SSRG International Journal of Electrical and Electronics Engineering
ISSN: 2348-8379/ https://doi.org/10.14445/23488379/IJEEE-V12I7P110

Volume 12 Issue 7, 147-157, July 2025

Original Article

Comparative Analysis of the Snake and Grasshopper Optimization Algorithms in Improving Reliability Indices of the 330kV Grid of Nigeria

Maman Jimoh Lawal[1], Oghenewvogaga Oghorada[2], Babatunde Adetokun[3]

[1,2,3]*Electrical & Electronics Engineering Department, Nile University of Nigeria, Abuja, Nigeria.*

[1]*Corresponding Author : lawalmj@gmail.com*

Received: 07 May 2025 Revised: 09 June 2025 Accepted: 08 July 2025 Published: 31 July 2025

Abstract - *Nigeria's 330kV transmission network has long been plagued by frequent failures, inefficiencies, and instability, resulting in widespread power outages and economic losses***.** *This study addresses the reliability issues of the 330kV network of Nigeria by the application of Snake Optimization Algorithm (SOA) and Grasshopper Optimization Algorithm (GOA) to outage data obtained from the System Operator from 2022 to 2023. Using ETAP software, base values were established for the key reliability indices: ASAI, SAIDI, SAIFI, and CAIDI. The SOA and GOA significantly improve these metrics: ASAI increases from 0.9989 to 0.9999, while SAIDI, SAIFI, and CAIDI show substantial reductions, indicating fewer and shorter outages. Specifically, SAIDI dropped from 9.4140 to 1.3107 (SOA) and 1.0301 (GOA); SAIFI declines from 3.2684 to 0.9915 and 0.9738; and CAIDI declines from 2.8800 to 1.3220 and 1.0580. These results demonstrate the efficacy of the metaheuristic algorithms as optimisation techniques for improving power system reliability.*

Keywords - *Grasshopper optimization algorithm, Grid, Reliability indices, Snake optimization algorithm.*

1. Introduction

The dependability of a power system is vital for its planning and operation, fueled by the increasing need for more reliable service [1]. A reliable power system can provide energy at a specified quality and characteristics consistent with statutory standards. Nigeria's electricity supply falls short of demand, resulting in a mismatch that accounts for a sizeable proportion of network outages. Also, outages associated with power system disturbances stem from insufficient generation capacity, inadequate maintenance of grid equipment, and varied sources of perturbation arising from snags in network configurations. Prolonged and frequent power cuts limit access to essential services and basic comforts of life. Despite generating electricity commercially for over a century, the country's slow pace in developing and maintaining energy infrastructure continues to hinder a reliable power supply for its population [2]. As the most populous nation in Africa, its rapidly expanding industrial sector and growing population place immense pressure on the national power infrastructure. Reliable electricity is essential for sustainable socioeconomic development, yet the country's transmission system suffers from inefficiencies, frequent failures, and adverse economic consequences. Over the past few years, Nigeria's national energy infrastructure has experienced several blackouts, often resulting in prolonged outages and widespread disruptions [3]. Several analytical, heuristics, and metaheuristics algorithms have been applied to reduce the failure rate and improve the reliability values. Analytical methods such as the Markov model, state space, contingency enumeration methods, and others are used to evaluate reliability indices. Likewise, metaheuristics algorithms use Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Grasshopper Optimization Algorithm (GOA), Jelly Fish Search Algorithm, Snake Optimization Algorithm (SOA), amongst others, to enhance the performance of the reliability indices [4]. The study by [5] utilized the PSO technique for load flow analysis and voltage regulation enhancement in Nigeria's 330kV transmission network. The research aimed to address persistent power failures by ensuring efficient power distribution and improved power quality. The results indicated an error margin of -3.1051 in the first iteration. Also, while the PSO is effective, it can sometimes get trapped in local optima, leading to suboptimal voltage regulation. Also, the work by [6] focused on distribution companies with mixed-aged power infrastructure, which continuously degrades. One of the key challenges in aging systems is the lack of spare parts, which often results in unexpected investments towards expensive upgrades when outdated components fail. To tackle this, Condition-Based Maintenance (CBM) utilizing Neural Networks was employed to maintain the reliability of aging equipment. This method improved system stability and restored faulty assets by forecasting potential failures through regular inspections and risk evaluations. The CBM approach led to a 19.15% reduction in the average number of customers' monthly power outages, thereby enhancing the SAIDI. It also improved the SAIFI by 20.63% and enhanced the CAIDI by 36.1%. Likewise, [7] assessed and improved the reliability of the Debre Berhan Power Distribution Network through the use of fuzzy logic optimization techniques. However, it should be noted that the fuzzy logic requires extensive rule-based configurations, making it computationally intensive when applied to large-scale power networks. Other related works, such as the study by [4], proposed a novel application of the modified Jelly Fish Search Algorithm for evaluating SAIFI, SAIDI, CAIDI, ASAI, and ASUI in a radial distribution system. The relationship between the failure rate, repair time, and unavailability was modelled. Case studies on a 3-load-point system and IEEE Bus confirmed that the approach accurately tracked performance index variation.

However, limitations include possible premature convergence and challenges in maintaining the exploration-exploitation balance during optimization. Also, [8] investigated the enhancement of the distribution system reliability by optimally placing reclosers using Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Mayfly Algorithm (MA). Reliability indices (SAIFI, SAIDI, CAIDI, ASAI, AENS) significantly improved on a 58-bus system after recloser deployment. The GA and MA achieved better optimization results, while PSO converged faster. However, the study is limited by its focus on a single test system and lacks real-world data validation. Similarly, the work by [9] presented an innovative methodology for assessing power system reliability, transitioning from component-level modeling to system-wide indicator evaluation. It integrated a detailed Reliability Block Diagram (RBD) approach with a Monte Carlo simulation to compute SAIFI, SAIDI, and EENS.

While the model improved flexibility in analyzing various configurations and maintenance strategies, it is limited by high computational demand and limited scalability to large, real-time systems. The study conducted by [10] assessed the Dangila distribution network in Ethiopia using SAIFI, SAIDI, CAIDI, ASAI, and ENS to evaluate base reliability, which was significantly below national standards. A distributed generation unit was optimally placed at different distances along the chosen feeder using the DIgSILENT and sequential Monte Carlo simulation. Reliability indices improved most when the generator was placed farthest, achieving SAIFI = 20.09 and SAIDI = 25.1, meeting national standards. However, the analysis was limited to a radial network, excluding meshed or ring topologies that may yield different reliability outcomes.

1.1. Problem Statement

The Nigerian transmission grid suffers from frequent outages and aging infrastructure, which leads to poor reliability indices, including SAIFI, SAIDI, CAIDI, EENS, and AENS. From the records, the grid is technically weak and highly vulnerable to disturbances [11]. These challenges have persisted for a long time due to several identified issues, such as insufficient wheeling capacity, poor voltage stability and profiles, frequent vandalism, and funding constraints. These issues are driven by inadequate system planning, delayed fault-clearing response, and limited grid flexibility. These challenges collectively impact the reliability and efficiency of Nigeria’s power transmission system [12]. To address the challenges, this research makes several key contributions to enhancing the reliability of Nigeria’s 330kV network through the application of the Snake Optimization Algorithm (SOA) and the Grasshopper Optimization Algorithm (GOA). These metaheuristic algorithms offer robust solutions to these complex, non-linear problems.

1.2. Research Gap and Contribution of the Research

Following the review of related works, the following gaps were observed:

- Most reliability assessments, particularly in the Nigerian context, are constrained to specific transmission zones or feeders, lacking holistic national-level evaluations. Broader grid-wide assessments are necessary for comprehensive transmission planning.
- Whereas several studies utilized metaheuristic algorithms, only a few conducted rigorous cross-comparisons to benchmark performance.

Therefore, this work applied SOA and GOA to enhance the reliability of Nigeria’s high-voltage 330kV network. The contributions of this research work include:

- The data used for this study are unique and have not been utilized by any of the research reviewed. The outage data was used to recalibrate the 330kV model in ETAP to obtain the ASAI, SAIDI, SAIFI, and CAIDI for the base case, SOA, and GOA scenarios.
- The application of SOA and GOA metaheuristic approaches was used to optimize the failure rate to obtain enhanced reliability indices - ASAI, SAIDI, SAIFI, and CAIDI.
- The improvement of the ASAI, SAIDI, SAIFI, and CAIDI after the application of the optimization algorithms enhanced the overall grid resilience and service continuity.
- The enhanced reliability analysis was applied to a large-scale network, which differs from some of the literature that applied theirs to small-scale networks.
- The use of SOA and GOA offers robust solutions to complex, non-linear problems. The SOA enhances convergence in multi-solution spaces, while the GOA effectively handles constraint-heavy scenarios. Applying these algorithms supports intelligent decision-making for minimizing outages. Ultimately, their integration strengthens reliability, improves system indices, and ensures a more resilient grid.

The following sections are organized in this manner: Section 2 focuses on reliability indices, Section 3 on optimization algorithms, Section 4 on materials and methods, Section 5 on the results, and Section 6 on the conclusion.

2. Reliability Indices and Optimization Algorithms

The study evaluated reliability using the System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), Customer Average Interruption Duration Index (CAIDI), and Average Service Availability Index (ASAI).

2.1. Reliability Indices

2.1.1. SAIDI

SAIDI quantifies the typical length of all power outages by computing the ratio of the cumulative time customers experience interruptions to the entire customer base of the utility, accounting for both those impacted by service disruptions and those who remain unaffected [13]. The formula for calculating the SAIDI is shown in Equation (1) [14]:

$$SAIDI = \frac{\sum_{i=1}^{n} N_i U_i}{\sum_{i=1}^{n} N_t} \tag{1}$$

Where U_i represents the duration of equipment failures, N_i denotes the entire number of customers at the load point, while N_t indicates the total number of customers served.

2.1.2. SAIFI

SAIFI gauges the typical frequency of power outages encountered by customers each year [2]. It is quantified as the number of interruptions per year and is formally articulated through the mathematical expression provided in Equation (2) [14]:

$$SAIFI = \frac{\sum_{i=1}^{n} N_i \lambda_i}{\sum_{i=1}^{n} N_t} \tag{2}$$

Where λ_i is the frequency of equipment interruptions.

2.1.3. CAIDI

CAIDI measured in hours, represents the average duration needed to restore service following an outage [15]. It is mathematically defined as the ratio of SAIDI to SAIFI, as Equation (3) [16]:

$$CAIDI = \frac{SAIDI}{SAIFI} \tag{2}$$

2.1.4. ASAI

ASAI is the portion of time that customers have access to electricity during a specified period. It is usually expressed as a percentage and is computed using the formula provided in Equation (4) [14].

$$ASAI = \frac{8760 - SAIDI}{8760} \tag{4}$$

2.2. Optimization Algorithms

An optimization algorithm is important for the following reasons:

2.2.1. Optimal Preventive Maintenance Scheduling

- Identifies critical system components (transformers, transmission lines) with high failure probabilities.
- Schedules cost-effective maintenance before failures occur.
- Impact: Reduces unplanned outages (lower SAIFI).

2.2.2. Predictive Fault Detection and Component Replacement

- Uses historical outage data to predict weak points in the grid.
- Optimizes when and where to replace aging equipment.
- Impact: Fewer catastrophic failures (e.g. transformer explosions).

2.2.3. Optimal Resource Allocation (repair crews, spare parts)

- Minimizes response time by positioning crews/stocks near high-risk zones.
- Impact: Faster repairs → Lower CAIDI & SAIDI.

2.2.4. Enhanced Network Reconfiguration

- Automatically reroutes power during faults to isolate outages faster.
- Uses graph-based optimization to minimize affected customers.
- Impact: Shorter blackouts → Improved ASAI.

2.2.5. Load Balancing and Overload Prevention

- Optimizes power flow to prevent line/cable overheating.
- Impact: Reduces thermal failures (major cause of outages).

2.2.6. Appropriate Positioning of Single or Multiple-Shot Auto-Reclosers

- It circumvents transient faults induced outages, which constitute about 50% of 330kV transmission line faults.
- Impact: Reduces transmission line failure frequency.

In this research, the SOA and the GOA were utilized to calculate SAIDI, SAIFI, CAIDI, and ASAI. These optimization techniques, including SOA and GOA, help minimize both the frequency and duration of failures in power systems.

2.2.7. Snake Optimization Algorithm

As reported by Zheng et al. [17], the SOA is inspired by the mating behavior of snakes. In nature, snakes compete for optimal mates under favorable conditions - adequate food and low temperatures. The SOA starts by generating a random initial population and operates through exploration and exploitation. During the exploration phase, the algorithm simulates the behaviors of both male and female snakes to search the solution space, assuming an equal population of each. This phase involves repeatedly seeking new potential solutions. Once exploration is complete, the algorithm moves to the exploitation phase, where it fine-tunes and enhances the discovered solutions. This process of alternating between exploration and exploitation continues iteratively until a predefined number of iterations (T) is reached, ultimately yielding optimal or near-optimal solutions to the given problem. SOA can efficiently search and converge toward promising solutions in complex optimization scenarios by imitating snakes' mating behaviour. During the exploration, the food is assumed to be scarce, prompting snakes to move randomly in search of sustenance. The exploration is modelled as shown in (5) and (6) respectively:

$$X_{i,m}^{t+1} = X_{rand,m}^{t} \pm C_2 \times A_m\big((X_{max} - X_{min}) \times rand + X_{min}\big) \quad (5)$$

$$X_{i,f}^{t+1} = X_{rand,f}^{t} \pm C_2 \times A_f\big((X_{max} - X_{min}) \times rand + X_{min}\big) \quad (6)$$

Where $X_{i,m}^{t+1}$ and $X_{i,f}^{t+1}$ indicate the ith male and female positions, $X_{rand,m}^{t}$ and $X_{rand,f}^{t}$ are the positions of random males and females selected from the population, where t represents the current iteration and rand is a random value, and C_2, it is a constant that is set to 0.05.

The A_m and A_f measures the male and female abilities to get food, respectively, and they are calculated using (7) and (8) respectively:

$$\exp\left(\frac{-f_{rand,m}}{f_{i,m}}\right) \quad (7)$$

$$\exp\left(\frac{-f_{rand,f}}{f_{i,f}}\right) \quad (8)$$

Where $f_{rand,m}$ and $f_{rand,f}$ are the fitness values of $X_{rand,m}^{t}$ and $X_{rand,f}^{t}$ respectively.

The fitness values correspond to the ith male and female. In the exploitation phase, with food assumed to be available, the subsequent positions are calculated based on the ambient temperature (TEMP).

Alternatively, the snake functions in either combat or reproductive modes, with the algorithm randomly alternating between them. In combat mode, their updated positions are calculated using Equations (9) and (10), while in reproductive mode, position updates are dictated by Equations (11) and (12).

$$X_{i,m}^{t+1} = X_{i,m}^{t} \pm C_3 \times FM \times rand \times \left(X_{best,f} - X_{i,m}^{t}\right) \quad (9)$$

$$X_{i,f}^{t+1} = X_{i,f}^{t} \pm C_3 \times FF \times rand \times \left(X_{best,m} - X_{i,f}^{t}\right) \quad (10)$$

$$X_{i,m}^{t+1} = X_{i,m}^{t} \pm C_3 \times M_m \times rand \times \left(Q \times X_{i,f}^{t} - X_{i,m}^{t}\right) \quad (11)$$

$$X_{i,f}^{t+1} = X_{i,f}^{t} \pm C_3 \times M_f \times rand \times \left(Q \times X_{i,m}^{t} - X_{i,f}^{t}\right) \quad (12)$$

Where FM and FF represent the fighting abilities of males and females. The SOA helps by intelligently finding the best operational strategies for the 330kV grid. It balances exploration and exploitation, identifies weaknesses, suggests reconfigurations, and ultimately reduces the number and duration of outages, improving the overall reliability and stability of the 330kV grid of Nigeria.

2.2.8. Grasshopper Optimization Algorithm

Grasshoppers typically appear solitary in the wild but can form some of the largest swarms among all species [18]. Grasshopper swarms can reach continental scales, posing a serious threat to farmers. What makes them particularly unique is that both nymphs and adult grasshoppers exhibit swarming behavior. As the nymphs mature into adults, they take to the skies, forming airborne swarms that migrate across vast distances. During the larval stage, their movement is slower and more gradual, whereas in adulthood, their behavior shifts to sudden, long-range movements. A key trait of grasshopper swarms is their collective search for food sources. Drawing from this behavior, the search strategy incorporates both exploration and exploitation. During the exploration, agents are prompted to execute abrupt, expansive movements, whereas in the exploitation phase, their movements are more confined and targeted. Grasshoppers naturally perform both exploration and exploitation, along with target-seeking behavior. Hence, mathematically modelling these behaviors makes it possible to develop a new nature-inspired optimization process. The mathematical model to show the swarming behavior of grasshoppers is given in (13) [19]:

$$X_i = S_i + G_i + A_i \quad (13)$$

Where Xi represents the position of the ith grasshopper, Si denotes the social interaction, Gi indicates the gravity force on the ith grasshopper, and Ai reflects the wind advection.

$$c = C_{max} - l\,\frac{C_{max} - C_{min}}{L} \quad (14)$$

Where C_{max} and C_{min} are the maximum and minimum values, and L is the maximum iterations. The GOA improves the reliability of Nigeria's 330kV grid by simulating grasshoppers' intelligent search behavior, first broadly exploring many options and then refining the best strategies to optimize maintenance, switching, and load management plans, leading to fewer and shorter outages.

2.3. Objective Function

The SOA and the GOA were utilized to optimize the failure rate to improve the reliability indices.

The failure rate is inversely proportional to the Mean Time Between Failures (MTBF) as shown in Equation (15):

$$\lambda = \frac{1}{MBTF} \quad (15)$$

The design goal of this work is to minimize the failure rate to improve the reliability indices as shown in Equation (16):

$$minimize, i = 1 \sum N(failure\_rate\ i + outage\_duration\ i) \quad (16)$$

While maintaining the following constraints:

2.3.1. Load Balance Constraints

The total generated power is required to balance the sum of load demand and system losses, as indicated in (17).

$$\sum P_{generation} = \sum P_{load} + \sum P_{losses} \quad (17)$$

2.3.2. Voltage Limit Constraints

Bus voltages must stay within acceptable operational limits (0.85 – 1.05 p.u) as captured in (18);

$$V_{min} \leq V_i \leq V_{max} \quad (18)$$

2.3.3. Line Thermal Limit Constraints

Lines must operate within their rated capacity as shown in (19):

$$|P_{ij}| \leq P_{ij}^{max} \quad (19)$$

2.3.4. Transformer Loading Limits

Transformers must operate within their rated capacity as shown in (20):

$$Loading_{transformer} \leq 100\% \quad (20)$$

3. Materials and Methods

The 330kV network of Nigeria was developed in the Electrical Transient Analyzer Program (ETAP).

The network was limited to only the 330kV buses and the power plants due to the availability of outage data obtained from the grid controller at the National Control Center, Osogbo, Nigeria.

The indicative sample outage data collected for this work spans the period of 2022 – 2023 and is given in Table 1.

Table 1. Outage data from the grid controller

Date	330kV Lines	Duration	Load
31/05/2023	Afam/Alaoji line 1	70 min	149 MW
31/05/2023	Afam/Alaoji line 2	206 min	145 MW
27/05/2023	Ajah/Alagbon line 1	338 min	51 MW
03/08/2023	Ajah/Alagbon line 2	704 min	118 MW
: :	: :	: :	: :
: :	: :	: :	: :

The data used for the work covers a period of one year. The information captures the 330kV lines outage, outage duration, load loss, and the customers affected. The base case data showed 594 failures. Thus, the failure rate was calculated using Equation (21):

$$Failure\ Rate\ (\lambda) = \frac{Number\ of\ Failures}{Total\ Operating\ Time\ (hours)} \quad (21)$$

Based on this, a failure rate value of 0.0678 was used as the base case value. Before carrying out reliability analysis of the network, a power flow simulation based on Newton-Raphson's method was applied to the developed 330kV network to obtain a converged solution.

Next, the failure rate for the base case and minimized value for SOA and GOA were applied to determine the ASAI, SAIDI, SAIFI, and CAIDI.

The one-line diagram using the ETAP program is presented in Figure 1.

Figure 1 shows the application of the reliability analysis to the modelled 330kV network of the Nigerian grid using the ETAP software.

After the base case results were obtained, the optimized results in snake and grasshopper optimization techniques were determined. The optimization parameters used for the SOA and GOA are given in Table 2 below:

Table 2. Optimization parameters

Parameter	SOA	GOA
Maximum Iteration	200	200
Search Agents	30	30
C1 (Exploration Balance Controller)	0.5	----
C2 (Movement scaling factor in exploration phase)	0.05	----
C3 (Movement scaling factor in exploitation phase)	2	----
C_{max} (Initial maximum value of the contraction coefficient)	----	1
C_{min} (Initial minimum value of the contraction coefficient)	----	0.0004

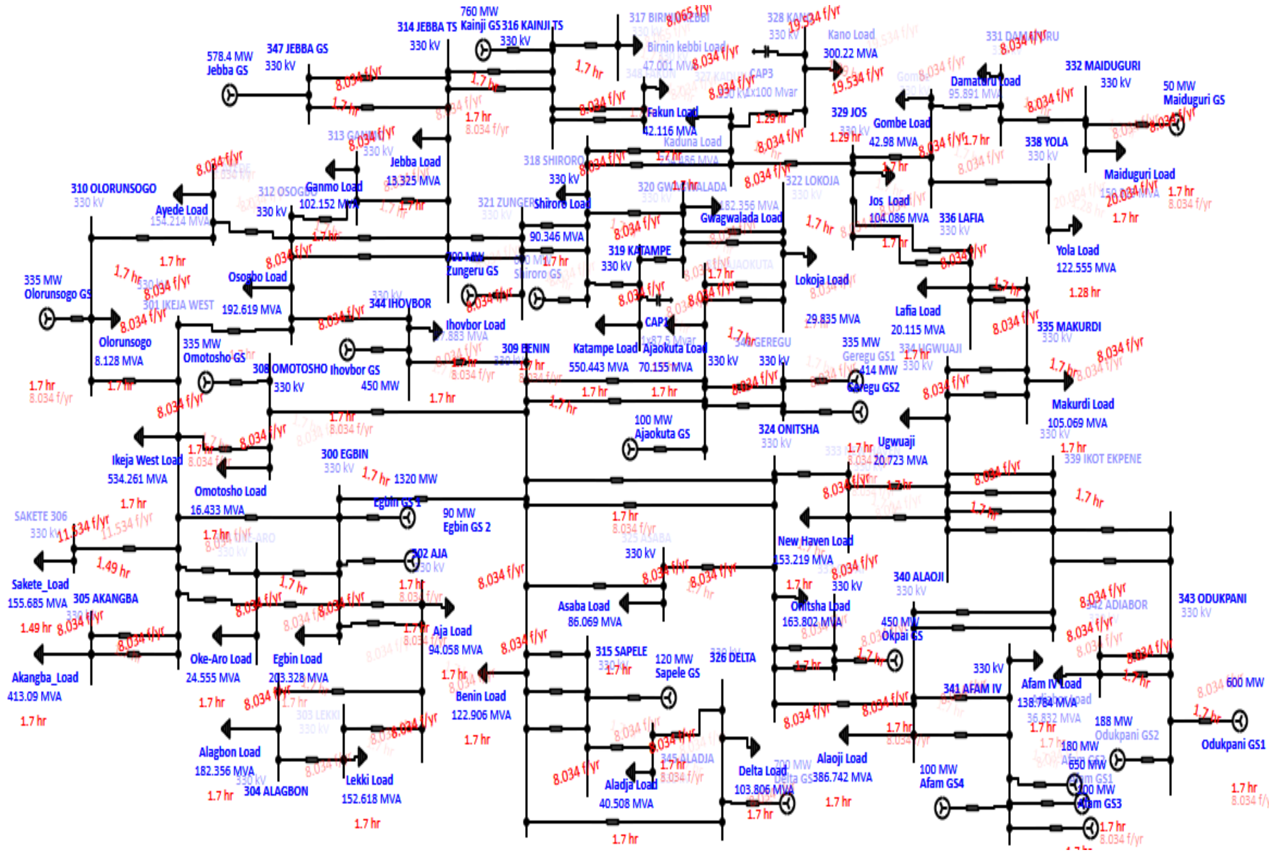


Fig. 1 One-line diagram for the 330kV grid network of Nigeria

3.1. Reliability Assessment using SOA

Reliability assessment in power systems involves evaluating the ability of a system to deliver continuous and quality power to consumers under various operating conditions. The SOA effectively solves complex optimisation problems like improving power system reliability indices. The steps for reliability assessment using the SOA include:

(a) Define the Optimization Problem:
- Objective: Minimize SAIDI, SAIFI, and CAIDI while maximizing ASAI.
- Constraints: System capacity limits and power flow constraints

(b) Input Data:
- Load profiles.
- Network topology.
- Reliability data (e.g., failure rates, repair times).
- Initial parameters for SOA

(c) Initialize the Population:
- Generate a set of candidate solutions randomly

(d) Evaluate Fitness:
- Evaluate the reliability performance of each solution based on ASAI, SAIDI, SAIFI, and CAIDI.

(e) Snake Optimization Process:
- Simulate the adaptive movement of snakes to explore and exploit the solution space:

  (i) Exploration Phase: Snakes explore new areas of the search space to locate promising solutions.
  (ii) Exploitation Phase: Snakes converge towards optimal solutions by fine-tuning their positions.

(f) Position Update:
- Update the position of each candidate solution using the SO movement equations.

(g) Fitness Update:
- Recalculate the reliability indices for the updated positions.

(h) Convergence Check:
- Check whether the stopping criteria (e.g., maximum iterations or minimal improvement) are met.

(i) Output Results:
- Output the optimized reliability indices

The flow chart for achieving the reliability assessment using the SOA is shown in Figure 2.

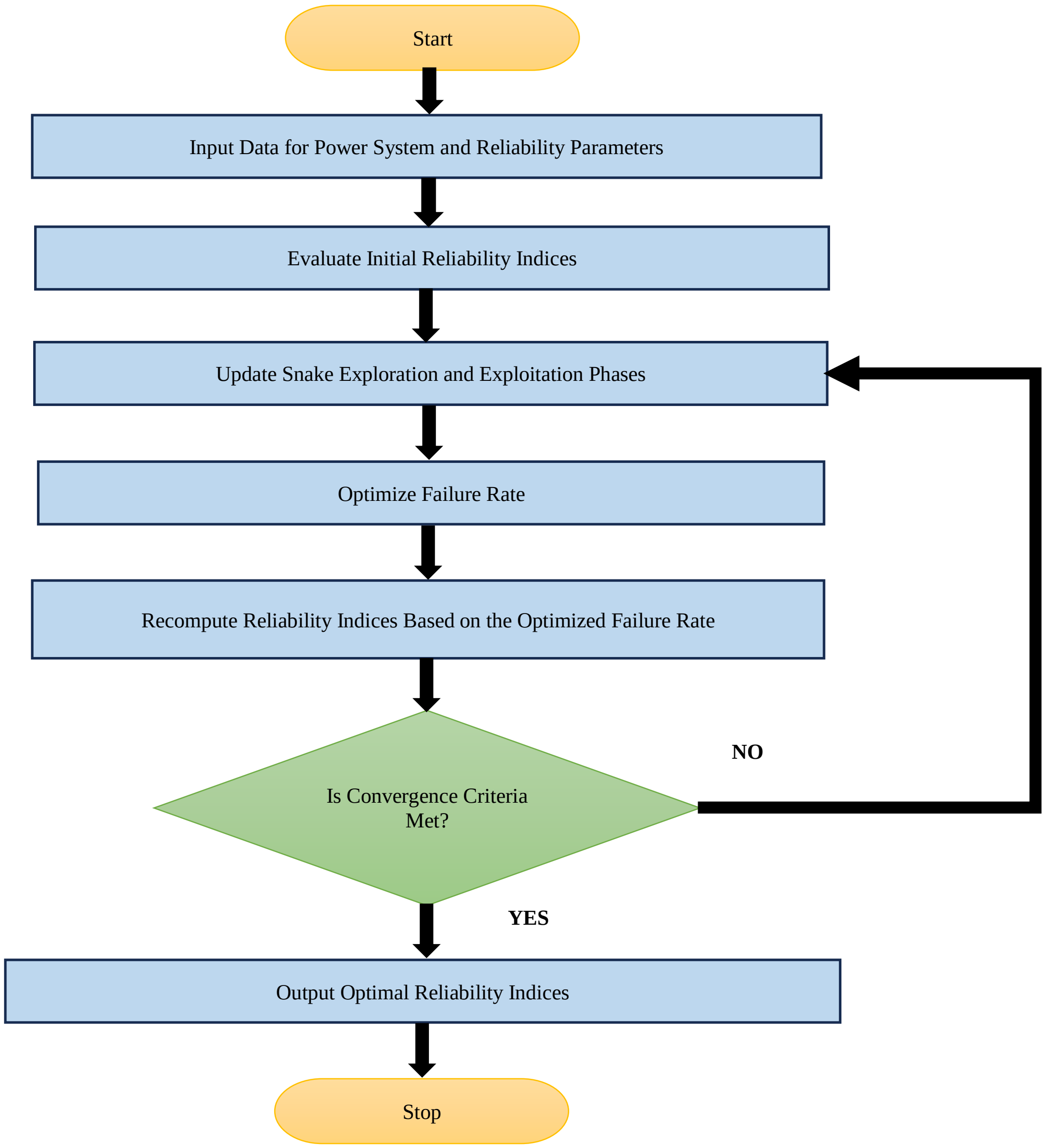


Fig. 2 Flow chart for reliability assessment using SOA

3.2. Reliability Assessment using GOA

The GOA is modelled after the natural swarming behaviour of grasshoppers. It is highly effective for addressing optimization challenges, such as evaluating and improving reliability in power systems. The steps for reliability assessment using the GOA include:

(a) Problem Definition:
- Objective: (i) Minimize SAIDI, SAIFI, and CAIDI, (ii) Maximize ASAI.
- Constraints: (i) Power flow equations, (ii) Network voltage and current limits.

(b) Input Data:
- Load profiles and network topology.
- Failure rates and repair times for system components.
- GOA parameters (e.g., swarm size, number of iterations, search boundaries).

(c) Initialize the Swarm:
- Represent each grasshopper as a candidate solution.

(d) Evaluate Fitness Function:
- Compute reliability indices (ASAI, SAIDI, SAIFI, CAIDI) for each candidate solution.

(e) Grasshopper Optimization Process:
- Social Interaction: Grasshoppers are attracted to better solutions (leaders).
- Repulsion: Grasshoppers maintain diversity to avoid premature convergence.
- Position Update: Update the position of each grasshopper using GOA's mathematical model.

(f) Constraint Handling:

- Apply penalties for solutions violating system constraints.

(g) Fitness Re-Evaluation:

- Recompute reliability indices for updated positions.

(h) Convergence Check:

- Stop if the maximum iteration is reached

(i) Output Results:

- Display the optimized reliability indices.

The flowchart for conducting reliability assessment with the GOA is shown in Figure 3.

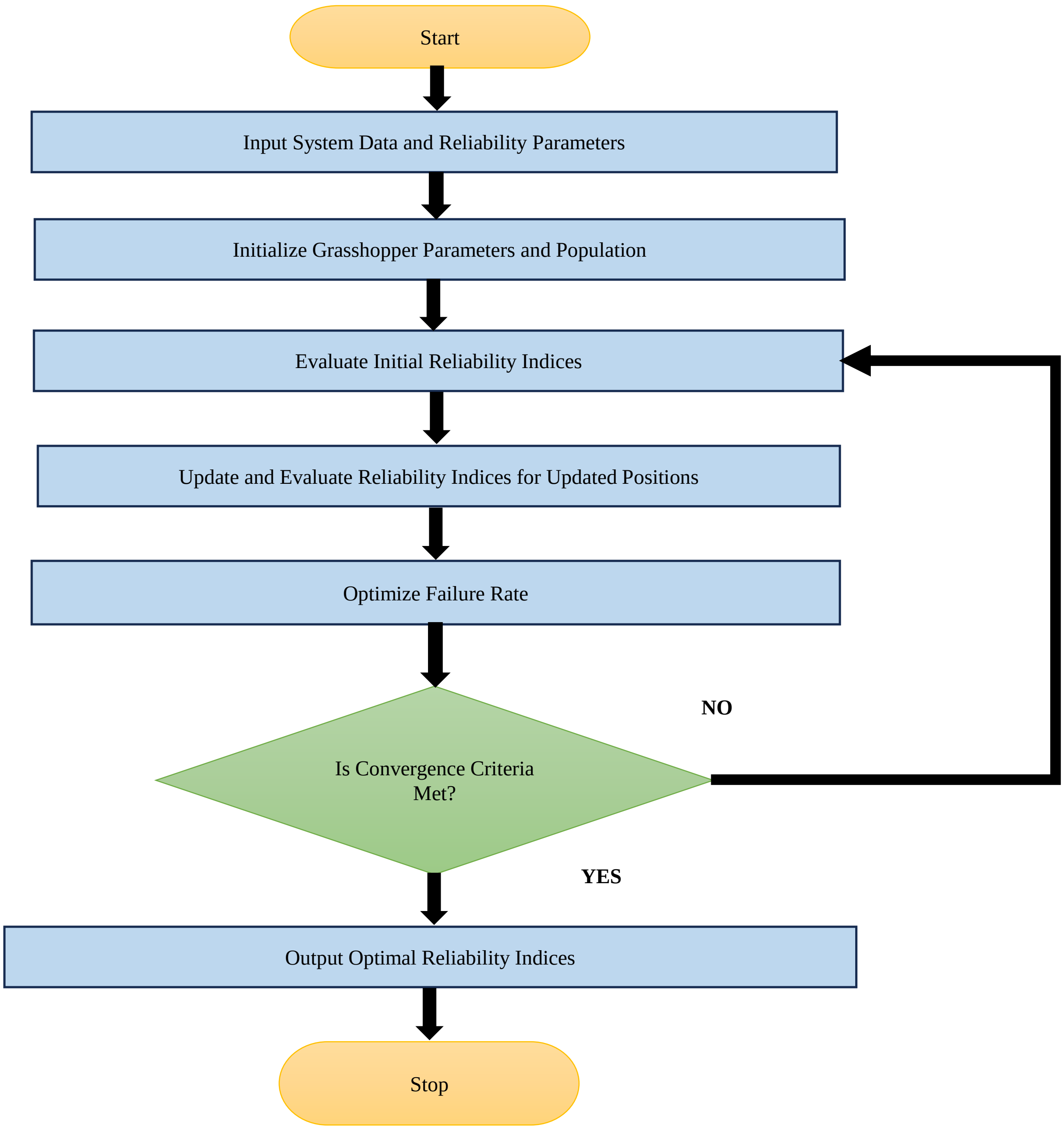
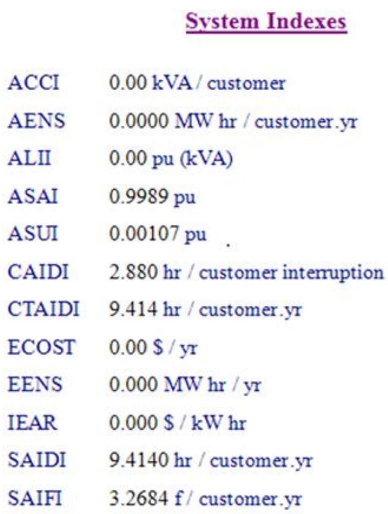


Fig. 3 Flow chart for reliability assessment using GOA

4. Results and Discussion

The ETAP program was used to determine the reliability metrics for the base case, SOA, and GOA scenarios.

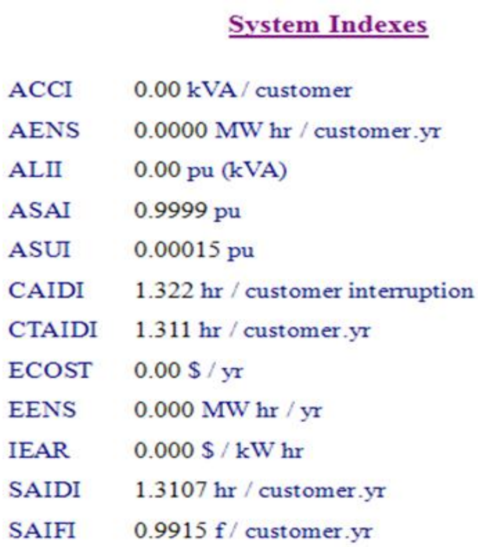
The reliability assessment results for the case study scenarios are shown in Figures 4 - 6, respectively.



System Indexes

ACCI	0.00 kVA / customer
AENS	0.0000 MW hr / customer.yr
ALII	0.00 pu (kVA)
ASAI	0.9989 pu
ASUI	0.00107 pu
CAIDI	2.880 hr / customer interruption
CTAIDI	9.414 hr / customer.yr
ECOST	0.00 $ / yr
EENS	0.000 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	9.4140 hr / customer.yr
SAIFI	3.2684 f / customer.yr

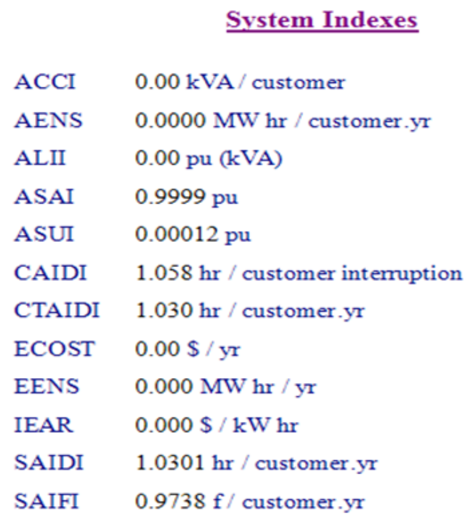
Fig. 4 Reliability metrics for the base case scenario



System Indexes

ACCI	0.00 kVA / customer
AENS	0.0000 MW hr / customer.yr
ALII	0.00 pu (kVA)
ASAI	0.9999 pu
ASUI	0.00015 pu
CAIDI	1.322 hr / customer interruption
CTAIDI	1.311 hr / customer.yr
ECOST	0.00 $ / yr
EENS	0.000 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	1.3107 hr / customer.yr
SAIFI	0.9915 f / customer.yr

Fig. 5 Reliability metrics for the SOA



System Indexes

ACCI	0.00 kVA / customer
AENS	0.0000 MW hr / customer.yr
ALII	0.00 pu (kVA)
ASAI	0.9999 pu
ASUI	0.00012 pu
CAIDI	1.058 hr / customer interruption
CTAIDI	1.030 hr / customer.yr
ECOST	0.00 $ / yr
EENS	0.000 MW hr / yr
IEAR	0.000 $ / kW hr
SAIDI	1.0301 hr / customer.yr
SAIFI	0.9738 f / customer.yr

Fig. 6 Reliability metrics for the GOA

Table 3. Comparing reliability indices for all the scenarios

Reliability Indices	Base Case	SOA	GOA
ASAI	0.9989	0.9999	0.9999
SAIDI	9.4140	1.3107	1.0301
SAIFI	3.2684	0.9915	0.9738
CAIDI	2.880	1.3220	1.0580

The summary of the reliability indices' results was compared as shown in Table 3 for the base case, SOA case, and GOA case. From the results of reliability indices in Table 3, the ASAI improved from 99.89% in the base case to 99.99% after the optimization using the SOA and the GOA. The SAIDI value improved from a base case value of 9.4140 to 1.3107 using the SOA, and 1.0301 using the GOA. Furthermore, the SAIFI value improved from 3.2684 in the base case to 0.9915 using the SOA, and 0.9738 for the GOA, while the CAIDI's improvement was from 2.880 in the base case to 1.3220 using the SOA and finally to 1.0580 when the GOA was applied. The results of the comparative analysis for the three scenarios are shown in Figure 7.

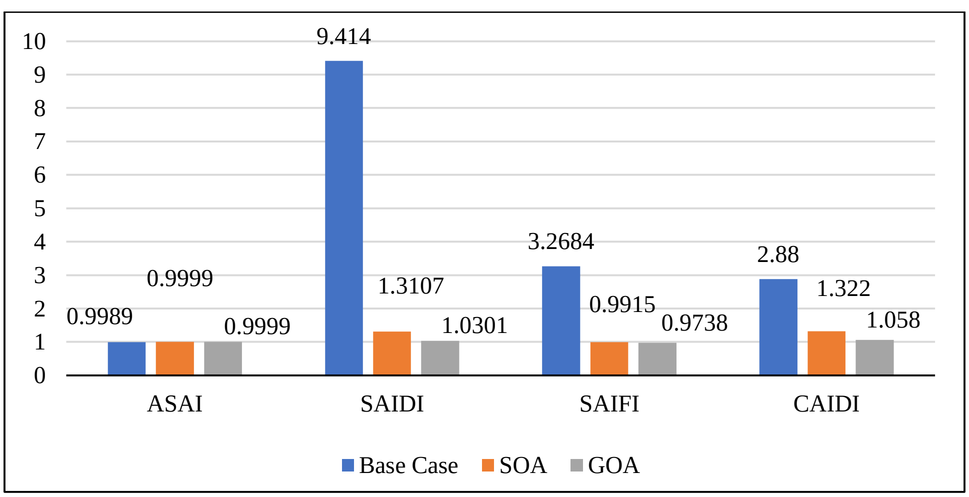


Fig. 7 Comparative analysis of all the studied scenarios

The results imply that the SOA and GOA improved all reliability indices (ASAI, SAIDI, SAIFI, and CAIDI), leading to less frequent and shorter-duration outages compared to the base case scenario. The improved value of ASAI indicates that the system's availability is optimal. The reductions in SAIDI and SAIFI suggest better network reliability and enhanced performance, while the reduction in CAIDI means quicker response to faults and faster restoration in the event of outages. Therefore, in a practical case, if the failures on the 330kV network of Nigeria are reduced, ASAI will improve; SAIDI, SAIFI, and CAIDI will also be minimized. In addition to the requirements for proper configurations of power system switching, control and relaying parameters/devices, adopting strategies such as swift clearance of faults on transmission lines, transformers, and feeders can enhance the reliability of power supply to customers. Therefore, the results of the research demonstrated that the use of metaheuristic SOA and GOA offered robust solutions that improved the reliability of the indices. These algorithms stand out for their strong global search capability, fast convergence, and robustness in handling multi-objective constraints, making them highly suitable for improving technical and operational reliability indices in real-world power systems.

5. Conclusion

This study highlighted the efficacy of applying metaheuristic algorithms - the SOA and the GOA - for improving the reliability indices of Nigeria's 330kV transmission network. The study utilized outage data sourced from the System Operator. By optimizing the failure rate, ASAI, SAIDI, SAIFI, and CAIDI were improved. The results show an improvement of ASAI from 99.89% in the base case to 99.99% after applying SOA and GOA. There was a reduction in SAIDI from 9.4140 in the base case to 1.50 and 1.3107 hours/customer/year, respectively, after applying SOA and GOA. Also, the SAIFI decreased from 3.2684 to 0.9915 and 0.9738 interruptions/customer/year after the SOA and GOA were applied, respectively. Also, the CAIDI improved from 2.880 hr/ customer interruption in the base case to 1.3220 and 1.0580 hr/customer interruption, respectively, after the optimization. These improvements signify the potential of the Snake and Grasshopper Optimization Algorithms in enhancing power system reliability by optimizing outage management and fault recovery strategies. Implementing this approach on a larger scale could lead to reduced economic losses, better customer satisfaction, and a more resilient and efficiently operated electric power grid.

5.1. Future Research

The future research, which is ongoing, will consider the optimal allocation of auto-reclosers to enhance the reliability of the transmission system by reducing the incidence of transient faults. Also, the connection of renewable energy power plants to the most vulnerable buses to further enhance the reliability of the Nigerian electric power network is recommended for further research.

References

[1] Luqman Maraaba et al., "Neural Networks Based Dynamic Load Modeling for Power System Reliability Assessment," *Sustainability*, vol. 15, no. 6, pp. 1-16, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Omowumi Grace Olasunkanmi et al., "Impact of a HVDC Link on the Reliability of the Bulk Nigerian Transmission Network," *Energies*, vol. 15, no. 24, pp. 1-16, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[3] E.A. Tebepah, H.N. Amadi, and O.N. Igbogidi, "Electric Power Transmission Upgrade in Nigeria: The Present Status," *International Journal of Engineering Research and Development*, vol. 20, no. 4, pp. 128-133, 2024. [Google Scholar] [Publisher Link]

[4] K.C. Archana, Y.V Sivareddy, and V. Sankar, "Risk Assessment of Radial Distribution Systems using Modified Jelly Fish Search Algorithm to Analyse the Performance Indices," *International Journal of Electrical and Electronics Research*, vol. 12, no. 2, pp. 453-460, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] K.Q. Blue-Jack et al., "Evaluation of Load Flow Analysis of the Nigerian 330kV Transmission Network Using Particle Swarm Optimization Technique," *Journal of Recent Trends in Electrical Power System*, vol. 7, no. 3, pp. 42-59, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[6] Moyahabo Dominic Ramere, and Opeyeolu Timothy Laseinde, "Improving the Reliability of Power Distribution Substations Equipment for Life Extension by considering Condition Based Maintenance," *Procedia Computer Science*, vol. 232, pp. 2289-2301, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[7] Desta Tegegne Asradew, "Reliability Analysis and Improvement of Debre Berhan Power Distribution Reliability Analysis and Improvement of Debre Berhan Power Distribution Network by Using Fuzzy Logic Optimization Technique," *American Journal of Electrical and Computer Engineering*, vol. 5, no. 2, pp. 45-45, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[8] Behzad Mostafapour, and Saeed Seyedtabaii, "Convergence Rate Assessment in Optimal Re-Closers Placement," *5th National Conference on New Technologies in Electrical and Computer Engineering*, Isfahan, Iran, pp. 1-6, 2025. [Google Scholar] [Publisher Link]

[9] Giovanna Adinolfi et al., "Innovative Method for Reliability Assessment of Power Systems: From Components Modeling to Key Indicators Evaluation," *Electronics*, vol. 13, no. 2, pp. 1-22, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[10] Addisu Mamo, and Abraham Hizkiel, "Reliability Assessment and Enhancement of Dangila Distribution System with Distribution Generation," *Cogent Engineering*, vol. 10, no. 1, pp. 1-10, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[11] Obinna Kingsley Obi, Chinedu Chigozie Nwobu, Odigbo Abigail Chidimma, "Critical Contingency Analysis: Enhancing Stability in Nigeria's 330kV Grid," *International Journal of Advances in Engineering and Management*, vol. 7, no. 1, pp. 123-130, 2025. [CrossRef] [Publisher Link]

[12] G.A. Adepoju, M.A. Sanusi, and M.A. Tijani, "Application of SSSC to the 330kV Nigerian Transmission Network for Voltage Control," *Nigerian Journal of Technology*, vol. 36, no. 4, pp. 1258-1264, 2018. [CrossRef] [Google Scholar] [Publisher Link]

[13] D.C. Oyiogu, C.A. Obiora-Okeke, and A.O. Aniagboso, "Customer Reliability Indices Evaluation of Umudike 11kV Distribution Feeder," *IRE Journals*, vol. 7, no. 9, pp. 145-151, 2024. [Google Scholar] [Publisher Link]

[14] Moch Arfi Almi, and Tri Wrahatnolo, "Analysis of the 20 kV Distribution Network System Reliability Index Technically and Economically using the Section Technique Method and RNEA at the Margorukun Feeder," *Indonesian Journal of Electrical and Electronics Engineering*, vol. 8, no. 1, pp. 32-40, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[15] Gerald A. Abantao et al., "Reconceptualizing Reliability Indices as Metrics to Quantify Power Distribution System Resilience," *Energies*, vol. 17, no. 8, pp. 1-13, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[16] Mohammed Jawad Abed, and Anis Mhalla, "Reliability Assessment of Grid-Connected Multi-Inverter for Renewable Power Generation Sector," *Arab Gulf Journal of Scientific Research*, vol. 42, no. 1, pp. 68-84, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[17] Weimin Zheng et al., "A Compact Snake Optimization Algorithm in the Application of WKNN Fingerprint Localization," *Sensors*, vol. 23, no. 14, pp. 1-16, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[18] Abhishek G. Neve, Ganesh M. Kakandikar, and Omkar Kulkarni, "Application of Grasshopper Optimization Algorithm for Constrained and Unconstrained Test Functions," *International Journal of Swarm Intelligence and Evolutionary Computation*, vol. 6, no. 3, pp. 1-7, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[19] Shahrzad Saremi, Seyedali Mirjalili, and Andrew Lewis, "Grasshopper Optimisation Algorithm: Theory and Application," *Advances in Engineering Software*, vol. 105, pp. 30-47, 2017. [CrossRef] [Google Scholar] [Publisher Link]