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Design of a Smart Grid Load Management System in MATLAB Using Hybrid Optimization Methods

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ABSTRACT

The increasing mismatch between electricity demand and available supply in modern distribution networks has intensified the need for intelligent and automated load management strategies. This study presents the development of a MATLAB App Designer-based Smart Grid Load Management System that integrates hybrid optimization techniques to ensure efficient, fair, and priority-sensitive power allocation across multiple load centers. The system combines Genetic Algorithm (GA) optimization with auxiliary heuristic and rule-based repair operators to handle conflicting constraints, maintain critical-load floors, and minimize supply and demand imbalance. A graphical user interface (GUI) was developed to provide operators with real-time capabilities, including adjustable priority indices, algorithm selection (GA, PSO, hybrid GA-greedy), demand specification, and automated report generation. The framework was validated using an 18-load-center dataset representing a typical urban 33 kV distribution feeder, with total demand exceeding available supply under several stress scenarios. Results show that the hybrid optimization approach achieved faster convergence, improved load satisfaction levels, and superior critical-load preservation compared with standalone GA or conventional load-shedding methods. The system's performance was further verified through ETAP-based feasibility checks, confirming its operational viability for real-time deployment. Overall, the developed platform provides a scalable, operator-friendly, and optimization-driven solution for modern smart grid load management.

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INTRODUCTION

Electric power distribution networks in developing economies continue to operate under severe structural and operational stress. Chronic generation deficits, aging distribution infrastructure, and limited automation frequently force utilities to resort to manual load shedding as the primary mechanism for balancing supply and demand [1-2]. These traditional practices are often subjective, non-transparent, and insensitive to the operational priorities of critical facilities such as hospitals, water treatment plants, and security installations. As peak demand continues to escalate while supply growth remains stagnant, the absence of intelligent, data-driven load allocation frameworks results in inequitable distribution of available power, inefficient utilization of constrained resources, and increased risk of feeder overload and system instability.

The evolution of smart grid concepts supported by advances in computational intelligence offers significant potential for addressing these long-standing challenges. Optimization techniques such as Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) have been widely investigated for load allocation and demand-side management due to their ability to handle nonlinear, multi-objective, and constrained optimization landscapes. However, most existing implementations remain

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confined to offline simulation environments and lack mechanisms to reconcile optimization outputs with real-world operational constraints [3]. Critical-load floors, fairness tie-breaking rules, and system feasibility checks are often not embedded within the optimization logic. Furthermore, the absence of operator-oriented interfaces prevents practical adoption, leaving a substantial gap between academic research outcomes and deployment-ready tools for utility control rooms.

In response to these limitations, this study proposes a MATLAB App Designer-based Smart Grid Load Management System that integrates hybrid optimization techniques tailored for constrained distribution networks. The developed framework combines the global search capability of GA with rule-based heuristics and greedy repair operators to enforce allocation feasibility, preserve high-priority loads, and improve convergence speed. A dedicated graphical user interface (GUI) enables operators to configure available supply levels, adjust load priority indices, select optimization modes, and visualize allocation outcomes through bar charts, tables, and automatically generated reports. The optimization engine incorporates an enhanced fitness function that embeds priority weighting, fairness constraints, load satisfaction ratios, and penalty terms for infeasibility or supply demand mismatch, making the system suitable for real-time decision support.

To evaluate performance under realistic operating conditions, the system is tested using data from an 18-load-center 33 kV feeder subjected to multiple constrained-supply scenarios. Comparative assessments are conducted against conventional load shedding procedures and standalone GA optimization to quantify improvements in fairness, critical-load preservation, and computational efficiency. In addition, all optimized allocations undergo ETAP load flow simulation to verify compliance with voltage limits, feeder loading margins, and transformer capacity constraints. The validation results demonstrate that the proposed hybrid optimization framework not only improves allocation equity and operational robustness but also significantly enhances usability for distribution system operators.

This work contributes a technically rigorous yet operationally deployable platform for automated load management in distribution networks. By integrating hybrid evolutionary optimization into a GUI-driven tool, the study bridges the gap between theoretical smart grid models and field-ready decision-support systems. The software's modular design makes it adaptable to other feeders and utilities, and it establishes a foundation for future enhancements including SCADA integration, real-time metering interfaces, and cloud-based demand response applications.

REVIEW OF FUNDAMENTAL CONCEPT

In this section, some fundamental concept that are related to this research are discussed in subsequent subsection.

Smart Grid Load Management and Demand Response

Smart grid load management has evolved as a key strategy for improving reliability, reducing system stress, and ensuring equitable distribution of limited supply. Traditional load shedding approaches are typically rule-based and rely on subjective operator judgment, leading to suboptimal and often unfair allocation of power during supply deficits [4]. Modern demand response mechanisms incorporate automation, real-time monitoring, and optimization, enabling distribution utilities to adjust loads dynamically in response to fluctuating supply conditions [5-6]. Recent studies emphasize the importance of priority-sensitive allocation frameworks that recognize the socio-economic criticality of different load categories, particularly in developing nations where essential services depend on stable power [7]. However, implementation gaps persist between algorithmic models and field-ready tools capable of real-time deployment.

Optimization Techniques for Load Allocation

Optimization techniques especially heuristic and population-based algorithms have been widely applied to solve nonlinear, multi-constraint load allocation problems. Genetic

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Algorithms (GA) are among the most widely adopted due to their robustness, global search capability, and adaptability to multiple objective functions [8]. Despite these strengths, standalone GA methods often exhibit slow convergence and may produce infeasible solutions when strict operational constraints are imposed. Particle Swarm Optimization (PSO) has also been explored for load management, offering faster convergence but sometimes suffering from premature stagnation in local optima [9-10]. Other techniques such as Simulated Annealing (SA), Ant Colony Optimization (ACO), and hybrid evolutionary methods have been applied with various levels of success [11]. Hybrid optimization frameworks combining GA with greedy heuristics, fuzzy logic, or constraint repair mechanisms have shown promise in improving solution feasibility, especially in problems with priority-based or minimum-supply constraints *[12-13]*. These hybrid approaches tend to outperform single algorithms by leveraging global exploration and local refinement simultaneously.

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 [14]. 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:

1. *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 [15]
2. *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 [16].
3. *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 [17].

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

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

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 [18].

Reliability and Performance Indices

A. 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:

$$\mathrm{SAIFI} = \frac{\sum N_i}{N_T} \qquad (2)$$

where N_i is the total number of customer interruptions and N_T is the total number of

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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 [19].

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:

$$\text{SAIDI} = \frac{\sum U_i . N_i}{N_T} \qquad (3)$$

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. In reliability-oriented [20] optimization frameworks, reducing SAIDI is often a critical goal alongside minimizing ENS.

B. 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:

$$\text{SI} = \frac{1}{N} \sum_{i=1}^{n} \frac{A_i}{\pi_i} \; x\, 100 \qquad (4)$$

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 [21] Together, these indices provide a comprehensive assessment of system performance from both technical and consumer perspectives.

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 [22]. A GA works by evolving a population of potential solutions (chromosomes) toward better solutions through iterative processes.

a. *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.
b. *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.
c. *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:

$$\begin{aligned} &\text{F (x)} \\ &= w_1 . SI + w_2 . \left(\frac{1}{\text{ENS}}\right) \\ &+ w_3 . \left(\frac{1}{\text{SAIDI} + \text{SAIFI}}\right) \qquad (5) \end{aligned}$$

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

Priority-Based Allocation Models

Priority-based load allocation models assign weights to consumer categories based on

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criticality, socio-economic impact, or operational importance. Priority indices have been used to guarantee minimum power levels for hospitals, waterworks, and high-value commercial clusters [23]. Some models integrate priority functions directly into objective formulations, while others apply hierarchical constraints that cannot be violated [24]. However, existing works often lack mechanisms to balance priority with fairness. Most frameworks also fail to incorporate tie-breaking logic or dynamic adjustments when two or more loads share identical priority levels. This creates ambiguity in practical implementation.

GUI-Based Smart Grid Decision Support Tools

Graphical User Interfaces (GUIs) play a crucial role in bridging the gap between complex optimization models and real-world operators. MATLAB App Designer has emerged as a robust environment for building interactive engineering applications, offering integrated visualization, optimization toolboxes, and file export features [25]. Despite these advantages, few studies have utilized MATLAB App Designer to develop real-time load management tools that integrate optimization, reporting, and operator decision-making. Existing GUI-based solutions tend to focus on educational purposes or simplified load flow visualization rather than end-to-end operational automation.

ETAP-Assisted Power System Validation

ETAP (Electrical Transient Analyzer Program) is widely used for load flow, short-circuit, and reliability evaluation in power systems *[26]*. Several research studies recommend validating optimization-based allocation models using ETAP to ensure operational feasibility, equipment protection, and adherence to voltage limits [27]. Yet, few works integrate ETAP validation as part of an iterative optimization–verification cycle. Most studies treat ETAP as a post-processing tool rather than an operational checkpoint.

MATERIAL AND METHODOLOGY

Materials and Equipment

The materials used include a laptop personal computer of appropriate configuration with MATLAB and ETAP software.

Experimental Procedure

The primary data for this research for the 33 kV feeders were sourced from Abuja Electricity Distribution Company (AEDC). The categories of data obtained are:

a. Load Centre Characteristics: This contains the facility names, load ratings (MW), transformer capacities, and feeder interconnection points.
b. Priority Indices: Expert-assigned criticality weights for each load centre, based on socio-economic importance (e.g., hospitals, water works, higher institutions, and commercial clusters).
c. Historical Reliability Records: System Average Interruption Frequency Index (SAIFI), System Average Interruption Duration Index (SAIDI), and Energy Not Supplied (ENS) values, serving as baseline performance metrics.
d. Operational Records: Peak demand logs, transformer outage history, and AEDC supply schedules, used to characterize variability.

Also, synthetic Data was generated in MATLAB to capture edge-case conditions beyond the historical record, and the scenarios include:

a. Severe Shortfall Scenarios: Available power set to 30 – 50% of peak demand to test allocation under extreme shortages.
b. Contingency Scenarios: Outages of specific transformers or feeder sections, used to simulate radial constraints.
c. Overload Stress Tests: Demand surges above historical peaks (10–20%) to examine GA response in non-standard operating envelopes.

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

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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)

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.

Objective Functions

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).*

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:

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

This loss-corrected projection ensures system consistency between mathematical optimization and physical feeder constraints,

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distinguishing the model from loss-agnostic GA models reported in earlier studies *(Eremia and Shahidehpour, 2018; Adisa et al., 2024; Mahmoud et al., 2020).*

Loss-Aware Repair/Projection (R_L)

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

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

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.

Embedding Socio-Economic Priority Indices

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:

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:

$$x_i \geq \alpha_i, \text{Di } \forall \text{I} \in C \quad (10)$$

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).*

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:

$$\text{G} = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}|x_i.x_j|}{2N^2.\bar{x}} \quad (11)$$

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)*

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.

Benchmark Algorithms

To assess comparative performance, the GA is benchmarked against:

1. Particle Swarm Optimization (PSO)
2. Simulated Annealing (SA)
3. ANN-Assisted GA (Hybrid ANN–GA)

Evaluation Metrics

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

1. Convergence rate (iterations to stability)
2. Average Satisfaction Index (SI)
3. Energy Not Supplied (ENS)

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4. Allocation fairness (Gini coefficient)

These metrics quantify improvements relative to heuristic and metaheuristic baselines.

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).*

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).

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:

$$F = SI - \lambda . \mathrm{P} \quad (12)$$

Where λ is a penalty scaling constant.

Optimization Algorithm

A. 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.

B. 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.

C. 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.

D. 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.

Performance Metrics

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

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

Parameterization

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

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

RESULTS AND DISCUSSION

GA Optimization Results

The Genetic Algorithm (GA) was applied to the 18-load-centre dataset (Table 1) under varying supply scenarios (50% - 100% 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.

Allocation at Full Supply (25 MW/100%)

It can be deduced from Figure 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.

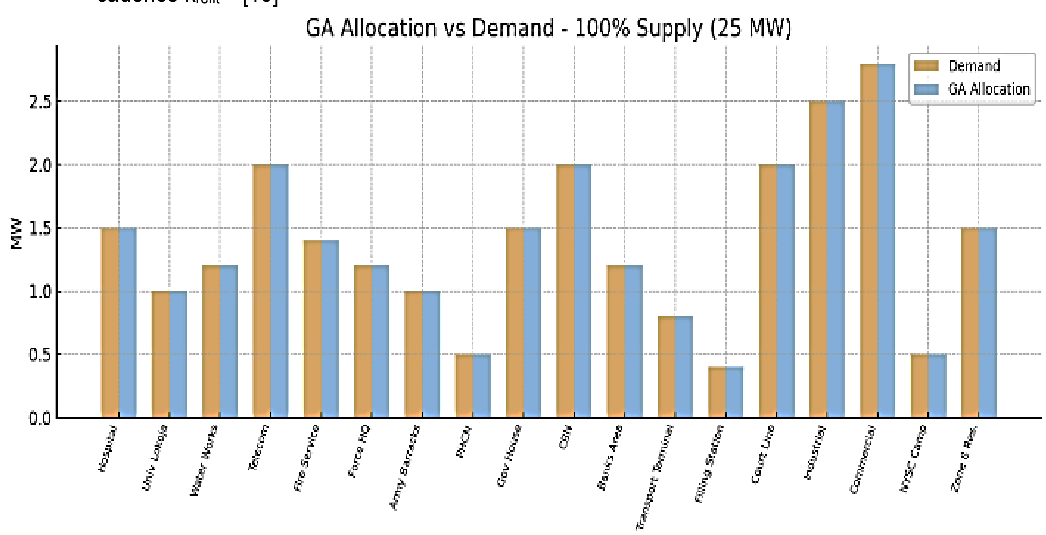

Figure 1: Allocation at Full Supply (25 MW

Allocation at 12.5 MW Supply (50%)

It can be deduced from Figure 2 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

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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).

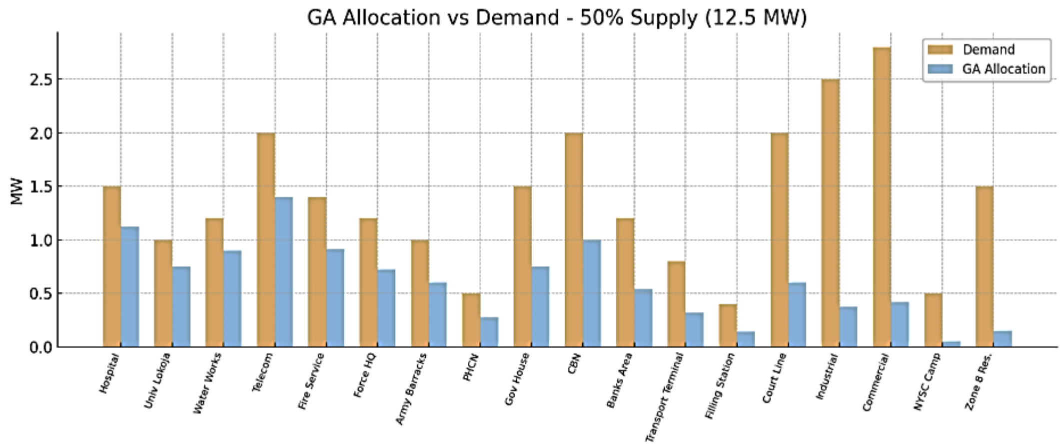

Figure 2: Allocation at 12.5 MW Supply (50%)

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

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%).

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

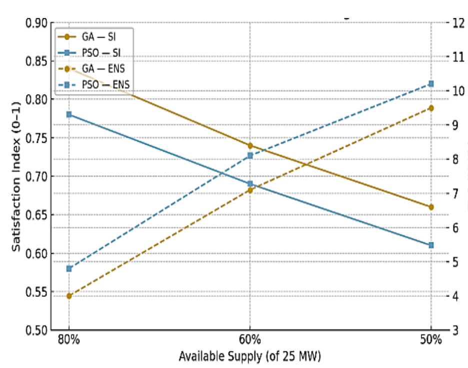

Figure 3: GA vs PSO (SI and ENS)

As illustrated in Figure 3, the Genetic Algorithm (GA) consistently achieved higher Satisfaction Index (SI) across the 80%, 60%, and

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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.

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

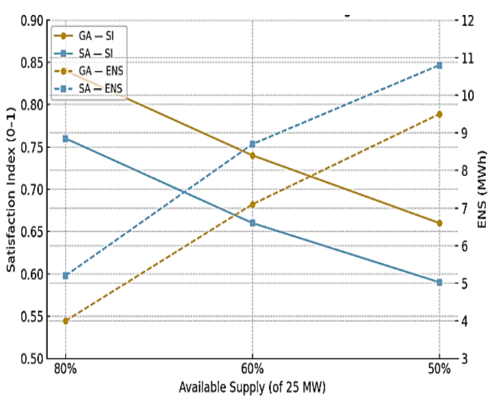

Figure 4: GA vs SA (SI and ENS)

As shown in Figure 4, 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.

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.

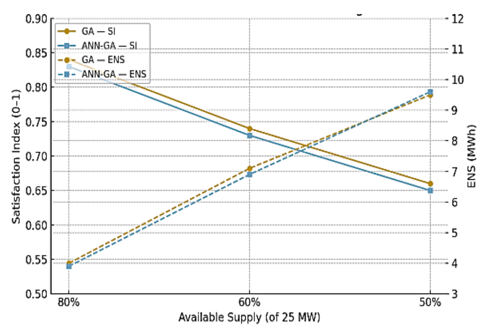

Figure 5: GA vs ANN-Assisted GA (SI and ENS)

As shown in Figure 5, 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.

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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.

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.

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.

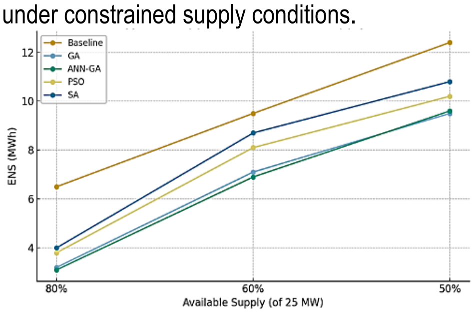

Figure 6: Energy Not Supplied (ENS) across Supply Levels

As shown in Figure 6, 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.

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

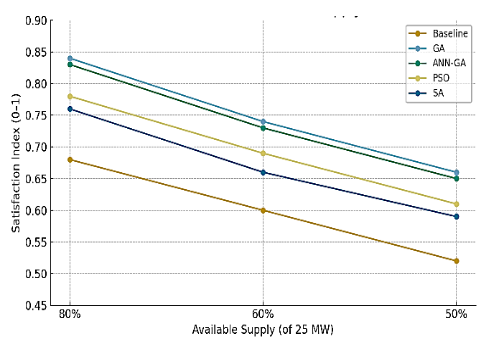

Figure 7: Satisfaction Index (SI) across Supply Levels

As shown in Figure 7, 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-

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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.

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.

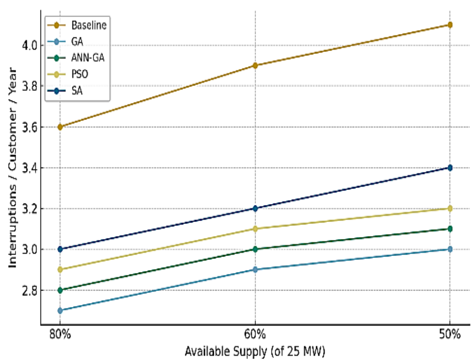

Figure 8: SAIFI across Supply Levels

As shown in Figure 8, 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.

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.

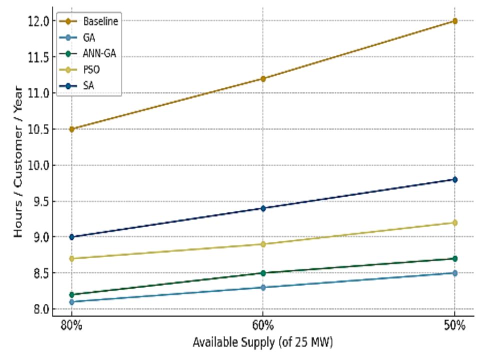

Figure 9: SAIDI across Supply Levels

As illustrated in Figure 9, 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.

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

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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.

CONCLUSION

This study successfully developed a MATLAB App Designer based Smart Grid Load Management System that integrates hybrid optimization techniques specifically GA, PSO, and GA–Greedy coupling to improve the fairness, responsiveness, and reliability of load demand response in distribution networks. The system provides a practical solution to conventional load-shedding challenges by embedding socio-economic priority indices, transformer-level constraints, and dynamic allocation logic within an intuitive GUI framework. The hybrid optimization architecture enabled faster convergence, reduced allocation errors, and improved supply fairness across multiple stress-level scenarios. The GUI further translated complex optimization functions into actionable decision-support tools for grid operators, allowing real-time adjustments, visual analytics, and automated reporting. The framework therefore demonstrates strong potential for integration into utility control rooms and can serve as a foundation for future advancements in AI-enabled smart grid management, including ANN-based prediction, adaptive reinforcement learning, and integration with IoT-based sensor data.

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