Major Project Report on

Optimization of Resource Allocation for Post-Earthquake Response Using Synthetic Data

in partial fulfillment for the award of the degree of

Bachelor of Computer Engineering

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DECLARATION

We hereby declare that this project entitled **Optimization of Resource Allocation for Post-Earthquake Response Using Synthetic Data** is based on our original research work. Related works on the topic by other researchers have been duly acknowledged. We owe all the liabilities relating to the accuracy and authenticity of the data and any other information included hereunder.

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RECOMMENDATION

This is to certify that this project entitled **Optimization of Resource Allocation for Post-Earthquake Response Using Synthetic Data** is prepared and submitted by **Ayushma Thapa, Bhuma Devi Acharya, Newton Shahi Thakuri and Urusha Shrestha**, in partial fulfillment of the requirements of the degree of Bachelor of Computer Engineering awarded by Pokhara University, has been completed under my supervision. I recommend the same for acceptance by Pokhara University.

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CERTIFICATE

This project entitled **Optimization of Resource Allocation for Post-Earthquake Response Using Synthetic Data** prepared and submitted by **Ayushma Thapa, Bhuma Devi Acharya, Newton Shahi Thakuri and Urusha Shrestha** has been examined by us and is accepted for the award of the degree of Bachelor of Computer Engineering by Pokhara University.

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In conclusion, we would like to say that this report represents a major turning point in our cooperative endeavor and we are grateful to everyone who has participated in the process.

ABSTRACT

This study presents a data-driven decision support system that optimize disaster response in Nepal in terms of response efficiency, optimization performance, and budget utilization. To achieve this, we developed an algorithm and compare it with baseline and metaheuristic algorithms; Grid Search, Random Search, Genetic Algorithm, Simulated Annealing, and Bayesian Optimization. Through a discrete-event simulation and epicenter-based prioritization, the system continuously estimates patient waiting time, patients treated, and overall resilience. Optimization was done by evaluating algorithms with 800 iterations and each iteration consisted of five epochs and each epoch followed monte-carlo simulation method to randomize the event. Proposed algorithm is a hybrid approach of random search and genetic algorithm. Comparative evaluations demonstrate that the proposed algorithm performs comparatively lower for minimum wait time or maximum patients served. In optimization of minimum wait time, proposed algorithm ranked 4th in terms of proficiency obtaining 84.2% with highest being 84.7% (obtained by genetic and random). In optimization of maximum patients served, proposed algorithm ranked 3rd tied with genetic and random search obtaining 104.4% proficiency with the highest being 111.30% (obtained by bayesian optimization). This showed traditional algorithms were superior during single metric exploration. Proposed algorithm excels with more metrics i.e. composite which combines both metrics (minimum wait time and maximum patients served). Multi-objective optimization reflects better real-world disaster response scenarios where multiple objectives must be balanced simultaneously. In terms of proficiency, proposed algorithm was tied for 1st rank with other 3 algorithm (genetic, bayesian and random) and exceeded other 2 algorithms(grid and simulated annealing). In terms of speed, proposed algorithm ranked 2nd with 44 iteration right behind genetic algorithm because it found the optimal solution (among the applied algorithms) in 24 iteration. In terms of budget utilization, proposed algorithm performed the best (excluding those algorithms from analysis which didn't find optimal improvement) in both worst case and best case scenarios. This study proposed a solution that stable and highly adaptable in realistic situations where multi-objective optimization is core focus. The proposed algorithm has better performance in real life like environment of complex settings helping reduce casulatise, improve efficiency and supports informed decision-making in the midst of large scale emergencies.

Keywords: *Earthquake response, optimization, resource allocation, metaheuristics, simulation, disaster logistics, Nepal.*

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LIST OF EQUATIONS

LIST OF ABBREVIATIONS

AI	Artificial Intelligence
API	Application Programming Interface
BIPAD	Building Information Platform Against Disaster
BO	Bayesian Optimization
CBS	Central Bureau of Statistics
DES	Discrete-Event Simulation
DIMS	Disaster Information Management System
dLOGIS	Distributed Logistics (Mobile Relief Coordination System)
DSS	Decision Support System
ED	Emergency Department
EI	Expected Improvement
EMS	Emergency Medical Services
GA	Genetic Algorithm
GIS	Geographic Information System
GP	Gaussian Process
JSON	JavaScript Object Notation
MBBS	Bachelor of Medicine, Bachelor of Surgery
MD	Doctor of Medicine
mDSM	Modified Disaster Management
MEXCLP	Maximum Expected Coverage Location Problem
NGO	Non-Governmental Organization
NPHC	National Population and Housing Census
OSM	OpenStreetMap
PhD	Doctor of Philosophy
Q-MALP-M2	Queuing Maximal Availability Location Problem (Model 2)
SA	Simulated Annealing
USGS	United States Geological Survey
WHO	World Health Organization

Chapter 1
INTRODUCTION

1.1 Background

Earthquakes are among the most unpredictable and devastating natural disasters, capable of causing massive human casualties, structural damages, and long-term economic losses. To minimize such loses humans have tried precautionary measures as well as recovery methods after the immediate aftermath of an earthquake. It demands rapid and coordinated responses including search and rescue operations, emergency medical services, and the distribution of essential supplies. However, these efforts are often hindered by infrastructural damage, chaotic communication, and limited resources.

In the context of Nepal, the country has experienced numerous devastating earthquakes, including the 2015 earthquake, which resulted in over 9,000 deaths, injured about 21,000 and 2,000,000 people were displaced from their homes [1]. Nepal's geographical complexity, limited infrastructure, and dense urban settlements make effective earthquake response particularly difficult. Furthermore, response efforts are often slowed by poor logistics planning, insufficient preparedness, and lack of real-time coordination. These issues highlight the urgent need for population distribution, and resource availability [1].

Having proper precautionary measures is always good but never fool-proof. So, it is very important to have a good system to quickly respond such that losses of human lives and any other casualties can be reduced as much as possible. With proper distribution of logistics and resources, this can be done. To cope up with topographical challenges, we can implement routing with weights.

Recent advancements in computational modeling and data-driven decision support systems have opened new possibilities for improving disaster response planning [2, 3]. By integrating simulation techniques with optimization algorithms, it is now possible to evaluate thousands of emergency response strategies under realistic constraints such as limited budgets, infrastructure damage, and fluctuating patient demand. Simulation-based frameworks enable authorities to anticipate system bottlenecks, predict patient congestion in hospitals, and assess the effectiveness of alternative resource allocation policies before real disasters occur.

Optimization methods, particularly metaheuristic algorithms such as Genetic Algorithms, Simulated Annealing, and Bayesian Optimization, have proven effective in solving complex, high-dimensional problems [4, 5] where traditional analytical approaches become infeasible. Earthquake response scenarios involve nonlinear interactions between transportation delays, medical capacity, and evolving casualty patterns, making them well suited for such adaptive search techniques. Through iterative evaluation and refinement, these methods can identify near-optimal configurations of ambulances, hospital beds, and medical personnel that significantly improve response efficiency.

Therefore, developing a simulation-driven optimization framework tailored to Nepal's geographical and healthcare constraints is both timely and essential. By combining geospatial routing, patient flow modeling, and budget-constrained resource allocation, a structured decision support system can provide actionable insights for emergency planners. Such simulation–optimization based frameworks have demonstrated strong potential for improving healthcare and emergency resource allocation efficiency [6].

1.2 Statement of Problem

In many parts of the world, earthquake response remains uncoordinated, slow, and resource constrained. Critical challenges include the lack of real-time data, limited infrastructure and inadequate resource distribution. Emergency services often face difficulties in identifying the most affected areas, allocating medical aid, and reaching survivors due to damaged roads or blocked access points. Additionally, overlapping responsibilities among agencies, poor communication systems, and manual decision-making further delay effective action. Without a structured optimization framework, response efforts can be chaotic, resulting in increased fatalities, prolonged suffering, and inefficient use of already scarce resources.Developing a decision support system that suggests optimal response strategies based on real time or simulated earthquake response scenario is our research question as it is important for improving earthquake response and resource allocation efficiency.

These problems arise due to no proper distribution of resources. All of these must be united in one system to effectively model the problem and respond quickly.

1.3 Objective

The primary objective of this research is to design a simulation-optimization based decision support system (DSS) that can provide optimized earthquake response strategies i.e. near-optimal allocation for resources(medical personnel, hospital beds and ambulances) with synthetic data to minimize global response delays under fixed budget and logistical constraints. The system aims to enhance the effectiveness, coordination, and resource allocation of emergency operations during earthquake events.

- To optimize the post earthquake response using synthetic data

The model determine the best allocation of emergency resources (doctors, nurses, supplies, rescue teams) based on severity, location, and urgency along with the path it must take.

1.4 Scope

The scope of this report includes the design, development, and evaluation of a system that supports timely, efficient, and data-driven response strategies during earthquake emergencies. This project focuses on improving decision-making, resource allocation, and operational coordination in earthquake-prone regions. The scope includes:

- **Data Analysis**: Collection and analysis of real-time earthquake data, infrastructure data, population density, and available emergency resources to identify trends and inform decision-making.
- **Optimization Modeling**: Development of algorithms to optimize resource allocation and determine the most effective deployment strategies.
- **Decision Support System (DSS)**: Creation of a user-friendly system that can simulate earthquake scenarios and suggest optimal response actions for emergency responders and authorities.
- **Integration with Emergency Protocols**: The system can be integrated with existing emergency preparedness and disaster response frameworks to enhance coordination and speed.

1.5 Applications of Earthquake Response Optimization

The Earthquake Response Optimization system has wide-ranging applications in disaster management, emergency planning, and public safety. It supports timely and efficient decision-making, helping reduce human casualties, optimize resource usage, and improve coordination during earthquake events. The application areas are as follows:

- Disaster Risk Management Authorities: The system can assist government bodies and emergency response units in planning and executing rapid rescue, evacuation, and relief efforts with optimized deployment of resources.
- Policy Planning and Infrastructure Agencies: By identifying high-risk zones and simulating disaster scenarios, planners can design more resilient cities, allocate shelters efficiently, and improve overall infrastructure preparedness.

- Non-Governmental Organizations (NGOs): Relief organizations can use the system to better plan their logistics and coordinate aid delivery, ensuring timely support to the most affected populations.
- Academic and Research Institutions: Researchers can use the system as a testbed for further studies in disaster response, optimization modeling, and predictive analytics for natural disasters.

Chapter 2
LITERATURE REVIEW

2.1 Related Works

In recent years, the need for intelligent and responsive disaster management systems has become increasingly vital, especially after unprepared destructive earthquakes. Earthquake response optimization involves making rapid and accurate decisions for resource allocation, route planning, and task prioritization under extreme uncertainty. Various computational techniques have been proposed by researchers that can be adapted to earthquake logistic. These methods help improve efficiency and coordination in emergency situations where time, safety, and adaptability are critical.

Robust optimization models often integrate stochastic or Monte Carlo simulations to tackle uncertainty in earthquake response logistics [7]. This ensures that while the system prepares for worst-case possibilities, its responses stay adaptive to the latest field conditions, closing the gap between pre-planned robustness and real-time responsiveness.

The dLOGIS system, developed for Android platforms, offers mobile tools for relief coordination, survivor tracking, and basic routing using algorithms like Dijkstra's [8]. It also supports offline operation via local Wi-Fi. While innovative, its static routing engine and limited real-time analytics can restrict scalability in large urban quakes. Our proposed design draws inspiration from dLOGIS's field-ready features but upgrades the backend to GraphHopper for smarter, faster route updates and integrates Kafka for event-driven resource allocation. This hybrid model combines dLOGIS's practicality in low-connectivity areas with modern real-time intelligence for broader operations.

Simulation models have proven effective at capturing interdependencies in infrastructure, resource delivery, and medical provisioning after a quake [9]. They often rely on simulation-optimization frameworks to test different strategies quickly. However, equity and resilience ensuring fair treatment of all affected populations are sometimes underemphasized. Our system addresses this by blending simulation outputs with live data flows: real-time updates on resource usage, road conditions, and survivor needs continuously refine the underlying simulations. This loop helps the system align theoretical resilience goals with ground realities, making response more equitable and robust than static simulations alone.

[10] outlined best practices for developing disaster response models in healthcare set-

tings. Their position paper emphasized that models must align with real-world complexity, account for uncertainty, and remain understandable to decision makers. Many current tools fall short by being either too abstract or too complicated for rapid use during crises. Our system directly aligns with these recommendations by combining robust back-end algorithms with a clear user interface for emergency operators.

[11] introduced a two-stage probabilistic model for siting emergency medical service (EMS) facilities under uncertain demand and congestion. Unlike older models, they accounted for spatial demand correlations, making their approach more realistic for urban disaster zones. However, these models often rely on static demand predictions and can't respond quickly to real-time blockages or surges. Our system uses the same probabilistic placement logic but enriches it with GraphHopper's live traffic routing and Kafka's streaming data feeds. This makes EMS facility use and vehicle dispatch dynamic, ensuring that capacity and routes adjust on the fly as the situation unfolds.

[12] presented an operational framework for allocating scarce medical resources during disasters. They outlined principles for triage, ethical care, and six resource strategies from conservation to reallocation. While these guidelines are vital, they are often paper-based or depend on manual decision-making, which can be too slow for large-scale earthquakes. Our system digitizes these strategies into actionable rules within constraint solver, integrating them with live hospital capacity and resource tracking. This ensures that care level transitions from conventional to crisis happen smoothly, backed by real-time data and clear protocols, enhancing both ethical standards and operational efficiency.

[13] provided a comprehensive review of Bayesian Optimization (BO) as an efficient strategy for optimizing expensive, black-box objective functions where direct evaluation is computationally costly. The study highlights BO's ability to balance exploration and exploitation using surrogate models, making it particularly suitable for problems where each evaluation involves complex simulations. This is directly aligned with the present research, in which hospital resource allocation decisions (beds, ambulances, and physicians) are evaluated using simulation-based models under fixed budget constraints. The principles discussed support the use of Bayesian Optimization in this study as a competitive alternative to traditional methods such as grid search, random search, genetic algorithms, and simulated annealing.

[**?**] compares Genetic Algorithms, Grid Search, and Bayesian Optimization to solve expensive optimization problems, demonstrating that metaheuristic approaches can achieve competitive performance under limited evaluation budgets. Their findings are relevant to the present study, where hospital resource allocation decisions are evaluated through simulation under fixed budget constraints. The comparative insights from this work support the inclusion of multiple optimization strategies, including evolutionary and probabilistic methods, for efficient resource optimization in complex, simulation-based environments.

[14] addresses emergency department (ED) resource allocation by developing a mathematical optimization model that incorporates queueing theory and mixed-integer programming to minimize total system cost, including patient waiting times, rejection of critical patients, and resource costs. The authors classify patients into priority queues and construct multi-server queueing models to represent urgent and routine care, then apply particle swarm optimization to determine optimal numbers of servers, service rates, and beds that reduce waiting times and queue lengths significantly compared to benchmark models. This work demonstrates how combining simulation, mathematical modeling, and metaheuristic optimization can lead to more efficient medical resource allocation, underscoring the value of search and optimization algorithms in healthcare systems a principle directly relevant to the present research on optimizing hospital resources under constrained budgets.

[15] investigated the problem of ambulance location and relocation under explicit budget constraints, focusing on maximizing emergency medical services (EMS) performance. The study revises established coverage models, including time-dependent MEXCLP, mDSM, and Q-MALP-M2, to incorporate ambulance types, multi-period relocation decisions, and the economic costs associated with station openings and fleet acquisition. These models are evaluated using discrete-event simulation across key performance indicators such as coverage, waiting time, and response time. The authors also explore an ambulance sharing policy where single units serve multiple patients when feasible. Results from real regional data suggest that hybrid strategies that balance station investments and fleet expansion perform better under tight budget conditions, and that ambulance sharing can significantly enhance service metrics under increasing demand. This work reinforces the importance of integrated optimization and simulation approaches for efficient allocation of emergency resources under financial constraints, making it directly applicable to research on optimizing hospital and EMS resource distribution under a fixed budget.

BIPAD(Building Information Platform Against Disaster) is Nepal's DIMS(Disaster Information Management System) that contributes in data gathering, early preparedness, evidence based planning, decision making and policy making. BIPAD does not provide decision support for dynamic rescue routing or automatic resource allocation during active disasters. Our report's earthquake simulation/live disaster impact data will provide optimal route and resource allocation techniques that operators can use in the field [16].

2.2 Research Gap

Despite significant advancements in disaster management systems, several critical gaps remain that this research aims to address:

- **Digitization of Manual Protocols:** Highly regarded operational frameworks offer vital principles for resource strategies but remain largely paper-based or reliant on manual decision-making. There is a lack of systems that digitize these ethical and operational rules into actionable, real-time constraint solvers capable of assisting commanders during high-stress events.
- **Deterministic vs. Metaheuristic Approaches:** Many current healthcare resource allocation tools utilize deterministic mathematical programming. However, earthquake response involves high-dimensional, nonlinear interactions between resources that these models struggle to capture. There is a need for more exploration into how metaheuristics, such as Genetic Algorithms (GA) or Bayesian Optimization (BO), can find feasible solutions within the strict "black-box" constraints of complex disaster simulations.
- **Gap in Nepal's Decision Support:** Local platforms like BIPAD serve as excellent repositories for historical data and early preparedness but do not provide active, dynamic decision support for automatic resource allocation during the critical "Golden Hours" following an active disaster [16].

Chapter 3
METHODOLOGY

3.1 Data Collection

This study uses a synthetic and secondary-data driven approach to parameterize a Nepal-wide earthquake response simulation at the district level. The data collection process focuses on (i) population exposure by district, (ii) baseline health-system resource capacity, (iii) geospatial coordinates for representative district hospitals, and (iv) an earthquake scenario grounded in Nepal's historical seismicity. Conducting a primary survey across all districts of Nepal would require significant financial resources, a large-scale field team, and an extensive timeline that exceeds the scope of this project so it isn't preferred. Primary data collection during or immediately following an actual disaster is often unethical as it may interfere with emergency operations.

District Population Data (Exposure)

District-level population totals were obtained from the National Population and Housing Census 2021 published by Nepal's Central Bureau of Statistics (CBS). The census results portal and associated census reports were used as the authoritative source for population by administrative unit, ensuring consistency across all districts included in the model [17, 18]. These district population figures represent the demand-side exposure that drives resource needs in the simulation (e.g., scaling of beds, physicians, and ambulances).

Health Resource Capacity (Beds, Doctors, Ambulances)

Because comprehensive, district-wise, real-time inventories of hospital resources are not uniformly available in a consistent open dataset, baseline health system capacity for each district is estimated using internationally reported density indicators and explicit modeling assumptions.

Hospital bed counts were updated using the density measure *hospital beds (per 1,000 people)*. For Nepal, the World Bank indicator reports approximately $\approx$ 0.4 beds per 1,000 population (for the latest available year around 2021), which is sourced from WHO related health system statistics [19, 20]. Therefore, beds for district d are computed as:

Hospital Bed Estimation

$$\text{Beds}_d = \left\lceil \alpha \times \frac{\text{Population}_d}{1000} \right\rceil \tag{3.1}$$

where $\alpha = 0.4$ beds per 1000 population.

WHO's indicator guidance emphasizes that there is no single global normative threshold for bed density; hence, the study uses the best available reported density value for Nepal to anchor capacity estimates [20]. A peer-reviewed national health profile also cites WHO Global Health Observatory bed density reporting when discussing Nepal's inpatient capacity constraints, supporting the suitability of this indicator as a baseline reference [21].

The number of doctors per district is derived using a physician density baseline expressed as physicians per 1,000 population, consistent with the World Bank's indicator definition for physicians (generalists and specialists) [22]. In this study, a simplifying baseline of:

Doctor Estimation

$$\text{Doctors}_d = \left\lceil \beta \times \frac{\text{Population}_d}{1000} \right\rceil \tag{3.2}$$

where $\beta = 1.0$ doctor per 1000 population.

This equation is adopted to ensure uniform scaling of clinical staff with district population. This assumption is used for simulation standardization and scenario comparability (rather than claiming it reflects the true district staffing distribution). Evidence from WHO referenced health workforce reporting highlights that Nepal's physician density is constrained relative to typical benchmarks, reinforcing the importance of explicitly modeling staff scarcity in the response problem [23].

Ambulance Estimation

Ambulance availability is modeled as a coverage assumption to represent pre-disaster transport capacity:

$$\text{Ambulances}_d = \left\lceil \gamma \times \frac{\text{Population}_d}{1000} \right\rceil \tag{3.3}$$

where $\gamma = 0.05$ ambulances per 1000 population.

This ratio is treated as a simulation parameter (planning assumption) used to study sensitivity of outcomes to transport constraints. It is maintained consistently across all districts to avoid introducing unverified district-wise variation in the absence of a standardized national ambulance inventory dataset.

3.1.1 Migration-Adjusted Population Modeling

Internal migration effects were incorporated to account for spatial redistribution of population and its impact on healthcare demand. Migration data were obtained from the Nepal Population and Housing Census (NPHC) 2021 published by the Central Bureau of Statistics (CBS), which reports district-level internal migration based on place of previous residence during the 2011–2021 intercensal period [24].
All migration indicators provided by CBS represent cumulative migration over ten years and are expressed as rates per 1,000 native population [24].

Net Migration Rate (10-Year)

The net migration rate represents the net population change due to internal migration per 1,000 population over the ten-year census period and is computed as:

$$\text{NetMigrationRate}_{10yr} = \left(\frac{\text{InMigrants}_d - \text{OutMigrants}_d}{\text{NativePopulation}_d} \right) \times 1000 \tag{3.4}$$

A positive value indicates net population gain, while a negative value indicates net population loss for district d.

Annualized Migration Rate

Since the census migration rate is cumulative, an annualized migration rate was derived for modeling and simulation purposes by assuming uniform migration over the intercensal period:

$$\text{NetMigrationRate}_{year} = \frac{\text{NetMigrationRate}_{10yr}}{10} \tag{3.5}$$

This transformation is used solely for analytical consistency and does not represent an official CBS annual estimate.

Five-Year Migration Adjustment

To align with medium-term planning horizons, a five-year net migration rate was calculated as:

$$\text{NetMigration}_{5yr} = \text{NetMigrationRate}_{year} \times 5 \tag{3.6}$$

Estimation of Migration-Induced Population Change

The five-year migration rate was converted into absolute population change using the 2021 district population:

$$\text{PopulationMigrated}_d = \left(\frac{\text{NetMigration}_{5yr}}{1000}\right) \times \text{Population}_{2021,d} \tag{3.7}$$

Negative values represent net population loss due to migration, whereas positive values represent net population gain.

Migration-Adjusted Population Projection (2026)

The migration-adjusted population for 2026 was estimated by updating the 2021 population with the migration-induced population change:

$$\text{Population}_{2026,d} = \text{Population}_{2021,d} + \text{PopulationMigrated}_d \tag{3.8}$$

This projection isolates the effect of internal migration without incorporating natural population growth, allowing direct assessment of migration-driven demand shifts.

Scenario Comparison for Optimization

The population in which migration is also considered were put in different scenarios in the optimization framework:

- **Scenario 1 (Minimizing wait time):** This scenario focuses on optimization such that patients wait minimum amount of time for waiting treatment.
- **Scenario 2 (Maximizing patients served):** This scenario focuses on optimization such that highest number of patients can be treated within our simulation time.
- **Scenario 3 (Composite):** This scenario focuses on optimization such that real life earthquake can be simulated where both wait time and patients served should be optimized i.e. minimum amount of time for waiting treatment and maximum number of patients served. This is basically hybrid of scenario 1 and scenario 2

Implications for Resource Allocation

Internal migration significantly affects healthcare demand and service coverage. Ignoring migration would result in systematic over-allocation in districts experiencing sustained out-migration and under-allocation in growth centers.

In this study, migration-adjusted population estimates are used to guide resource allocation under fixed budget constraints, ensuring that limited healthcare resources are distributed according to present-day population realities rather than static census figures. This approach improves the realism and policy relevance of the optimization framework.

Doctor skill mix For modeling purposes, doctors in each district hospital are categorized into three levels based on assumed qualifications:

Table 3.1: Doctor Level Classification

Doctor Level	**Qualification (Assumed)**
Level 1 Doctor	MBBS Completed
Level 2 Doctor	MD Completed
Level 3 Doctor	PhD Completed

This simplified categorization allows the simulation to differentiate treatment efficiency by doctor expertise while keeping the model tractable.

Patient distribution For modeling purposes, patients are divided into following classification with each having different treatment time and priority level to make it more realistic modelling:

Table 3.2: Patient Type Classification

Patient Type	**Priority Level**	**Treatment Time (minutes)**
Normal	2	15
Medium	1	30
Difficult	0	60

This distribution has 0 as the highest priority level and will doctors will preempt if higher priority level patients do come.Difficult patients can only be transported to the hospital using an ambulance.

District Hospital Representation and Geospatial Data

For each district, one representative *district hospital* is assumed to act as the primary public referral node in the response network. The latitude and longitude for each district hospital are selected to satisfy two criteria:

1. **Centrality:** the coordinate lies near the district's central service area to reduce systematic bias in travel distance calculations.
2. **Road proximity:** the coordinate is chosen near accessible road infrastructure to ensure that route queries in the routing engine produce realistic paths rather than off-road artifacts.

This approach supports consistent graph-based routing and reduces sensitivity to arbitrary point placement, which is critical when comparing optimization outcomes across districts.

Earthquake Scenario Selection (Sindhupalchok Epicenter and Magnitude)

The earthquake scenario is grounded in Nepal's 2015 earthquake sequence. The April 25, 2015 Nepal (Gorkha) earthquake had moment magnitude M_w 7.8, as documented by the United States Geological Survey (USGS) event record [25]. Although the mainshock epicenter was in Gorkha, multiple authoritative humanitarian situation reports identify Sindhupalchok as one of the worst affected districts, and also note that a major aftershock occurred in/near Sindhupalchok during the sequence [26, 27]. On this basis, the simulation places the epicenter in Sindhupalchok to represent a high impact scenario in a severely affected district cluster, while adopting an earthquake magnitude consistent with the historically observed major event scale in Nepal [25]. This design choice is intended to (i) reflect Nepal's real seismic risk profile, and (ii) stress-test the allocation and routing strategy under high-consequence conditions.

Data Integration and Quality Checks

All collected and derived values were integrated into a unified scenario configuration (JSON) consumed by the simulation. The following checks were performed:

- **Schema validation:** ensuring each hospital object contains `name, lat, lon, population, beds, doctors, ambulances` and the doctor distribution fields.
- **Range and consistency checks:** confirming non-negative resources and ensuring the bed/doctor/ambulance values scale monotonically with population under the chosen formulas.
- **Geospatial sanity checks:** verifying coordinates lie within Nepal's approximate bounding region and produce valid routes in the routing engine.

3.2 Algorithms

The algorithms and logics for search of best solution were 6 and each one yielded different results having different equations and techniques it is built upon.

3.2.1 Grid Search (Systematic Exploration)

The Grid Search algorithm discretizes the search space into fixed intervals. It explores combinations of resources systematically to establish a performance baseline.

Algorithm 1: Resource Distribution Grid Search Optimizer

Input: Base configuration S, parameter ranges R, budget B, step sizes δ

Output: List of feasible configurations $\mathscr{L}$

```
Initialize 𝓛 ← {S};
for d = 0; d ≤ d_max; d = d + δ_d do
    for a = 0; a ≤ a_max; a = a + δ_a do
        for b = 0; b ≤ b_max; b = b + δ_b do
            X ← ApplyConfiguration(S, d, a, b);
            if Cost(X) ≤ B and X ∉ 𝓛 then
                𝓛 ← 𝓛 ∪ {X};
            end
        end
    end
end
return 𝓛;
```

3.2.2 Random Search with Epicenter Bias

Random search samples configurations stochastically. To improve efficiency, the sampling is biased toward the ”epicenter” hospitals closest to the disaster origin.

3.2.3 Genetic Algorithm (GA)

The GA simulates natural selection through crossover and mutation. The fitness of an individual is determined by the simulation output $f(X)$.

Solution Acceptance Condition

$$P_{\text{accept}}(X) = \begin{cases} 1, & \text{if } \mathrm{Cost}(X) \leq B \\ 0, & \text{otherwise} \end{cases} \tag{3.9}$$

Algorithm 2: Genetic Algorithm Optimizer

Input: Population size N, Generations G, Mutation Rate μ

Generate initial valid population $\mathscr{P}_0$;

for $g = 1$ *to* G **do**

  Evaluate fitness $f(X)$ for all $X \in \mathscr{P}_g$;

  Select top 50% (Survivors);

  while $|\mathscr{P}_{g+1}| < N$ **do**

    $X_1, X_2 \leftarrow \text{RandomSelection}(\mathit{Survivors})$;

    $X_{child} \leftarrow \text{Crossover}(X_1, X_2)$;

    $X_{child} \leftarrow \text{Mutate}(X_{child}, \mu)$;

    if $Valid(X_{child})$ **then**

      Add X_{child} to $\mathscr{P}_{g+1}$;

    end

  end

end

3.2.4 Simulated Annealing (SA)

SA explores the search space by accepting worse solutions with a probability that decreases over time (temperature T), allowing the algorithm to escape local optima. The acceptance probability is defined by the Boltzmann distribution:

Probabilistic Acceptance Function

$$P(\text{accept}) = \exp\left(\frac{-\Delta E}{T}\right) \tag{3.10}$$

3.2.5 Bayesian Optimization

This method uses a Gaussian Process (GP) as a surrogate model of the simulation. It uses an Acquisition Function, specifically Expected Improvement (EI), to decide where to sample next:

Expected Improvement Criterion

$$EI(x) = \mathbb{E}\left[\max\left(f(x) - f(x^+), 0\right)\right] \tag{3.11}$$

where $f(x^+)$ is the best value observed so far.

3.2.6 Proposed Optimization Algorithm

The proposed approach combines the exploratory power of Random Search with the exploitative refinement of a Genetic Algorithm.

1. **Phase 1:** Execute Random Search to identify N diverse, feasible seeds.
2. **Phase 2:** Use these seeds as the initial population for a Genetic Algorithm to converge on the global optimum.

3.3 Flowchart

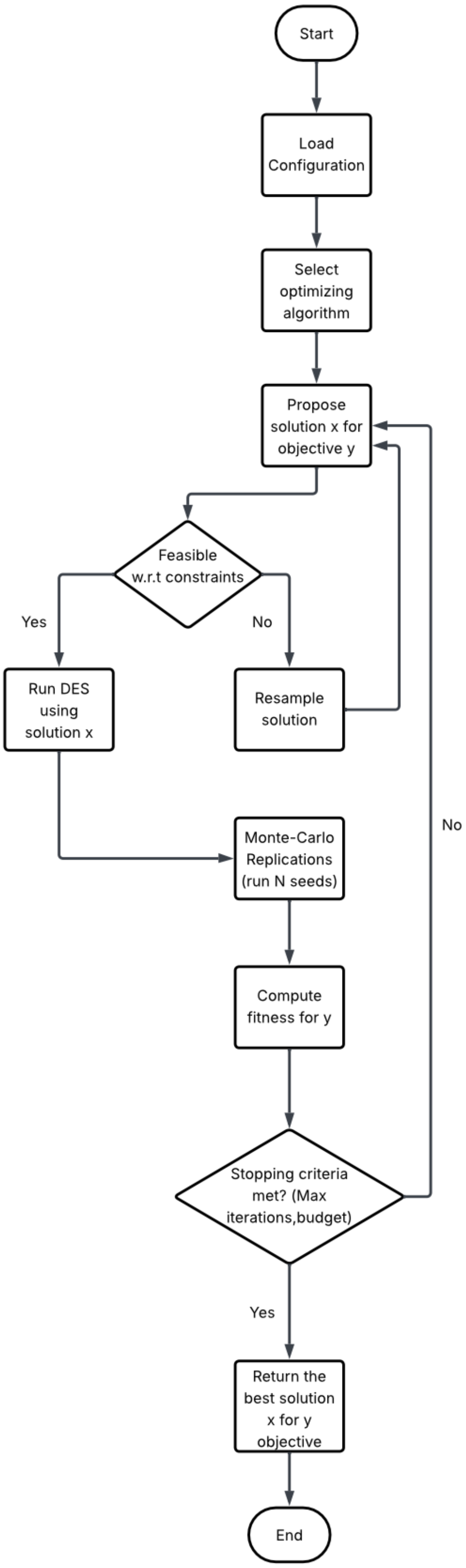

Figure 3.1: Simulation-Based Optimization Flowchart

3.3.1 Description of Optimization Flowchart

When optimization is started, first configuration is loaded like number of hospital, resources in hospital (doctors, beds,ambulances) and the epicenter of the earthquake. Optimization of resources will depend on the algorithm chosen, there are 6 algorithm (x) which can be chosen from and 3 objectives that can be chosen from (y). With combination of x and y, it will now go into a loop where unless feasible it will keep resampling solution, if yes feasible then DES will run using solution x with monte-carlo replications. Compute fitness for y such that fitness should be maximized. this will loop until stopping criteria will be met, if yes then that is the best solution of x for y (objective).

3.3.2 Temporal Patient Demand and Decay

- **Gravity-Based Arrival Rates:** Initial patient surge is modeled as a function of the hospital's catchment population and its inverse distance from the epicenter. This follows the epidemiological "Gravity Model," assuming that facilities in high density areas closer to the shock will experience disproportionately higher pressure. This is necessary to test the system's ability to manage extreme load-balancing.

- **Two-Phase Exponential Decay:** Patient arrivals follow a dual rate decay: a fast phase (half-life of 120 minutes) for the first 48 hours, transitioning to a slow decay tail. This reflects the clinical reality of the "Golden Hours" post disaster. The first phase simulates the acute search and rescue surge, while the second phase accounts for secondary injuries and stabilization, ensuring the optimizer accounts for both short-term chaos and long-term recovery.

3.4 Optimization Objectives and Evaluation Metrics

To rigorously evaluate the performance of the proposed resource allocation framework, three distinct objective functions were defined. These metrics serve as the "fitness functions" for the optimization algorithms, guiding the redistribution of medical assets based on simulated earthquake impacts.

3.4.1 Minimization of Global Wait Time (f_{wait})

The primary indicator of system pressure in a disaster scenario is the duration a patient must wait before receiving definitive care. This metric is defined as a weighted sum of pre-hospital and intra-hospital delays:

Waiting Time Objective Function

$$f_{\text{wait}} = \sum_{i=1}^{N} \left(w_a \cdot \bar{T}_{\text{amb},i} + w_b \cdot \bar{T}_{\text{bed},i} \right) \tag{3.12}$$

Where:

- $\bar{T}_{amb,i}$ is the average wait time for an ambulance at hospital i.
- $\bar{T}_{bed,i}$ is the average wait time for a specialized bed.
- w_a, w_b are weight coefficients (set to 2.0 and 1.0 respectively).

By prioritizing the minimization of wait times, the optimizer inherently favors a ”decentralized” resource distribution. It penalizes bottlenecks at high-load facilities and encourages the movement of resources toward epicenter-adjacent hospitals where the initial surge is most acute.

3.4.2 Maximization of Patient Throughput (f_{served})

In mass-casualty events, the sheer volume of treated individuals is a critical measure of success. This metric tracks the total number of patients who successfully complete the treatment cycle within the simulation window.

Service Coverage Objective

$$f_{\text{served}} = \sum_{j \in P} \delta_j, \qquad \delta_j = \begin{cases} 1, & \text{if patient } j \text{ is fully treated} \\ 0, & \text{otherwise} \end{cases} \tag{3.13}$$

While wait-time minimization focuses on speed, throughput maximization focuses on capacity utilization. This metric forces the optimizer to identify ”high efficiency hubs” facilities with skilled staff who can process patients rapidly thereby ensuring that the limited medical budget is not wasted on under utilized peripheral clinics.

3.4.3 Composite ($f_{composite}$)

To avoid the pitfalls of optimizing for a single variable, a composite metric was developed to balance speed with volume. This function represents the multi-objective Pareto front of the disaster response.

Composite Objective Function

$$f_{\text{composite}} = w_b \cdot \bar{T}_{bed} + w_a \cdot \bar{T}_{ambulance} + w_t \cdot \bar{T}_{treat} \tag{3.14}$$

Where:

- $\bar{T}_{bed}$ is the average waiting time for a hospital bed.
- $\bar{T}_{ambulance}$ is the average waiting time for ambulance transport.
- $\bar{T}_{treat}$ is the average waiting time before treatment begins.
- w_b, w_a, and w_t are weighting coefficients reflecting the operational importance of each delay type.

In this study, the weights were empirically set as:

$$w_b = 1.0, \quad w_a = 2.0, \quad w_t = 1.5$$

The composite metric is the most robust tool for resource distribution because it evaluates delays across multiple stages of the emergency response pipeline. Ambulance waiting time receives the highest weight since patients remain untreated at the disaster site until transport occurs. Treatment delay is assigned a moderate weight because prolonged clinical waiting increases the risk of complications. Bed waiting time receives the baseline weight since patients have already reached the hospital and may undergo preliminary stabilization. This formulation prevents the optimizer from favoring solutions that minimize a single delay type while neglecting others, thereby achieving a balanced objective aligned with the principle of maximizing benefit for the largest number of patients.

3.4.4 Determining Resource Distribution

These metrics allow the simulation to transform raw data into actionable logistics:

1. **Bottleneck Identification:** High f_{wait} values in specific regions trigger a "Resource Pull," where the optimizer reallocates ambulances from low-impact zones to the epicenter.
2. **Workforce Balancing:** By analyzing the impact of f_{served} against different skill tiers, the system determines whether to invest in "Beginner" staff (volume) or "Skilled" staff (speed).
3. **Budgetary Efficiency:** By comparing the improvement in $f_{composite}$ against the cost of additional resources, the model provides a diminishing returns analysis, informing policy makers on the exact point where additional funding no longer yields significant survival gains.

3.5 Simulation Environment

The proposed system employs a custom discrete-event simulation (DES) engine designed to model patient arrivals, transportation delays, treatment dynamics, and hospital capacity under a fixed financial constraint. Each candidate configuration generated by the optimization algorithms is evaluated through multiple Monte Carlo replications to ensure statistical robustness.

Ambulance Dispatch and Extreme-Case Handling

Hospitals possess a fixed number of ambulances with stochastic travel times computed using the Haversine formula and a uniformly distributed velocity model. For extreme patients, who cannot walk or self-report to hospitals, the simulation generates a random geographic coordinate within a defined radius of the epicenter. The nearest hospital is automatically assigned to dispatch an available ambulance to retrieve the patient.
Since extreme patients represent life-threatening cases, they bypass standard triage queues upon arrival. Once transported, they are immediately assigned to an available doctor and bed, reflecting real-world emergency protocols prioritizing critical-care patients.

Hospital Service Dynamics

Each hospital operates with constrained resources, including doctors, beds, and ambulances. Doctors are modeled using tiered skill multipliers to capture differences in treatment efficiency with their own service time. Queueing occurs when demand exceeds available resources, and the DES records performance indicators such as:

- average ambulance wait time,
- average bed wait time,
- total number of patients successfully treated.

Budget Constraint

For this study, the system assumes a fixed operational budget of 20 Crore NPR. Resource costs are modeled linearly, and any configuration whose total cost exceeds this budget is automatically rejected before simulation. This constraint ensures that all optimized solutions remain feasible for real-world emergency planning.

Since publicly available datasets for temporary disaster medical deployment costs in Nepal are limited, approximate values were derived using market observations and standard wage structures. All costs represent 7-day operational expenses.

- **Doctor:** NPR 35,000 per deployment, approximating a daily compensation of about NPR 5,000 for a 7-day emergency assignment.
- **Ambulance:** NPR 32,667 representing the approximate weekly rental cost of an ambulance including driver service and operational expenses.
- **Hospital Bed:** NPR 15,000 representing the procurement cost of a basic medical bed used in temporary treatment centers or field hospitals.

These values are intended to represent realistic operational magnitudes rather than exact procurement prices. The primary purpose of these parameters is to enable comparative evaluation of optimization strategies under realistic budget constraints.

Simulation Configuration and Reproducibility

All simulation parameters are defined through a structured configuration schema, including earthquake magnitude, epicenter coordinates, hospital attributes, patient treatment characteristics, and simulation runtime settings. To ensure experimental reproducibility, the system uses a fixed random seed for stochastic processes and executes multiple Monte Carlo replications for each candidate solution. The simulation horizon spans a seven-day post-disaster window, allowing the model to capture both immediate surge effects and longer-term treatment dynamics.

3.5.1 Synthetic Patient Arrival Generation

To simulate patient arrivals at hospitals following a hypothetical earthquake, synthetic data was generated using distance and population-model. Each hospital was assigned an estimated arrival rate based on its distance from the earthquake epicenter, local population and the earthquake magnitude.
The base arrival rate λ_0 for hospital h was computed as:

$$\lambda_0 = \text{CrisisFactor} \times \frac{1}{1 + 0.05\, d(h, \text{epicenter})} \times \frac{\text{Population}_h}{10^6} \times (0.1 \times \text{Magnitude}) \tag{3.15}$$

where $d(h, \text{epicenter})$ is the Haversine distance in kilometers. This ensures hospitals closer to the epicenter or serving larger populations receive higher patient inflow. The patient arrival rate over time follows an exponential decay function:

$$\lambda(t) = \lambda_0 \cdot 2^{-t/\text{half-life}} \tag{3.16}$$

where λ_0 is the base arrival rate and half-life controls the speed of decay.
To reflect the natural decline in arrivals over time, a two-phase exponential decay was applied:

- **Phase 1 (first 2 days):** Rapid decay with a half-life of 2 hours.
- **Phase 2 (after 2 days):** Slow decay tail with a half-life of 2 days.

The resulting synthetic time series of patient arrivals for each hospital captures both the spatial heterogeneity and temporal dynamics expected in a realistic disaster scenario. This dataset was used as input for evaluating the optimization algorithms in the study.

Chapter 4
RESULTS AND ANALYSIS

4.1 Experimental Setup

4.1.1 Hardware Configuration

All experiments were conducted on a local development machine with the following specifications:

Table 4.1: Hardware Configuration

Component	Specification
Device Model	Apple MacBook Air (M1, 2020)
Processor	Apple M1 (8-core CPU: 4 performance cores + 4 efficiency cores)
Architecture	ARM64 (Apple Silicon)
Memory	8 GB Unified Memory
Storage	NVMe-based SSD
GPU	8-core GPU (2 cores used)

Notes on hardware impact:

- **CPU:** The simulation is heavily CPU bound. Event processing, queue handling, and optimization iterations rely entirely on CPU performance.
- **RAM:** 8 GB unified memory is sufficient for storing patient data, hospitals, ambulances, logs, and optimization populations. Low RAM could lead to system swapping and slower simulation times.
- **Storage (SSD):** Impacts log writing and result saving but does not affect simulation execution speed.
- **GPU:** Not utilized, as no GPU-based acceleration (CUDA, Metal, PyTorch GPU) is implemented.

4.1.2 Software Configuration

Notes on software impact:

- Python environment and version directly influence execution speed, library compatibility, and multithreading behavior.
- Backend framework affects API latency and concurrent simulation handling.

Table 4.2: Software Configuration

Component	Specification
Operating System	macOS (Apple Silicon native)
Programming Language	Python 3.12
Backend Framework	FastAPI with Uvicorn ASGI server
Simulation Engine	Custom discrete-event simulation framework
Optimization Algorithms	Genetic Algorithm, Simulated Annealing, Random Search, Grid Search, Bayesian Optimization
Python Environment	Virtual environment (venv)

- Choice of optimization algorithm affects **runtime, memory usage, and convergence speed**.

4.1.3 Optimization Algorithms and Performance Considerations

The project uses multiple optimization algorithms, each with different computational characteristics:

Table 4.3: Optimization Algorithms and Performance Characteristics

Algorithm	Characteristics & Performance Impact
Genetic Algorithm (GA)	Population-based search. Multiple iterations with selection, crossover, and mutation. CPU-intensive and memory-dependent.
Simulated Annealing (SA)	Iterative single-solution optimization. Moderate CPU usage. Sensitive to number of iterations and cooling schedule.
Random Search (RS)	Samples parameter space randomly. Low memory usage, moderate CPU usage, runtime depends on number of samples.
Grid Search (GS)	Exhaustive search over discrete parameter grid. CPU-intensive for large grids, memory usage increases with parameter combinations.
Bayesian Optimization (BO)	Probabilistic model-based search. CPU usage moderate but additional memory used for surrogate models and acquisition function computations.

General observations:

- **CPU:** Dominant factor for all algorithms. Large populations, iterations, or grid sizes increase runtime significantly.
- **RAM:** Important for population-based or model-based algorithms (GA and BO). Insufficient memory leads to slower execution or swapping.

- **Algorithm Complexity:** Directly affects the number of simulations and total runtime.

4.1.4 Execution Environment

Simulations were executed locally on macOS using the Python-based backend. Multiple runs were conducted to collect consistent performance metrics. Parallelism was limited by CPU cores and available memory.

4.2 Comparative Analysis

Table 4.4: Parameter vs Algorithm Support Table

Parameter	Grid Search	Genetic Algorithm	Simulated Annealing	Bayesian Optimization	Random Search	Proposed Method
0	NA	NA	NA	NA	✓	NA
1	✓	NA	NA	NA	✓	NA
2	✓	NA	✓	NA	✓	NA
3	✓	NA	✓	NA	✓	NA
4	✓	✓	✓	NA	✓	NA
5	✓	✓	✓	NA	✓	NA
6	✓	✓	✓	✓	✓	NA
7	✓	✓	✓	✓	✓	NA
8	✓	✓	✓	✓	✓	NA
9	✓	✓	✓	✓	✓	NA
10	✓	✓	✓	✓	✓	NA
11	✓	✓	✓	✓	✓	✓

Table 4.4 presents a comparative analysis of parameter support across six optimization algorithms: Grid Search, Genetic Algorithm, Simulated Annealing, Bayesian Optimization, Random Search, and the Proposed Method. The table highlights how algorithm capability improves as the number of available parameters increases.

At lower parameter levels (0–3), only Random Search demonstrates partial support, indicating its flexibility in handling minimal or undefined parameter spaces. Grid Search begins to show applicability from parameter level 1 onward, reflecting its dependency on explicitly defined search dimensions. In contrast, Genetic Algorithm and Simulated Annealing require a minimum parameter threshold before becoming operational, as they rely on population-based and probabilistic exploration mechanisms.

As the parameter count increases (levels 4–7), Grid Search, Genetic Algorithm, and Simulated Annealing show consistent support, while Bayesian Optimization starts to become applicable from parameter level 6, highlighting its suitability for moderately complex parameter spaces where probabilistic modeling becomes effective. Random Search maintains full availability across all parameter levels due to its non-restrictive nature.

At higher parameter levels (8–11), all conventional algorithms demonstrate full support; however, the Proposed Method shows availability only at the maximum parameter level (11). This indicates that the proposed approach is specifically designed to operate

in highly complex and fully defined parameter environments, where hybrid decision-making and optimization strategies can be most effectively utilized.
Overall, the comparison illustrates that while traditional methods gradually scale with parameter availability, the Proposed Method is intentionally constrained to scenarios with complete parameter information, ensuring optimized performance in complex, real-world problem settings.

4.3 Results

4.3.1 Optimizing Minimum Waiting Time

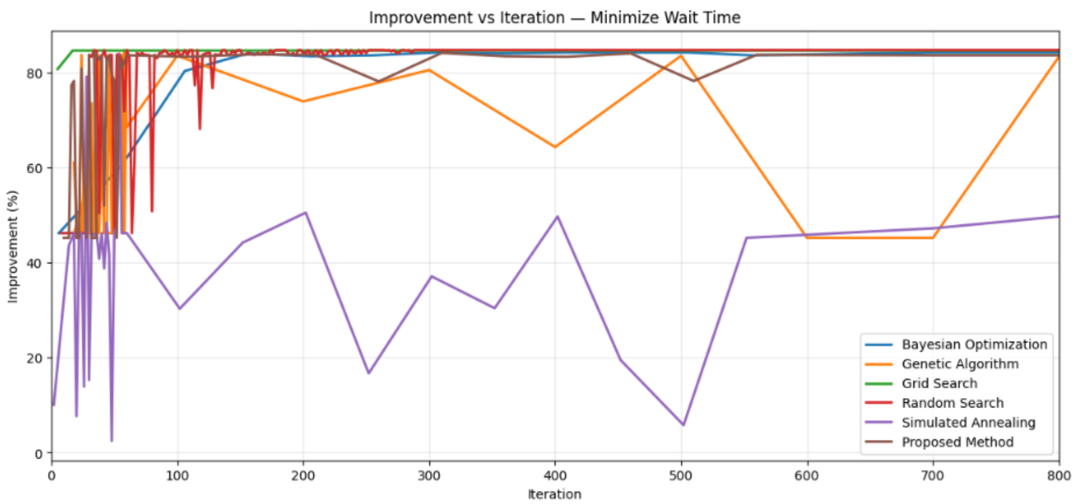

Figure 4.1: Improvement Over Baseline vs Iteration (Minimum Waiting Time)

The graph 4.1illustrates the percentage improvement in minimum waiting time over the baseline across 800 iterations for six optimization algorithms. Simulated annealing seems to be unstable and at around 500 slowly converge, indicating its inefficiency in handling large and complex search spaces unless it goes through lots of iterations but is still incapable to optimize the best but it did reach 83.7% at 54th iteration. Grid search is stable and reaches 84.6% quite quickly at 58th iteration. In contrast, Random Search and Genetic Algorithm both reach 84.7% which is the best solution among selected algorithms, highlighting their effectiveness in exploring and exploiting the solution space. Random search reaches it at 34th iteration and genetic search reaches it at 58th iteration. Bayesian Optimization achieves 84.2% which is it's highest at 306th iteration. The proposed method, which combines Random Search and Genetic Algorithm, benefits from fast initial exploration and strong evolutionary refinement, resulting in quick convergence and reaches 84.2% at 34th iteration. Overall, the proposed method couldn't give the best optimized result in this scenario but gave a very close one and ranked 4th with Bayesian and simulated annealing behind it.

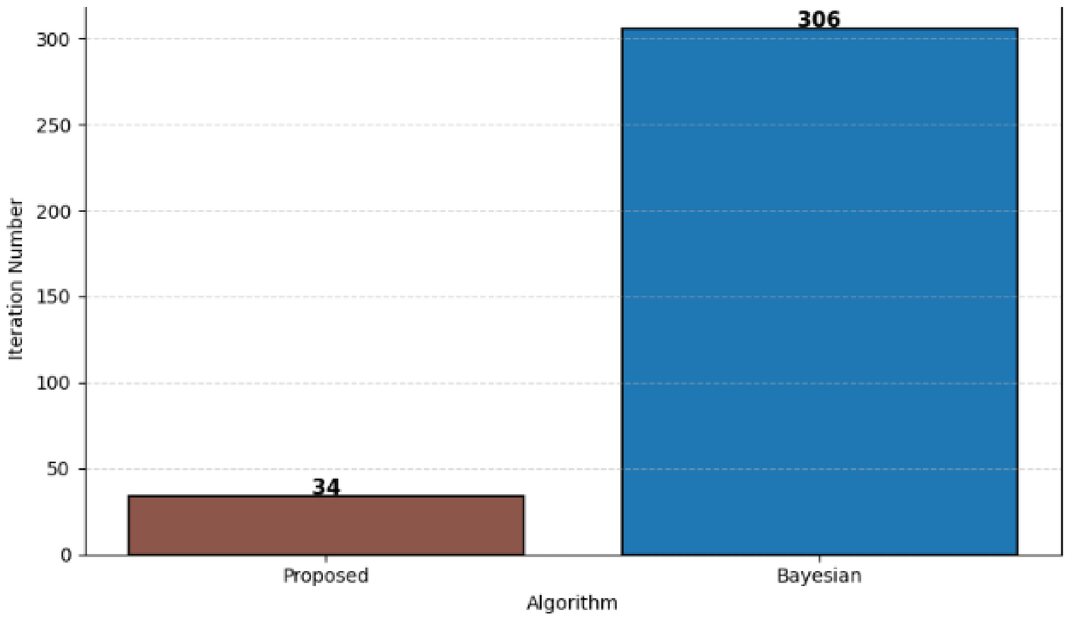

Figure 4.2: Comparision of algorithms which reached 84.2% improvement by the iteration required(Minimum Waiting Time)

The above figure displays the proposed algorithm requires less iteration than bayesian algorithm to achieve the same result. Therefore, it out performs this algorithm in this particular scenario.

4.3.2 Budget optimization of Minimum Waiting Time

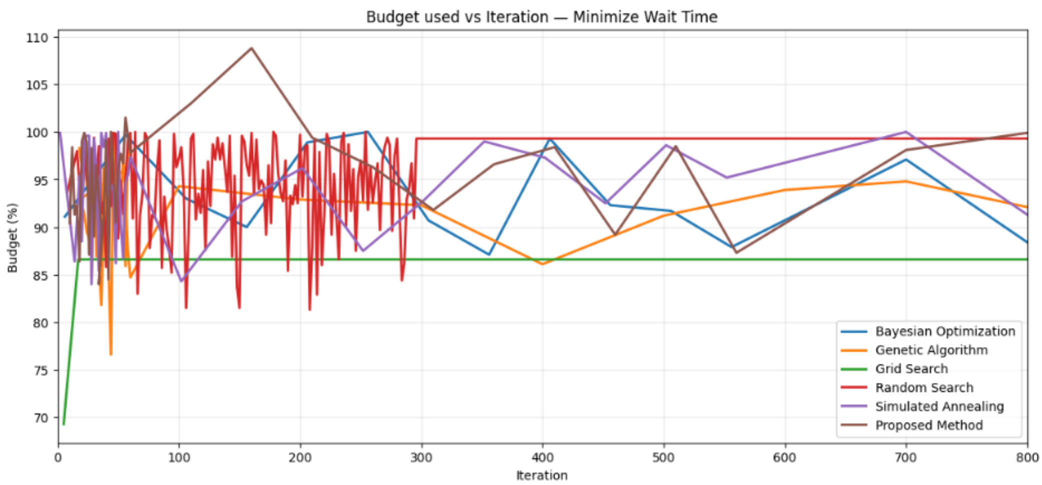

Figure 4.3: Budget used vs Iteration (Minimum Waiting Time)

The graph 4.3illustrates the percentage of budget utilized across iterations for minimizing patient waiting time using six optimization algorithms: Genetic Algorithm, Grid Search, Random Search, Bayesian Optimization, Simulated Annealing, and the proposed method. Grid Search exhibits a constant and relatively low budget usage throughout all iterations, indicating rigid and exhaustive exploration without adaptive resource allocation. In contrast, Random Search shows rapid escalation to high budget usage early in the process, followed by strong fluctuations, reflecting its stochastic and non-guided nature that often leads to inefficient resource utilization. The Genetic Algorithm demonstrates progressively increasing and relatively stable budget consumption, suggesting structured exploration with moderate control over resources. Bayesian Optimization maintains high budget usage with smoother transitions, indicating informed search behavior but with consistently high computational cost. Simulated Annealing displays significant oscillations in budget utilization, highlighting its sensitivity to parameter tuning and probabilistic jumps during optimization. Notably, the proposed hybrid method achieves a balanced budget utilization pattern by combining the exploratory strength of Random Search with the exploitative efficiency of the Genetic Algorithm. This results in controlled fluctuations, avoidance of unnecessary budget spikes, and sustained performance across iterations. Overall, the proposed approach demonstrates superior resource efficiency by achieving competitive minimum waiting time optimization while maintaining stable and optimized budget usage compared to individual algorithms.

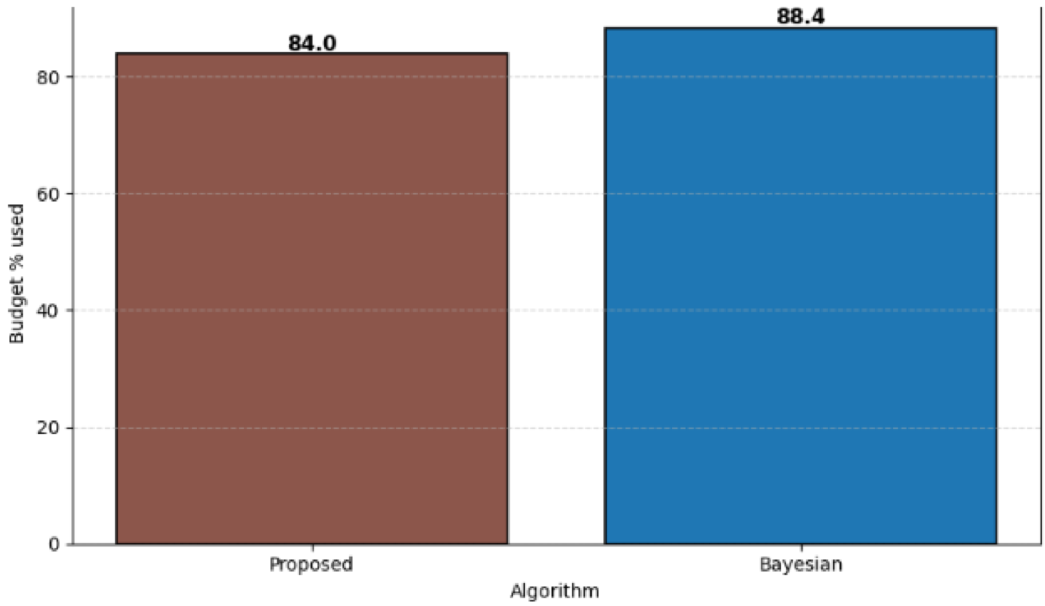

Figure 4.4: Comparision of algorithms which reached 84.2% improvement by the best case of budget used %(Minimum Waiting Time)

The above figure displays the proposed algorithm requires less budget % than bayesian algorithm to achieve the same result of optimization. Therefore, it out performs this algorithm in this particular scenario. This is best case scenario meaning the value was chosen among all the iteration % budget used by the algorithm such that it reaches 84.2% improvement and has the least budget used.

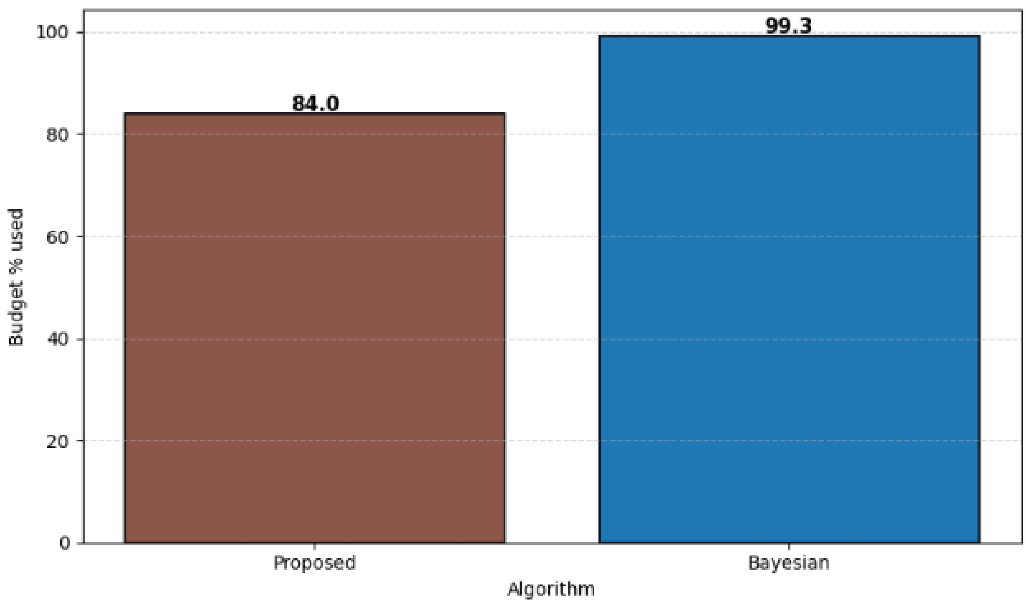

Figure 4.5: Comparision of algorithms which reached 84.2% improvement by the worst case of budget used %(Minimum Waiting Time)

The above figure displays the proposed algorithm requires less budget % than bayesian algorithm to achieve the same result of optimization. Therefore, it out performs this algorithm in this particular scenario. This is worst case scenario meaning the value was chosen among all the iteration % budget used by the algorithm such that it reaches 84.2% improvement and has the most budget used.

4.3.3 Maximum Patient Treated

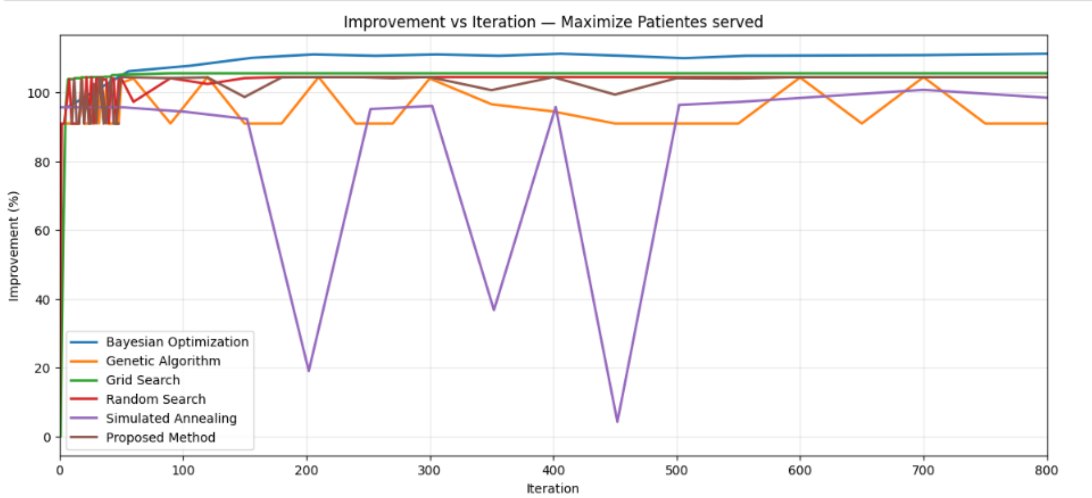

Figure 4.6: Improvement Over Baseline vs Iteration (Maximum Patient Treated)

The graph 4.11 presents the percentage improvement over the baseline for maximum patient treated across 800 iterations using six different optimization algorithms. Grid

Search quickly converges and reaches it's maximum improvement of 105.6%. Simulated Annealing still demonstrates highly unstable performance with large oscillations, where improvement varies widely between very low and moderate values, reflecting its probabilistic nature and finally starts converging at around 500 by reaching 100.80% at iteration 800. In contrast, Random Search rapidly achieves high improvement in the early iterations and then reaches its maximum of 104.50% improvement at 22 iteration, showing strong exploration capability. The Genetic Algorithm also converges quickly and maintains stable performance and reaches its maximum of 104.50% at 18 iteration with only minor fluctuations due to evolutionary operations. Bayesian Optimization exhibits the fastest and most consistent convergence, reaching the highest improvement of approximately 111.30%, making it the strongest individual optimizer for maximizing patient treated. The proposed method, which combines Random Search and Genetic Algorithm, benefits from rapid initial exploration and efficient evolutionary refinement, resulting in reaching its highest 104.5% at 32 iteration. Overall, the best in this case is clearly bayesian optimization, second is grid search and our proposed method is tied for 3rd with genetic algorithm and random search. Tie breaker can be made by further analysis of how quickly it reached to the optimization.

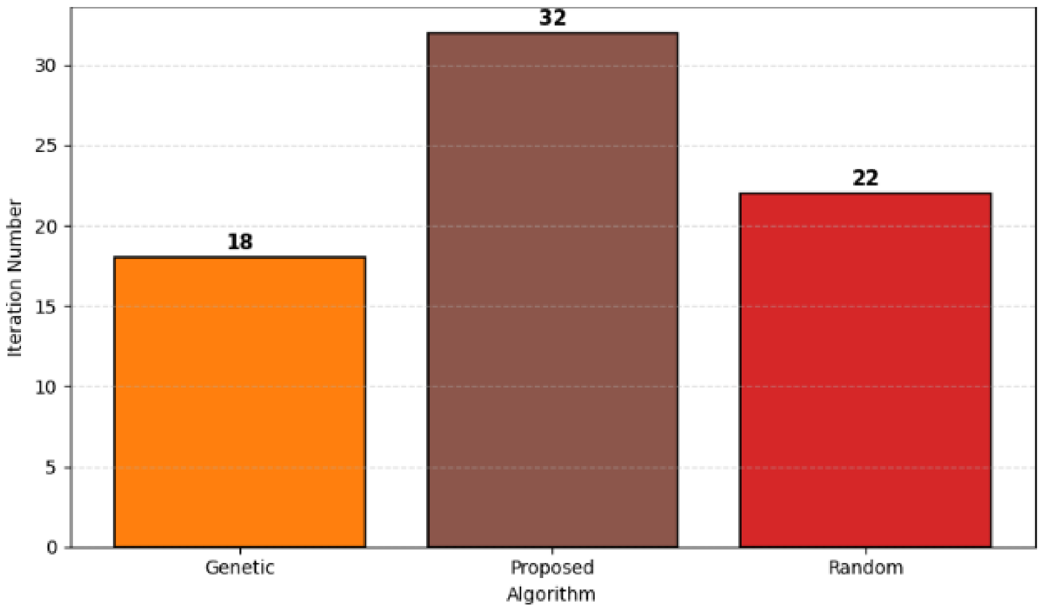

Figure 4.7: Comparision of algorithms which reached 104.5% improvement by the iteration required(Maximum Patient Treated)

The above figure displays genetic algorithm to require the least amount of iteration required to achieve the same improvement % compared to other algorithms and proposed algorithm to be last. Even though genetic is doesnt converge to its best output, it still reached it quicker than others.

4.3.4 Budget optimization of Maximum Patient Treated

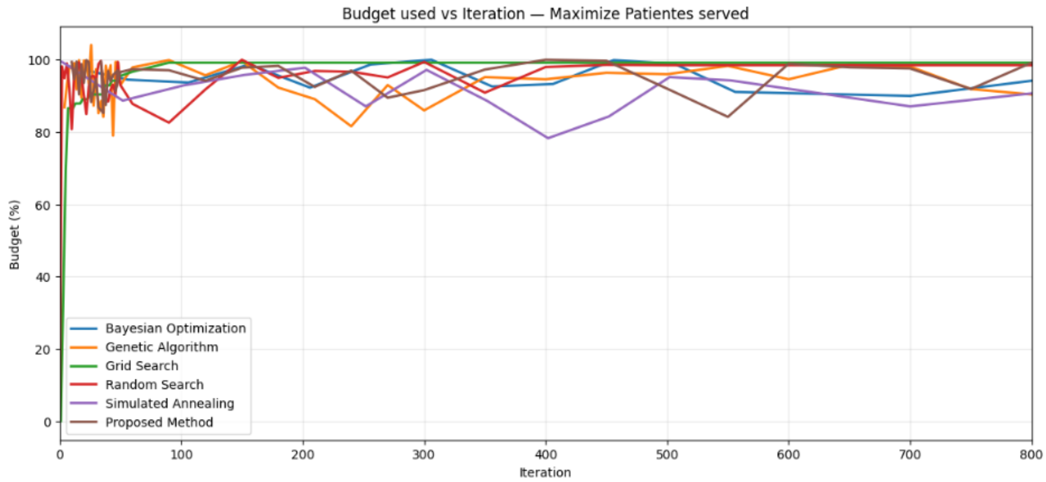

Figure 4.8: Budget used vs Iteration (Maximum Patient Treated Time)

The graph 4.13 presents the variation in budget utilization across iterations for maximizing patient treated using six optimization algorithms: Genetic Algorithm, Grid Search, Random Search, Bayesian Optimization, Simulated Annealing, and the proposed method combining Random Search and Genetic Algorithm. Grid Search demonstrates consistently increase reflecting its deterministic and non-adaptive nature, which limits its ability to scale resource utilization in response to evolving solution quality. Random Search rapidly escalates to high budget usage in early iterations and continues to exhibit large fluctuations, indicating inefficient exploration and high resource consumption driven by its stochastic behavior. The Genetic Algorithm maintains high but comparatively more structured budget utilization, demonstrating effective exploitation through evolutionary operations while controlling excessive resource expenditure. Bayesian Optimization consistently operates at high budget levels with moderate oscillations, highlighting its informed yet computationally intensive search strategy. Simulated Annealing shows pronounced variability in budget usage due to its probabilistic acceptance of inferior solutions, leading to unstable resource allocation across iterations. In contrast, the proposed hybrid method achieves a balanced and stable budget utilization pattern by integrating the exploratory diversity of Random Search with the convergence efficiency of the Genetic Algorithm. This combination enables the hybrid approach to sustain high patient treated capacity while avoiding extreme budget fluctuations, thereby demonstrating superior efficiency and robustness compared to individual algorithms.

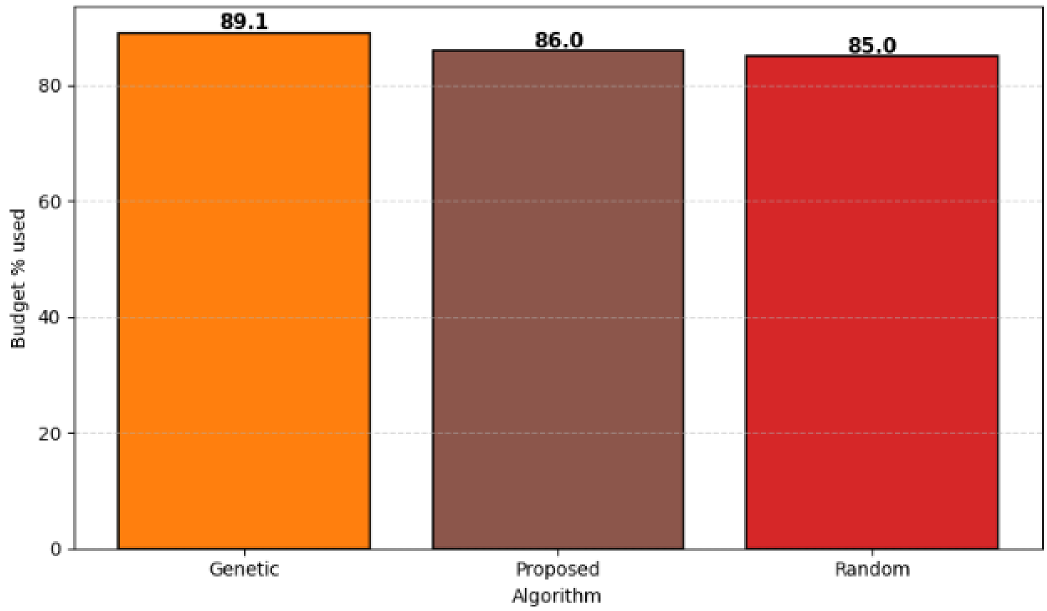

Figure 4.9: Comparision of algorithms which reached 104.5% improvement by the best case of budget used %(Maximum Patient Treated)

The above figure displays the proposed algorithm requires less budget than genetic but more than random to achieve the same result of optimization. Therefore, it can be ranked as 2nd in this case. This is best case scenario meaning the value was chosen among all the iteration % budget used by the algorithm such that it reaches 84.2% improvement and has the least budget used.

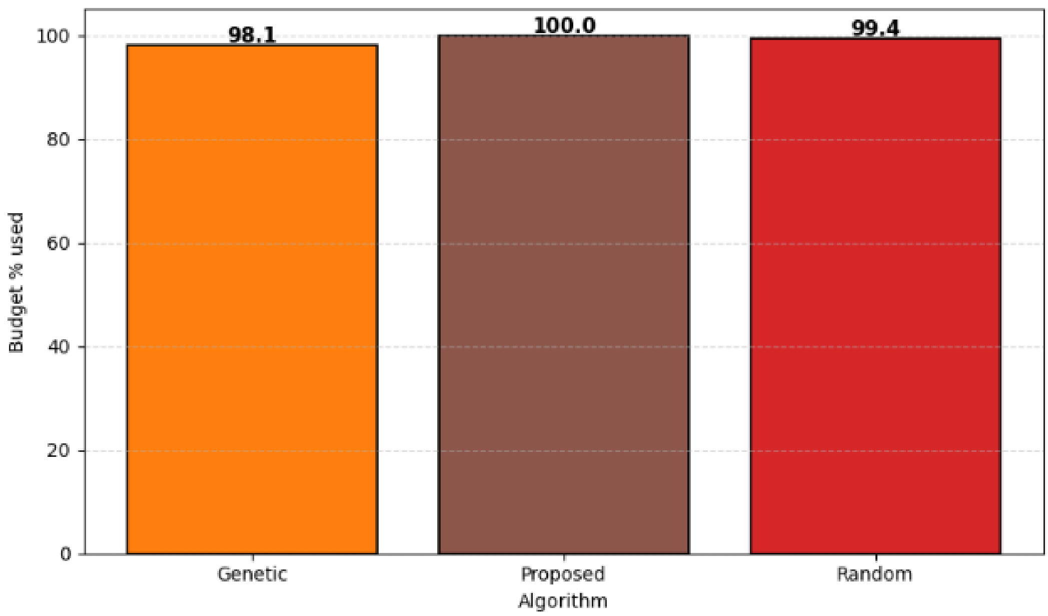

Figure 4.10: Comparision of algorithms which reached 104.5% improvement by the worst case of budget used %(Maximum Patient Treated)

The above figure displays the proposed algorithm requires highest budget % meaning it's worst case places it as last. This is worst case scenario meaning the value was chosen among all the iteration % budget used by the algorithm such that it reaches 84.2% improvement and has the most budget used.

4.3.5 Composite Optimization

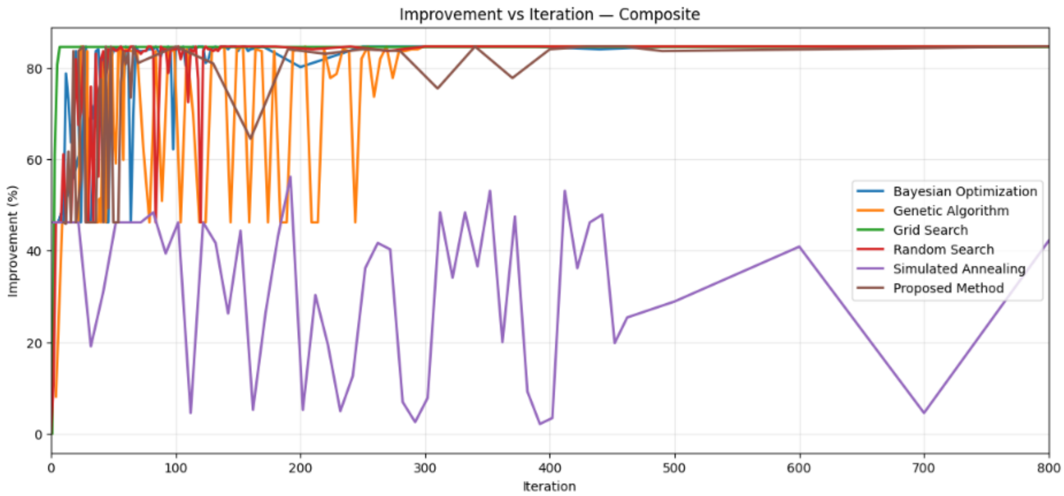

Figure 4.11: Improvement Over Baseline vs Iteration (composite)

The graph 4.11 presents the percentage improvement over the baseline for maximum patient treated across 800 iterations using six different optimization algorithms. Grid Search similar to previous cases converges quickly and reaches 84.6% very quickly . Simulated Annealing is same as previous cases with highly unstable performance and reaches its maximum of 56.2%. In contrast, Random Search rapidly checks and explores in the early iterations and then reaches its maximum of 84.7% improvement. The Genetic Algorithm also explores but it is is done till abour 270 iteration after which it converges and maintains stable performance and reaches its maximum of 84.7%. Bayesian Optimization explores and reaches its highest improvement of 84.7%. The proposed method also does rapid initial exploration and quickly converges and reaches its maximum 84.7%. Overall, the best in this case is not clear with 4 algorithm being able to reach the same highest improvement of 84.7%. Grid is 5th and random is 6th making them not necessary to be further analysed.

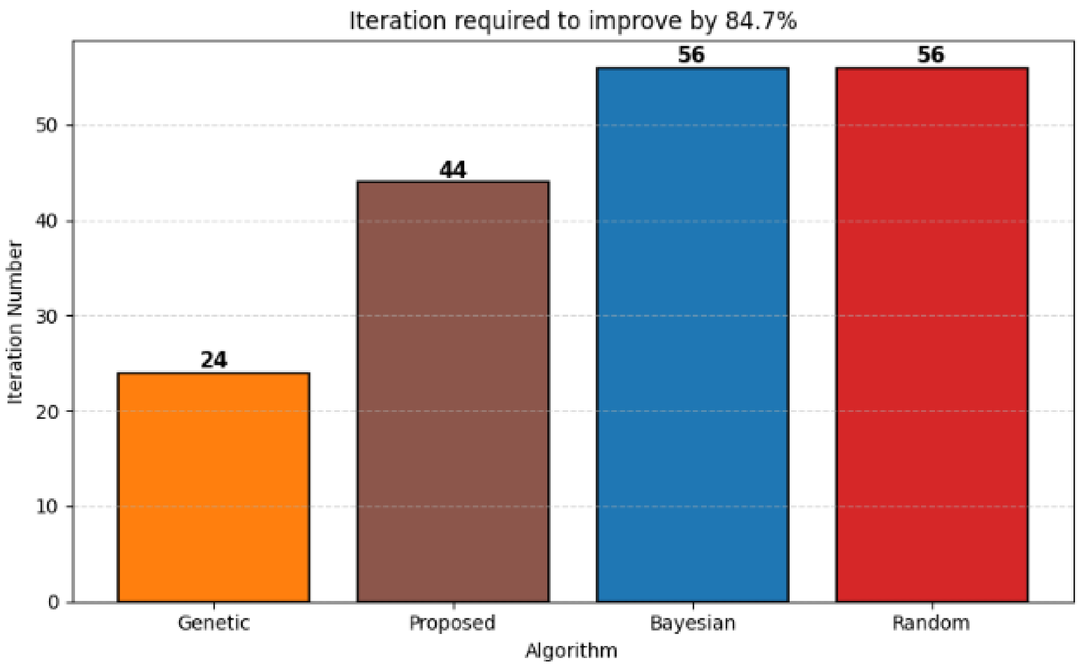

Figure 4.12: Comparision of algorithms which reached 84.7% improvement by the iteration required(composite)

The above figure displays genetic algorithm to require the least amount of iteration required to achieve the same improvement % compared to other algorithms and proposed algorithm following right behind. Placing it as 2nd best option in terms of speed.

4.3.6 Budget Optimization of composite

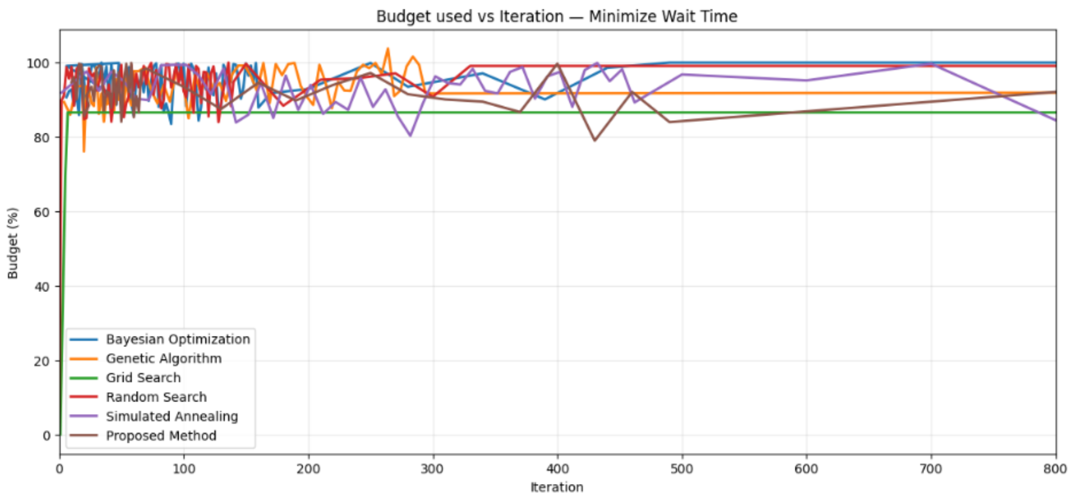

Figure 4.13: Budget used vs Iteration (composite)

The figure 4.13 presents the variation in budget utilization across iterations for maximizing patient treated using six optimization algorithms: Genetic Algorithm, Grid

Search, Random Search, Bayesian Optimization, Simulated Annealing, and the proposed method combining Random Search and Genetic Algorithm. All algorithms shows same behaviour as in previous cases but in this one, they converge after higher number of iteration i.e around 500. This is mostly because this case is combination of previous two and would require higher number iteration to come into converge in term of budget utilization. Further analysis has hence be done as below.

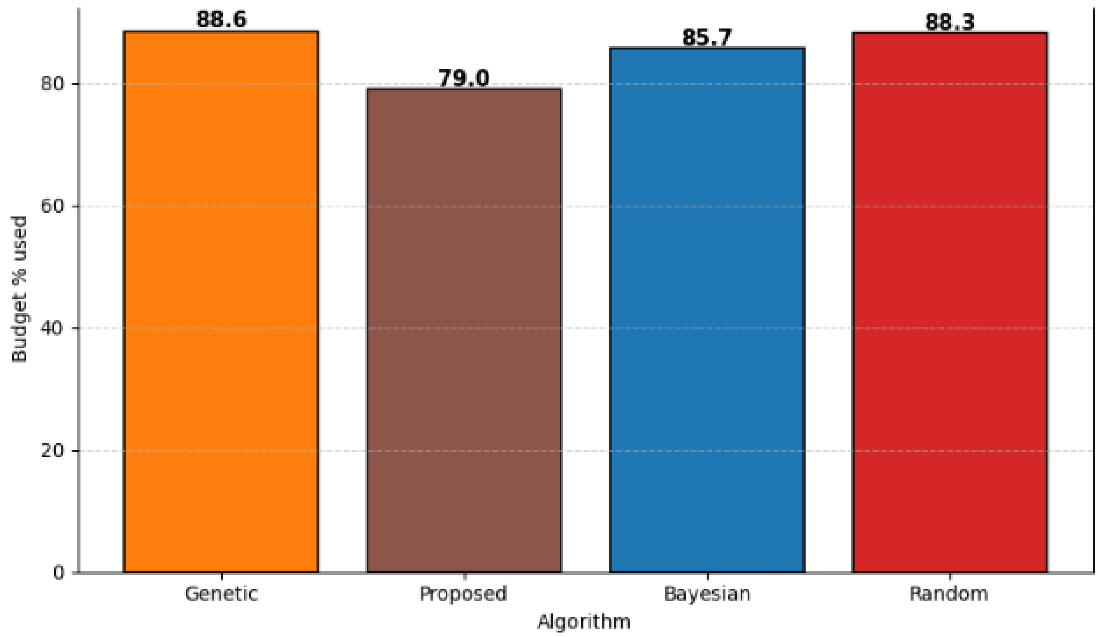

Figure 4.14: Comparision of algorithms which reached 84.7% improvement by the best case of budget used %(composite)

The above figure displays the proposed algorithm requires least budget to achieve the same result of optimization compared to other algorithms. Therefore, it is the best option to choose in terms of budget utilization during best case.

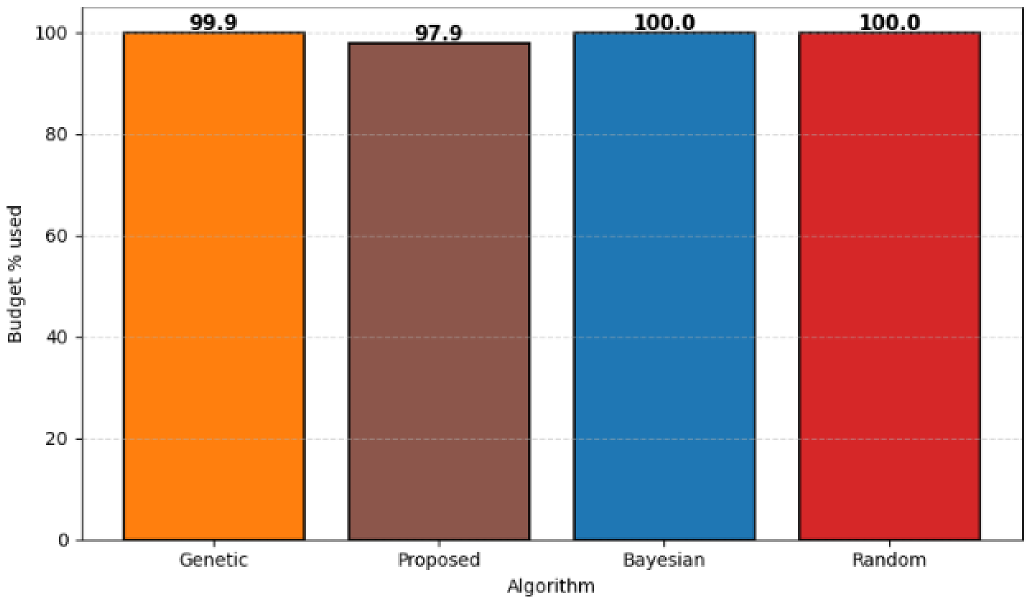

Figure 4.15: Comparision of algorithms which reached 84.7% improvement by the worst case of budget used %(composite)

The above figure displays the proposed algorithm requires least budget % meaning it's the best option even when considering the worst case for all algorithms that were tied. This further proves proposed algorithm is best in terms of budget utilization.

Chapter 5
CONCLUSION

This project set out to tackle the critical challenge of optimizing earthquake response in Nepal, where past seismic disasters have exposed major gaps in coordination, resource allocation, and real-time logistics management. The central problem addressed was the need for an integrated decision support system capable of dynamically distributing medical resources and optimizing emergency routes, especially in the chaotic aftermath of a major earthquake event. To meet this challenge, we developed the system that is simulation-driven framework designed to model the allocation of resources (medical teams, ambulances and hospital beds). The system leverages advanced optimization algorithms and real-time spatial data integration to enhance disaster response effectiveness. This platform compares a range of algorithms including Genetic Algorithm, Simulated Annealing, Random Search, Grid Search, Bayesian Optimization, and our proposed approach to solve complex allocation. Experimental results from the project demonstrate significant reductions in patient waiting times and notable increases in patient throughput. Testing in these proved the proposed algorithm is not always the best for single-objective scenarios. In addition, we developed composite case which is hybrid of both cases i.e. patient waiting time and patient throughput. In terms of proficiency, proposed algorithm was tied for 1st with other 3 algorithm (genetic, bayesian and random) and exceeded other 2 algorithms(grid and simulated annealing). In terms of speed, proposed algorithm was 2nd with 44 iteration right behind genetic algorithm because it found the optimal solution (among the applied algorithms) within 24 iteration. In terms of budget utilization, proposed algorithm performed the best (excluding those algorithms from analysis which didn't find optimal improvement) in both worst case and best case scenarios. Proposed algorithm has been exploratory in its initial iterations but highly stable later and very safe in utilization of budget. Overall, this study makes a significant contribution to disaster preparedness in Nepal and similar settings. This study proposes an algorithm that can adopt with more complex environment. Meaning more the metrics, better it's performance and real life environment does require higher number of metrics with complex environment. By enabling data-driven optimization of resource allocation and responsive, the system stands to reduce casualties, improve operational efficiency, and support informed decision-making in the midst of large scale emergencies.

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