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Convergence and transmission-loss performance of a hybrid Artificial Bee Colony–Firefly Algorithm for economic load dispatch of the Nigerian 330 kV power system

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Abstract
Economic Load Dispatch (ELD) is an important optimization problem in power-system operation because it seeks to allocate generation among available generating units while satisfying system demand and operating constraints. This study investigates the convergence and transmission-loss performance of a Hybrid Artificial Bee Colony–Firefly Algorithm (ABC–FA) for the ELD problem of the Nigerian 330 kV power system. Three population-based optimization approaches, namely Artificial Bee Colony (ABC), Firefly Algorithm (FA), and Hybrid ABC–FA, were implemented in MATLAB and evaluated under load-demand conditions ranging from 2000 MW to 4000 MW. The hybrid approach combines the exploration capability of ABC with the exploitation characteristics of FA. Convergence characteristics were evaluated from the variation of the objective-function value with iteration number, while transmission losses were assessed through power-balance verification. The reported convergence curves show rapid improvement during the initial search stage followed by gradual convergence as the algorithms approach their final solutions. The Hybrid ABC–FA generally demonstrated faster convergence and improved final solution characteristics compared with the individual algorithms. For transmission losses, the verified results show that the ABC and Hybrid ABC–FA methods produced physically plausible loss estimates across the investigated load levels, while two standalone FA cases at 2000 MW and 2500 MW were identified in the report as problematic and were therefore excluded from the comparative loss analysis. The study demonstrates the potential of hybrid swarm-intelligence optimization for improving the computational performance of economic dispatch in the Nigerian 330 kV power system.

Keywords: Economic load dispatch, Artificial Bee Colony, Firefly Algorithm, Hybrid ABC–FA, convergence, transmission loss, Nigerian 330 kV Power System

Introduction

Economic Load Dispatch (ELD) is a fundamental optimization problem in power-system operation. Its purpose is to determine the appropriate generation allocation among available generating units while satisfying the required system demand and generator operating constraints. Efficient dispatch is important for improving the utilization of generating resources and reducing unnecessary operating costs (Aliyu *et al.*, 2025; Chen *et al.*, 2022) [3, 4].

The Nigerian 330 kV transmission network forms the backbone of the national electricity grid and connects major generating stations with load centres. Nigeria's power sector has been widely discussed in relation to generation adequacy, network constraints and the need for improved system operation (Aliyu *et al.*, 2013; International Energy Agency, 2022) [2, 5]. The generating stations considered in this study include Egbin, Delta, Sapele, Afam, AES, Okpai, Calabar, Kainji, Jebba and Shiroro.

Conventional optimization techniques may encounter difficulties when applied to nonlinear and constrained ELD problems. Consequently, population-based metaheuristic techniques have been investigated for power-system optimization. The Artificial Bee Colony (ABC) algorithm has been extensively studied for constrained optimization (Akay & Karaboga, 2011; Karaboga & Basturk, 2007) [1, 6] and for broader engineering applications (Karaboga *et al.*, 2014) [7]. The present study considers ABC and the Firefly Algorithm because of their search capabilities and develops a hybrid ABC–FA approach intended to combine their complementary characteristics.

The study therefore focuses specifically on the convergence behaviour and transmission-loss characteristics of ABC, FA and Hybrid ABC–FA for the Nigerian 330 kV system. Five load-demand conditions, from 2000 MW to 4000 MW in 500 MW increments, were considered.

Objective of the study

The objective of this paper is to evaluate and compare the convergence behaviour and transmission-loss performance of ABC, FA and Hybrid ABC–FA when applied to Economic Load Dispatch of the Nigerian 330 kV power system.

Methodology

The mathematical formulation below follows the ELD formulation in the original research report. The study considers thermal units Egbin, Delta, Sapele, Afam, AES, Okpai and Calabar, together with hydro units Kainji, Jebba and Shiroro, and evaluates load demands of 2000, 2500, 3000, 3500 and 4000 MW. The hydro generation cost is treated as negligible in the adopted model.

1. Mathematical Formulation of the Hydro-Thermal ELD Model

Hydro units are included in the power-balance constraint, while the thermal-unit fuel cost coefficients are used in the generation-cost objective. This formulation is consistent with the report's statement that Kainji, Shiroro and Jebba are treated as hydro stations with negligible fuel cost.

Objective function

The objective function for the ELD problem is to minimize the total generation cost, given by equation (1);

$$\text{Min. } F = \sum_{i=1}^{NT}\left(a_i P_{Gi}^2 + b_i P_{Gi} + c_i\right) + \sum_{j=1}^{NH}\left(d_j P_{GH}^2 + e_i P_{Gj} + f_j\right) \qquad \ldots(1)$$

Where, F is the total fuel and operational cost ($/h), P_{Gi} is the power output of hydro unit i (MW), P_{Hj} is the power output of hydro unit j (MW), d_j, e_j, fj are the cost coefficients of hydro unit j, N_T is the number of thermal units and N_H is the number of hydro units.

The fuel cost coefficients adopted for the thermal generating units are presented in Table 1.

Table 1: The fuel cost coefficients of the Nigerian Thermal Stations

Thermal Unit	a	B	C
Egbin	12787	13.10	0.031
Delta	525.74	6.13	1.200
Sapele	6929	7.84	0.130
Afam	1998	56.00	0.0092
AES	3886	22.00	0.453
Okpai	480.58	10.30	1.130
Calabar	2732	38.70	0.050

The hydro generating stations (Kainji, Shiroro and Jebba) are considered in the power balance equation since their fuel cost is assumed negligible in the adopted ELD model.

Power balance constraint

$$\sum P_{Ti} + \sum P_{Hi} = P_D + P_{LOSS} \ \ldots (2)$$

Where, P_{LOSS} is the power transmission losses (MW), $\sum P_{Ti}$ is the summation of the thermal power of generation unit i (MW), $\sum P_{Hi}$ is the summation of hydropower generating unit i (MW) and P_D

The transmission losses are calculated using Kron's loss formula in equation (3);

$$P_{LOSS} = \sum_{i=1}^{N}\sum_{j=1}^{N} P_i B_{ij} P_j + \sum_{I=1}^{N} B_{io} P_i + B_{OO} \qquad \ldots(3)$$

Where, is the Kron transmission loss coefficient matrix, is the transmission loss coefficient vector and is the constant transmission loss coefficient.

The loss coefficients adopted for the Nigerian 330 kV power network are expressed in Equation (4) and (5);

$$B_o = \begin{bmatrix} 0.0029 & -0.0005 & -0.0003 & -0.0013 & -0.0002 & -0.0003 & -0.0013 & 0.0024 & -0.0005 & -0.0013 \\ -0.0005 & 0.0024 & 0.0004 & -0.0009 & 0.0009 & -0.0001 & -0.0001 & -0.0004 & 0.0006 & -0.0002 \\ -0.0003 & 0.0004 & 0.0012 & -0.0001 & 0.0005 & 0.0006 & -0.0002 & -0.0003 & 0.0005 & -0.0003 \\ -0.0013 & -0.0009 & -0.0001 & 0.0039 & -0.0005 & 0.0006 & -0.0019 & -0.0011 & -0.0008 & -0.0019 \\ -0.0002 & 0.0009 & 0.0005 & -0.0005 & 0.0010 & 0.0002 & -0.0000 & -0.0002 & 0.0007 & -0.0001 \\ -0.0003 & -0.0001 & 0.0006 & 0.0006 & 0.0002 & 0.0011 & -0.0007 & -0.0002 & 0.0000 & -0.0008 \\ -0.0013 & -0.0001 & -0.0002 & -0.0019 & 0.0011 & -0.0007 & 0.0117 & -0.0011 & 0.0020 & -0.0010 \\ 0.0024 & -0.0004 & -0.0003 & -0.0011 & -0.0007 & -0.0002 & -0.0011 & 0.0024 & -0.0005 & -0.0003 \\ -0.0005 & 0.0006 & 0.0005 & -0.0008 & 0.0007 & 0.0000 & 0.0020 & 0.0005 & 0.0034 & 0.0017 \\ -0.0010 & 0.0017 & -0.0003 & -0.0019 & 0.0001 & -0.0008 & 0.0099 & -0.0010 & 0.0017 & 0.0273 \end{bmatrix}$$

… (4)

$$B_o = \begin{bmatrix} 0.0177 \\ 0.0084 \\ -0.0045 \\ -0.0155 \\ 0.0010 \\ -0.0032 \\ -0.0291 \\ 0.0122 \\ -0.0091 \end{bmatrix} \text{ and } B_{OO} = 0.1188 \qquad \ldots(5)$$

The report states that transmission losses are calculated using Kron's loss formula and that the Nigerian 330 kV network is represented by a loss-coefficient matrix, a loss-coefficient vector and a constant loss coefficient. The exact coefficient set should be retained exactly as supplied in the underlying simulation model.

Generator operating limits

For thermal generating units, the power output of each unit must operate within specified minimum and maximum operating limits to ensure safe, stable, and efficient system performance. The constraints define the allowable generation range for thermal and hydro generators. These operational constraints are represented mathematically in equations (6);

$$P_{Gimin} \leq P_{Gi} \qquad \ldots(6)$$

For reliable hydroelectric power generation, the amount of water discharged by each hydro unit must not exceed the total available water in the reservoir. In addition, thermal generating units are subjected to ramp rate constraints, which limit the rate at which their power output can increase or decrease between consecutive operating periods. These constraints help maintain system as presented in equations (7) and (8);

$$Q_{\text{Hjmin}} \leq Q_{\text{Hj}} \leq Q_{\text{Hjmax}} \qquad \ldots (7)$$

$$Q_{\text{Hj}} \leq Q_{\text{available}} \qquad \ldots (8)$$

The thermal units are therefore constrained by their minimum and maximum operating limits. The report also describes operating limits for the hydro units and water-discharge constraints, together with ramp-rate constraints for thermal generators where applicable.

2. Nigerian 330 kV Power System

The transmission network was modeled under steady-state operating conditions, and the

Economic Load Dispatch problem was solved using the Hybrid Artificial Bee Colony and Firefly Algorithm (ABC–FA) to determine the optimal generation schedule that minimizes the total operating cost while satisfying system constraints.

The adopted Nigerian power network is suitable for this study because it reflects the practical operational characteristics of the Nigerian electricity grid, including dependence on thermal generation, hydroelectric support, renewable energy integration challenges, and transmission losses. Figure 1 shows the single line diagram of Nigeria 330kV network under consideration;

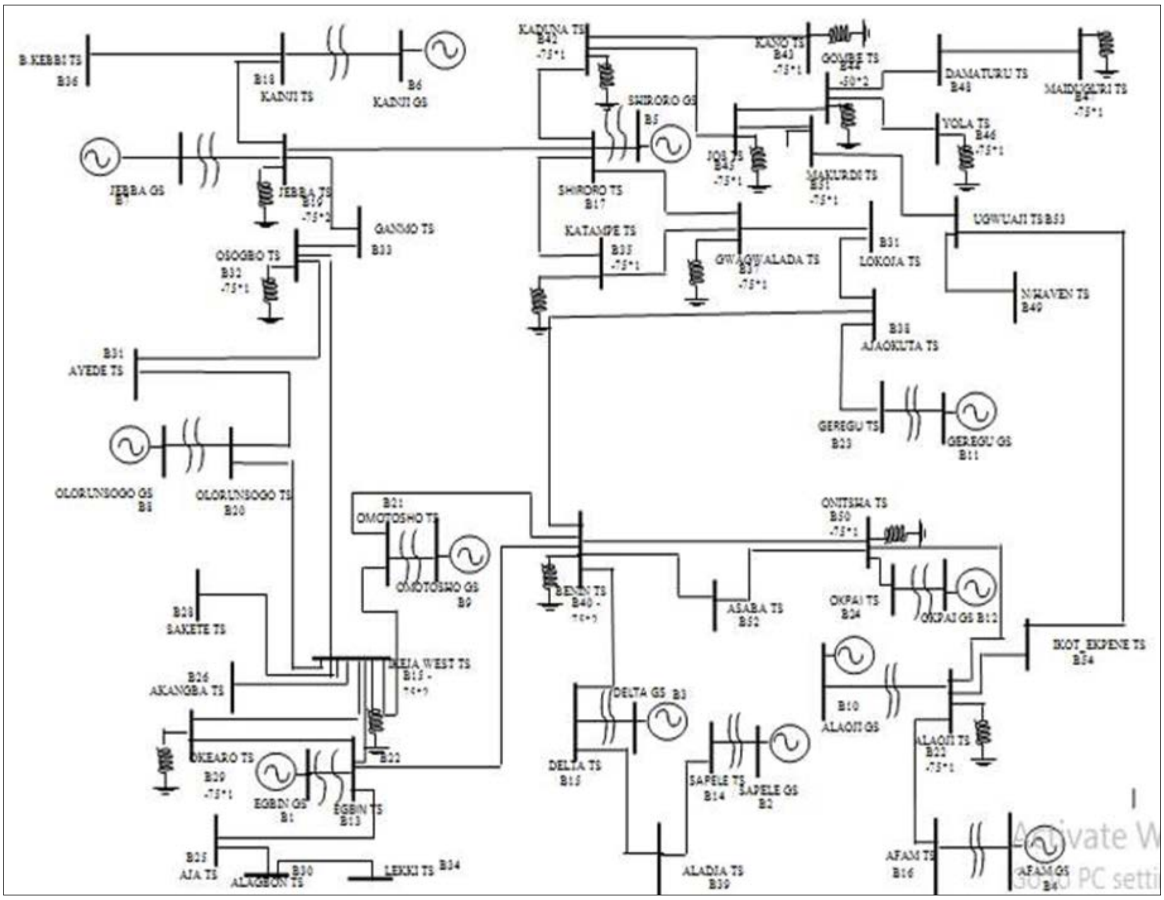

Fig 1: The Nigerian 330kV Network Single Line Diagram

3. Artificial Bee Colony Algorithm

The Artificial Bee Colony (ABC) algorithm was implemented as one of the optimization approaches for solving the Economic Load Dispatch (ELD) problem. The algorithm is a population-based metaheuristic inspired by the foraging behaviour of honeybees. As shown in Figure 2, the process begins with the initialization of feasible candidate solutions and evaluation of their objective-function values. The employed-bee phase generates new solutions around existing food sources, while the onlooker-bee phase selects promising solutions based on their fitness. The scout-bee phase replaces solutions that fail to improve after a specified number of trials, thereby maintaining population diversity. The best solution is retained at each iteration, and the process continues until the specified termination criterion is satisfied. The resulting best generation schedule and corresponding minimum generation cost are obtained as the ABC solution to the ELD problem. Figure 2 Flow chart of the general optimization process using the ABC algorithm

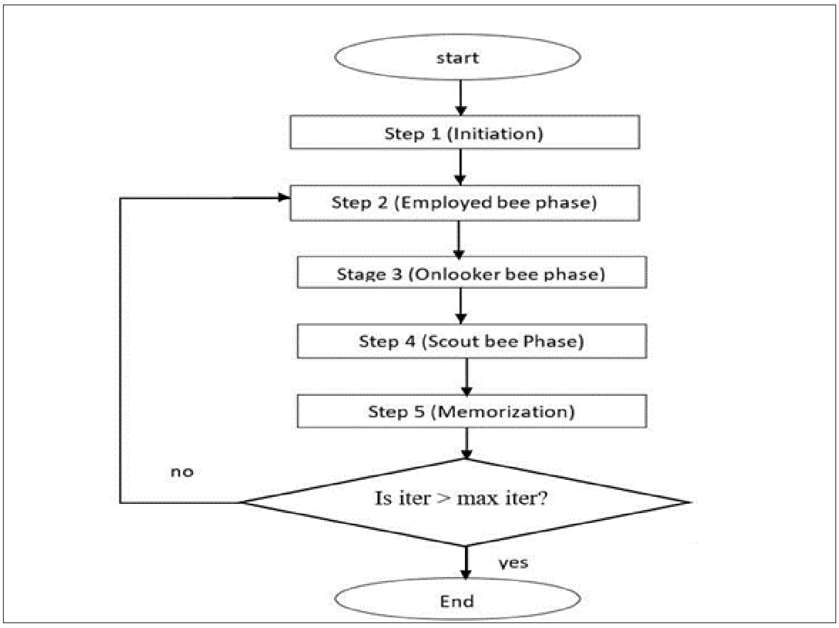

Fig 2: Flow chart of the general optimization process using ABC algorithm

4. Firefly Algorithm

The Firefly Algorithm (FA) was implemented as the second standalone optimization technique for solving the ELD problem. The algorithm is based on the attraction behaviour of fireflies, where the brightness of a firefly represents the quality of its corresponding solution. As presented in Figure 3, the process starts with the initialization of candidate solutions and evaluation of their objective-function values. The attractiveness between fireflies is determined according to their relative brightness, and less attractive fireflies move toward more attractive solutions to generate new candidate solutions. The new solutions are evaluated and the best solutions are retained for subsequent iterations. This process is repeated until the specified termination criterion is satisfied, after which the best generation schedule and corresponding minimum generation cost are obtained.

Figure 3 Flow chart of the general optimization process using the Firefly Algorithm

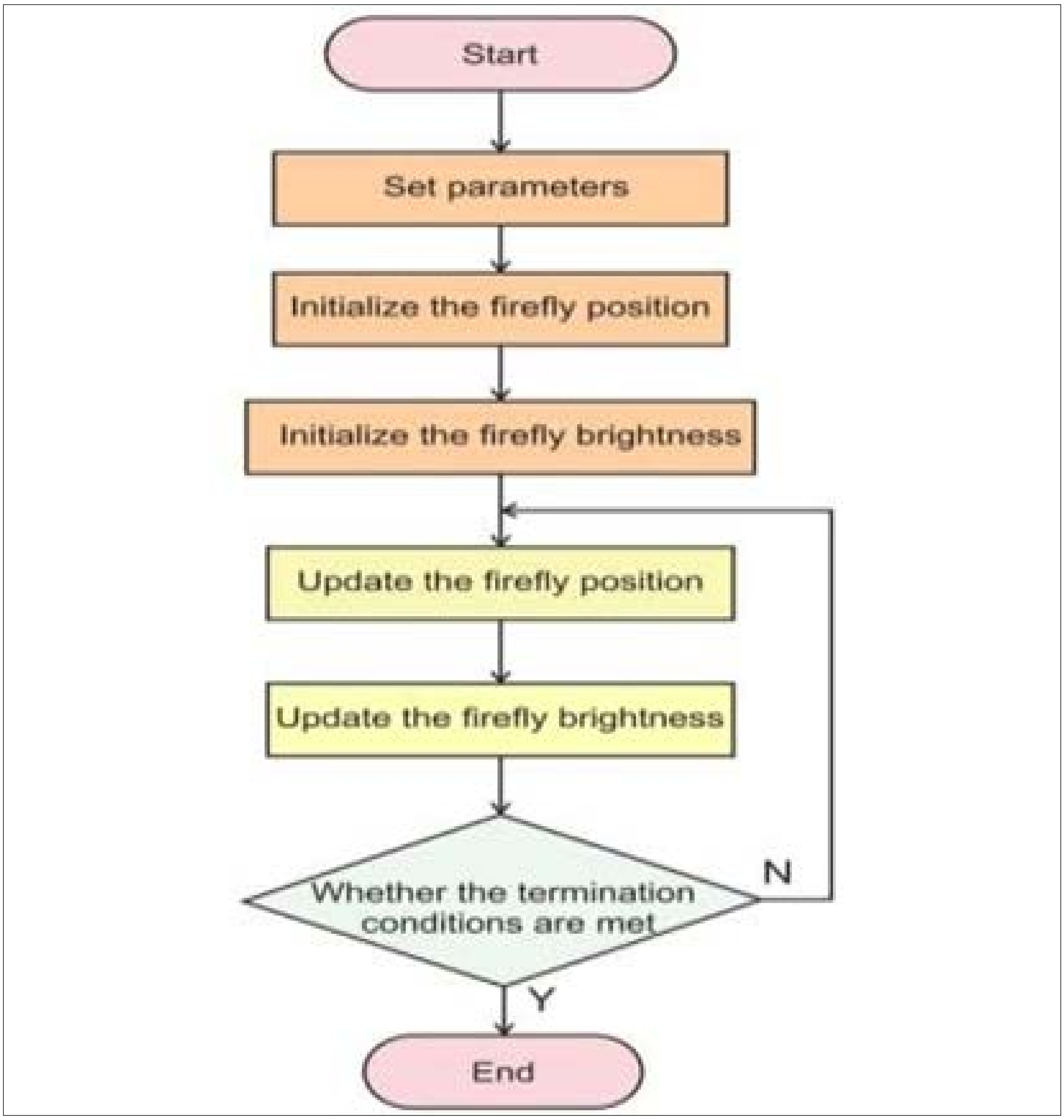

Fig 3: Flow chart of the general optimization process using FA algorithm

5. Hybrid ABC–FA Algorithm

The Hybrid ABC–FA algorithm combines the complementary search characteristics of ABC and FA to improve the balance between exploration and exploitation. As shown in Figure 4, the process begins with population initialization and objective-function evaluation. The ABC mechanism is employed to explore the search space and identify promising candidate solutions, after which the FA mechanism is applied to improve these solutions through its attraction-based search process. The resulting solutions are evaluated and the best feasible solution is retained at each iteration. The process continues until the specified termination criterion is reached. The proposed hybrid ABC–FA algorithm was implemented in MATLAB and evaluated for load demands ranging from 2000 MW to 4000 MW. The final output is the best generation schedule and its corresponding minimum generation cost.

Figure 4 Flow chart of the Hybrid ABC–FA algorithm

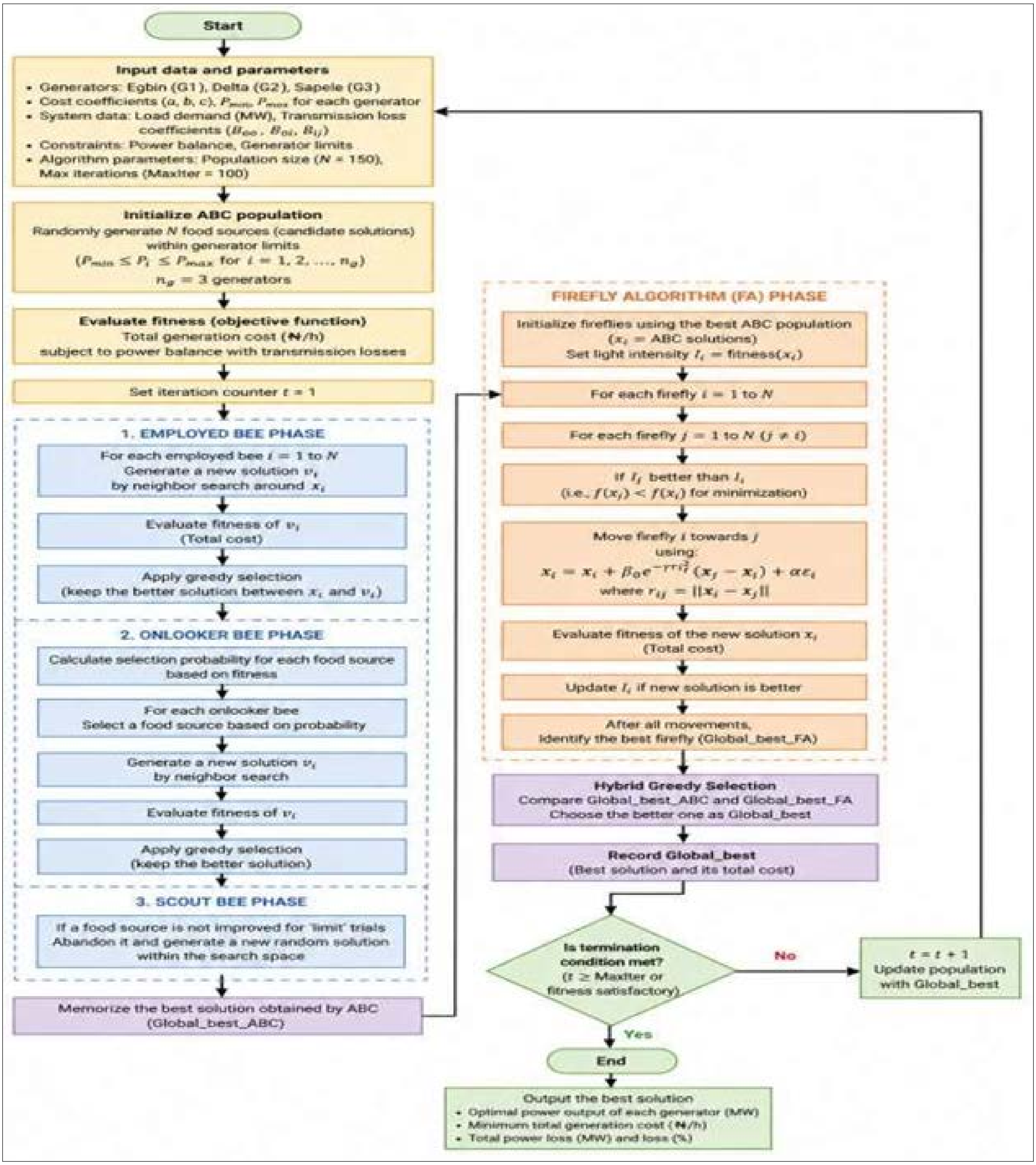

Fig 4: Hybrid ABC -FA algorithm Flowchart

Results and Discussion

1. Convergence Performance

Convergence performance was evaluated by plotting the objective-function value against the number of iterations for the investigated load-demand levels of 2000, 2500, 3000, 3500, and 4000 MW. The convergence curves generally show a rapid improvement in the objective-function value during the initial iterations, followed by a gradual reduction in the rate of improvement as the algorithms converge toward promising regions of the search space.

The results indicate that the Hybrid ABC–FA algorithm generally achieves faster convergence and lower final objective-function values than the standalone ABC and FA algorithms. This improved convergence behaviour can be attributed to the complementary exploration and exploitation characteristics incorporated into the hybrid approach. At higher load demands, particularly 3500 and 4000 MW, the convergence curves exhibit significant improvement during the early iterations before gradually stabilizing toward the final solution.

Figures 5–9 present the convergence behaviour of the three optimization algorithms under the different load-demand scenarios.

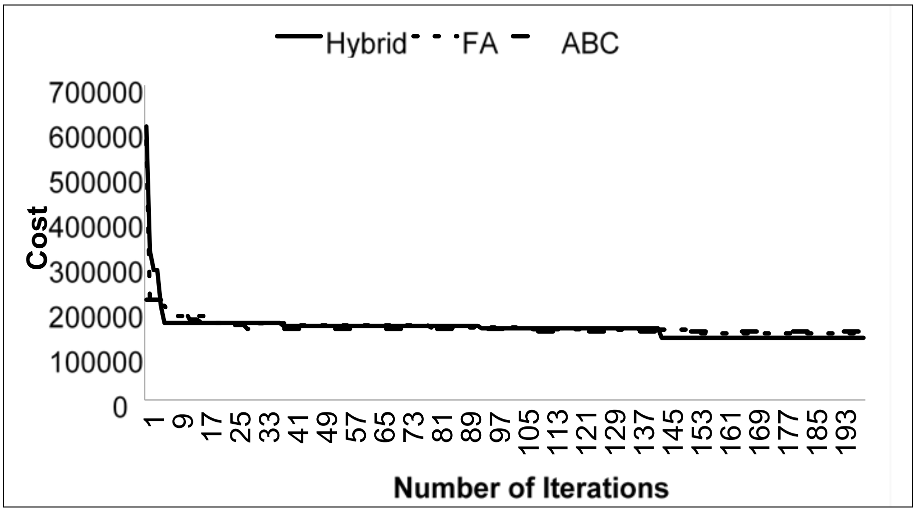

Fig 5: Convergence of the Algorithms at 2000MW load Demands

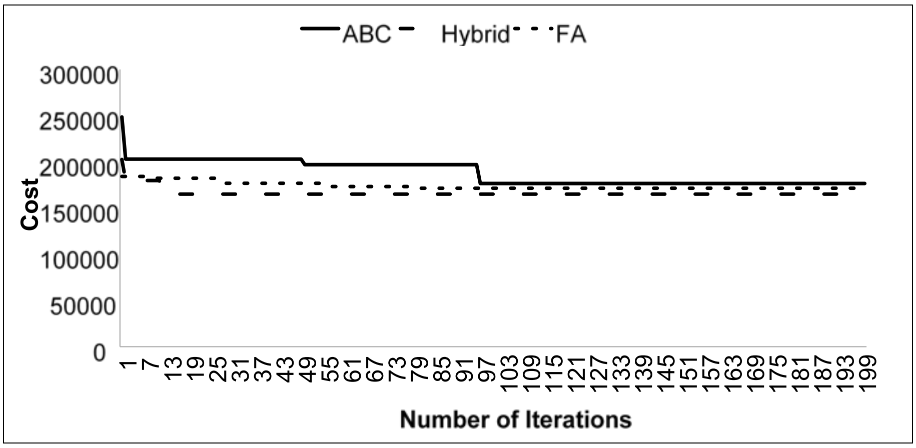

Fig 6: Convergence of the Algorithms at 2500MW load Demands

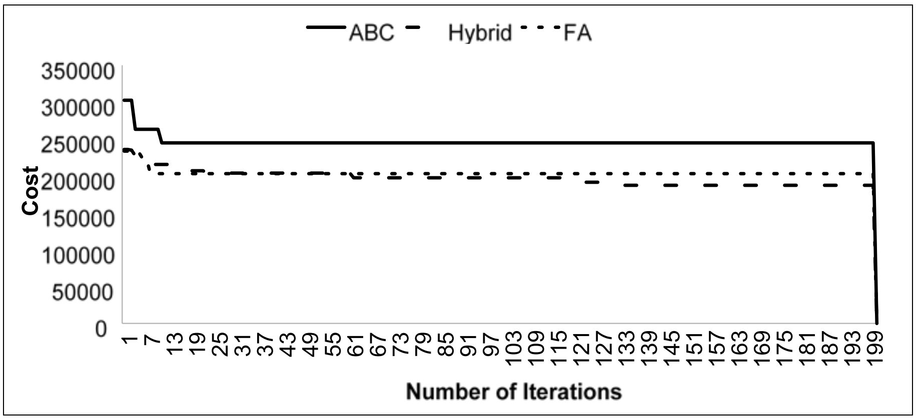

Fig 7: Convergence of the Algorithms at 3000MW Load Demands

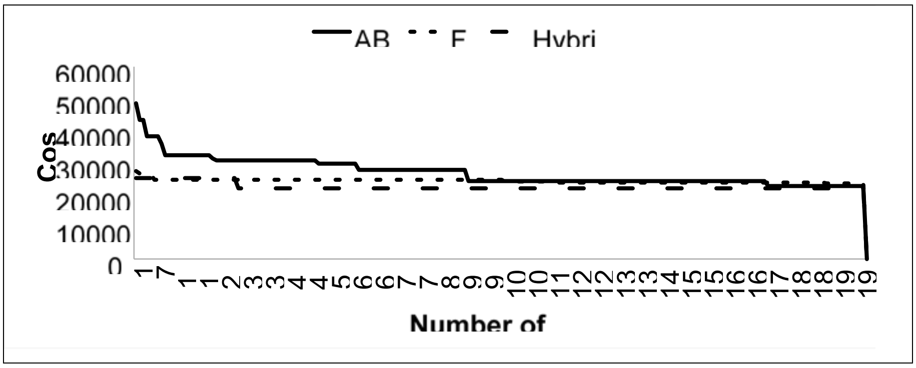

Fig 8: Convergence of the Algorithms at 3500MW Load Demand

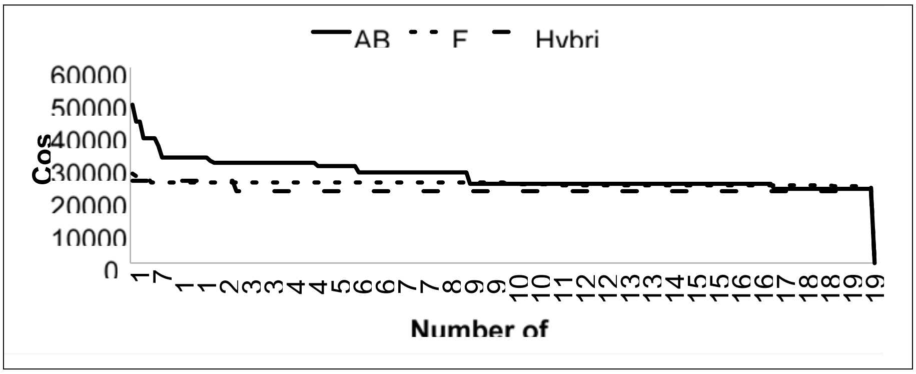

Fig 9: Convergence of the Algorithms at 4000MW Load Demand

2. Transmission-Loss Performance

Transmission losses were evaluated through power-balance verification by comparing total generation with the specified load demand. Economic dispatch studies commonly treat transmission losses as an important part of the dispatch formulation and system operating constraints (Kunya *et al.*, 2023) [8]. The following table contains the verified cases retained for this publication.

Table 1: Verified transmission-loss results

Load demand (MW)	Algorithm	Total generation (MW)	Transmission loss (MW)	Loss (%)
2000	ABC	2013.61	13.61	0.676
2000	Hybrid ABC–FA	2003.23	3.23	0.161
2500	ABC	2507.16	7.16	0.285
2500	Hybrid ABC–FA	2511.84	11.84	0.471
3000	ABC	3007.73	7.73	0.257
3000	FA	3004.56	4.56	0.152
3000	Hybrid ABC–FA	3006.99	6.99	0.233
3500	ABC	3512.49	12.49	0.356
3500	FA	3517.39	17.39	0.495
3500	Hybrid ABC–FA	3505.36	5.36	0.153
4000	ABC	4018.54	18.54	0.461
4000	FA	4035.89	35.89	0.889
4000	Hybrid ABC–FA	4042.61	42.61	1.054

3. Treatment of Problematic FA Cases

Two FA cases in the source report were not retained for comparative analysis. At 2000 MW, FA produced 1804.16 MW against a 2000 MW demand, corresponding to a reported deficit of 195.84 MW. At 2500 MW, FA produced 2706.24 MW against a 2500 MW demand, corresponding to a reported 206.24 MW loss (7.621%). The source report itself identifies these cases as data/constraint problems and recommends that the FA values be rechecked. They are therefore excluded from the present publication rather than being presented as valid performance results.

4. Discussion of Transmission Losses

The verified results show that transmission losses vary with both load demand and optimization algorithm. At 2000 MW, Hybrid ABC–FA produced a reported loss of 3.23 MW (0.161%), compared with 13.61 MW (0.676%) for ABC. At 2500 MW, ABC produced 7.16 MW (0.285%), while Hybrid ABC–FA produced 11.84 MW (0.471%).

At 3000 MW, the reported losses were relatively small for all three algorithms, with ABC, FA and Hybrid ABC–FA producing 0.257%, 0.152% and 0.233%, respectively. At 3500 MW, Hybrid ABC–FA produced the lowest reported loss of 0.153%, compared with 0.356% for ABC and 0.495% for FA.

At 4000 MW, however, Hybrid ABC–FA produced 1.054%, compared with 0.461% for ABC and 0.889% for FA. Thus, the hybrid algorithm did not produce the minimum transmission loss at every load level. This indicates that convergence performance and transmission-loss performance should not be treated as identical measures of optimization quality.

Conclusion

This study investigated the convergence and transmission-loss performance of Artificial Bee Colony, Firefly Algorithm and Hybrid ABC–FA approaches for Economic Load Dispatch of the Nigerian 330 kV power system. The convergence results reported in the study indicate that all algorithms initially improve rapidly before approaching a more stable solution region. The Hybrid ABC–FA generally demonstrates faster convergence and improved final solution characteristics compared with the individual ABC and FA methods.

Transmission-loss analysis showed that the verified ABC and Hybrid ABC–FA results remained within the physically plausible range reported in the study, while two FA cases at 2000 MW and 2500 MW were identified as problematic and excluded from the comparative analysis. The results demonstrate that hybridizing ABC and FA provides a promising approach for improving the convergence behaviour of metaheuristic optimization applied to ELD in the Nigerian 330 kV power system. However, the hybrid method does not necessarily minimize transmission losses at every load level. Future work may therefore incorporate transmission loss explicitly into the optimization objective.

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