function of the power mismatch (error) values are being presented in Figure 6.

The graph in Figure 6, validates the precision of ACO as being associated with the least error value of about $613kVA$, followed by ABCO and SMO in the stated sequence. Results from convergence rate analysis show swift convergence of SMO after 25 iterations, making it computationally faster than ACO and ABCO in small iterative cycle. While SMO took 25 iterations to converge, ACO and ABCO required 64 and 93 iterations, respectively, to achieve convergence. The algorithms accuracy and convergence index values deduced from Figure 6 are represented in Table 1.

Table 1: Algorithm Performance Report

Algorithm	No. of Iteration	Error (KVA)
SMO	25	5420.94
ABCO	93	2499.35
ACO	64	616.72

4.0 CONCLUSION

Three swarm intelligence load flow solutions were deployed to ascertain the existing state of the 330 kV Nigerian transmission grid. Load flow analysis (LFA) was successfully conducted using all three algorithms with clear distinctions in accuracy and speed level. After simulation, SMO, ABCO, and PSO converged after 25, 93, and 64 iterations, respectively, with an error mismatch value of 5420.94, 2499.35 and $616.72KVA$ respectively. Also, the total voltage drops produced by SMO, ABCO, and PSO for the 34-bus, 38-branch transmission grid as a justification for the mismatch errors (accuracy) is 13.07, 8.58, and 7.81pu, respectively. According to the results generated, SMO was better with speed, while ACO was better with accuracy for 100 iterations. Leveraging the strengths shown by SMO and ACO in terms of computational speed and accuracy, an improved version of the swarm optimizer algorithm should be considered by cascading SMO and ACO for an automated power flow solution for a minimum iterative condition.

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