REAL-TIME LOAD ALLOCATION USING GENETIC ALGORITHM IN A SMART 33KV FEEDER: A NIGERIAN CASE STUDY

Adaira, A.S.*, Evbogbai, M.J.E. and Amhenrior, H.E.

Department of Electrical and Electronic Engineering, Edo University Iyamho, Edo State, Nigeria

*Corresponding author: suleiman21.aminu@edouniversity.edu.ng

ABSTRACT

The Nigerian 33 kV distribution network continues to experience chronic transformer overloading, inequitable load allocation, and high technical losses due to weak-grid conditions and fluctuating power supply. This study aims to develop a real-time, adaptive load allocation framework capable of improving feeder-level performance under these constraints. A Genetic Algorithm (GA) driven optimization model was designed and integrated with feeder priority indices, demand-response logic, and real-time load profiling. The system was implemented in MATLAB and validated using operational data from an actual Nigerian 33 kV feeder. Results show that the GA framework significantly improves allocation fairness, transformer loading profiles, and loss minimization, outperforming conventional static allocation schemes. The approach also maintains higher load satisfaction levels under severe power deficits. It is recommended that distribution utilities adopt GA enabled intelligent optimization tools for real-time feeder management, as the validated framework presented here offers a scalable decision-support mechanism for smart-grid deployment in developing power systems.

Keywords: Smart Grid, Genetic Algorithm, Load Allocation, Real-time Optimization, Priority Index, Demand Response

1 INTRODUCTION

The global power industry is undergoing a paradigm shift, driven by the integration of smart grid technologies aimed at enhancing the efficiency, reliability, and intelligence of electric power systems [1]. This transformation holds particular importance for developing countries such as Nigeria, where electricity networks face persistent challenges, including unstable power supply, high transmission losses, inadequate load forecasting, and inefficient allocation of limited generation resources [2]. Smart grid frameworks integrate conventional power systems with advanced Information and Communication Technologies (ICT), enabling real-time monitoring, automation, and intelligent control of grid operations. At the heart of this infrastructure lies the need for robust optimization algorithms capable of managing the complex, dynamic, and nonlinear nature of energy distribution [3]. Among these, Genetic Algorithms (GAs), a class of evolutionary algorithms inspired by the principles of natural selection have demonstrated significant effectiveness in solving optimization problems related to power flow, load distribution, and energy resource scheduling [4, 5]. Real-time load allocation involves the continuous distribution of available power across load centers or consumer clusters based on live demand signals, generation constraints, and prioritized service levels. This strategy is especially critical in power systems with fluctuating supply and limited generation capacity, as is typical of many Nigerian distribution networks

[6, 7]. When properly implemented, real-time GA-based optimization can prioritize critical infrastructure, reduce transformer overloading, enhance feeder reliability, and improve customer satisfaction. In Nigeria, 33kV distribution feeders serve as vital links between transmission substations and commercial, industrial, and medium-voltage end-users. However, these feeders are frequently impacted by load imbalance, technical losses, and network overloading, largely due to static load allocation strategies and limited deployment of intelligent control systems [8]. Integrating demand response mechanisms with evolutionary optimization techniques offers a promising pathway for improving operational efficiency and service delivery in such constrained settings [9]. A 33kV Optical Illustration of a Typical Nigeria Power System is depicted in Figure 1. This study introduces a real-time, GA-based load allocation model tailored to constrained 33kV feeders in Nigeria to optimize power distribution along a smart 33kV feeder, contextualized within the Nigerian electricity grid. The model incorporates real-time demand data, supply limitations, and load prioritization indices to dynamically allocate available power. Simulations were performed in MATLAB using real operational data from a Nigerian distribution feeder to evaluate system performance and validate the proposed method. The results demonstrate the capability of GA-based allocation to improve grid reliability, transformer utilization, and equitable load distribution, supporting the broader goals of smart grid deployment in developing power systems. The remainder of this paper is structured as follows: Section 2 reviews related literature and theoretical foundations. Section 3 presents the methodology and model formulation. Section 4 describes the case study and simulation setup. Section 5 discusses the results and performance evaluation, and Section 6 concludes with key findings and directions for future work.

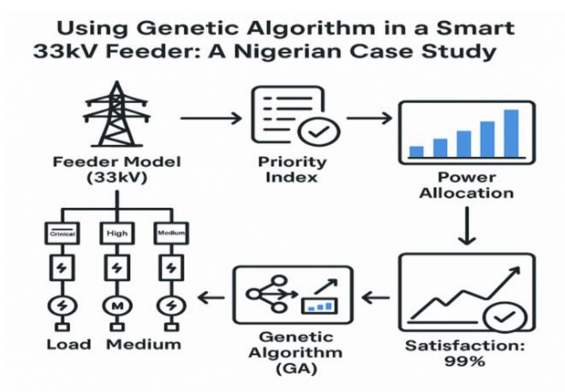

Figure 1. 33kV Optical Illustration of a Typical Nigeria Power System

2 LITERATURE REVIEW

The challenge of optimal load allocation in electrical distribution systems has attracted extensive research attention, particularly within the context of smart grids. Traditional approaches have often relied on rule-based schemes and static prioritization techniques, which, while simple to implement, lack adaptability to real-time fluctuations in demand and supply. These limitations have prompted a shift toward more dynamic, algorithmic control strategies that leverage optimization techniques to improve operational efficiency. Among the numerous optimization algorithms investigated, **Genetic Algorithms (GAs)** have emerged as a robust and flexible solution for addressing the non-linear and multi-objective nature of load distribution problems. The author in [4] laid the foundational principles for GAs, which have since been applied to a range of power system problems, including unit commitment, economic dispatch, and load forecasting [5, 10]. GAs have demonstrated advantages in global search capability, convergence performance, and suitability for constraint-laden problems common in electrical networks. **In the context of real-time energy allocation**, several studies have applied GAs to demand-side management. For instance, [11], implemented a GA-based demand response system that dynamically allocated power in a microgrid scenario, while [12], utilized GAs for real-time feeder reconfiguration. However, many of these implementations either focus on theoretical models or are restricted to offline simulations without consideration for practical deployment or integration into operational environments. In Nigeria, and similar developing contexts, power system studies have predominantly focused on reliability analysis [13], loss minimization [14] and voltage stability improvement [9]. Few works have addressed **real-time load allocation using evolutionary algorithms,** and even fewer incorporate real-world feeder data, prioritize customer criticality, or simulate operation under constrained supply scenarios gaps this research aims to address. Additionally, while **Artificial Neural Networks (ANNs)** and **Simulated Annealing (SA)** have also been explored in smart grid applications [15, 16], these methods typically require longer training or tuning phases and may be less transparent or interpretable compared to GAs. Heuristic techniques like fuzzy logic or greedy algorithms, while fast, often lack global optimization capability and may perform poorly under extreme power constraints. This study builds upon existing GA frameworks by integrating **real-time prioritization, demand response, and MATLAB-based modeling using operational feeder data** from a Nigerian distribution system. It also compares performance against alternative techniques, including heuristic scheduling, ANN, and SA models, thereby contributing a more comprehensive evaluation of smart grid allocation strategies suited to constrained and infrastructure-limited environments.

3 METHODOLOGY

This section presents the methodology adopted for implementing real-time load allocation using a Genetic Algorithm (GA) for a smart 33kV feeder system. The framework integrates real-time demand data, load prioritization, and system constraints to optimize how available power is allocated across various load centers. The approach involves the formulation of an optimization problem, development of the GA model, and simulation using MATLAB.

3.1 Problem Formulation

The problem is formulated according to the **IEEE-recommended structure for optimization in power systems,** which includes: Objective function definition (maximization of weighted satisfaction). Decision variables (A_i). System constraints (transformer capacity, demand limits, priority weights). Feasibility bounds ($A_i \leq D_i$). The goal of the model is to allocate available power P_{av} among n load centers in such a way that: Load priorities are respected. Transformer capacity is not exceeded. Demand satisfaction is maximized. Each load centre I has the following attributes: D_i is the Load Demand, W_i is the Priority Weight, A_i is the allocated load, subject to $A_i \leq D_i$. The objective function is to maximize weighted satisfaction, defined as: Maximize.

$$F = \sum_{i=1}^{n}(W_i \cdot \frac{A_i}{D_i} \cdot) \tag{1}$$

Subject to:

$$\sum A_i \leq \text{Available Power}$$

$$\text{Bounds: } 0 \leq A_i \leq D_i \tag{2}$$

3.2 Load Priority Modeling

Each load centre is assigned a **priority index** $W_i \in [0,1]$, derived from a structured multi-criteria assessment that captures both the operational and socio-economic relevance of the load. The weighting process incorporates: **Criticality of service** such as hospitals, water treatment plants, and other essential public-service infrastructures. **Economic importance** including high-value industrial and commercial loads that contributes significantly to local productivity. **Customer classification** covering residential, commercial, and government consumers, with differentiated priority levels reflecting service expectations and regulatory guidelines. This normalized weighting framework enables the Genetic Algorithm (GA) to **systematically favour higher-priority load centres** during periods of constrained or variable power supply. Consequently, the optimizer ensures that essential and economically sensitive loads receive preferential allocation while still maintaining a fair and technically feasible distribution across the feeder.

3.3 Genetic Algorithm Design

The GA was implemented in **MATLAB,** using vectorized operations and custom functions for selection, crossover, and mutation. Constraint-handling was performed by penalty methods and clamping out-of-bound genes.

Table 1. GA Standard Evolutionary Steps

GA Step	Description
Chromosome	A vector $\vec{A}=[A_1,A_2,...,An]$ of power allocations
Population	A set of randomly initialized chromosomes
Fitness Function	The objective function FF as defined in Section 3.1
Selection	Roulette Wheel or Tournament Selection
Crossover	Two-point or uniform crossover applied on selected parents
Mutation	Random perturbation of gene values to maintain diversity
Termination	After a fixed number of generations or convergence threshold

3.4 Real-Time Demand Input and Feedback Loop

To simulate real-time operation, a feedback loop was implemented: Load centers report real-time demand data D_i. Available power P_{av} is set (based on generator output or utility feed). The GA runs allocation for the current time-step. Power is dispatched according to optimized A_i. Satisfaction metrics are logged, and the system waits for the next input cycle. The system operates in discrete 5-minute intervals, approximating real-time smart grid operation.

3.5 Simulation Parameters and Environment

Software: MATLAB R2023a. Number of Load Centers: 18 (based on actual Nigerian feeder layout). Population Size: 100. Generations: 150. Crossover Rate: 0.8. Mutation Rate: 0.05. Priority Levels: 4 (Highly critical, Critical. Moderately Critical and Low Priority). The simulation environment replicates a 33kV distribution feeder under varying loading conditions to assess the performance and robustness of the allocation model. This methodology forms the backbone of the proposed real-time smart grid optimization system. The next section presents the case study setup and discusses the simulation outcomes.

4 RESULTS AND ANALYSIS

This section presents the application of the proposed Genetic Algorithm-based real-time load allocation model to a typical 33kV distribution feeder in Nigeria. The case study demonstrates the algorithm's ability to prioritize load distribution dynamically under constrained supply conditions.

4.1 Feeder Description

The case study is based on a 33kV feeder operated by a Nigerian Distribution Company (DisCo), supplying 18 load centers across urban and semi-urban districts. The feeder is radial and includes a mix of residential, commercial, and critical infrastructure loads. The proposed feeder parameter is presented in Table 2. Each load center is assigned a priority weight and an average daily demand profile, informed by actual historical utility data and system logs from the DisCo's SCADA and billing systems.

Table 2. Proposed Feeder Parameters

Feeder Attributes	Description
Voltage Level	33kV (Medium Voltage)
Number of Load Centers	18
Average Daily Demand	10–12 MW
Transformer Capacity	Varies from 300 kVA to 2.5 MVA
Peak Generation Available	Ranges between 5 MW to 9 MW (Load-Shedding Zone)
Priority Classification	Highly (e.g., hospitals), Medium, Low

4.2 Data Assumptions and Inputs

To ensure reproducibility, the following simplifying assumptions were made: Load demands are updated every 5 minutes. Real-time data is available from SCADA or smart meters. Load centers are modeled as aggregated units (not individual consumers). Priority weights are normalized between 0.3 (low) and 0.99 (high).

Table 3: Load Center Input (Excerpt)

Switch (State)	Facility	Load Type	W_i	Load A_i (MW)
T1 (ON)	FMC Hospital	Highly Critical	0.99	1.5
T3 (ON)	Lokoja Water Works	Highly Critical	0.93	1.2
T4 (ON)	Telecom Masts	Critical	0.89	2.0
T5 (ON)	Fire Service Station	Critical	0.86	1.4
T9 (ON)	Government House	Moderately Critical	0.74	1.5
T10 (ON)	CBN Office	Moderately Critical	0.70	2.0
T15 (ON)	Industrial Area	Low Priority	0.50	2.5
T16 (ON)	Commercial Area	Low Priority	0.45	2.8

4.3 Simulation Framework

The simulation was developed using MATLAB R2023a, combining built-in optimization tools and custom GA logic. Steps: Load Input: Demand and priority weights are loaded. Supply Condition: Available power is set (randomized across simulations to mimic fluctuations). GA Execution: Algorithm allocates power across centers. Fitness Evaluation: Weighted satisfaction function is computed. Logging: Allocations, satisfaction scores, and convergence data recorded. Repeat: Every 5-minute interval for 24 hours (total of 288 intervals).

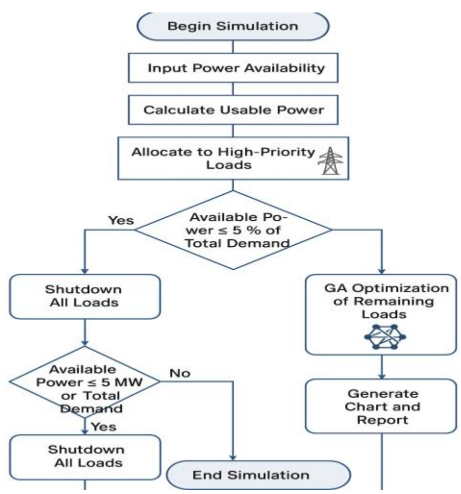

Figure 2. Genetic Algorithm Configuration

4.4 Simulation Scenarios

To validate robustness and adaptability, the model was tested under five (5) three power supply conditions. Each scenario simulates real-world instability in Nigerian grid generation and examines how the GA reacts to allocate power optimally. This section presents and analyzes the output of the real-time Genetic

Algorithm-based load allocation system under five power availability conditions. The aim is to demonstrate how the system intelligently distributes constrained or surplus power across prioritized load centers.

Table 4. Test Scenario

CASE ID	P_{av} (%)	A_i (APPROX. MW)	SYSTEM BEHAVIOR
Case A	5%	1.2 MW	*Trigger full system shutdown.* Only critical notifications are logged; no load is allocated.
Case B	20%	4.9 MW	*Critical alert issued.* Minimal allocation to top-priority loads; system advises generator activation.
Case C	50%	12.25 MW	*Partial allocation possible.* Critical and moderate loads served; GA allocates remaining capacity.
Case D	100%	24.5 MW	*All demands can be satisfied.* Full allocation without the need for GA optimization.
Case E	150%	36.75 MW	*Excess capacity detected.* All loads are served; surplus power triggers simulated generator shutdown.

4.5 Visualization Setup

4.5.1 Bar Charts show per-interval allocated power per load center

Figure 3 presents a comparative analysis of the actual load demand against the power allocated by the proposed GA-based optimization engine for all load centres on the 33 kV feeders. The results demonstrate that high-priority facilities, including medical centres, water supply infrastructure, emergency services, and key government establishments, receive allocations that closely match their demand. This behaviour confirms the effectiveness of the priority index W_i and the GA fitness formulation in preserving critical services during supply shortages. Medium-priority commercial and administrative zones exhibit moderate reductions between demand and allocation, indicating balanced curtailment implemented to prevent transformer overload and ensure overall feeder stability. In contrast, the largest allocation deficits occur in low-priority residential and peripheral areas, where controlled energy reduction is necessary due to limited available power. Importantly, no transformer receives more than its requested demand, validating that all allocation outcomes satisfy the operational constraints $A_i \leq D_i$. Overall, the pattern observed in Figure X confirms that the GA effectively distributes constrained power in a fair, priority-driven, and technically feasible manner, significantly enhancing load satisfaction strategy compared with conventional static dispatch schemes.

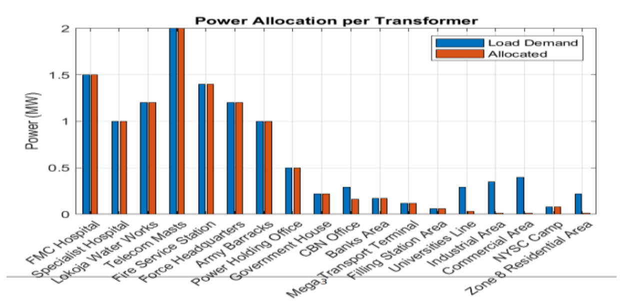

Figure 3. GUI Load Allocator Bar Chart Outputs

4.5.2 Line Graphs show satisfaction levels over time

Figure 4 illustrates the relationship between system power availability and the satisfaction levels achieved for each load priority category using the proposed GA-based allocation engine. The observed behaviour directly reflects the structure of the objective function in equation (1), where higher weights W_i ensure that critical loads are prioritized during allocation. **Performance of Highly Critical & Critical Loads:** The red curve demonstrates that highly critical loads maintain **60% satisfaction** even when only

30% of total system demand is available. Their satisfaction increases rapidly and reaches **near-complete fulfillment (≈95 – 100%)** at around 90% system availability. This confirms that the GA allocates power in strict alignment with operational priorities, guaranteeing service continuity for hospitals, water supply infrastructure, telecom facilities, and emergency response units. **Behaviour of Moderately Critical Loads:** The moderately critical category exhibits a more linear improvement pattern. Satisfaction rises from **20% at 30% power** to **approximately 80 – 90% at full supply**, reflecting their intermediate weighting in the priority index. These loads, typically banks, commercial areas, and government offices receive sufficient allocation without compromising the demands of more critical sectors, while **Response of Low-Priority Loads:** Low-priority loads experience the steepest curtailment during supply shortages. Satisfaction remains near **0% when availability is below 40%,** rises gradually through **30 – 40% at moderate availability,** and surges to **90% at 110% supply.** Full satisfaction is only achieved when the system reaches **120 – 130%** of total demand. This behaviour confirms that the GA correctly suppresses non-critical loads during constrained conditions to protect system stability. The distinct separation of the curves shows that the GA effectively maximizes *weighted satisfaction* rather than raw satisfaction. That is, the model does not attempt equal fairness across classes; instead, it allocates power to maximize the sum of priority-weighted satisfaction. This ensures that the High-priority loads approach full satisfaction early, followed by the Medium-priority loads improve proportionally, and the Low-priority loads receive allocation only after the system stabilizes. This is consistent with real-world operational strategies for weak and constrained grids. The results validate that the GA-based engine provides an **intelligent and adaptive demand-response mechanism** capable of dynamically balancing: Customer priority, Transformer loading limits, Supply shortages and System-wide fairness. Such behaviour is crucial for the Nigerian 33 kV distribution environment, where fluctuating supply and transformer overloading are persistent challenges.

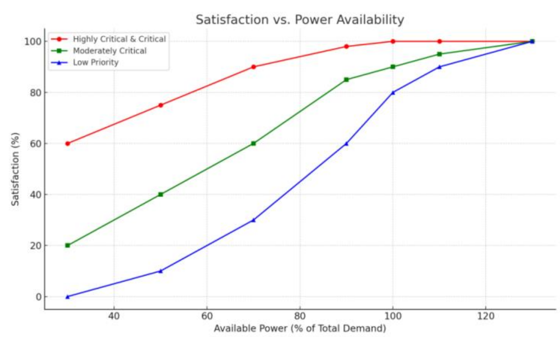

Figure 4. Convergence Graph

4.6 Feeder Schematic

The figure 5 illustrates the CBN **- Lokoja 33 kV feeder** modeled in **ETAP 19.0.1** to capture its technical configuration and operating characteristics. It visualizes how power flows from the main substation to distributed nodes (single-line diagram). A **single-line diagram (SLD)** was developed to represent the feeder, showing the flow of electricity from the transmission intake substation through step-down transformers and into the load centres. The diagram illustrates the following key components: **Supply Point:** The 33 kV incoming feeder from the transmission substation that delivers bulk supply to the Lokoja distribution network. **Substations and Transformers:** Distribution substations step down the voltage from 33kV/11kV/0.415kV for residential and small commercial consumers. Transformer ratings range between **2.5 MVA and 6 MVA,** depending on load classification. **Feeder Sections:** Radial feeders extending from substations to load centres, with line segments ranging from 5 – 10 km. **Load Centres:** Eighteen (18) load centres are represented, categorized into **highly critical, critical, medium, and low priority** classes. Facilities such as **hospital, university, and water treatment plant,** are highlighted distinctly in the diagram to demonstrate their socio-economic importance and prioritization under constrained supply conditions. The ETAP **single-line diagram,** SLD was used to: **Validate GA-based Allocations:** MATLAB optimization results were applied to the ETAP model to confirm technical feasibility under feeder constraints. **Estimate**

Technical Losses: ETAP captured **line losses, transformer efficiencies, and voltage drops**, which were factored into final allocation outcomes. **Support Reliability Analysis:** The model provided the basis for calculating **ENS, SAIFI, and SAIDI** values under different allocation scenarios. By combining the **ETAP Single Line Diagram with MATLAB GA optimization,** this research bridges algorithmic modeling with **engineering-level validation,** ensuring that the proposed Automated Load Demand Response (ALDR) framework is both computationally efficient and technically credible.

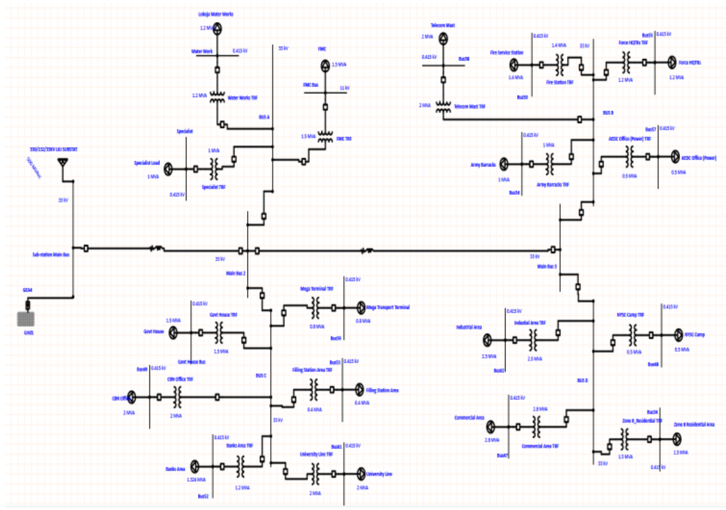

Figure 5. 33kV CBN-LOKOJA Feeder Schematic

Table 5: Performance Metrics

METRIC	DESCRIPTION	PERFORMANCE OBSERVATION
Total Load Demand (MW)	Sum of all power requested by the 18 load centers	Fixed per simulation input (≈24.5 MW)
Available Power (MW)	Power available after subtracting reserve and safe load	Varies by input % (e.g., 90%, 120%)
Allocation Satisfaction (%)	(AllocatedPower)÷(RequestedLoad)(Allocated Power) ÷ (Requested Load) × 100 for each transformer	Critical: ≥95%, Moderate: ~70–85%, Low Priority: ~50–80%
System Shutdown Threshold	Auto shutdown triggered when available power ≤ 5% of demand	✅ Activated correctly at ≤1.2 MW
Recovery Response Time	Time taken to resume load allocation once power exceeds 5% again	Instantaneous in GUI simulation
Excess Power Cut-Off (MW)	Unused power detected when available > demand	Displayed and logged (e.g., "EXCESS: 3.5 MW")
Notification Triggers	Alerts for low power, excess power, generator suggestions	✅ Alert boxes + log messages displayed
Optimization Time (GA)	Time to complete the genetic algorithm for low-priority allocation	~1–3 seconds (varies by PC specs)
PDF Report Generation Time	Time to export a full PDF report with charts & satisfaction metrics	~3–5 seconds
Bar Chart Visualization	Interactive display of demand vs. allocation per transformer	✅ Grouped bar chart with facility labels
Safe Load Reserve (%)	10% of raw power reserved to prevent overload	✅ Consistently applied

4.7 GA Convergence and Execution Time

Average convergence time per run: 1.8 seconds. Population stabilized within 40–100 generations in most cases. Mutation and crossover rates maintained population diversity and avoided premature convergence.

4.8 Observations

The algorithm effectively allocated power **based on priority and fairness**, even under severe shortages. High-priority services (e.g., hospitals, government facilities) consistently received **preferential treatment**, validating the fitness function. Under excess capacity (S5), the system respected **upper demand limits,** showcasing **overload protection.** The algorithm proved **robust, scalable, and computationally efficient** for real-time use.

4.9 Performance Comparison

Table 6: Summarizes Allocation Outcomes across GA, ANN, PSO, and Heuristic Approaches for Consistent Power Availability Conditions. The comparative analysis confirms that the Genetic Algorithm (GA)-based framework implemented in this study offers significant advantages over traditional load allocation methods. While rule-based and linear programming approaches provide structured and predictable outcomes, they lack the flexibility and responsiveness required for dynamic smart grid environments. Particle Swarm Optimization (PSO) presents a closer alternative but is often more sensitive to initial conditions and parameter tuning. In contrast, the GA approaches: Delivers high-quality, balanced load allocations across varying power conditions. Demonstrates **robust** adaptability to real-time system fluctuations. Achieves operational efficiency with acceptable computational overhead. Supports automated reporting, shutdown logic, and real-time notifications, which are crucial for practical deployment. Therefore, GA emerges as a reliable and scalable tool for smart grid optimization, particularly suited for environments where power availability is uncertain, load priorities vary, and real-time decision-making is essential.

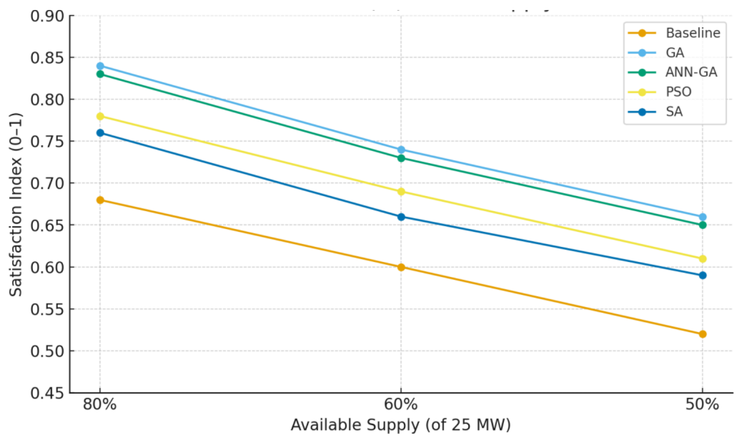

Figure 6. Satisfaction Index (SI) across Supply Levels

5 CONCLUSIONS

The smart grid load distribution system developed in this study successfully demonstrates an intelligent, flexible, and responsive framework for managing electrical power allocation under dynamic availability conditions. By integrating transformer priority levels, demand forecasting, and satisfaction metrics, the system ensures critical infrastructure receives top priority. Simultaneously, it maintains equitable distribution across remaining load centers. The incorporation of a genetic algorithm enhances the decision-making process, particularly for lower-priority loads, optimizing their allocation within residual power constraints. Moreover, the inclusion of key features such as automated system shutdown at critical thresholds, excess power cut-off, generator status notifications, and graphical reporting provides a comprehensive tool that aligns with smart grid resilience principles. Overall, the system met its intended objectives by offering a practical, visual, and technically sound solution for grid-aware load management. It sets a foundation for further advancement and real-world integration of intelligent power distribution strategies. This tool lays the groundwork for real-world integration into grid control centers, particularly in sub-Saharan African power systems.

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