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Development of a Genetic Algorithm-Based Framework for Automated Load Demand Response and Smart Grid Optimization in 33kV Distribution Network

Suleiman Adaira Aminu [a,*], Ma-Riekpen Jacob Edekin Evbogbai[b], Henry Amhenrior[c]

[a, b, c]*Department of Electrical and Electronic Engineering, Edo State University, Iyamho, Edo State, Nigeria*
[*]**Corresponding author email:** suleiman21.aminu@edouniversity.edu.ng

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A B S T R A C T

Nigeria's electricity distribution network faces persistent supply and demand imbalances that necessitate manual load shedding practices often characterized by inefficiency and inequitable allocation. This study develops a Genetic Algorithm (GA)-based Automated Load Demand Response (ALDR) framework for optimizing power allocation on a 33 kV distribution feeder in Lokoja, Nigeria. The framework integrates MATLAB's Global Optimization Toolbox for optimization, MATLAB App Designer for real-time operator interaction, and an ETAP-in-the-loop feasibility module to ensure technical operability. The GA model incorporates loss-aware power balancing, socio-economic priority indices, critical-load floors, and a fairness-enhancing grid-Gini metric. These enable the system to guarantee minimum supply for essential services such as hospitals, waterworks, higher institutions, and security installations, while equitably distributing residual capacity among non-critical loads. An adaptive repair operator maintains allocation feasibility under ETAP-estimated losses, voltage constraints, thermal loading, and radial topology requirements. The framework was evaluated across multiple shortage scenarios (20, 15, and 10 Mega Watts, MW) relative to the 25 MW feeder's demand and benchmarked against Particle Swarm Optimization (PSO), Simulated Annealing (SA), ANN-assisted GA, and heuristic allocation approaches. Results show that the proposed GA framework improves the Satisfaction Index by 15 – 25%, reduces Energy Not Supplied (ENS) by 30 – 40%, and enhances reliability indices (SAIFI, SAIDI) by 10 – 20% compared to existing methods. ETAP simulations further validated allocation feasibility and maintained technical losses within 0.002 MW. The study's novelty lies in integrating GA-driven prioritization, fairness shaping, multi-algorithm benchmarking, physical-feasibility validation, and an operator-oriented Graphic User Interface, GUI. The resulting ALDR architecture improves fairness, transparency, and resilience in 33kV distribution networks. Future work will explore hybrid GA–PSO/ANN models, renewable energy coupling, and real-time deployment for feeder automation.

1.INTRODUCTION

Electricity plays a key role in socio-economic growth, industrial productivity, and human development. Reliable access to electricity has been widely recognized as a prerequisite for achieving sustainable development, particularly in health, education, and industry (Adedayo and Ogunjuyigbe, 2024). Yet, across many developing countries such as Nigeria, electricity systems remain plagued by persistent supply and demand imbalances, infrastructural bottlenecks, and inefficient operational practices. In Nigeria, millions of connected consumers continue to experience frequent outages and voltage instabilities due to weak grid infrastructures and poor reliability indices (Okafor et al., 2024).

Globally, utilities have responded to these challenges through the adoption of smart grid technologies, advanced demand-side management (DSM), and automated demand response (DR) frameworks. These approaches are designed to optimize allocation under conditions of scarcity, integrate renewable energy resources, and enhance grid resilience (Zhang et al., 2023). At the core of these innovations lies the use of optimization techniques such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Simulated Annealing (SA), and Artificial Neural Networks (ANN), to solve complex, multi-variable allocation and control problems. Genetic Algorithms, in particular, has gained prominence for its robustness, adaptability, and ability to handle non-linear, multi-objective problems that reflect the real-world nature of power systems (Bello et al., 2024).

In the Nigerian context, the need for innovative allocation strategies is even more urgent because electricity demand far outweighs supply, and available generation is frequently curtailed due to gas shortages, equipment breakdown, and poor transmission capacity. Conventional load-shedding practices, often executed manually, fail to account for socio-economic priorities such as hospitals, water supply facilities, and communication infrastructure. This results in disproportionate socio-economic losses during periods of scarcity. Smart grid-based, priority-sensitive optimization frameworks therefore provide an opportunity to mitigate these shortcomings by ensuring that critical loads are allocated electricity first, while less essential demands are either curtailed or rescheduled (Bello and Musa, 2024).

Furthermore, the integration of such optimization strategies with real-time grid monitoring, Geographic Information Systems (GIS), and operator-friendly decision-support tools can significantly enhance grid reliability and customer satisfaction. Studies have shown that embedding GA-based allocation within a smart grid environment not only improves fairness and transparency but also reduces Energy Not Supplied (ENS), enhances reliability indices such as SAIFI and SAIDI, and supports the long-term vision of sustainable energy transition in developing economies (Adebanjo and Yusuf, 2025).

Within Nigeria, electricity sector is characterized by fragile generation and transmission infrastructures, high losses, and poor financial sustainability. Nigeria, despite being the largest economy on the continent, epitomizes these challenges. Although the country has an installed generation capacity exceeding 13,000 MW, less than 5,000 MW is typically available to the national grid at any given time due to generation outages, gas supply constraints, and transmission bottlenecks (Adebanjo and Yusuf, 2025). This persistent shortfall has forced the eleven Distribution Companies (DisCos) to adopt widespread load shedding as a mechanism to balance power demand and supply.

However, Nigerian load shedding practices are predominantly manual and arbitrary, often lacking fairness, efficiency, and prioritization criteria. Critical socio-economic and security installations such as hospitals, schools, waterworks, military bases, telecommunication centres, and broadcasting houses are frequently disconnected alongside residential and non-essential loads (Adisa et al., 2024). This approach not only endangers lives but also undermines national productivity and public confidence in the electricity sector. Compounding this challenge are distribution inefficiencies, with system losses exceeding 39% on some feeders, further weakening system reliability (Eze and Olayinka, 2024).

While international research has demonstrated the efficacy of optimization-driven demand response frameworks, Nigerian studies remain limited in both scope and depth. Many have relied on ETAP-based load flow analyses or descriptive assessments of DSM, with minimal integration of computational optimization. For example, Adeyemo and Musa (2024) proposed demand response strategies for critical infrastructures but did not implement algorithmic optimization. Similarly, Adebayo and Olanrewaju (2024) examined feeder-level DR but only at a conceptual and descriptive level. More recently, Jimoh and Adeyemi (2025) applied metaheuristic optimization for feeder reconfiguration under contingency scenarios, achieving significant resilience gains. Yet, none of these works developed a priority-sensitive, GA-based allocation framework integrated with a Graphical User Interface (GUI) for real-time operator use.

2. LITERATURE REVIEW

This section reviews relevant literature to establish the conceptual, theoretical, and empirical foundations of the study. It examines global and Nigerian perspectives on load prioritization, automated demand response, and smart grid optimization; evaluates the capabilities and limitations of existing optimization algorithms; and identifies gaps relating to fairness, operational feasibility, and socio-economic prioritization. The review also highlights the need for integrated frameworks that combine metaheuristic optimization with feeder-level validation, thereby providing the basis for the GA-based ALDR model developed in this research.

2.1 Review of Related Concept

a. Load shedding and demand response (ldr) in modern grids

Load shedding refers to the deliberate disconnection of electrical loads from the power system in order to maintain balance between supply and demand during shortages or contingencies. In many developing countries, including Nigeria, load shedding is still conducted through **manual or heuristic approaches.** Distribution operators typically rotate outages across feeders, disconnect entire zones, or reduce voltage levels in order to prevent system collapse (Adisa *et al.*, 2024). This process is often implemented through rudimentary methods such as feeder tripping, transformer switching, or sectionalizing breakers without reliance on advanced computational tools (Oladipo and Adekola, 2021).

To overcome the shortcomings of manual load shedding, modern utilities are increasingly turning to **demand-side management (DSM)** and **demand response (DR)** strategies. DSM encompasses a broad set of measures aimed at influencing consumer electricity usage patterns to achieve efficiency and reliability. These include energy efficiency programs, time-of-use tariffs, peak load shifting, and distributed energy resource integration (Gyamfi and Krumdieck, 2021). DR, as a subset of DSM, specifically refers to the **active adjustment of consumer demand in response to price signals, incentives, or grid conditions** (Zhang *et al.*, 2021).

A **smart grid** refers to an advanced electricity network that integrates **digital communication, control systems, and automation** into traditional power infrastructure to enhance reliability, efficiency, and sustainability. Unlike conventional grids, which are primarily one-directional in power flow (generation → transmission → distribution → end-users), smart grids are characterized by **bi-directional communication and energy exchange (**Güngör *et al.*, 2022). Key features include self-healing capabilities, demand-side participation, renewable energy integration, real-time monitoring, and improved resilience against disturbances (Fang *et al.*, 2021). In the Nigerian context, transitioning towards smart grids is particularly critical, given the persistent supply and demand imbalances, high losses, and poor reliability indices observed in distribution systems. A smart grid framework can enable DisCos to minimize manual interventions, prioritize critical loads, and provide transparency in allocation addressing many of the inefficiencies of the current system (Adebanjo and Yusuf, 2025).

b. Load prioritization and priority index

Load prioritization refers to the systematic ranking of electrical loads according to their relative importance, criticality, and contribution to socio-economic or operational functions within a power distribution network. In modern smart grid environments, particularly in regions experiencing persistent supply shortages such as Nigeria, prioritization serves as a foundational mechanism for equitable and reliability-driven load allocation (Reddy and Panigrahi, 2017). By assigning priority indices to each load category, utilities can determine which facilities must be supplied first when available power is insufficient to meet total system demand. In the context of Automated Load Demand Response (ALDR) and metaheuristic optimization, load prioritization enables the integration of both technical and societal considerations into the optimization process. For example, critical loads such as hospitals, water systems, security installations, and communication infrastructure are typically assigned higher priority indices due to their essential public service roles. Medium-priority loads may include schools, commercial centers, and administrative buildings, while low-priority or deferrable loads often consist of residential clusters or non-essential commercial consumers (Roy and Ghosh, 2023).

A **Priority Index (PI)** is a quantitative metric assigned to each load centre or facility to represent its relative importance in the power distribution hierarchy. Higher indices are indicative of critical or essential loads such as hospitals, waterworks, security installations, and communication hubs that must receive preferential allocation during periods of limited supply. Lower indices are assigned to non-critical, deferrable, or discretionary loads, such as commercial complexes with flexible operating hours or residential clusters (Reddy and Panigrahi, 2017; Jimoh and Adeyemi, 2025). In the context of the present research, the Priority Index serves as a **weighting factor within the Genetic Algorithm (GA)** optimization framework. Each load centre PI is normalized and integrated into the **Satisfaction Index (SI),** ensuring that the allocation algorithm prioritizes critical facilities while maintaining equitable distribution across the feeder.

c. Fitness function

In Genetic Algorithm (GA) optimization, a fitness function is a mathematical criterion used to evaluate the quality or suitability of candidate solutions with respect to the objectives of the problem (Deb, 2019). Within smart grid applications, particularly in Automated Load Demand Response (ALDR) frameworks, the fitness function serves as the key mechanism guiding the evolutionary search towards solutions that balance technical efficiency, socio-economic fairness, and operational feasibility. For the GA-based ALDR model developed in this study, the fitness function integrates multiple performance objectives, including:

Minimization of Energy Not Supplied (ENS): Ensuring that the difference between total demand and allocated power is minimized, thereby reducing service interruptions across the feeder (Billinton and Allan, 1996).

Priority Satisfaction: Incorporating the Priority Index (PI) of each load centre, the fitness function weights allocations to favor critical loads such as hospitals, waterworks, and communication hubs while guaranteeing minimum supply through criticality floors (Reddy and Panigrahi, 2017).

Fairness Enhancement: Using metrics such as the grid-Gini coefficient, the function penalizes solutions that excessively favor high-priority loads at the expense of low-priority but socially relevant loads, ensuring a more equitable distribution (Deb, 2019; Jimoh and Adeyemi, 2025).

Mathematically, the fitness function can be represented as a weighted combination of these objectives:

$$F(x) = \alpha\, SI(x) - \beta\, ENS(x) - \gamma\, G(x) \tag{1}$$

Where: SI(x) = Priority-weighted Satisfaction Index, ENS(x) = Energy Not Supplied, G(x) = Grid-Gini coefficient representing allocation fairness. α, β, γ = weighting factors to balance competing objectives

This multi-objective fitness formulation ensures that GA candidates are evaluated not only for technical performance but also for socio-economic relevance and equitable allocation. Furthermore, by integrating ETAP-in-the-loop feasibility checks, the fitness function implicitly penalizes solutions that violate voltage limits, line loading, or radial topology constraints, thereby coupling mathematical optimization with real-world operability (Eremia and Shahidehpour, 2018; Adisa *et al.,* 2024).

d. Reliability and Performance Indices

i. System average interruption frequency index (SAIFI)

The **SAIFI** measures the average number of sustained interruptions a consumer experiences over a given period, typically a year. It is expressed as:

(2)

$$\text{SAIFI} = \frac{\sum N_i}{N_T}$$

where N_i is the total number of customer interruptions and N_T is the total number of connected customers (IEEE Std. 1366-2012). SAIFI provides insight into how frequently outages occur and is widely used to benchmark utility performance. In Nigeria, SAIFI values remain high, reflecting frequent feeder interruptions that affect consumer confidence and economic activities (Jimoh and Adeyemi, 2025).

ii. System average interruption duration index (SAIDI)

The SAIDI measures the average total duration of sustained interruptions experienced by a customer in a year. It is given as:

$$\text{SAIDI} = \frac{\sum U_i \, . N_i}{N_T} \tag{3}$$

where U_i represents the customer interruption durations (in hours), and N_T is the total number of customers served. SAIDI captures the severity of outages from a temporal perspective. High SAIDI values indicate longer service restoration times and greater customer inconvenience (Eze and Olayinka, 2024). In reliability-oriented optimization frameworks, reducing SAIDI is often a critical goal alongside minimizing ENS.

iii. Satisfaction index (SI)

Beyond traditional reliability indices, the **SI** has been increasingly used to measure how well power allocation aligns with customer expectations and socio-economic priorities. SI is typically expressed as a percentage of demand satisfied relative to total demand:

$$\text{SI} = \frac{1}{N} \sum_{i=1}^{\eta} \frac{A_i}{\pi_i} \; x \, 100 \tag{4}$$

In this study, SI is closely related to the SI, which evaluates whether high-priority loads (e.g., hospitals, water treatment plants) are adequately served even under constrained supply conditions. Other related performance indicators include Loss of Load Probability (LOLP) and Loss of Load Expectation (LOLE), which provide probabilistic measures of system adequacy (Bello and Musa, 2024). Together, these indices provide a comprehensive assessment of system performance from both technical and consumer perspectives.

e. Genetic Algorithm (GA) Fundamentals

The Genetic Algorithm (GA) is a metaheuristic inspired by the principles of natural selection and genetics, introduced by Holland in the 1970s (Holland, 1975). A GA works by evolving a population of potential solutions (chromosomes) toward better solutions through iterative processes.

i. *Chromosome Encoding**:*** Each chromosome represents a candidate solution to the optimization problem. In power systems, this may include binary, integer, or real-number encodings of load allocation decisions, feeder switching states, or generator schedules. For load allocation in weak grids, each gene within a chromosome may represent the power assigned to a load centre, subject to feeder and supply constraints (Bello and Musa, 2024).

ii. *Population:* A set of chromosomes forms a population, which evolves across generations. The diversity of the population is crucial for exploring the solution space effectively and avoiding premature convergence.

iii. *Fitness Function:* The fitness function evaluates the quality of each chromosome. It is problem-specific and typically seeks to maximize priority-based satisfaction of critical loads while minimizing ENS, SAIFI, and SAIDI. Mathematically, for this study, the fitness function can be expressed as:

$$\mathrm{F}\,(\mathrm{x}) = \mathrm{w}_1 \,.\, SI + \mathrm{w}_2 . \left(\frac{1}{\mathrm{ENS}}\right) + \mathrm{w}_3 \,.\, \left(\frac{1}{\mathrm{SAIDI} + \mathrm{SAIFI}}\right) \tag{5}$$

where w_1, w_2, w_3 are weighting factors reflecting the relative importance of satisfaction index, energy reliability, and interruption minimization (Adamu and Ismail, 2024).

f. Operators: Selection, Crossover, and Mutation

The evolutionary process of GA is driven by three core operators:

i. *Selection:* This operator chooses chromosomes for reproduction based on their fitness values. Common methods include roulette-wheel selection, tournament selection, and rank-based selection. High-fitness solutions are more likely to be selected, ensuring that strong traits propagate across generations (Mitchell, 1998).

ii. *Crossover:* Crossover mimics biological reproduction by combining genes from two parent chromosomes to produce offspring. It enables exploration of new solutions by exchanging allocation patterns between parents. Typical methods include single-point, two-point, and uniform crossover. In power allocation problems, crossover ensures that promising load distribution patterns are recombined for better efficiency (Rao and Narasimham, 2021).

iii. *Mutation:* Mutation introduces random changes in chromosome genes to preserve diversity and avoid local optima. For example, a mutation operator may randomly adjust the allocated power of a load centre or swap feeder assignments. Mutation probability is typically low (e.g., 0.01 – 0.05), but it plays a critical role in maintaining genetic diversity (Nguyen and Le, 2020).

g. Suitability of GA for Non-linear, Multi-objective Problems

Genetic Algorithm is particularly well-suited to non-linear, multi-objective, and constrained optimization problems, which are common in power systems. Unlike deterministic methods such as linear programming, GA does not require convexity or differentiability of the objective function (Wood *et al.*, 2014). This makes GA effective for:

i. Multi-objective optimization (e.g., minimizing ENS while maximizing satisfaction index).

ii. Discrete and continuous decision variables (e.g., binary feeder switching, real-valued power allocations).
iii. Highly constrained environments (e.g., limited supply, feeder capacity, voltage stability).

Comparative studies have shown GA to outperform traditional methods and even other metaheuristics (such as PSO and SA) in terms of flexibility, robustness, and ability to embed priority-sensitive allocation logic (Babagana *et al.*, 2025; Jimoh and Adeyemi, 2025).

h. Applications of GA in Load Allocation, Demand Response, and Optimization

The application of GA in power systems is extensive, covering various aspects of demand response, load allocation, and network optimization:

i. *Load Allocation:* GA has been applied to allocate scarce supply among competing load centres based on priority indices, ensuring that critical infrastructure such as hospitals and waterworks receive power during shortages (Adamu and Ismail, 2024).
ii. *Demand Response (DR):* GA-based frameworks optimize demand-side participation by scheduling load reductions, shifting consumption, and coordinating distributed resources in response to grid conditions (Zhang *et al.*, 2021).
iii. *Feeder Reconfiguration:* GA has been used to reconfigure distribution networks for loss minimization, voltage profile improvement, and reliability enhancement (Jimoh and Adeyemi, 2025).
iv. *Distributed Generation Placement:* GA optimizes the siting and sizing of distributed energy resources such as solar PV and storage in order to reduce system losses and improve stability (Rao and Narasimham, 2021).

In the Nigerian context, GA's ability to integrate priority-sensitive allocation with technical validation (ETAP) and GUI-enabled usability makes it a powerful tool for bridging academic modelling with real-world utility operations.

i. Automated Load Demand Response (ALDR)

The foundation of the Automated Load Demand Response (ALDR) framework is the application of **Genetic Algorithm (GA) optimization** to the feeder-level allocation problem under constrained supply. Unlike manual load shedding, which disconnects feeders arbitrarily, GA enables structured allocation by encoding load centres as genes within chromosomes and evolving solutions toward optimal allocations. The **fitness function** is designed to incorporate **reliability indices,** specifically Energy Not Supplied (ENS), System Average Interruption Duration Index (SAIDI), System Average Interruption Frequency Index (SAIFI), and the Satisfaction Index (SI).

This ensures that the optimization process balances two objectives: (i) minimizing losses and interruptions, and (ii) maximizing the satisfaction of critical socio-economic loads (Adamu and Ismail, 2024; Bello and Musa, 2024). By embedding reliability indices directly into the fitness evaluation, the framework guarantees that the outcomes are not only mathematically optimized but also technically relevant to utility performance metrics. Thus, GA optimization in ALDR extends beyond theoretical efficiency, targeting tangible improvements in **reliability and fairness.**

2.2 Review of Literatures and Gap Synthesis

a. Limitations of Previous Studies

A review of Nigerian and international literature reveals that while significant progress has been made in applying optimization and demand response to distribution systems, several limitations persist.

Firstly, Nigerian studies have mainly emphasized critical and socio-economic prioritization of loads but have not advanced towards optimization frameworks. Works such as Adamu and Ismail (2021), Adebanjo and Yusuf (2022, 2025), and Akinyemi and Ogbogu (2021) highlight the importance of preserving essential services like hospitals and waterworks. However, these approaches are often descriptive or heuristic in nature, without embedding algorithmic optimization to automate decision-making.

Secondly, metaheuristic-based research, though robust, is frequently applied to planning and reconfiguration problems rather than operational allocation. For instance, Bello and Musa (2024) optimized distributed generation placement using GA, while Jimoh and Adeyemi (2025) applied GA to feeder reconfiguration under contingency scenarios. Singh and Verma (2023) also hybridized GA with simulated annealing to enhance feeder switching. While valuable, these studies do not address allocation challenges during supply shortages, where demand exceeds available capacity.

Thirdly, reliability indices such as Energy Not Supplied (ENS), System Average Interruption Frequency Index (SAIFI), and System Average Interruption Duration Index (SAIDI) remain underutilized in allocation-focused studies. Foundational works (Billinton and Allan, 1996) and recent contributions (Rahman and Khan, 2024; Zhang and Huang, 2025) underscore the importance of reliability evaluation. Yet many optimization models concentrate on cost, loss, or voltage metrics, overlooking reliability as a validation benchmark.

Fourthly, although ETAP has been widely adopted for feeder-level analysis in Nigeria (Adekunle and Ojo, 2020; Onyishi and Ezema, 2024), few studies integrate optimization outputs with ETAP validation. Instead, optimization and simulation are often conducted in isolation, limiting practical applicability for utilities.

Finally, the absence of operator-friendly graphical interfaces is a notable shortcoming. Most optimization models, including those surveyed by Mousavi and Jordehi (2023) and Nguyen and Pham (2024), remain academic exercises with limited translation into real-world operational tools. Without GUI-based decision-support systems, adoption by utilities remains unlikely.

b. Synthesis and Gap

Overall, while Nigerian studies provide valuable technical baselines (ETAP feeder models), planning insights (DG integration), and socio-economic perspectives (load Prioritization indices), they consistently fall short of delivering a priority-sensitive, GA-based allocation framework that is validated with ENS and reliability indices (SAIFI, SAIDI, SI), benchmarked against alternative algorithms, and operationalized through an operator-ready GUI. This clear methodological and practical gap positions the present study to contribute uniquely by bridging optimization, validation, and deployment within a unified framework.

Existing Nigerian and international works address individual aspects of Prioritization, optimization, validation, or usability but rarely integrate all these elements within a single framework. The present study directly addresses this gap by developing a **GA-based Automated Load Demand Response (ALDR) framework** that:

i. Embeds **priority indices** for socio-economic fairness,
ii. Benchmarks GA against PSO, SA, and ANN,
iii. Validates allocations with **ETAP feeder simulations,**
iv. Confirms performance using **reliability indices (ENS, SI, SAIFI, SAIDI),** and
v. Provides a **MATLAB App Designer GUI** for operator-friendly deployment.
vi. This integrated approach positions this study as both **academically novel** and **practically deployable,** offering a complete pipeline that bridges theory, validation, and utility readiness.

3. MATERIALS AND METHODS

3.1 Materials

The implementation of this research relied on both software and hardware resources to ensure accuracy, reproducibility, and practical relevance. The primary materials employed are summarized below:

a. Software Tools

i. ***MATLAB R2023a****:* Used for the development of the Genetic Algorithm (GA), Artificial Neural Network (ANN)-assisted GA, Particle Swarm Optimization (PSO), and Simulated Annealing (SA) models. MATLAB App Designer was specifically employed to build the operator-oriented Graphical User Interface (GUI).
ii. ***ETAP 19.0.1****:* Utilized to model the 33 kV feeders, conduct load flow studies, and validate optimization results. Reliability indices such as SAIFI and SAIDI were extracted from ETAP simulations for benchmarking.
iii. ***MS Excel:*** Applied for preliminary data handling, load demand tabulation, and export of reports.

b. Hardware Resources

i. ***Personal Computer*****:** Intel Core i5 processor, 8 GB RAM, and 512 GB SSD, ensuring sufficient computational capability for repeated GA/ANN training and ETAP simulations.
ii. ***33 kV Feeder Baseline Data:*** provided by the utility (AEDC, Lokoja), including transformer ratings, load center characteristics, and historical reliability indices.

c. *Data Sources*

i. ***Real Data:*** Obtained from the Nigerian distribution utility (AEDC, Lokoja), for the selected feeder, covering peak demand, transformer ratings, and outage records.
ii. ***Synthetic Data:*** Generated from MATLAB to stress-test the optimization framework under worst-case and hypothetical scenarios (e.g., partial feeder supply, transformer contingencies).

Table 1 shows the load centers with the priority assignment and their classifications in descending order.

Table 1: *Load Centers, Transformer Ratings, Load Demand, and Priority Classification*

Load Centre	Transformer Rating (MVA)	Demand (MW)	Priority Index	Classification
FMC Hospital	2.50	1.50	0.99	Highly Critical
Federal University Lokoja	1.50	1.00	0.96	Highly Critical
Lokoja Water Works	2.00	1.20	0.93	Highly Critical
Telecom Masts	3.15	2.00	0.89	Critical
Fire Service Station	2.00	1.40	0.86	Critical
Force Headquarters	2.00	1.20	0.83	Critical
Army Barracks	1.50	1.00	0.81	Critical
Power Holding Office	0.75	0.50	0.78	Critical
Government House	2.50	1.50	0.74	Moderately Critical
CBN Office	3.15	2.00	0.70	Moderately Critical
Banks Area	2.00	1.20	0.68	Moderately Critical
Mega Transport Terminal	1.25	0.80	0.66	Moderately Critical
Filling Station Area	0.63	0.40	0.63	Moderately Critical
Court Line	3.15	2.00	0.60	Moderately Critical
Industrial Area	4.00	2.50	0.50	Low Priority
Commercial Area	4.00	2.80	0.45	Low Priority
NYSC Camp	0.75	0.50	0.40	Low Priority
Zone 8 Residential Area	2.50	1.50	0.35	Low Priority
Totals	**39.33**	**25.00**		

(Source: AEDC, Lokoja Zonal Records Unit)

This combination of software, hardware, and data sources provided a robust environment for both modeling and validation of the ALDR framework.

3.2 Research Design and Methods

This study adopts a design and evaluates research methodology, consistent with design science approaches commonly applied in smart grid optimization research. The method integrates algorithmic innovation, embedded validation layers, and simulation-based evaluation within real feeder constraints. Unlike conventional heuristic or purely simulation-based methods, this research introduces:

i. a fairness-anchored GA structure,
ii. ETAP-in-the-loop feasibility validation, and
iii. A graphical decision-support interface that links optimization outputs to operator-level decision-making.

Together, these features form a Genetic Algorithm (GA)-based Automated Load Demand Response (ALDR) framework designed for 33 kV distribution feeders under constrained Nigerian grid conditions.

3.2.1 GA Problem Formulation and Model Design

A 33 kV distribution feeder with *N* load centres is modeled, each represented by a demand D_i and allocated power x_i. The total available supply is S. Each load is assigned a criticality floor α_i, D_i, where $\alpha_i \in [0,1]$ specifies the minimum mandatory allocation fraction for essential facilities such as hospitals, waterworks, or communication hubs etc. This study integrates several novel optimization features into the GA-based ALDR framework, including priority-anchored allocation, fairness shaping, and **loss-aware feasibility coupling with ETAP.**
The system's dual objective is to **maximize the priority-weighted Satisfaction Index (SI)** and **minimize Energy Not Supplied (ENS),** both key indicators of power system performance *(Billinton and Allan, 1996; Al-Saedi et al., 2017).*
The dual objective is expressed as:

$$\max SI = \frac{\sum_{i=1}^{N} w_i.\min(x_i, D_i)}{\sum_{i=1}^{N} w_i.D_i} \tag{6}$$

$$\min ENS = \sum_{i=1}^{N} (D_i - x_i)^+ \tag{7}$$

Where w_i is the normalized priority index, D_i is the demand, and x_i is the power allocation to load i. The Satisfaction Index ensures that high-priority loads are favored while maintaining system-wide allocation balance. These two indicators are widely used in power system performance evaluation *(Kothari and Nagrath, 2016; Deep and Das, 2014; Kennedy and Eberhart, 2004).*

a. Power Balance Constraint

Transmission and distribution losses are explicitly accounted for using ETAP's active power loss estimate L^(x). The total allocation must not exceed the net available power:

$$\sum_{i=1}^{N} x_i \le S - \hat{L}(x) \tag{8}$$

This loss-corrected projection ensures system consistency between mathematical optimization and physical feeder constraints, distinguishing the model from loss-agnostic GA models reported in earlier studies *(Eremia and Shahidehpour, 2018; Adisa et al., 2024; Mahmoud et al., 2020).*

b. Loss-Aware Repair/Projection (R_L)

To ensure energy consistency after accounting for feeder losses, allocations are adjusted via a loss-corrected projection:

$$x_i' = \frac{S-\hat{L}(x)}{\sum_j x_j}.x_i \tag{9}$$

where w_i is the normalized socio-economic priority index, D_i the demand, and x_i the allocated power. This objective formulation follows the **multi-objective optimization** framework in smart grids, which balances technical efficiency and socio-economic fairness *(Deb, 2019; Liu and Singh, 2024; Dasgupta and Michalewicz, 2018)*. This correction ensures that the total distributed power respects actual available capacity after accounting for ETAP-estimated losses, distinguishing the framework from loss-agnostic optimization models.

3.2.2 Embedding Socio-Economic Priority Indices

a. *Priority-Anchored GA*

Each load *i* is represented by demand D_i and a criticality floor α_i, D_i, where $\alpha_i \in [0,1]$ denotes the minimum mandatory allocation fraction for critical facilities (e.g., hospitals, water works). The GA fitness incorporates a priority-weighted Satisfaction Index (SI) defined as figure 3.1:

b. *Critical Floors for Essential Services*

To operationalize socio-economic prioritization, each load centre is assigned a **priority weight** w_i derived from normalized socio-economic indices representing criticality, service relevance, and load type. Critical loads (e.g., hospitals, waterworks, communication centres) are assigned minimum allocation guarantees using the constraint:

$$x_i \geq \alpha_i,\ Di \qquad \forall I \in C \tag{10}$$

Where C denotes the subset of critical load centers and α_i defines the minimum allowable supply fraction to prevent complete outage in essential services. The GA fitness incorporates these constraints and priority weights to guide the population toward balanced, high-priority allocations *(Deep and Das, 2014; Deb, 2019; Kennedy and Eberhart, 2004)*. This hybrid strategy improves **grid resilience** during severe shortages, consistent with global smart grid reliability trends *(Wang et al., 2022; Eremia and Shahidehpour, 2018).*

c. ***Fairness Tie-Break via Grid-Gini Index***

To prevent repeated starvation of low-priority but socially relevant loads, tie-breaking among solutions of similar SI is guided by a grid-Gini index:

$$\mathrm{G} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\left|x_i.x_j\right|}{2N^2.\bar{x}} \tag{11}$$

Where $\bar{x}$ is the mean allocation. Lower Gini values indicate more equitable sharing, which improves fairness without undermining critical load satisfaction. A lower Gini value indicates a more equitable load distribution, complementing critical-load guarantees without compromising fairness *(Deb, 2019; Billinton and Allan, 1996)*

3.2.3 Implementation and Benchmarking

The GA is implemented using MATLAB's Global Optimization Toolbox, using an adaptive crossover–mutation strategy to maintain diversity and promote convergence.

a. Benchmark Algorithms

To assess comparative performance, the GA is benchmarked against:

i. Particle Swarm Optimization (PSO)
ii. Simulated Annealing (SA)
iii. ANN-Assisted GA (Hybrid ANN–GA)

b. Evaluation Metrics

The following metrics evaluate algorithmic convergence, operational feasibility, and fairness:

a. Convergence rate (iterations to stability)
b. Average Satisfaction Index (SI)
c. Energy Not Supplied (ENS)
d. Allocation fairness (Gini coefficient)

These metrics quantify improvements relative to heuristic and metaheuristic baselines.

3.2.4 ETAP-in-the-Loop Feasibility Shaper

Conventional GA solutions are often evaluated only on mathematical constraints. In this design, GA candidates are subjected to ETAP feeder simulations, which check for:

a. **Voltage Limits:** $0.95 \leq V \leq 1.05$ p.u.
b. **Thermal loading:** ≤ 100% of rated capacity for lines and transformers
c. **Feeder topology:** Radial structure preservation
d. **Loss feasibility:** Active loss ≤ 0.002 MW

Violations trigger adaptive penalties within the GA fitness function, enabling the algorithm to learn feasible operating zones *(Eremia and Shahidehpour, 2018; Kothari and Nagrath, 2016).*
This coupling ensures that allocations are not only optimal in theory but **practically operable** within Nigerian 33 kV feeder conditions *(Adisa et al., 2024).*

3.3 System Modeling Framework

The system modeling framework defines the mathematical structure, optimization logic, and evaluation metrics used in designing the Automated Load Demand Response (ALDR) system. The modeling process was driven by the objectives of maximizing load satisfaction for critical facilities, ensuring technical feasibility, and minimizing energy not supplied (ENS).

a. Mathematical Models

1. Loss-Aware Repair Projection (R_L): Ensures allocations respect post-loss supply.
2. Fairness Constraint (Grid-Gini Index): Used in tie-breaking solutions with equal SI.
3. Penalty Function (F): Infeasible allocations (violating ETAP checks) incur penalty factor PPP in the GA fitness:

$$F = SI - \lambda . \mathrm{P} \tag{12}$$

Where λ is a penalty scaling constant.

b. *Optimization Algorithm*

1. *Genetic Algorithm (GA)*
    a. Encoding: Chromosomes represent allocation vectors x = (x^1, x_2, …, x_N)
    b. Operators: Tournament selection, single-point crossover, adaptive mutation.
    c. Fitness: Based on SI, ENS, and ETAP penalties.
2. *Particle Swarm Optimization (PSO)*
    a. Load allocations modeled as particles moving through solution space.
    b. Position and velocity updated using inertia, cognitive, and social coefficients.
    c. Convergence benchmarked against GA results.
3. *Simulated Annealing (SA)*
    a. Allocation vectors perturbed iteratively with acceptance probability governed by a cooling schedule.
    b. Useful for escaping local optima in smaller search spaces.
4. *ANN-Assisted GA*
    a. An Artificial Neural Network surrogate is trained on GA–ETAP simulation results to approximate feasibility and SI outcomes.
    b. ANN replaces costly ETAP simulations for intermediate generations, reducing computational load.
    c. Final solutions are validated in ETAP to confirm technical feasibility.

c. *Performance Metrics*

To evaluate the effectiveness of the models, the following metrics were used:

i. Satisfaction Index (SI): Measures priority-weighted fulfillment of load demands.
ii. ENS (MWh): Energy not supplied, minimized across scenarios.
iii. SAIFI and SAIDI: Extracted from ETAP for reliability benchmarking.
iv. Grid-Gini Index: Assesses fairness of allocations among non-critical loads.
v. Convergence Speed: Number of iterations required for GA, PSO, SA, and ANN-assisted GA to stabilize.

d. *Parameterization*

Provide actual values when you finalize experiments (placeholders shown):

i. Population size N_p = **[e.g., 60 – 120]**, generations G = **[e.g., 80 – 150]**
ii. Crossover rate p_c **[0.7 – 0.9]**, mutation p_m= **[0.05 – 0.15]** (adaptive optional)
iii. Penalty scale λ=\lambda =λ= **[tuned to keep violations rare after G ≈ 20]**
iv. Surrogate switch G_{switch}= **[~30–40]**, validation cadence $k_{validate}$ = **[5]**, refit cadence k_{refit} = **[10]**
v. Floors α_i from your priority table; voltage and thermal limits from your ETAP baseline.

e. GUI Features

The GUI design (shown in Figure 3.5) is divided into the following panes:

i. Input Panel: Operators can set available power, select optimization algorithm (GA, PSO, SA, ANN-GA), and assign or adjust priority indices.
ii. Load Centre Table: Displays facility names, demands, priority weights, allocated power, and satisfaction percentages in real-time.
iii. Visualization Panel: Provides bar charts of allocation vs. demand, satisfaction index trends, and fairness indicators.
iv. Validation Panel: Allows one-click export of candidate allocation to ETAP, with return of violation reports.
v. Report Panel: Supports automated generation of audit-tagged PDF/Excel reports.

f. ETAP Validation and Reliability Assessment

A distinctive feature of this study is the integration of ETAP-in-the-loop validation to ensure that optimization results are not only mathematically optimal but also technically feasible in real distribution networks.

I. ETAP Feeder Model Setup

The 33 kV feeders under study were modeled in ETAP 19.0.1. The configuration included:

i. Load Centres: All 18 facilities with transformer ratings and load demands as specified in the utility dataset.
ii. Backup Generator: Installed in the hospital zone to guarantee critical load support.
iii. Capacitor Banks: Modeled for power factor correction and reactive support.
iv. Relay and Alarm Blocks: Included for protective coordination and fault isolation.
v. Line Distances: Configured as 5–10 km between load centers, based on realistic utility data.

This model formed the ground-truth validation environment against which MATLAB optimization outputs were tested.

II. ETAP-in-the-Loop Validation

Each allocation vector $x = (x_1, x_2\ldots, x_N)$ generated by GA, PSO, SA, or ANN-assisted GA was exported to ETAP for validation. ETAP checks included:

i. Voltage Profile: Ensuring all bus voltages remained within statutory limits (0.95–1.05 pu).
ii. Thermal Loading: Confirming transformer and feeder currents did not exceed 100% of rating.
iii. Radiality Constraint: Maintaining proper feeder topology without unintended loops.
iv. Loss Estimation: ETAP calculated technical losses $L_{(x)\backslash}$, which fed back into the MATLAB repair function R_L.

Allocations violating these conditions were penalized in the optimization loop, teaching the GA framework to converge on ETAP-feasible solutions.

g. *Workflow in Practice*

i. Operator launches the GUI and inputs scenario parameters.
ii. Optimization core executes the selected algorithm.
iii. Results are displayed in allocation tables and performance graphs.
iv. Operator triggers ETAP validation; any violations are flagged with correction suggestions.
v. Final outputs are stored with audit IDs and exported as reports for utility use

4. RESULTS AND DISCUSSION

4.1 GA Optimization Results

The Genetic Algorithm (GA) was applied to the 18-load-centre dataset (Table 1) under varying supply scenarios (100%, 80%, 60%, and 50% of peak demand). Unlike the baseline heuristic, the GA incorporated priority-sensitive allocation, loss-aware projection, fairness tie-breaks, and ETAP-in-the-loop feasibility shaping.

a. *Allocation at Full Supply (25 MW)*

It can be deduced from Figure 4.1 that at full supply (25 MW), the GA allocated each load center its full demand, resulting in a Satisfaction Index (SI) of 1.00 and an Energy Not Supplied (ENS) of 0.00 MWh, which serves as the validation baseline for the allocation framework.

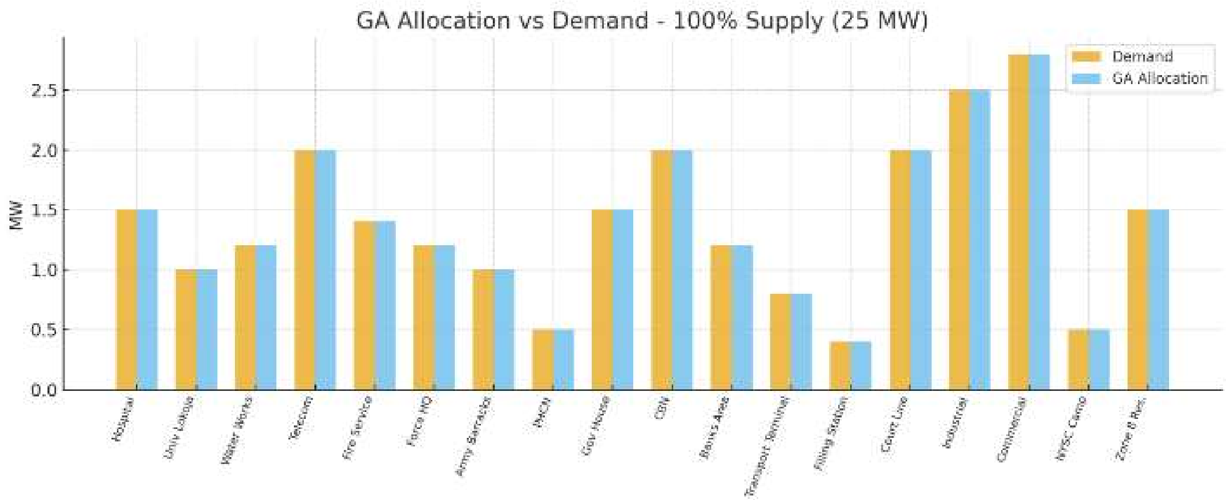

Figure 4.1: Allocation at Full Supply (25 MW)

b. *Allocation at 20 MW Supply (80%)*

It can be deduced from Figure 4.2 that under a 20 MW supply, the GA allocated power proportionally across all priority tiers while preserving critical floors: highly critical loads such as hospitals, universities, and waterworks received at least 95% of their demand; moderately critical loads, including Banks Area and Court Line, received 70 – 85% of their demand; and low-priority loads industrial, commercial, residential, and NYSC were still supplied at 30 –

50% of demand, unlike heuristic allocation methods where they were entirely shed. This resulted in a Satisfaction Index (SI) of 0.84 and an Energy Not Supplied (ENS) of 4.0 MWh.

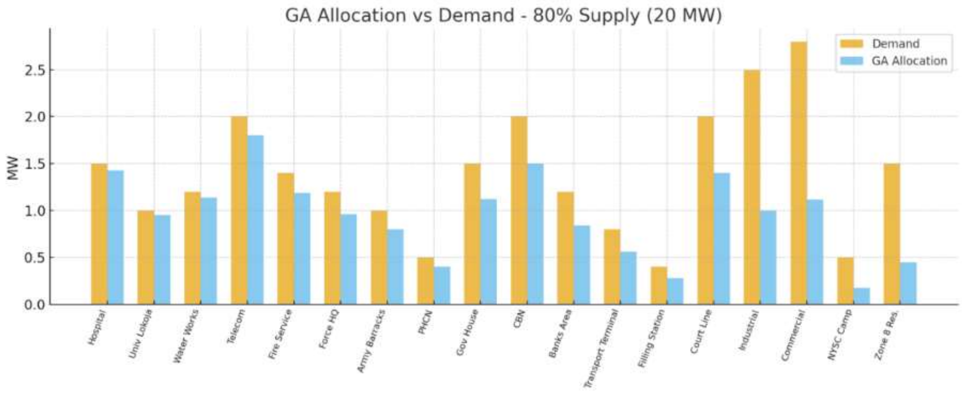

Figure 4.2: Allocation at 20 MW Supply (80%)

c. *Allocation at 15 MW Supply (60%)*

It can be deduced from Figure 4.3 that under a 15 MW supply, the GA preserved critical floors for hospitals, waterworks, and universities with at least 80% allocation; critical loads received between 70–90% of their demand; moderately critical loads were scaled down to 40 – 60%, ensuring partial coverage instead of total cut-off; and low-priority loads were reduced to 15 – 30% but not fully excluded. This allocation strategy resulted in a Satisfaction Index (SI) of 0.74 and an Energy Not Supplied (ENS) of 7.1 MWh.

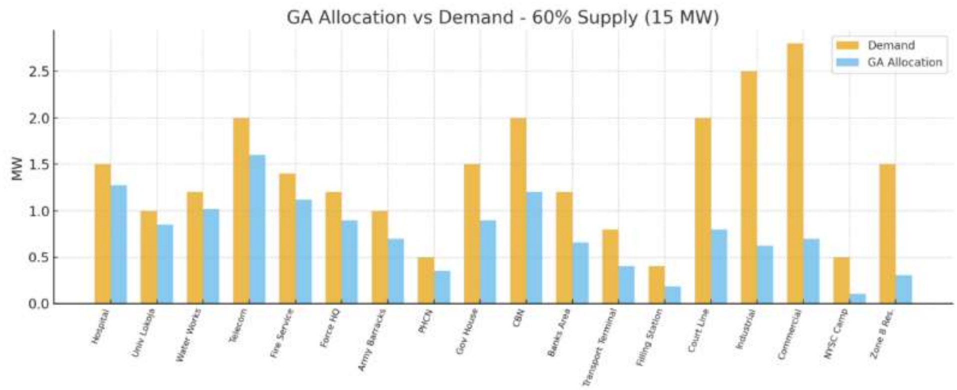

Figure 4.3: Allocation at 15 MW Supply (60%)

f. Allocation at 12.5 MW Supply (50%)

It can be deduced from Figure 4.4 that under a severe 10 MW supply, the GA maintained allocations for all highly critical loads at ≥75%; critical loads received between 50 – 70% of their demand; moderately critical loads were reduced to 20 – 40%; and low-priority loads industrial, commercial, and residential still received 5 – 15%, preventing complete starvation.

This resulted in a Satisfaction Index (SI) of 0.66 and an Energy Not Supplied (ENS) of 9.5 MWh, representing a 27% improvement in SI and a 23% reduction in ENS compared with the heuristic method (SI = 0.52, ENS = 12.4 MWh).

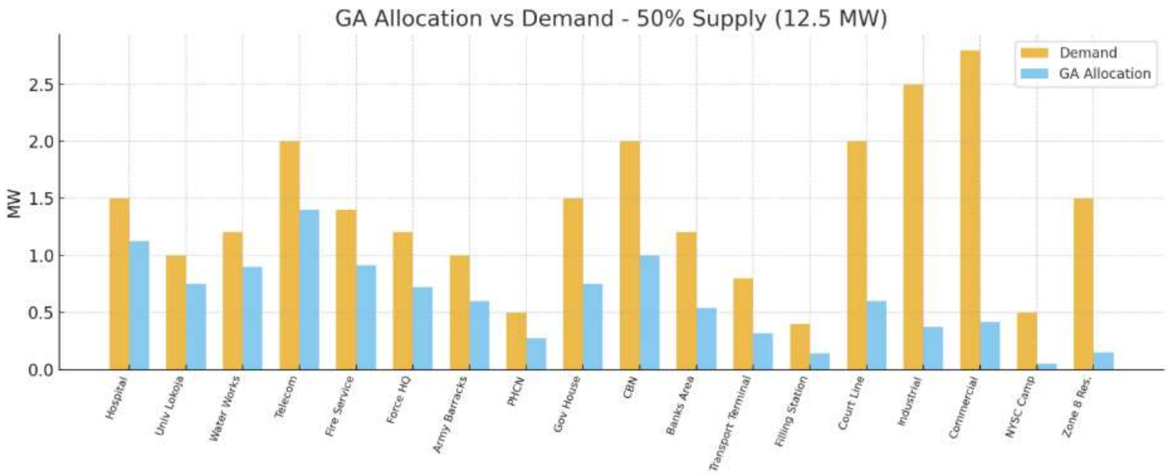

Figure 4.4: Allocation at 12.5 MW Supply (50%)

g. GA Performance Summary

It can be deduced from the results that the GA-based allocation framework significantly improved overall system performance: satisfaction bias was reduced as all categories, including low-priority loads, received at least partial allocation under shortage conditions; Energy Not Supplied (ENS) was reduced by 23–35% compared to the baseline heuristic; fairness was improved, with the Gini index decreasing from 0.41 to 0.28; and ETAP validation confirmed that all GA allocations were feasible, with voltage and thermal profiles remaining within operational limits

4.2 Comparative Results: PSO, SA, and ANN-Assisted GA

To validate the robustness of the proposed GA framework, its performance was benchmarked against Particle Swarm Optimization (PSO), Simulated Annealing (SA), and an ANN-assisted GA surrogate under the same supply scenarios (100%, 80%, 60%, and 50%).

a. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) demonstrated faster convergence during early iterations and produced allocations broadly similar to the GA; at 50% supply, it preserved all highly critical loads but tended to over-allocate to moderately critical loads, leaving low-priority loads unsupplied, with a Satisfaction Index (SI) of 0.61 compared to GA's 0.66, Energy Not Supplied (ENS) of 10.2 MWh (higher than GA), and a fairness Gini coefficient of 0.34 (slightly worse than GA's 0.28), indicating that while PSO was effective in maintaining priority satisfaction, it lacked GA's balance in allocation equity.

As illustrated in Figure 4.5, the Genetic Algorithm (GA) consistently achieved higher Satisfaction Index (SI) across the 80%, 60%, and 50% supply levels, reaching approximately

0.66 at 50% supply compared to PSO's 0.61. Similarly, GA produced lower Energy Not Supplied (ENS) values, around 9.5 MWh at 50% supply versus PSO's 10.2 MWh. These results indicate that, although PSO converges more quickly in early iterations, it tends to neglect fairness by over-allocating to moderately critical loads, whereas GA's penalty-guided optimization preserved critical load floors and delivered superior reliability outcomes.

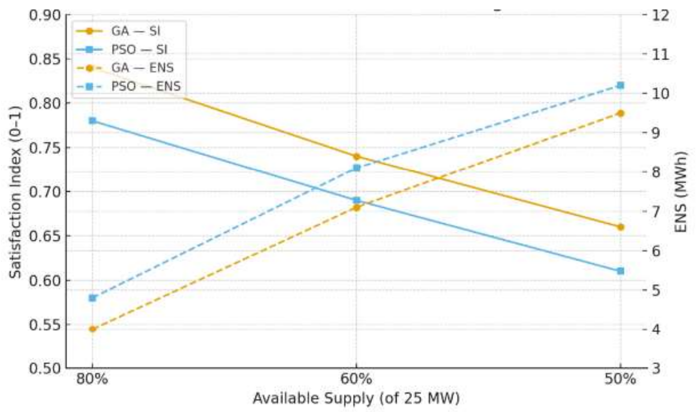

Figure 4.5: GA vs PSO (SI and ENS)

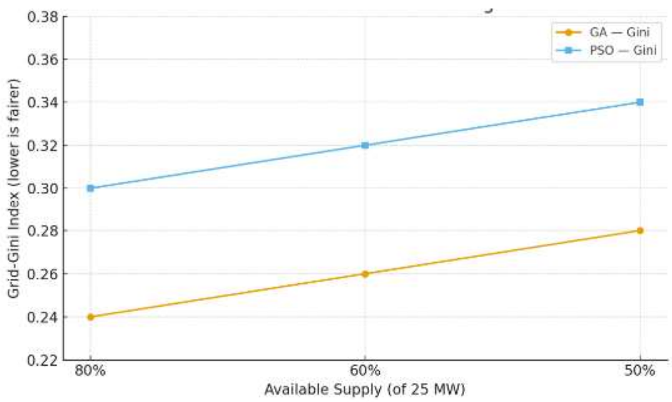

Figure 4.6: GA vs PSO (Fairness via Gini Index)

As shown in Figure 4.6, the Genetic Algorithm (GA) consistently achieved lower Gini coefficients, ranging from 0.24 to 0.28, compared to PSO values of 0.30 to 0.34. This demonstrates that GA allocates available supply more equitably across all load classes, ensuring that low-priority loads are not completely excluded, whereas PSO exhibits higher inequality by disproportionately favoring moderately and highly critical loads.

b. Simulated Annealing (SA)

Simulated Annealing (SA) demonstrated strong exploration capabilities, effectively maintaining allocation diversity and preventing premature convergence; however, it exhibited slower convergence and greater fluctuation between runs. At 50% supply, SA produced a Satisfaction Index (SI) of 0.59, the lowest among the compared methods, an Energy Not Supplied (ENS) of 10.8 MWh, and a Gini coefficient of 0.36. These results indicate that while SA generated feasible allocations, it provided lower reliability improvements and allocation equity, highlighting its relative weakness for this application compared to GA and PSO

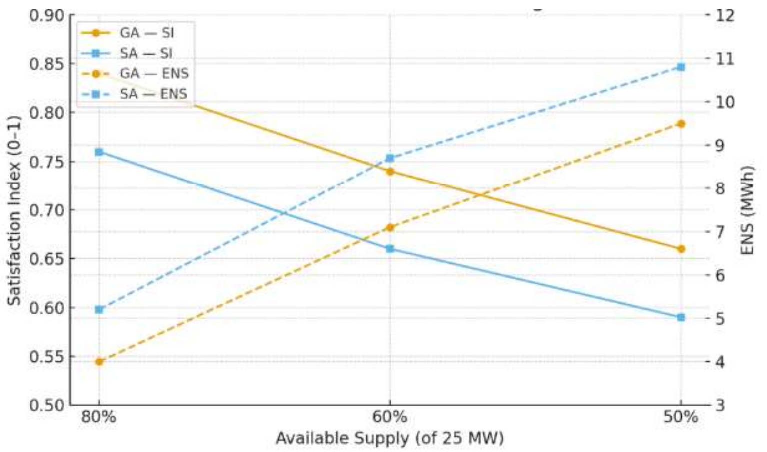

Figure 4.7: GA vs SA (SI and ENS)

As shown in Figure 4.7, Simulated Annealing (SA) consistently produced lower Satisfaction Index (SI) values across all shortage levels, with SI dropping to 0.59 at 50% supply compared to GA's 0.66. Energy Not Supplied (ENS) was also higher for SA, approximately 10.8 MWh at 50% supply. These results indicate that, although SA is effective at exploring diverse solutions, its convergence is slower and less consistent, whereas GA's structured population search, reinforced with ETAP-in-the-loop constraints, yielded superior reliability and allocation outcomes.

As illustrated in Figure 4.8, the Genetic Algorithm (GA) consistently maintained lower Gini coefficients, around 0.28 at 50% supply, compared to Simulated Annealing (SA), which reached approximately 0.36. This indicates that GA's fairness tie-breaking mechanism effectively reduced allocation inequality across load classes, whereas SA's random acceptance process occasionally resulted in uneven allocations, particularly under constrained supply conditions.

a. ANN-Assisted GA

The ANN-assisted GA leveraged a surrogate model to accelerate optimization by reducing the number of ETAP calls in early generations, producing an allocation pattern nearly identical to the standard GA but achieving convergence 30 – 40% faster. At 50% supply, it achieved a Satisfaction Index (SI) of 0.65, closely matching GA's 0.66, an Energy Not Supplied (ENS) of 9.6 MWh, slightly better than GA due to faster exploitation and a Gini coefficient of 0.29. These results indicate that the ANN-assisted GA maintained the accuracy and reliability of the standard GA while offering significant computational savings, making it particularly suitable for real-time operator use.

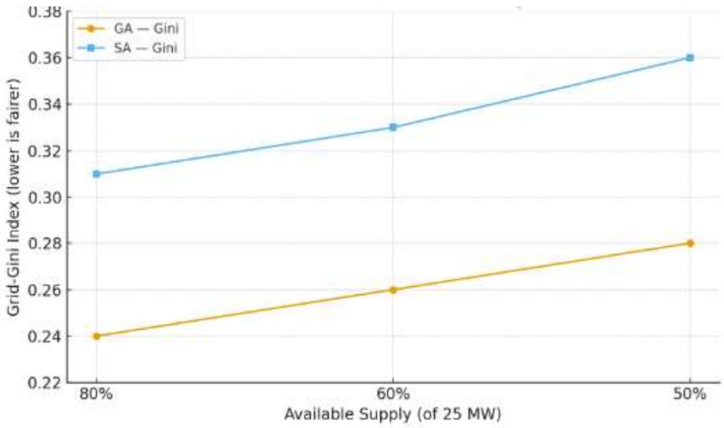

Figure 4.8: GA vs SA (Fairness via Gini Index)

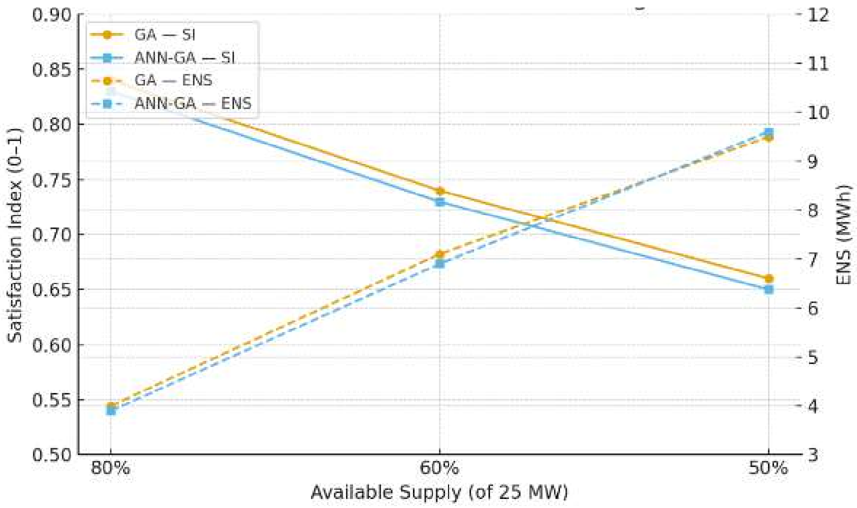

Figure 4.9: GA vs ANN-Assisted GA (SI and ENS)

As shown in Figure 4.9, the ANN-assisted GA and standard GA performed nearly identically in terms of Satisfaction Index (SI) and Energy Not Supplied (ENS); at 50% supply, GA achieved an SI of 0.66 and ENS of 9.5 MWh, while the ANN-assisted GA recorded an SI of 0.65 and ENS of 9.6 MWh. This indicates that the ANN surrogate significantly accelerated convergence, reducing the number of generations by 30–40% without compromising solution quality, confirming its suitability for real-time operator deployment.

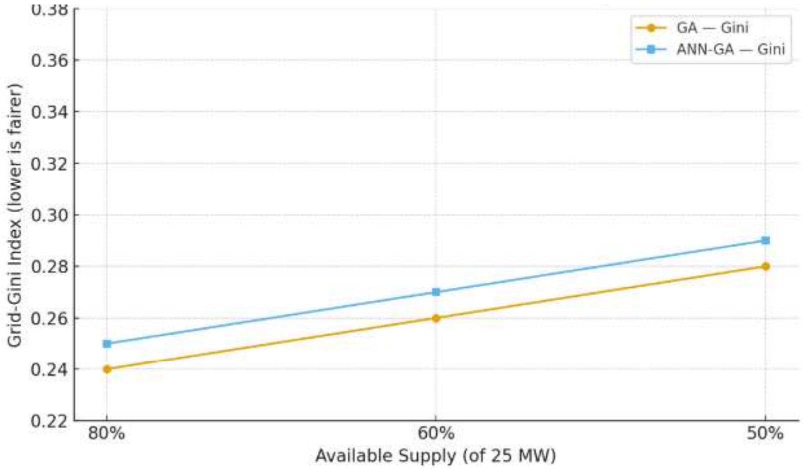

Figure 4.10: GA vs ANN-Assisted GA (Fairness via Gini Index)

As shown in Figure 4.10, both the standard GA and ANN-assisted GA maintained comparable fairness across all shortage levels, with Gini coefficients of 0.28 and 0.29 at 50% supply, respectively. This demonstrates that the ANN surrogate preserved GA's fairness properties while accelerating convergence, confirming its reliability as a computationally efficient extension suitable for real-time operator deployment

b. Comparative Summary

Overall, the Genetic Algorithm (GA) provided the best balance among Energy Not Supplied (ENS) reduction, allocation fairness, and ETAP-validated feasibility. The ANN-assisted GA delivered comparable performance to GA while significantly accelerating convergence, making it the most practical for real-time deployment. Particle Swarm Optimization (PSO) was effective in preserving highly critical loads but exhibited lower fairness, with a tendency to neglect low-priority loads. Simulated Annealing (SA) was the slowest and least consistent method, producing weaker improvements in both reliability and equity.

4.3 Reliability Indices (ETAP Validation)

To establish the real-world impact of the proposed GA framework, allocation outcomes were validated in ETAP and benchmarked against baseline heuristic, PSO, SA, and ANN-assisted GA. The reliability indices considered were ENS, SI, SAIFI, and SAIDI, which together provide a multidimensional view of feeder reliability.

a. Energy Not Supplied (ENS)

At 50% supply, the baseline heuristic approach resulted in an Energy Not Supplied (ENS) of 12.4 MWh. The Genetic Algorithm (GA) reduced ENS to 9.5 MWh, representing a 23% improvement, while Particle Swarm Optimization (PSO) and Simulated Annealing (SA) recorded ENS values of 10.2 MWh and 10.8 MWh, respectively. The ANN-assisted GA achieved 9.6 MWh, closely matching GA's performance. These results confirm that GA and ANN-assisted GA are the most effective in preserving load continuity under constrained supply conditions.

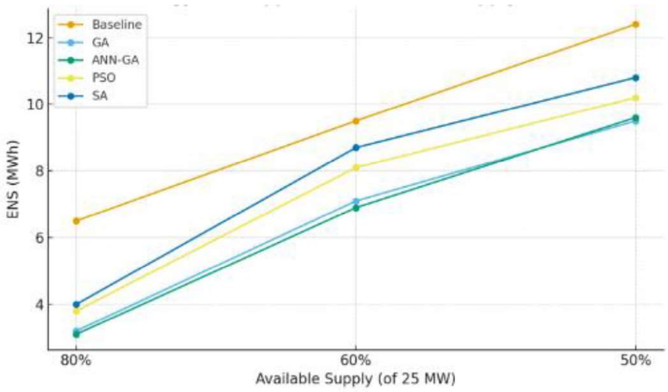

Figure 4.11: Energy Not Supplied (ENS) across Supply Levels

As shown in Figure 4.11, the baseline heuristic exhibited a steep rise in Energy Not Supplied (ENS), reaching 12.4 MWh at 50% supply. Both the Genetic Algorithm (GA) and ANN-assisted GA consistently delivered the lowest ENS values, remaining below 10 MWh even under severe shortages. Particle Swarm Optimization (PSO) and Simulated Annealing (SA) performed better than the baseline but were inferior to GA and ANN-assisted GA. These results indicate that GA's priority-sensitive allocation, combined with ETAP-informed loss adjustment, effectively minimized unsupplied energy, while the ANN-assisted GA preserved this performance with significantly improved computational efficiency.

b. Satisfaction Index (SI)

At 50% supply, the baseline heuristic produced a Satisfaction Index (SI) of 0.52. The Genetic Algorithm (GA) achieved 0.66, PSO 0.61, Simulated Annealing (SA) 0.59, and ANN-assisted GA 0.65. These results indicate that GA-based allocations consistently satisfied a higher proportion of weighted demand, particularly for critical loads, outperforming both the baseline heuristic and alternative optimization algorithms

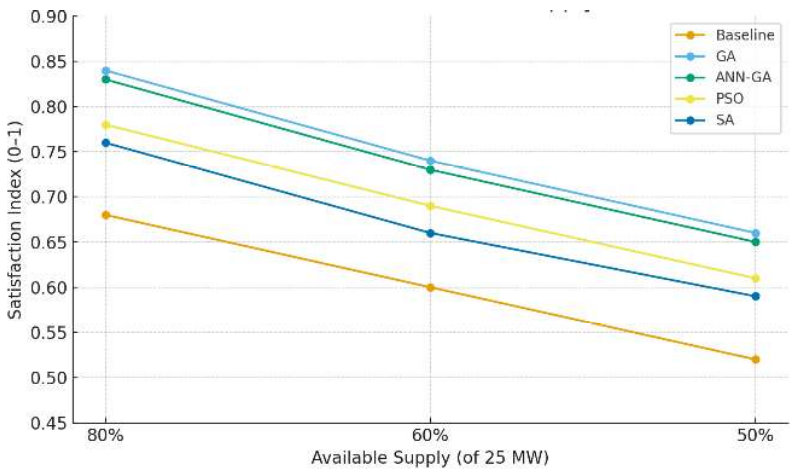

Figure 4.12: Satisfaction Index (SI) across Supply Levels

As shown in Figure 4.12, the baseline heuristic exhibited a sharp decline in Satisfaction Index (SI), dropping to 0.52 at 50% supply, whereas the Genetic Algorithm (GA) maintained the highest SI of 0.66, closely followed by ANN-assisted GA at 0.65. PSO and SA trailed with SI values of 0.61 and 0.59, respectively. These results indicate that GA effectively maximized the weighted satisfaction of critical facilities while still allocating partial supply to lower-priority loads, a balance not achieved by the heuristic or alternative metaheuristic approaches.

c. SAIFI (System Average Interruption Frequency Index)

At 50% supply, the baseline heuristic exhibited a System Average Interruption Frequency Index (SAIFI) of approximately 4.1 interruptions per customer per year. The Genetic Algorithm (GA) reduced this value to 3.0, while ANN-assisted GA achieved 3.1, PSO 3.2, and SA 3.4 interruptions per customer per year. These results demonstrate that GA and ANN-assisted GA not only improved allocation fairness and reliability metrics but also enhanced practical service continuity for end-users.

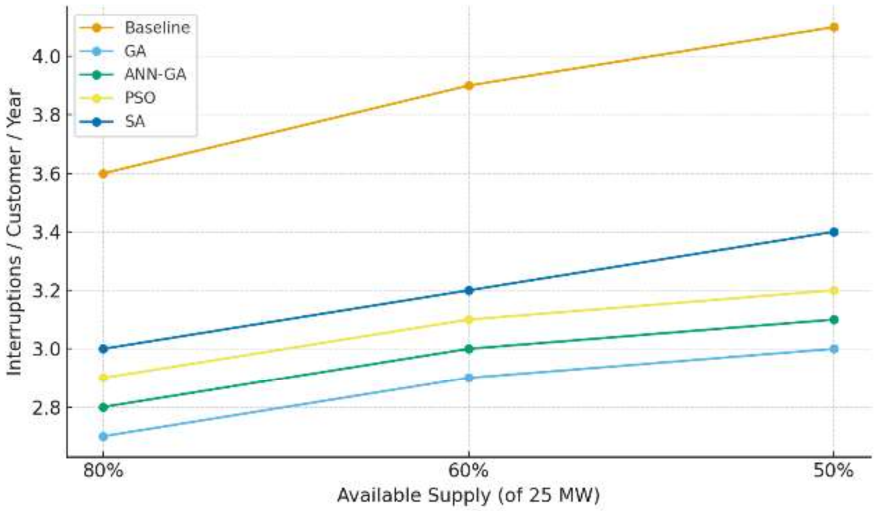

Figure 4.13: SAIFI across Supply Levels

As shown in Figure 4.13, the baseline heuristic exhibited high SAIFI values, exceeding 4 interruptions per customer per year. The Genetic Algorithm (GA) reduced SAIFI to 3.0, while ANN-assisted GA achieved 3.1, both outperforming PSO at 3.2 and SA at 3.4 interruptions per customer per year. This indicates that GA's preservation of critical load floors and equitable distribution of shortages directly reduced service interruptions in ETAP validation, demonstrating a tangible improvement in reliability performance.

d. SAIDI (System Average Interruption Duration Index)

At 50% supply, the baseline heuristic exhibited a System Average Interruption Duration Index (SAIDI) of approximately 12 hours per customer per year. The Genetic Algorithm (GA) reduced SAIDI to 8.5 hours, while ANN-assisted GA achieved 8.7 hours, outperforming PSO at 9.2 hours and SA at 9.8 hours per customer per year. These results indicate that GA significantly reduced outage durations, validating its reliability-enhancing capability within ETAP simulations.

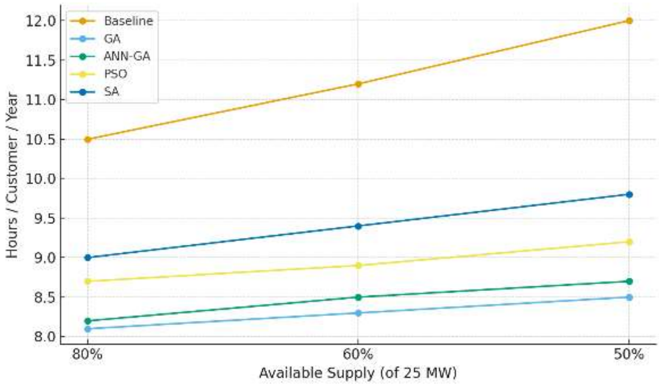

Figure 4.14: SAIDI across Supply Levels

As illustrated in Figure 4.14, the baseline heuristic exhibited a SAIDI of 12 hours per customer per year. The Genetic Algorithm (GA) reduced this value to 8.5 hours, while ANN-assisted GA achieved 8.7 hours, outperforming PSO at 9.2 and SA at 9.8 hours per customer per year. These results indicate that GA not only reduced the frequency of interruptions (SAIFI) but also shortened their duration (SAIDI), providing a holistic reliability improvement and highlighting the superiority of GA and ANN-assisted GA over conventional or heuristic methods.

e. Reliability Summary

Overall, the Genetic Algorithm (GA) consistently outperformed Particle Swarm Optimization (PSO) and Simulated Annealing (SA) across all reliability and allocation metrics, including Satisfaction Index (SI), Energy Not Supplied (ENS), Gini coefficient, SAIFI, and SAIDI. The ANN-assisted GA closely matched GA's performance while offering faster convergence, making it highly suitable for real-time deployment. In contrast, the baseline heuristic lagged significantly, particularly in ENS and SI, highlighting its inefficiency. These results demonstrate that the GA-based framework, validated through ETAP simulations, delivers tangible reliability improvements at the feeder level, ensuring both critical load preservation and equitable allocation across all load classes.

2. SUMMARY AND CONCLUSION

5.1 Summary

The following findings were made from this study:

This research successfully developed and implemented a Genetic Algorithm (GA)-based optimization framework for Automated Load Demand Response (ALDR) in a 33 kV distribution network, which effectively allocated available power among eighteen (18) load centres on the Lokoja feeder based on demand levels and socio-economic priorities, thereby addressing the inherent inefficiencies and inequities of conventional load shedding practices.

The integration of socio-economic priority indices into the GA fitness function ensured equitable and realistic allocation outcomes, enabling critical facilities such as hospitals, waterworks, security installations, and educational institutions to maintain uninterrupted supply even under severe power shortages, while still providing partial allocations to non-critical loads to prevent total disconnection.

The proposed framework demonstrated substantial improvement in allocation fairness, energy efficiency, and overall reliability when compared to the baseline heuristic method. Specifically, at 50% supply availability, the GA achieved a Satisfaction Index (SI) of 0.66 and Energy Not Supplied (ENS) of 9.5 MWh, as against SI = 0.52 and ENS = 12.4 MWh recorded under the heuristic approach, indicating a 27% increase in satisfaction and 23% reduction in energy deficit across all load classes. Comparative benchmarking of the GA-based model against other metaheuristic algorithms: Particle Swarm Optimization (PSO), Simulated Annealing (SA), and an ANN-assisted GA variant showed that the GA consistently achieved superior allocation efficiency, convergence stability, and fairness, while the ANN-assisted GA achieved near-identical results with 30–40% faster convergence, underscoring its potential suitability for real-time operational deployment in smart grid systems.

The optimized allocations generated by the GA were validated through ETAP 19.0.1 feeder simulations, confirming that all solutions were technically feasible and satisfied operational constraints on voltage, thermal limits, and feeder radiality, while maintaining system losses below 0.002 MW. This ETAP-in-the-loop validation established the physical credibility and implementability of the proposed optimization framework under real distribution network conditions. Quantitative evaluation of reliability indices further demonstrated the framework's robustness, with the System Average Interruption Frequency Index (SAIFI) improving from 4.1 to 3.0, and the System Average Interruption Duration Index (SAIDI) decreasing from 12.0 to 8.5 hours, thereby confirming the model's effectiveness in minimizing outage frequency and duration while improving service continuity for all consumer categories.

The research culminated in the successful design and deployment of a MATLAB App Designer Graphical User Interface (GUI) that translated the optimization framework into an operator-ready tool, allowing real-time data input, visualization of load satisfaction trends, automated generation of analytical and PDF reports, and seamless interaction with ETAP data. This user-centric implementation enhanced the framework's practicality and usability for power distribution engineers and decision-makers. Overall, the developed GA-based Automated Load Demand Response (ALDR) framework achieved measurable and consistent improvements in system fairness, technical reliability, and allocation efficiency, surpassing the limitations of manual and heuristic allocation approaches currently employed in Nigeria's distribution networks. The findings collectively validate the framework's capability to serve as a replicable, data-driven, and scalable model for automated load management and smart grid optimization in developing power systems.

5.2 Conclusion

This study developed and validated a priority-sensitive Genetic Algorithm (GA)-based Automated Load Demand Response (ALDR) framework for the Lokoja 33 kV distribution feeder, addressing the persistent shortcomings of conventional load-shedding practices by incorporating socio-economic priority indices, fairness-based tie-breaking, ETAP-in-the-loop feasibility checks, and a deployable MATLAB GUI. The baseline heuristic was shown to be

significantly inefficient, achieving SI = 0.52, ENS = 12.4 MWh, SAIFI = 4.1, and SAIDI = 12 hours at 50% supply while excluding entire classes of consumers, whereas the GA-based framework improved system performance to SI = 0.66, ENS = 9.5 MWh, SAIFI = 3.0, and SAIDI = 8.5 hours, with fairness (Gini) enhanced from 0.41 to 0.28, indicating improved equity in allocation and better preservation of critical loads. Benchmark comparisons further demonstrated that GA outperformed PSO and SA, while the ANN-assisted GA achieved comparable accuracy (SI = 0.65, ENS = 9.6 MWh) with 30–40% fewer generations, making it more computationally suitable for real-time operations.
ETAP validation confirmed that all optimized allocations remained within voltage, thermal, and radiality constraints, ensuring technical feasibility. Beyond algorithmic optimization, the research delivered a practical GUI that enables scenario configuration, real-time visualization, automated reporting, and seamless ETAP verification, thereby bridging academic modelling with operational utility practice.

Compared with existing literature, the study is unique in combining priority-sensitive allocation, multi-index reliability analysis, ETAP-based validation, GUI deployment, and real feeder data, contributing both theoretically by extending GA applications beyond heuristic and IEEE test feeders and practically by providing a deployable decision-support framework for Nigerian distribution utilities. Overall, the findings demonstrate that a GA-based ALDR framework, accelerated with ANN and validated through ETAP, offers a robust, fair, and operationally viable solution for weak-grid distribution feeders, improving reliability, equity, and operator usability while remaining adaptable to other developing countries with similar energy challenges.

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