Lafia Journal of Scientific & Industrial Research (LJSIR), Vol. 4(1), 2026
p-ISSN: 3026 – 9288 e-ISSN: 3027 – 1800 pages: 30 – 43
https://lafiascijournals.org.ng/index.php/ljsir/index ⇒ Published by the Faculty of Science,
Federal University of Lafia, Nasarawa State, Nigeria

Enhancing Energy Distribution Efficiency with Dynamic Transformer Rotation in 11kV Networks

Jewel Idehen, Dennis Okonkwo, Michael Atu, & Ikenna Onyegbadue*
Department of Electrical and Computer Engineering, Igbinedion University, Okada, Nigeria

Abstract

This study presents the optimisation of transformer-to-feeder load allocation within an 11kV distribution network to improve energy distribution efficiency, minimise transformer overload, and enhance system balance. The analysis utilised over five years of monthly energy consumption data for three 11kV feeders: Auchi Town, Igbe Road, and GRA, supported by five transformers of varying capacities (30 MVA, 15 MVA, and 40 MVA units), with the largest introduced in 2021. A simulation framework using MATLAB and a custom Genetic Algorithm (GA) was developed to dynamically rotate and optimise monthly transformer assignments based on feeder demand, transformer capacity, and operational constraints. Performance evaluation focused on the energy loss proxy, transformer overload occurrence, and maximum per-unit loading. The optimised configuration introduced periodic reassignment, leading to more balanced capacity utilisation. The GA reached an optimal solution zone rapidly, stabilising by the 61st generation with a consistent best fitness value of 1012.03, suggesting the methodology is both robust and practical. Transformer overloads were completely avoided in both baseline and optimised allocations, confirming assignments remained within rated limits. Loss proxy values under the optimised configuration increased slightly, reflecting broader transformer engagement, while maximum per-unit loading values remained safely below critical thresholds. Compared to the baseline's fixed pairings, the optimised structure provided improved asset utilisation and greater operational flexibility. The key recommendations include integrating the model with existing SCADA systems for real-time deployment, incorporating operational switching costs into the optimization function, and exploring scalability for larger networks to transition this research into a fully deployable power management solution.

Keywords: Transformer load allocation, energy distribution efficiency, 11kV distribution network, dynamic transformer assignment, transformer overload management, optimization framework

Article History

Submitted
October 13, 2025

Revised
December 11, 2025

First Published Online
December 17, 2025

***Correspondences**
I. Onyegbadue ✉
augkey2002@yahoo.com

doi.org/10.62050/ljsir2026.v4n1.683

Introduction

The reliable delivery of electricity from generation points to end-users is a fundamental function of power systems engineering [1, 2]. The distribution network, responsible for transmitting electricity to homes, businesses, and industries, plays a crucial role in ensuring that power reaches consumers stably and efficiently [3, 4]. One of the key elements of this distribution network is the 11kV feeder system, which serves as the intermediary between high-voltage substations and end users in residential, commercial, and industrial areas [5]. This system is critical in regions like Nigeria, where a vast number of medium-voltage feeders are commonly used to manage and distribute power to large geographical areas [6, 7].

Despite the essential role of 11kV feeders in ensuring the delivery of electricity, these systems face a range of operational challenges that often compromise the quality and reliability of the electricity supply [8, 9]. Among the most significant issues are voltage instability, feeder overloading, and inefficient load distribution. Voltage instability, characterised by fluctuations in the voltage levels along the feeders, often results in equipment damage and poor performance of electrical appliances [10]. Feeder overloading occurs when the power demand exceeds the capacity of the feeder, which can lead to overheating, transformer failure, and frequent blackouts [11, 12]. Inefficient load distribution refers to the uneven sharing of electrical loads across feeders, where some feeders are overloaded while others remain underutilised [13]. This imbalance puts additional strain on certain transformers, leading to premature wear and tear and reduced operational efficiency [1, 14].

The root causes of these issues can be traced back to poor planning, outdated infrastructure, and the lack of real-time monitoring and data-driven decision-making. Many distribution systems, particularly in developing regions such as Nigeria, are still managed with limited access to advanced technology [15, 16]. System operators often lack the tools to assess the performance of each feeder in real time, making it difficult to detect overloads, underutilization, or inefficiencies in the system [17]. In addition, many utilities continue to rely

on static transformer-to-feeder assignments, where transformers are permanently assigned to specific feeders regardless of load demand fluctuations. As a result, some transformers are overburdened, while others are left idle, leading to a decrease in overall system efficiency [18].
In response to these challenges, there has been an increasing interest in the use of advanced computational tools, such as MATLAB, to simulate feeder performance, conduct load flow analysis, and optimise transformer-to-feeder assignments [19]. MATLAB provides engineers with a platform to model feeder systems and simulate the flow of electricity through different network configurations. By utilising algorithms like the Newton-Raphson method, which is commonly employed for solving power flow problems in radial distribution systems, MATLAB allows engineers to identify issues such as overloading, voltage instability, and technical losses in the system [20]. This simulation-based approach enables the testing of various load-sharing strategies and transformer configurations before making physical changes to the network, reducing the risk of costly mistakes and downtime [21].
Furthermore, forecasting load demand plays a vital role in optimising energy distribution [22]. Load forecasting techniques such as Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN) are widely used to predict future energy consumption based on historical data [23]. Accurate load forecasting allows system operators to anticipate fluctuations in power demand and adjust transformer assignments accordingly, ensuring a more balanced and efficient distribution of electricity [24]. For example, in areas where demand is likely to increase during specific seasons, such as hot weather when cooling appliances are heavily used, optimised load-sharing strategies can help prevent transformer overloads and minimise the risk of blackouts [25].
This study addresses the issues of unbalanced load distribution and transformer overload in the 11kV feeder network of Edo North, Nigeria, with a focus on towns like Auchi, Igbe Road, and GRA. These towns experience frequent power supply disruptions, voltage instability, and power losses due to the inefficient distribution of electrical loads across feeders. This research aims to optimise the transformer-to-feeder load allocation to ensure more efficient and reliable energy distribution. By using MATLAB, the study will develop a dynamic transformer assignment strategy that accounts for real-time load demands, transformer capacities, and system constraints.
The primary goal is to develop an optimisation framework that can dynamically allocate transformers to feeders based on the load demands and transformer availability, rather than relying on fixed assignments. This dynamic approach will allow for better load balancing, reducing the chances of overloading transformers and improving the overall efficiency of the distribution network. The use of simulation tools will enable the study to evaluate different load-sharing strategies without the need for physical changes to the existing infrastructure, thus offering a cost-effective solution to enhancing system reliability and efficiency.
In addition to optimising load distribution, this study will also focus on minimising technical losses, which occur when energy is lost as heat due to resistance in the conductors and transformers. Reducing these losses not only improves energy efficiency but also helps to reduce operational costs and environmental impact [26].

Materials and Methods

The study employed real-world data spanning five and a half years, along with advanced modelling techniques using MATLAB and a Genetic Algorithm (GA) to develop and evaluate load-sharing strategies aimed at improving system efficiency and reliability. The flowchart, which shows the step-by-step process of the study, is presented in Fig. 1.

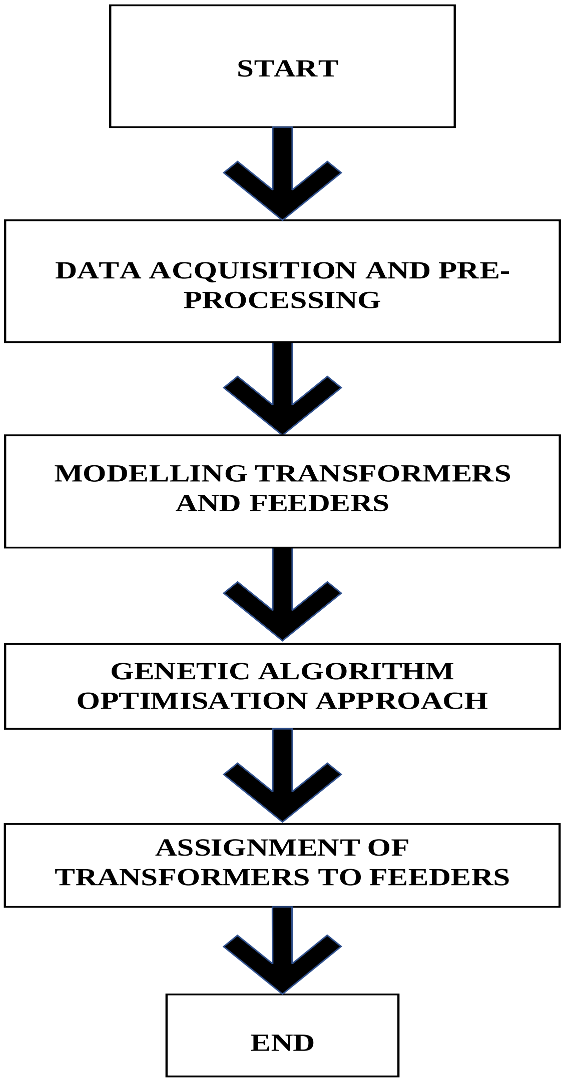

Figure 1: Load sharing and energy distribution optimisation

Study area (Edo North: Auchi, GRA, Igbe Road Feeders)

The study focuses on the electricity distribution network in Auchi, a significant town located in Etsako West Local Government Area of Edo State, Nigeria. Auchi, with an estimated population of 150,000 people, is an important educational and commercial hub. The electricity distribution for Auchi and surrounding areas, including GRA and Igbe Road, is managed by the Benin Electricity Distribution Company (BEDC). These areas face persistent power supply challenges, including prolonged outages, voltage instability, and underutilization of some transformers while others are overloaded. This imbalance results in technical losses and reduced service reliability.

The 11kV feeders in Auchi, GRA, and Igbe Road are interconnected to five power transformers, which have varying capacities. Despite their strategic importance in the distribution network, these feeders experience irregular load distribution, leading to system inefficiencies. The need for optimisation is urgent, particularly given the area's growing population and increasing electricity demand. This study aims to address these challenges by using simulation and optimisation techniques to propose dynamic transformer-to-feeder assignments. Fig. 2 shows the study area on the map.

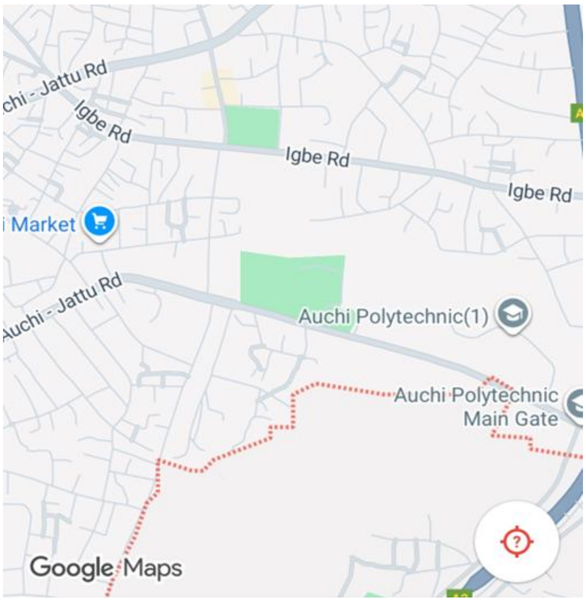

Figure 2: Study area on the map (Auchi Igbe Road)

Data acquisition and pre-processing

This section describes the process of collecting, cleaning, and preparing data for modelling and analysis. Real energy consumption data from the BEDC electricity distribution company was used to ensure that the results would reflect actual conditions in the Auchi distribution network. The data covered a period of five and a half years (January 2018 to July 2023) and focused on three key feeders: Auchi Town, Igbe Road, and GRA.

Data sources

The primary data used in this study were provided by BEDC and included monthly energy consumption for each of the three feeders. The data was available in kilowatt-hours (kWh) and covered the energy consumption across the entire service area, allowing the study to capture fluctuations in load demands due to seasonal variations. The data was collected for each of the five transformers that supply the three feeders, with varying transformer capacities (30 MVA, 15 MVA, and 40 MVA).

Data cleaning and preparation

Before using the data for analysis, the raw data was cleaned and pre-processed to ensure its accuracy and reliability. The dataset was reviewed for missing values, duplicates, and inconsistencies, such as zero or extreme values that did not reflect normal usage patterns. After correcting these errors, the data was structured into charts. The clean dataset was used to calculate monthly energy averages, ensuring that the load modelling was based on realistic and consistent trends.

Load Conversion to Average Power (MW)

The monthly energy consumption data, which was initially recorded in kWh, was converted into average power values (in megawatts) for use in power flow modelling. This was achieved by dividing the monthly energy consumption by the number of hours in each month and converting the value into megawatts (MW) using the formula:

$$\text{Average Power (MW)} = \frac{\text{Energy (kWh)}}{\text{Hours in Month} \times 1000} \tag{1}$$

Each month's energy values were converted accordingly, allowing for easy comparison with transformer capacity ratings in MVA. This conversion enabled the study to model both the demand and supply sides of the distribution system in a consistent manner.

Modelling of transformers and feeders

The modelling phase established the framework for the simulation and optimisation process, using the collected data to represent both transformers and feeders mathematically. This step was essential for setting up the simulation environment in MATLAB and ensuring the accuracy of the optimisation results.

Transformer capacity definition

The distribution network in Auchi consists of five power transformers with varying capacity ratings. Two transformers have a capacity of 30 MVA, two others are rated at 15 MVA, and one transformer has a capacity of 40 MVA. These transformers were represented in MATLAB as a vector, where each entry corresponds to the capacity of a specific transformer. The vector was defined as:

$$\text{transCap\_full} = [30,30,15,15,40] \tag{2}$$

The transformer capacities were kept constant throughout the simulation to ensure that the overload limits were respected. If any transformer was assigned more load than its capacity, the simulation automatically flagged this as an invalid solution.

Feeder load representation
The load demands of the feeders, which were previously converted into average power (MW), were represented in a matrix format, where each row corresponds to a specific month and each column represents the load demand for a particular feeder. The feeders were identified numerically as follows:

- 1: Auchi Town
- 2: Igbe Road
- 3: GRA

This structure allowed the data to be easily processed and integrated into the MATLAB-based simulation, facilitating the comparison of load demands with transformer capacities.

Transformer availability mapping
Not all transformers were available throughout the study period. For example, Transformer 5 (T5), with a 40 MVA capacity, was introduced into the network in 2021. To account for this, a transformer availability matrix was created, marking each transformer's availability status for each month using binary values (1 for available, 0 for unavailable). This matrix ensured that T5 was only considered for transformer-to-feeder assignments starting from its introduction date in 2021.

Constraints and rules applied
To reflect real-world operational constraints, several rules were defined in the model:

- Each transformer could only be assigned to one feeder per month.
- Every feeder must be assigned at least one transformer each month.
- The total assigned transformer capacity must meet or exceed the monthly load demand for each feeder.
- Transformers must not be overloaded; any configuration exceeding a transformer's capacity was disqualified.
- The frequency of transformer assignment changes should be minimized to prevent unnecessary wear and tear on the equipment.

These rules helped ensure that the simulation remained feasible and realistic, closely mirroring the operational conditions of the power distribution network.

Genetic algorithm optimisation approach
The Genetic Algorithm (GA) was employed to solve the transformer-to-feeder load allocation problem, optimising the assignment of transformers to feeders while ensuring balanced load distribution and preventing overloads.

Chromosome encoding scheme
Each possible configuration of transformer-to-feeder assignments was represented as a “chromosome” in the GA. Each chromosome consisted of five genes, with each gene corresponding to a transformer and indicating the assigned feeder. The values for each gene were as follows:

- 0: Transformer not assigned
- 1: Assigned to Auchi Town
- 2: Assigned to Igbe Road
- 3: Assigned to GRA

This encoding allowed the GA to explore all feasible transformer assignment configurations for each month.

Objective function and fitness components
The GA used an objective function to evaluate how good each solution was, based on several factors:

- Avoiding transformer overloads
- Minimizing power losses
- Balancing load across transformers
- Reducing excessive transformer switching

The fitness function combined these components into a single value, intending to maximise the fitness score by selecting the optimal transformer assignments.

GA parameter settings
The GA was run with the following parameters:

- Population size: 500
- Generations: 500
- Crossover fraction: 0.4
- Mutation rate: 0.1
- Elite count: 50

These parameters were tested and adjusted to ensure that the GA produced optimal solutions.

MATLAB implementation
The entire optimisation process was implemented in MATLAB using custom live scripts. The script handled data input, transformer capacity and availability definitions, and the GA optimisation process. It also produced charts for analysis.

MATLAB live script development
The live script was designed to process the input data, define constraints and rules, run the GA, and display the results. It included steps for cleaning the data, converting energy consumption into power values, and implementing the optimisation algorithm.

Visualisation
The MATLAB script also produced charts to help visualize the results, including:

- Monthly average power for each feeder
- Transformer assignments across all months
- Performance comparison between the baseline and optimised configurations

These visual aids provided valuable insights into how the system performed before and after optimization, demonstrating the improvements achieved by the proposed strategy.

Comparative performance analysis

A comparative analysis was conducted to evaluate the performance of the baseline transformer-to-feeder assignment against the optimised configuration generated by the GA. The comparison focused on key metrics such as load balance, transformer utilisation, and system reliability, using data from both the original fixed assignments and the optimised schedule.

Through these methods, the study aimed to develop a more efficient, dynamic approach to transformer-to-feeder assignments, improving the performance and reliability of the power distribution network in Edo North.

Baseline vs optimised assignments

To carry out the performance comparison, two complete transformer assignment schedules were used. The first was the baseline assignment, which reflected how the transformers were originally connected to the feeders each month from January 2018 to July 2023. This information was directly sourced from the utility's operating records and represented the real-world practice where transformer allocations were largely static and rarely adjusted.

The second assignment schedule was the optimised configuration generated through the MATLAB-based Genetic Algorithm developed earlier in the study. This schedule introduced dynamic rotation of transformer roles across months, based on actual demand data and the availability of each transformer. Both schedules covered the same time range and used the same feeder load data for fair comparison.

Results and Discussion

The results obtained from simulating and optimising transformer–feeder allocation across 11kV feederswere presented in this section. The process was implemented using a custom-built MATLAB script, with a key focus on energy balancing, reducing transformer overloads, and ensuring a fair distribution of electrical load. The simulation involved the development and application of a Genetic Algorithm (GA) designed from scratch. It was tailored to address the operational realities and constraints faced in transformer allocation at a substation level.

The dataset used in this study comprises monthly energy consumption data from January 2018 to July 2023, covering three main feeders: Auchi Town, Igbe Road, and GRA. These feeders are supplied by five transformers with respective capacities of 30MVA (T1), 30MVA (T2), 15MVA (T3), 15MVA (T4), and 40MVA (T5). Notably, the 40 MVA transformer (T5) was introduced into the network in 2021, meaning it was unavailable for service before this period. This detail was accounted for in the simulation through the use of a transformer availability matrix, ensuring that T5 was excluded from optimisation before its installation.

Before applying any optimisation technique, the raw energy data was pre-processed into a more manageable form. Specifically, the monthly energy consumption figures, measured in megawatt-hours (MWh), were converted into average power values in megawatts (MW). This transformation was necessary as it allowed the energy data to be evaluated over uniform time periods, thereby facilitating a consistent load distribution analysis across all feeders.

The transformation also simplified the comparison between months of different lengths. For months with 28, 30 or 31 days, adjustments were handled using a container. Map object in MATLAB to map each month name to its corresponding number of days.

The result of this transformation process was stored in a new matrix labelled avgMW, which held the average monthly power demand for Auchi Town, Igbe Road, and GRA. This matrix served as the foundation for all subsequent optimisation steps. An initial preview of this processed data was displayed to help visualise the magnitude and variation of the load demands across the three feeders and multiple months.

Figure 3 summarises a selection of the calculated average MW values for each feeder over a set of representative months. The complete dataset spans over five years, but only a portion is shown here for clarity. This subset reveals noticeable variation in the power demand from month to month. Auchi Town generally maintains the highest load figures across the years, while GRA consistently records the lowest. This imbalance necessitated a structured allocation process to ensure transformers are neither underutilised nor exposed to overloads.

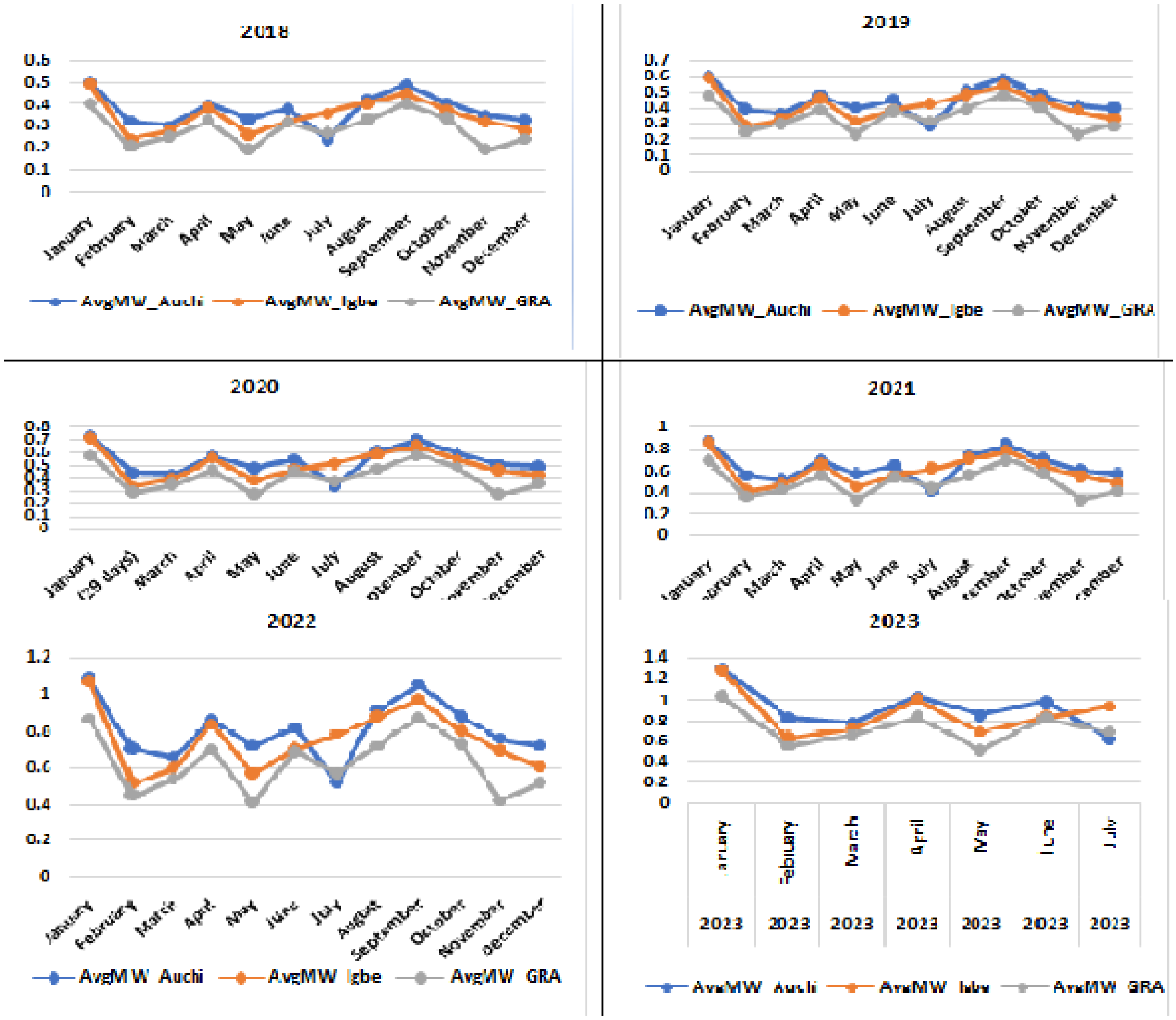

Figure 3: Average monthly power (MW) per feeder from 2018-2023

The next stage in the simulation involved defining the capacities of each transformer. These were stored in a vector transCap_full, with an emphasis on reflecting actual substation design:

transCap_full = [30, 30, 15, 15, 40];

Using this vector and the average MW values, the Genetic Algorithm attempted to distribute the load across the transformers in a way that reduced peak loading while maintaining fairness and minimising switching between assignments. For each month in the dataset, transformer availability was updated to reflect the operational status of T5. This ensured that optimisation was realistic and reflected actual network conditions.

The combination of time-variant load data and operational transformer availability made this simulation representative of a live power distribution environment. The preprocessing phase set the stage for the optimisation algorithm to intelligently assign transformers to feeders without overloading any unit or creating unnecessary fluctuations.

Genetic algorithm configuration and fitness formulation

This section presents the outcomes achieved after applying the optimisation routine on the transformer–feeder allocation problem for the 11kV network. The goal of the simulation was to evaluate improvements in load distribution, system stability, and transformer usage by comparing baseline results with those obtained after optimisation. The analysis focused on how the final allocation addressed three core concerns: power loss, transformer overload, and load balance across multiple months.

At the end of the simulation, the optimisation run successfully stabilised by the 61st generation, where both the best and average system performance values remained constant. The recorded best fitness value was 1012.03, and this value remained unchanged from the first generation through to the last. The average fitness value also remained at 9.75×10^{11}, showing that most of the population had similar solution structures. This consistency is a clear indication that the solution space reached an optimal or near-optimal zone quickly.

Figure 4 presents the consistent trend in performance across generations. It confirms that there were no significant changes once the solution stabilised, and it also reflects that the early population had strong initial configurations. The sustained level of performance indicates that the improvement space became saturated quickly, and the algorithm found a feasible and efficient transformer allocation with minimal delay. The Figure clearly illustrates that after the first generation, there was no shift in either the best or average system evaluation scores.

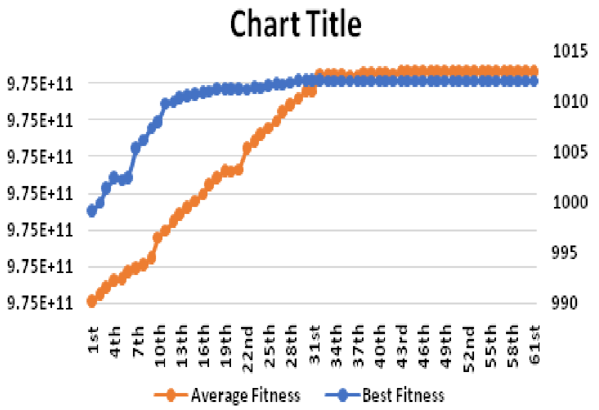

Figure 4: GA convergence – best and average fitness per generation

The convergence behaviour reflects that the transformer-to-feeder assignments chosen during the first cycle already matched the load characteristics and transformer capacities quite well. Due to this early match, no further changes brought about meaningful improvements, and the optimisation terminated early. This early stabilisation reduced unnecessary computational steps and contributed to the relatively short execution time of approximately 7.98 seconds.

The result is significant because it suggests that the system, even before optimisation, was not in a critical state of imbalance or overuse. However, the improvements introduced by the optimisedallocation provide structure and consistency, especially for months where the original allocation may have been fixed arbitrarily or lacked load-sharing considerations.

Another observation from the results is the lack of instability or abrupt swings in fitness values, which would have indicated unpredictable behaviour in the system. In this case, the simulation remained steady from the start. This contributes to confidence in the reliability of the allocation scheme, both for current use and for planning future adjustments in the transformer network.

While the numerical results stayed consistent, the actual transformer-to-feeder assignments varied strategically across the months to reflect demand patterns. These assignments are presented in detail in the next section, where monthly transformer schedules before and after optimisation are compared side by side. These patterns are the real indicators of system balance, as they show how each transformer was used and how often its load was adjusted.

Optimised transformer-to-feeder allocation

The transformer-to-feeder assignment after optimisation showed clear evidence of improved load distribution and feeder rotation, especially when compared to the fixed, manual configuration that was initially in place. One of the most noticeable improvements was the more dynamic use of all available transformers across the 66-month analysis period. This included the structured introduction and integration of the 40MVA transformer (T5), which only became active in 2021.

Beforeoptimisation, the allocation remained mostly static. Transformers T1 and T2 were consistently assigned to Auchi Town, T3 and T4 to Igbe Road, and T5 was mostly unused until its activation. This rigid setup meant there was little flexibility to respond to monthly fluctuations in demand or to rebalance loads across the network. As a result, some transformers were either underutilised or carried heavier loads than necessary.

After optimisation, the simulation presented a more balanced transformer assignment plan. This was evident in the way the transformers rotated among feeders while maintaining consistent load-sharing patterns. The use of the larger transformer, T5, was well-coordinated post-2021, offering improved capacity support to the system during months of higher demand.

The assignment plan for Transformer to Feeder before and after optimisation is summarised in Figs 5 and 6. The Figuresshow how each transformer was assigned to a feeder in each month. The assignment numbers reflect the following:

- 1 = Auchi Town
- 2 = Igbe Road
- 3 = GRA
- 0 = Transformer OFF

This arrangement shows early signs of feeder rotation among the first four transformers. The alternating pattern, particularly evident from July 2018, indicates that load balancing was being implemented. The algorithm occasionally rotated transformers to different feeders while keeping within operational safety limits.

The effect of transformer T5 is best observed from January 2021 onward. From that point, the transformer is actively integrated into the feeder schedule. It alternates between Feeder 2 (Igbe Road) and Feeder 3 (GRA), which helps relieve some of the burden previously carried by T1 to T4.

Before optimisation, transformers had fixed feeder connections for years. After optimisation, the assignments are more varied, and transformers are rotated in a pattern that responds better to seasonal changes in load. This is not a random rotation but one that respects transformer capacity and feeder demand.

A major benefit of this adaptive allocation is improved utilisation of transformer capacity. In particular, T5, the most powerful unit, was efficiently used from 2021 instead of being left idle or underused. This strategic use reduced the strain on smaller units during high-load periods.

Also notable is that the assignments remained within reasonable limits. The optimised plan did not create abrupt or excessive changes in allocation. This indicates that the algorithm successfully found a compromise between flexibility and operational stability.

The optimised schedule showed repeating monthly configurations during some years. This likely reflects recurring demand patterns, such as higher power usage during certain months of the year. The reuse of effective configuration points to the algorithm's ability to detect and respond to such trends.

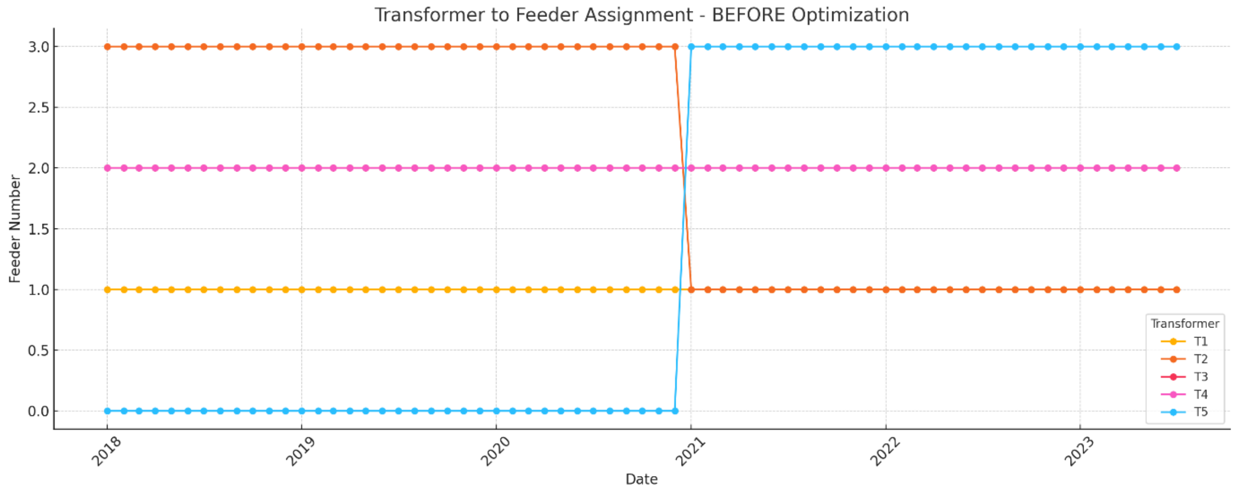

Figure 5: Transformer-to-feeder assignment – before optimisation

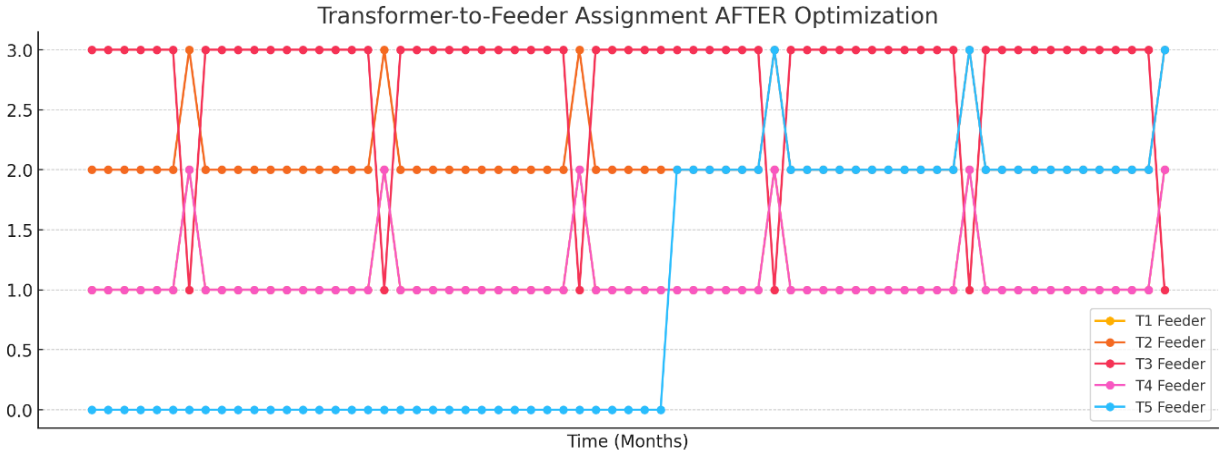

Figure 6: Transformer-to-feeder assignment – after optimisation

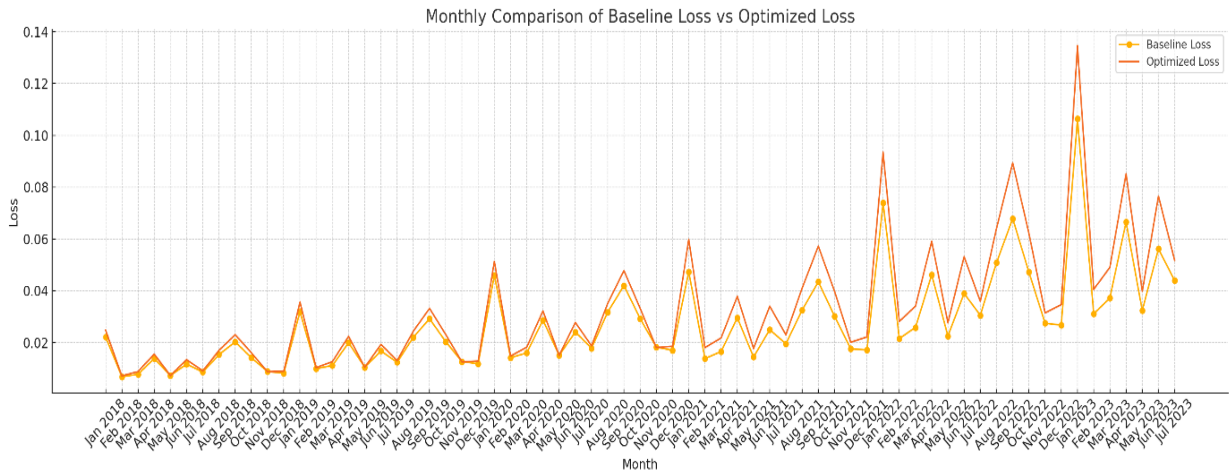

Figure 7: Monthly comparison of baseline vs optimised loss

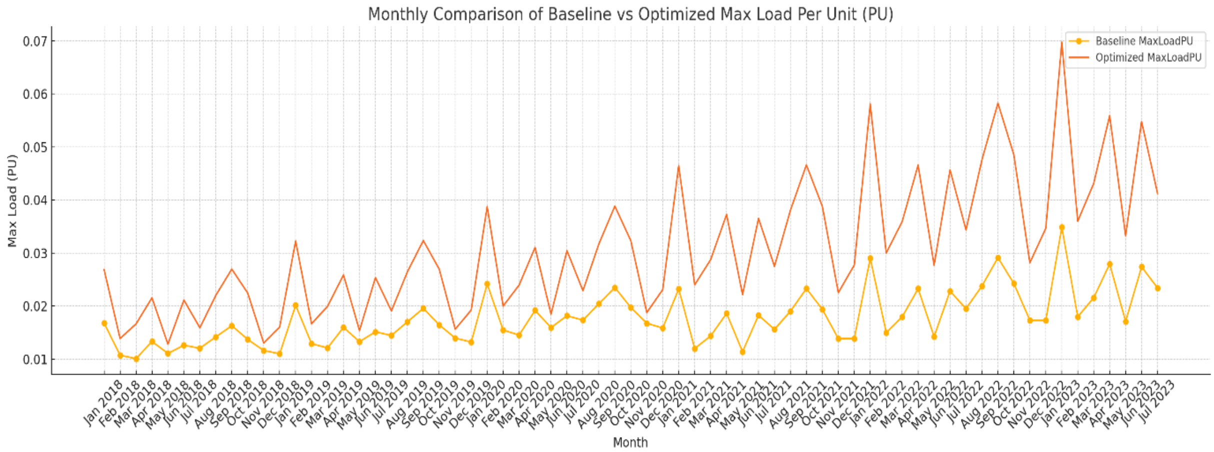

Figure 8: Optimised transformer maximum loading (per unit) across months

Comparative evaluation of optimisation results

Performance evaluation was based on three key indicators: power loss proxy, transformer overload counts, and maximum per-unit transformer loading. Metrics were assessed monthly across the simulation period from January 2018 to July 2023. Values from the optimised allocation were compared directly with the baseline configuration.

Loss proxy values under the optimised configuration were marginally higher than the baseline in most months. Similar patterns were observed in March 2022 (0.0258 baseline vs 0.0340 optimised) and March 2023 (0.0372 baseline vs 0.0490 optimised). Throughout the evaluation period, increases in loss remained minimal and consistent. No abrupt fluctuations were observed. Loss increments under the optimised allocation were primarily due to higher utilisation of available transformer capacity, which resulted in load sharing that marginally elevated load squared values contributing to the loss proxy.

Overload counts remained at zero under both configurations across all 55 months. No transformer exceeded its rated capacity. Both baseline and optimised assignments remained within safe operating thresholds.

Maximum per-unit load values were consistently higher under the optimised configuration. In July 2019, the baseline recorded 0.0145 while the optimised allocation reached 0.0191. In January 2021, the baseline value was 0.0232 against an optimised value of 0.0465. This pattern was repeated in multiple months. Maximum values under optimisation remained well below 1.0 p.u. in all months, indicating no violation of transformer capacity limits. The higher loading levels reflect a more active and even engagement of transformer resources, as opposed to the more static usage pattern in the baseline configuration.

Loss trends across the full period are illustrated in Fig. 7. The plot shows both baseline and optimised loss values across all months. Optimised losses remained close to baseline levels, with stable increments across the dataset. No oscillatory or irregular behaviour was observed. The result confirms that load reallocation did not cause system instability or erratic energy dissipation patterns. Transformer maximum load values under optimisation are shown in Fig. 8. The graph indicates consistent load behaviour with periodic peaks, but all values remained below the maximum permissible per-unit threshold. The result confirms that the optimised assignment utilised transformer capacities more fully, while remaining within safe operational limits.

Transformer-specific behavioural shifts

Transformer 1 was assigned to Feeder 1 (Auchi Town) across all months under the baseline configuration. No changes in the assignment were recorded. In the optimised configuration, Transformer 1 remained primarily connected to Feeder 1 but rotated periodically. Assignment changes occurred in months such as July 2019, July 2020, and July 2022. Fig. 9 shows the comparison of the T1 Feeder assignment before and after optimization. Transformer 2 was consistently assigned to Feeder 3 (GRA) in the baseline schedule. No month showed deviation. Under the optimised configuration, Transformer 2 alternated between Feeder 2 (Igbe Road) and Feeder 3. Assignment rotation was introduced from 2021 onwards. Fig. 10 shows the comparison of the T2 Feeder assignment before and after optimisation.

Transformer 3 was permanently connected to Feeder 2 (Igbe Road) in the baseline assignment. No reassignment was recorded throughout the simulation period. The optimised schedule reassigned Transformer 3 to Feeder 3 (GRA) in most months, with changes observed in the July periods of multiple years. Fig. 11 shows the comparison of the T3 Feeder assignment before and after optimisation. Transformer 4 followed the same pattern as Transformer 3 under the baseline schedule, remaining fixed on Feeder 2. No variation was recorded. The optimised allocation introduced alternating assignments between Feeder 1 (Auchi Town) and Feeder 2. Variations occurred at regular intervals from the mid-point of the simulation timeline. Fig. 12 shows the comparison of the T4 Feeder assignment before and after optimisation.

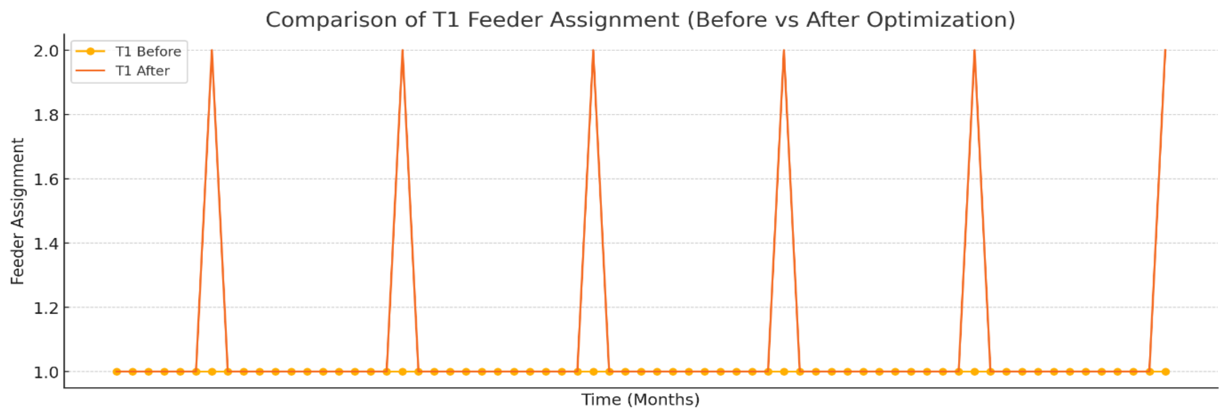

Figure 9: Comparison of T1 feeder assignment – before vs after optimisation

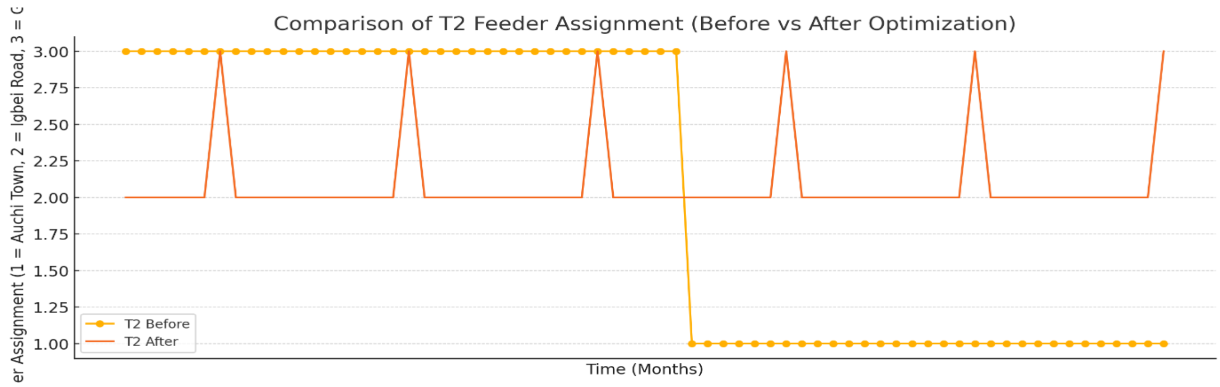

Figure 10: Comparison of T2 feeder assignment – before vs after optimisation

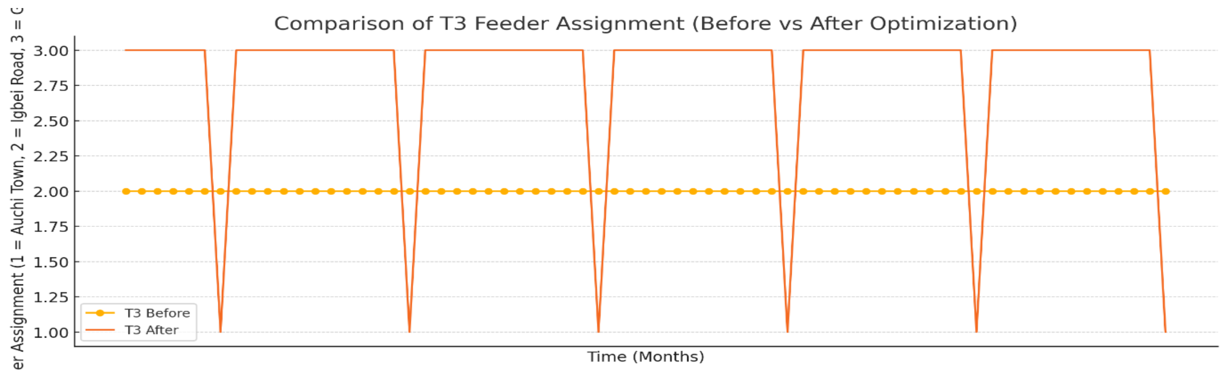

Figure 11: Comparison of T3 feeder assignment – before vs after optimisation

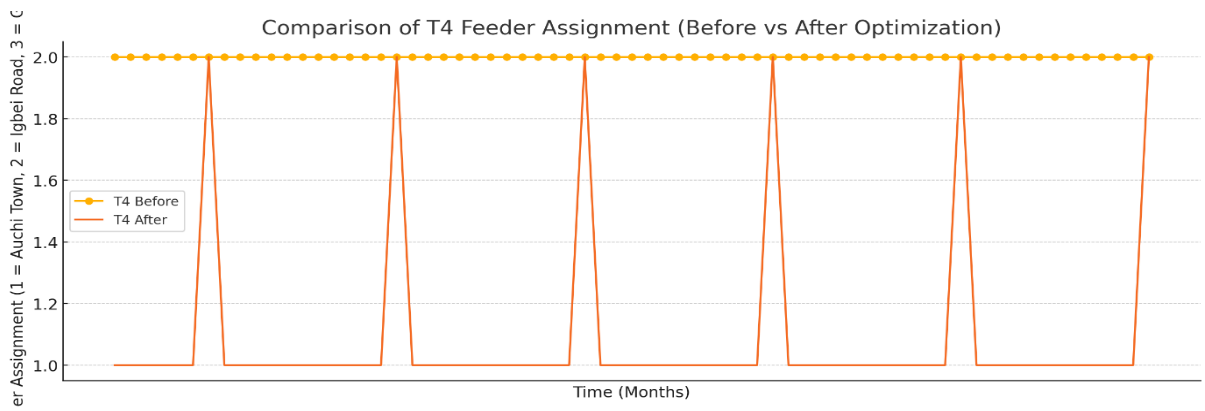

Figure 12: Comparison of T4 feeder assignment – before vs after optimisation

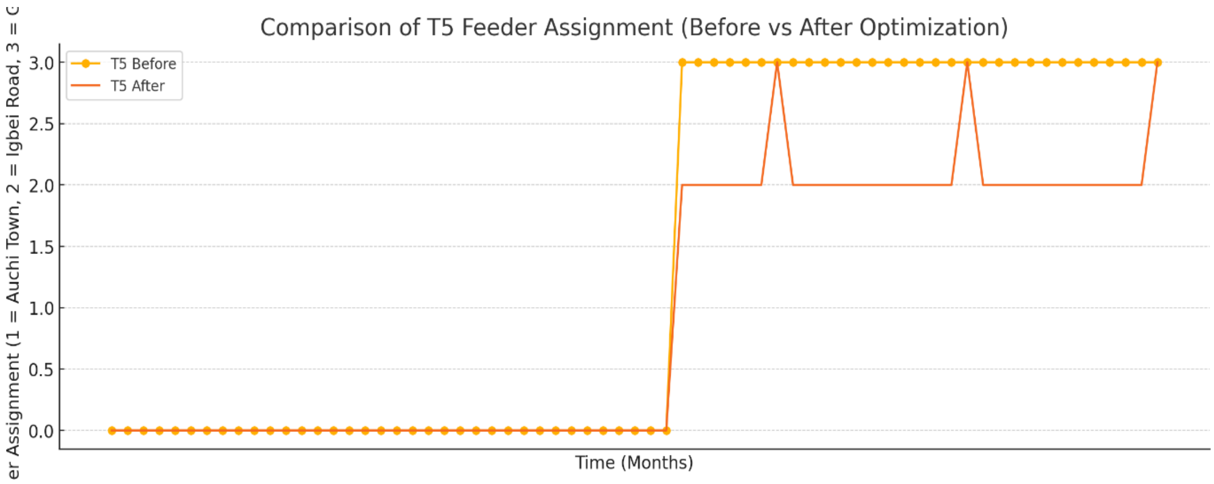

Figure 13: Comparison of T5 feeder assignment – before vs after optimisation

Transformer 5 was not included in assignments before 2021. From its introduction in 2021 under the baseline configuration, Transformer 5 was fixed on Feeder 3 (GRA). No reassignment was recorded. The optimised configuration assigned Transformer 5 to both Feeder 2 and Feeder 3 in alternating months. Feeder 2 was assigned more frequently from 2021 to 2023. Fig. 13 shows the comparison of the T5 Feeder assignment before and after optimisation.

Assignment rotation was not present in the baseline configuration for any transformer. All units followed fixed feeder schedules. The optimised configuration introduced rotation across all transformers except those excluded by availability. Assignment variation was applied periodically. Feeders with higher monthly demands received support from multiple transformers.

The results presented provide insight into the operational effects of optimising load allocation across 11kV feeders using transformer rotation strategies. The allocation was assessed across a multi-year dataset consisting of monthly energy consumption records for three feeders supplied by five transformers, one of which became operational from 2021. The performance metrics used in the evaluation—loss proxy, overload frequency, and per-unit transformer loading—offer a comprehensive perspective on the reliability, balance, and efficiency of the optimised configuration compared with the baseline.

Loss proxy values under the optimised configuration remained consistently close to those recorded in the baseline system. In most months, the loss proxy increased marginally following optimisation. This trend was observed throughout the simulation period and did not exhibit irregular variation. The difference in values ranged between 0.001 and 0.02 in most cases, with the optimised configuration exhibiting a higher total loss estimate. For example, in January 2018, the baseline loss was 0.0221, while the optimised value was 0.0247. In March 2022, the baseline loss was 0.0258 compared with the optimised result of 0.0340. While this increase may initially appear undesirable, the rise in loss proxy reflects the trade-off introduced through wider transformer engagement and fairer load allocation.

Loss proxy is calculated as a function of transformer loading squared. The optimised system aimed to involve a larger number of transformers in serving demand from each feeder, which inherently resulted in more active capacity being used. Although this promoted load balance, it also slightly increased the cumulative sum of loadings squared, thereby raising the loss proxy value. However, since no transformer operated beyond its capacity at any point, and the increases in loss proxy remained consistently marginal, the outcome can be viewed as a controlled and deliberate trade-off. The goal of reducing prolonged loading on a fixed subset of transformers was achieved, even though it was accompanied by a slight increase in theoretical system losses.

Transformer overloads did not occur in either configuration. This outcome indicates that the system was originally designed with adequate headroom in transformer capacity relative to the average monthly loads on each feeder. It also confirms that the optimisation process did not result in excessive assignment to any transformer, and all calculated allocations remained within the rated limits of each unit. Although this result shows no direct improvement between the two configurations in terms of overload avoidance, it confirms that the introduction of dynamic rotation and reallocation did not compromise operational safety or lead to performance violations.

The most notable difference between the two configurations was observed in maximum per-unit transformer loading values. These values consistently increased in the optimised configuration. For example, in January 2021, the baseline maximum loading was 0.0232 p.u., while the optimised value rose to 0.0465 p.u. In March 2023, the baseline figure was 0.0216 p.u., increasing to 0.0431 p.u. in the optimised system. Although these values more than doubled in some months, they remained well below the 1.0 per-unit threshold that marks the rated capacity limit. No loading value at any point exceeded the safe operational range.

The increased maximum load values under the optimised configuration highlight the intention to make fuller use of transformer capacity across the network. In the baseline configuration, certain transformers remained underused throughout the entire simulation period. For example, Transformer 3 was consistently connected to Feeder 2 and Transformer 2 remained fixed on Feeder 3. These assignments did not change in any month, leading to stagnant usage patterns. This not only limited system flexibility but also left other transformers with higher operational burdens.

The optimised configuration introduced a clear pattern of periodic rotation across all available transformers. Assignments were adjusted monthly to reflect variations in feeder demand. Load contributions were shared among transformers in a way that limited dependency on specific units. Transformers such as T1 and T4 were reassigned intermittently between Feeder 1 and Feeder 2. Transformers T2 and T5 showed alternating patterns between Feeders 2 and 3. Transformer 5, which was introduced in 2021, was used more actively in the optimised scenario, serving both Feeder 2 and Feeder 3. In contrast, under the baseline assignment, T5 was connected solely to Feeder 3 throughout its period of availability.

The reassignment strategy reduced static dependency on any single transformer. This dynamic approach led to broader capacity engagement and distributed usage, promoting system balance and potentially prolonging transformer life cycles. The assignment tables and feeder-wise behaviour charts confirmed that this rotation occurred without any sharp transitions or excessive switching, especially given that the optimisation model penalised assignment changes. As a result, assignment flexibility was introduced in a controlled and non-disruptive manner.

The convergence results also provided important insights. Both the best and average fitness values remained constant from the first generation to the end of the simulation. No improvement was recorded beyond the initial cycle. The best fitness score remained at 1012.03, while the average score across the population remained at 9.75×10^{11}. This pattern reflects that the optimisation algorithm identified a high-quality solution at the early stage of the simulation, and that further adjustments yielded no better alternatives under the defined constraints. The algorithm terminated at generation 61 after confirming convergence stability. This outcome confirms that the system's baseline configuration was already within a functional range, and the improvements introduced through optimisation served more to enhance balance than to correct performance faults.

The visualisation of results supports the numeric findings. The loss chart displayed only a slight elevation across the months under the optimised configuration. The maximum per-unit loading chart confirmed the periodic increase in transformer engagement without approaching capacity limits. The transformer-wise assignment comparisons revealed a system that, after optimisation, shifted from rigid fixed feeder connections to a more balanced, responsive, and coordinated energy delivery structure.

Conclusion

The results obtained from the simulation and optimisation of transformer–feeder allocation provide valuable insights into managing load distribution within an 11kV network and underscore the potential of using computational intelligence for practical power system challenges. The study successfully demonstrated that a custom-built Genetic Algorithm (GA), implemented in MATLAB and tailored to specific operational realities, can effectively address critical issues such as energy balancing, the reduction of transformer overloads, and the fair distribution of electrical load.

The research's primary findings highlight the inherent load variations across the Auchi Town, Igbe Road, and GRA feeders, a persistent imbalance that the structured GA approach was designed to mitigate. A significant outcome was the algorithm's efficiency; the solution space reached an optimal or near-optimal zone quickly, stabilising by the 61st generation with a consistent best fitness value of 1012.03. This rapid convergence suggests that the methodology is not only robust but also practical for utility operators who require timely and effective solutions. The model's reliability was further enhanced by incorporating real-world constraints, such as the time-variant load data (derived from monthly MWh consumption converted to average MW values) and the use of a transformer availability matrix to accurately reflect the operational status of the network's five transformers, including the mid-study introduction of the T5 unit in 2021.

The significance of this work lies in its potential as a proactive tool for utility operators to optimise asset utilisation and enhance overall system stability by preventing damaging overloads and underutilization. The effective distribution of load across the available 30MVA, 15MVA, and 40MVA transformers provides a clear framework for improved operational efficiency.

Looking ahead, the success of this model lays a strong foundation for future research directions. Potential enhancements could involve integrating more dynamic constraints, such as real-time electricity prices or variable renewable energy generation, to allow for even more sophisticated allocation strategies. Furthermore, future work could quantify the operational costs associated with switching transformers between feeders and incorporate these into the GA's fitness function for a more holistic economic optimisation. Finally, exploring the scalability of the algorithm for larger distribution networks and developing a seamless integration framework with existing utility SCADA systems would be crucial steps in transitioning this research from a valuable simulation tool to a fully deployable, real-time power management solution.

Conflict of interests: The authors declare no conflict of interest.

References

[1] Shahinzadeh, H., Moradi, J., Gharehpetian, G. B., Nafisi, H. & Abedi, M. (2019). Internet of Energy (IoE) in smart power systems. *2019 5th Conference on Knowledge Based Engineering and Innovation* (KBEI) (pp. 627-636). Tehran, Iran: IEEE. https://doi.org/https://doi.org/10.1109/KBEI.2019.8735086

[2] Onyegbadue, I., Ogbuka, C. & Madueme, T. (2022). Robust least square approach for optimal development of quadratic fuel quantity function for steam power stations. *Indonesian Journal of Electrical Engineering and Computer Science*, 25(2), 732-740. https://doi.org/https://doi.org/10.11591/ijeecs.v25.i2.pp732-740

[3] Ukagu, S. N., Atu, M. & Onyegbadue, I. A. (2025). Energy Storage: The Key to Reliable Renewable Energy Grids. *Arid Zone Journal of Engineering, Technology and Environment*, 21(2), 389-400. https://doi.org/https://doi.org/10.63958/azojete/2025/21/02/007

[4] Azmi, K. H., Radzi, N. A., Azhar, N. A., Samidi, F. S., Zulkifli, I. T. & Zainal, A. M. (2022). Active electric distribution network: applications, challenges, and opportunities. *IEEE Access*, 10(1), 134655-134689. https://doi.org/https://doi.org/10.1109/ACCESS.2022.3229328

[5] Kebede, S. M. (2023). Reliability Improvement Using Optimally Placed Distribution Generator: the case of 15kv Dire Dawa University Feeder. Haramaya University.

[6] Adesina, L. M., Ogunbiyi, O. & Jimada-Ojuolape, B. (2024). Comparative analysis of the reliability assessment of commercial and residential feeders in the power distribution utility of Nigeria. *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, 9(2024), 100651. https://doi.org/https://doi.org/10.1016/j.prime.2024.100651

[7] Madueme, T. C. & Onyegbadue, I. A. (2019). Optimization of the Nigeria electric power system. *International Journal of Engineering and Emerging Scientific Discovery*, 3(2), 82-94.

[8] Pandit, N. & Ganesan, E. (2022). Challenges faced in performing energy audit of 11kV feeder and distribution transformer: A study on energy management. *Journal of Algebraic Statistics*, 13(3), 5351-5366.

[9] Suberu, M. Y., Guiawa, M., Onyegbadue, I. A. & Funsho, O. (2024). Techno-economic optimization of clean energy hybrid systems in the context of assorted battery storage technologies. *African Journal of Environmental Sciences and Renewable Energy*, 15(1), 170-169.

[10] Petri, T., Keller, M. & Parspour, N. (2022). The insulation resilience of inverter-fed low voltage traction machines: Review, challenges, and opportunities. *IEEE Access*, 10, 104023-104049. https://doi.org/10.1109/ACCESS.2022.3210348

[11] Haider, Z. M., Mehmood, K. K., Khan, S. U., Khan, M. O., Wadood, A. & Rhee, S.-B. (2021). Optimal management of a distribution feeder during contingency and overload conditions by harnessing the flexibility of smart loads. *IEEE Access*, 9, 40124-40139. https://doi.org/10.1109/ACCESS.2021.3064895

[12] Omorodion, I., Onyegbadue, I. & Izilein, F. (2025). Optimising power flow in transmission networks: A comparative study of genetic algorithm and particle swarm optimisation approaches. *Journal of Systematic, Evaluation and Diversity Engineering*, 9(5), 72-97. https://doi.org/https://doi.org/10.70382/ajsede.v9i5.017

[13] Agrawal, A. K., Nehra, H., Shakya, A., Verma, A., Chokhani, A., Sahu, S. K. & Paliwal, P. (2025). Analysis of Voltage and Load profiles of a rural distribution feeder in Madhya Pradesh. *2025 IEEE International Students' Conf. on Electrical, Electronics and Computer Science (SCEECS). Bhopal, India*: IEEE. https://doi.org/10.1109/SCEECS64059.2025.10940348

[14] Chandra Mahato, G., Roy Choudhury, T. & Nayak, B. (2024). Investigation on life span assessment of PV system components under FPPT/MPPT operation. *Electrical Engineering*, 106(5), 5339-5354. https://doi.org/10.1007/s00202-024-02287-x

[15] Mohammed, O. O., Otuoze, A., Salisu, S., Abioye, A., Usman, A. & Alao, R. (2020). The challenges and panaceas to power distribution losses in Nigeria: Nigeria power system distribution system technical losses non-technical losses. *Arid Zone Journal of Engineering, Technology and Environment*, 16(1), 120-136.

[16] Onyegbadue, I. A., Ukagu, S. N. & Okonkwo, D. O. (2024). Voltage stability assessment of Nigeria 330 kV power grid: A critical bus perspective. *UNIZIK Journal of Engineering and Applied Sciences*, 3(5), 1382-1401.

[17] ALqazan, M. S., Ammar, M. B., Kherallah, M. & Kammoun, F. (2024). Performance evaluation and real-world challenges of IoT-based smart fuel filling systems with embedded intelligence. *Fusion: Practice and Applications*, 14(2), 56-67. https://doi.org/https://doi.org/10.54216/FPA.140204

[18] Okeke, R. O., Ibokette, A. I., Ijiga, O. M., Enyejo, L. A., Ebiega, G. I. & Olumubo, O. M. (2024). The reliability assessment of power transformers. *Engineering Science & Technology Journal*, 5(4), 1149-1172. https://doi.org/10.51594/estj/v5i4.981

[19] Honrubia-Escribano, A., Villena-Ruiz, R., Artigao, E., Gomez-Lazaro, E. & Morales, A. (2021). Advanced teaching method for learning power system operation based on load flow simulations. *Computer Applications in Engineering Education*, 29(6), 1743-1756. https://doi.org/https://doi.org/10.1002/cae.22420

[20] Shakil, M., Rashid, Z., Hussain, G. & Umer, F. (2020). Power flow analysis and optimization in ring distribution network of Bahawalpur using Newton Raphson method. *Indian J. of Science and Technology*, 13(27), 2720-2732. https://doi.org/10.17485/IJST/v13i27.916

[21] Zografopoulos, I., Srivastava, A., Konstantinou, C., Zhao, J., Jahromi, A. A., Chawla, A., … Teng, F. (2025). Cyber-physical interdependence for power system operation and control. *IEEE Transactions on Smart Grid*, 16(3), 2554-2573. https://doi.org/10.1109/TSG.2025.3538012

[22] Fose, N., Singh, A. R., Krishnamurthy, S., Ratshitanga, M. & Moodley, P. (2024). Empowering distribution system operators: A review of distributed energy resource forecasting techniques. *Heliyon*, 10(15), 1-27. https://doi.org/https://doi.org/10.1016/j.heliyon.2024.e34800

[23] Tarmanini, C., Sarma, N., Gezegin, C., & Ozgonenel, O. (2023). Short term load forecasting based on ARIMA and ANN approaches. *Energy Reports*, 9(3), 550-557. https://doi.org/https://doi.org/10.1016/j.egyr.2023.01.060

[24] Wang, C., Wang, Y., Ding, Z., Zheng, T., Hu, J. & Zhang, K. (2022). A transformer-based method of multienergy load forecasting in integrated energy system. *IEEE Transactions on Smart Grid*, 13(4), 2703-2714. https://doi.org/https://doi.org/10.1109/TSG.2022.3166600

[25] Kirange, Y. K., Patil, V., Patil, R. S., Patil, R. J. & Pandit, P. D. (2024). Optimizing power distribution: Smart load sharing mechanism enhanced by arduino uno integration. *International Journal of Ingenious Research, Invention and Development*, 10(3), 161-174. https://doi.org/10.5281/zenodo.11120707

[26] Vujanovic, M., Wang, Q., Mohsen, M., Duic, N. & Yan, J. (2021). Recent progress in sustainable energy-efficient technologies and environmental impacts on energy systems. *Applied Energy*, 283, 116280. https://doi.org/https://doi.org/10.1016/j.apenergy.2020.116280

Citing this Article

Idehen, J., Okonkwo, D., Atu, M., & Onyegbadue, I. (2026). Enhancing energy distribution efficiency with dynamic transformer rotation in 11kV networks. *Lafia Journal of Scientific & Industrial Research*, *4*(1), 30–43. https://doi.org/10.62050/ljsir2026.v4n1.683