INDUSTRIAL TRAINING DEFENSE
22EE4T001

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22EE01068

Optimizing Post Disaster Humanitarian Supply Chains Through Machine Learning and Multi Criterion Decision Making

Summer Internship Report

by

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1.Introduction

In the event of a natural or man-made disaster, the humanitarian supply chain (HSC) is a collection of coordinated actions meant to guarantee the effective transportation, storage, and distribution of necessities. Humanitarian logistics are motivated by **urgency, unpredictability**, and the desire to **lessen human suffering**, in contrast to traditional commercial supply chains that prioritize profit maximization and function within stable value chains. Decisions made in humanitarian logistics frequently have a direct impact on lives, raising the stakes considerably. According to studies, the timely and sustainable execution of relief efforts is greatly impacted by the thoughtful placement of storage facilities as well as the choice of trustworthy suppliers and distribution networks.

Usually, humanitarian operations take place in chaotic settings with rapidly shifting conditions and potentially compromised infrastructure. Although it can be difficult, efficient coordination between different governmental and non-governmental organizations is essential. Adequate resources, including people, food, shelter, medical supplies, and other necessities, must be available to support these operations and must be rapidly mobilized in times of emergency. Pre-disaster preparedness is crucial because logistics managers face additional challenges due to the high demand volatility and extreme time sensitivity. Actually, preparedness efforts account for as much as 80% of humanitarian logistics expenses, and research indicates that greater preparedness can drastically lower total response expenses.

Extreme uncertainty, urgency, and the need for real-time collaboration are key features that set the humanitarian supply chain apart from others. Humanitarian organizations are under pressure to make important decisions with limited financial and logistical re- sources. However, many still lack reliable systems for controlling operating expenses or gauging performance. In this regard, a transformative opportunity is presented by the integration of digital technologies, particularly artificial intelligence (AI) and machine learning (ML).

This study uses structured decision -making methods in conjunction with machine learning tools to improve the efficiency of humanitarian supply chains. Given the importance and urgency of humanitarian logistics, mathematical modeling is suggested as a way to maximize efficiency and reduce financial and human losses. These cuts not only increase the supply chain's efficiency but also lessen the wider societal effects that disasters have. More focused and efficient rescue operations are made possible by the use of machine learning algorithms, such as Decision Trees, K-Nearest Neighbors, Logistic Regression and Support Vector Classifier, to forecast and evaluate the risk levels of injured people. Additionally, affected areas are given relative importance (weights) using Multi-Criteria Decision-Making (MCDM) techniques

2. Research Objectives

This study aims to improve the effectiveness and efficiency of humanitarian supply chains (HSCs) in disaster situations by integrating modern analytical tools such as machine learning (ML), multi-criteria decision-making (MCDM) methods, and mathematical optimization. The focus is on reducing human suffering and financial losses by optimizing how rescuers, vehicles, and resources are allocated after a disaster.

To guide this goal, the research was structured around the following four key questions:

1**. How can humanitarian supply chains make better decisions with the use of machine learning?**
In order to prioritize essential patients for emergency care, this involves estimating the risk level of injured persons.

2. **What role should environmental, sourcing, and transportation policies play in disaster response planning?**
The study uses a bi-objective optimization model that takes into account environmental access, resource constraints, cost, and distance.

3. **What measures can be taken to lessen the harm that natural catastrophes cause to resources and people?**
To address this, aid is more effectively distributed where it is most needed by combining data-driven models with expert judgment.

4**. How can emergency response zones be prioritized using MCDM techniques?**
Disaster-affected locations are ranked using techniques like BWM and WASPAS according to factors including population, risk, and accessibility.

These guiding questions serve as the basis for the primary study goals, which are:

- to create a machine learning-based model that uses health data to categorize injured people according to their degree of severity.
- to assess and prioritize impacted areas according to their disaster risk and rescue priority using MCDM techniques (BWM and WASPAS).
- to create a bi-objective mathematical optimization model that strikes a compromise between reducing the overall operational cost and the total rescue distance.
- to use the integrated model on a real-world case study.
- to promote well-informed decision-making by doing sensitivity analysis on important parameters (such as the number of rescuers, budget, and injury levels).

2.1 Status of the Objectives

The project has effectively accomplished each of the four main research goals that were stated at the outset. By creating and assessing several classification models,

- the first goal—improving **victim classification** and triage through **machine learning**—was accomplished. The Decision Tree algorithm achieved the desired outcome of enhancing post-disaster response prioritization, having been chosen due to its high interpretability and robust performance metrics.
- The second goal, which was to use Multi-Criteria Decision-Making techniques to **prioritize impacted regions**, was also accomplished in full. The model successfully identified high-priority districts for resource allocation by employing WASPAS for ranking and the Best-Worst Method (BWM) to determine weights for pertinent criteria. Using Mixed-Integer Nonlinear Programming (MINLP) and LP-metric scalarization,

- the third goal—creating a bi-objective optimization model to **minimize travel distance and total operating costs**—was accomplished. The model offered the best possible placements for vehicles, rescuers, and relief centers.
- Lastly, by systematically varying important parameters like budget, patient count, and vehicle capacity, the fourth goal—conducting **sensitivity analysis**—was achieved. The model's practical applicability was confirmed when it demonstrated resilience and adaptability in a variety of operational scenarios. When taken as a whole, these goals show how well the suggested data-driven framework works to improve the dependability and efficiency of humanitarian logistics operations.

Summary of Research Objectives and Questions

- Use ML to predict patient severity and prioritize emergency care.
- Use MCDM (BWM + WASPAS) to rank districts by disaster risk.
- Build a bi-objective optimization model (distance + cost).
- Apply the model to a simulated disaster scenario based on synthetic data in Mizoram.
- Run sensitivity analysis to aid disaster planning.

Research questions addressed:

- How can ML improve HSC decisions?
- How should logistics and sourcing be handled post-disaster?
- What strategies reduce the impact of disasters?
- How can MCDM help prioritize affected areas?

3.Literature Review

The significance of integrating contemporary decision-support techniques and managing the humanitarian supply chain (HSC) effectively in disaster response has been the subject of numerous studies. Below are five key contributions that form the foundation for this research:

1. **Behl and Dutta** (Behl, A. and Dutta, P., 2019) emphasized the growing necessity of humanitarian operations' coordination and pre-disaster readiness. Their research highlighted how crucial it is to plan ahead of time in order to minimize overall damage and increase response effectiveness.
2. In order to promote greater supply chain awareness among donors, **Oloruntoba and Gray** (Oloruntoba, R., Gray, R., 2006) incorporated supply chain concepts into humanitarian aid operations. According to their research, supply chain planning is just as crucial in humanitarian situations as it is in business ones.
3. Resource allocation model under uncertainty was put forth by **Sarma et al**. (Sarma, 2020) with the goal of maximizing relief efforts in emergency situations. They concentrated on redistributing resources right away in order to cut down on delays and operational expenses.
4. Machine learning was used by **Brintrup et al.** (Brintrup, 2020) to forecast supply chain interruptions. Their research laid the groundwork for applying machine learning in dynamic and uncertain contexts, like post-disaster logistics.
5. **Budak et al**. (Budak, 2020) chose real-time location systems for humanitarian warehouses using MCDM techniques (fuzzy TOPSIS with interval-valued inputs). This illustrated how MCDM tools can be used to assess logistics infrastructure in disaster situations.

The utilization of ML and MCDM to enhance the effectiveness, adaptability, and readiness of humanitarian supply chains is supported by all of these studies taken together.

4.Methodology

In order to enhance humanitarian supply chain (HSC) operations during disasters, this study suggests an integrated methodology that combines machine learning (ML), bi-objective optimization, and multi-criteria decision making (MCDM). This work replicates the methodology from **Choudhary et al**. (Choudhary, 2023), where MCDM (WASPAS, BWM), ML-based severity classification, and a Pyomo-based bi-objective optimization model were used for post-disaster logistics planning. Three phases comprise the implementation of the methodology:

1.Affected areas are ranked using MCDM techniques according to accessibility, hazard level, area size, and population.

2.In order to prioritize rescue efforts, machine learning algorithms categorize injured people according to their level of severity.

3.To maximize resource allocation, a bi-objective mathematical model is developed, minimizing the overall cost and travel distance.

4.1 Multi Criterion Decision Making

Ranking the disaster-prone areas using real-world data and expert input is the main goal of the MCDM component. The Weighted Aggregated Sum Product Assessment (WASPAS) method and the Best-Worst Method (BWM) are the two particular approaches that are employed.

These methods assist in determining the relative importance of each district and allocating weights to different evaluation criteria. The distribution of vehicles and rescuers is determined by this ranking

4.1.1 Best Worst Method (BWM)

The Best Worst Method (BWM) is a multi-criteria decision-making (MCDM) technique developed by Jafar Rezaei in 2015. It helps determine the importance of different criteria by having decision-makers compare the "best" and "worst" criteria to all others. BWM is known for its effectiveness in reducing the number of pairwise comparisons needed while maintaining consistency.

Steps Of BWM:

1. **Define the criteria**: In this study, the criteria are:

- Population
- Area size
- Hazard factor
- Accessibility

2. **Select the Best (most important) and Worst (least important) criteria**

- For example, Hazard Factor is chosen as the best, and Area Size as the worst.

3. Assign preference values:

- Experts assign preference of the **Best** over others:

$$A_B = \left(a_{\{B1\}}, a_{\{B2\}}, \dots, a_{\{Bn\}}\right)$$

Where $a_{\{Bj\}}$ shows how much more important the best criterion is over criterion *j*

- Similarly, assign preferences of **all criteria over the Worst**:

$$A_W = (a_{\{W1\}}, a_{\{W2\}}, \dots, a_{\{Wn\}}\}$$

4. **Solve the following optimization model** to determine the optimal weights $(w_1, w_2, \dots, w_n)$

$$min\ \xi$$

$subject\ to$:

$$\left|\frac{W_B}{W_j} - a_{Bj}\right| \leq \varepsilon \qquad for\ all\ j$$

$$\left|\frac{W_W}{W_j} - a_{jW}\right| \leq \epsilon \qquad for\ all\ j$$

$$\sum_{j=1}^{n} w_j = 1 \qquad and$$

$$w_j \geq 0 \qquad for\ all\ j$$

where
w_j: weight of criterion j

w_B: weight of the **Best** (most important) criterion

w_W: weight of the **Worst** (least important) criterion

a_{Bj}: how strongly the Best is preferred over criterion j (from expert input, scale 1–9)

a_{Wj}: how strongly criterion j is preferred over the Worst

ξ: the **maximum allowed inconsistency** between the pairwise comparisons and the final weights.

4.1.2 Weighted Aggregated Sum Product Assessment (WASPAS)

The WASPAS method combines two popular MCDM approaches: the Weighted Sum Model (WSM) and the Weighted Product Model (WPM). It provides a more balanced and robust ranking of alternatives.

1. Normalize the Decision Matrix

- For Benefit Criteria:

$$x_{ij}^{*} = \frac{x_{ij}}{\max(x_{ij})}$$

$$where\ x_{\{ij\}}^{*}: normalized\ value\ of\ criterion\ j\ for\ alternative\ i$$

- For cost criteria

$$x_{ij}^{*} = \frac{\min(x_{ij})}{x_{ij}}$$

2. Calculate WSM (additive score)

$$Q_i^{(1)} = \sum (w_j \times x_{ij}*)$$

3. Calculate WPM (multiplicative score)

$$Q_i^{(2)} = \prod (x_{ij}^{*})^{w_j}$$

4. Combine both scores (for equal weightage use $\lambda = 0.5$

$$Q_i = \lambda \times Q_i^{(1)} + (1 - \lambda) \times Q_i^{(2)}$$

5. Rank Alternatives:

$$Higher\ Q_i values\ indicate\ better\ (higher\ priority) alternatives$$

Application in Study:

- Using expert data and municipality statistics, the WASPAS method was applied to all **11 districts of Mizoram**.
- Criteria used: Population, Area Size, Hazard Factor, Accessibility.
- The outcome ranked districts by priority for rescue and resource allocation.

4.2 Machine Learning

Rapidly determining the extent of injuries sustained by impacted individuals is essential for setting priorities for rescue efforts and distributing medical resources in the context of post-disaster humanitarian logistics. By learning from artificial or historical health datasets, machine learning (ML) provides a potent method to automate this classification process.

In this study, the degree of injury is predicted using a supervised machine learning model. Five levels of injury severity are distinguished: very low, low, medium, high, and very high. The distribution of resources, including ambulances and medical staff, is determined by these levels.

Data and Features:
Since real patient data was not available, a **synthetic dataset** was generated to simulate realistic post-disaster injury conditions. The dataset includes health-related features such as:

Variable	Variable Type	Variable	Variable type
Age	Integer	**Pulse rate**	Integer
Gender	Boolean	**Mobility**	Boolean
Pregnancy Status	Boolean	**Trapped Duration**	Integer
Consciousness Level	Boolean	**Blood Pressure**	Integer
Severe Bleeding	Boolean		

These variables serve as inputs to the machine learning model.

Model Selection and Training:
Several classification algorithms were tested, including:

- Logistic Regression
- K-Nearest Neighbors (KNN)
- Decision Tree
- Support Vector Classifier (SVC)

Figure:1 Model F1 Score Comparison

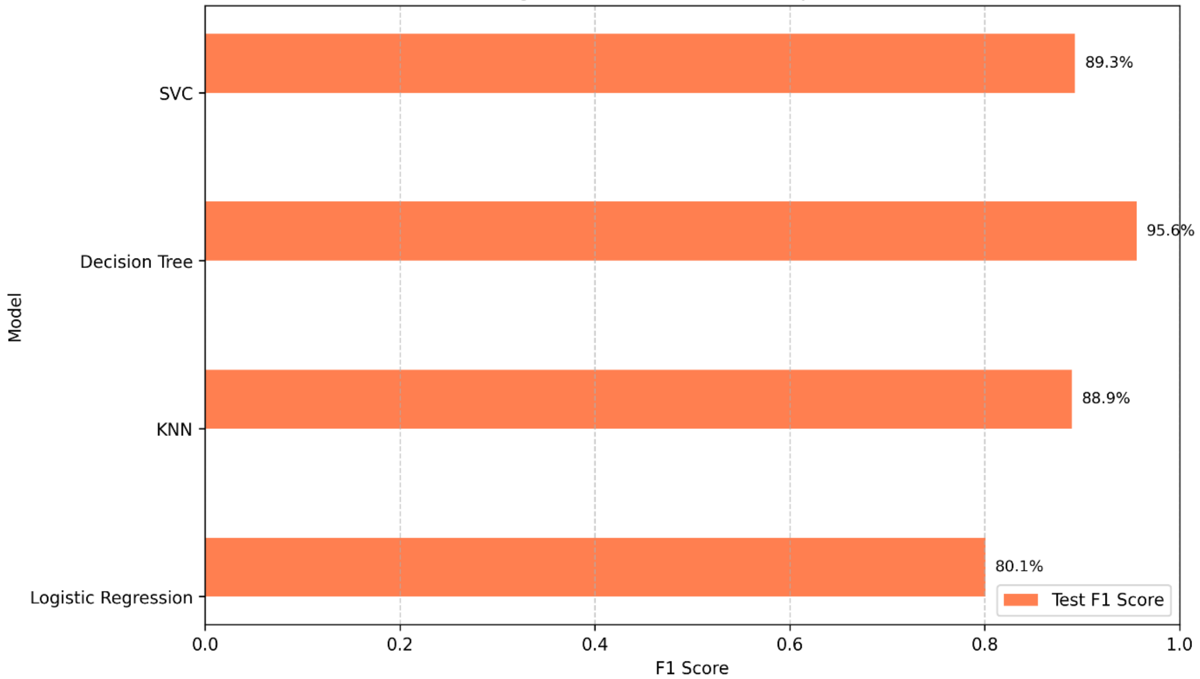
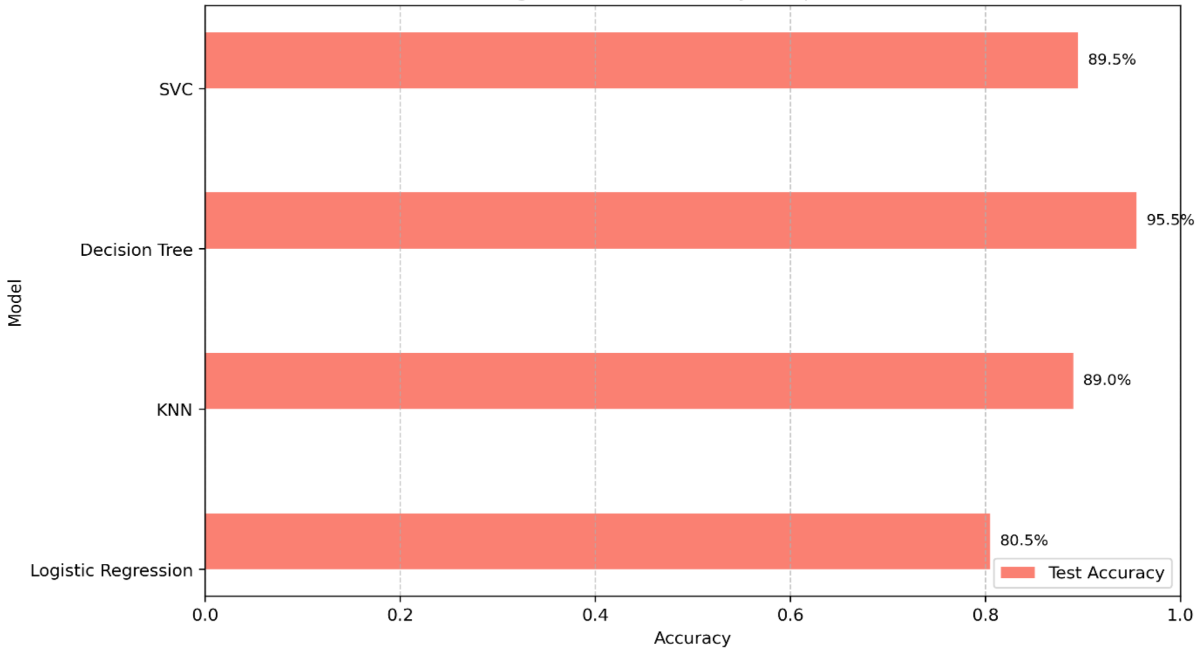


Figure:2 Model Accuracy Comparison



Among these, the **Decision Tree classifier** achieved the best performance in terms of accuracy and interpretability. The model was trained and tested on the synthetic dataset using standard preprocessing steps like normalization and train-test splitting.

Each individual in the synthetic scenario is assigned a severity level by the trained Decision Tree model. This classification serves as a critical input for the bi-objective optimization model, which uses it to prioritize patients and schedule rescue efforts accordingly.

4.2 Bi-Objective Optimization

Allocating resources in the wake of a disaster in a way that minimizes operational expenses and human suffering is crucial. A bi-objective mixed-integer linear programming (MILP) model that simultaneously optimizes two competing goals is used in the study to address this:

1. **Minimize total distance travelled by rescue vehicles** (to reduce response time and fuel use).
2. **Minimize total operational cost**, including expenses for activating relief centers, deploying vehicles, and training rescuers.

The optimization model uses inputs from both the **MCDM (area priority scores)** and **Machine Learning (severity of injured individuals)** components. These inputs are used to assign priorities to districts and patients.

Model Inputs and Parameters:

- **District priority scores**: Obtained from the WASPAS method (MCDM).
- **Injury severity levels**: Predicted using the trained Decision Tree model (ML).
- **Vehicle capacity**: Number of patients a vehicle can transport (e.g., 2).
- **Relief centre capacity and cost**
- **Rescue team availability**
- **Distance matrix** between patients and relief centres
- **Time periods** to allow for phased rescue scheduling

Objective Functions:

1. Z_1: $\boldsymbol{Minimize\ Total\ rescue\ travelling\ distance}$

$$Z_1 = \sum_{\{I\}} \sum_{\{J\}} \sum_{\{M\}} \sum_{\{O\}} \sum_{\{S\}} \sum_{\{L\}} X_{\{i,j,o,m,s,l\}} \cdot D_{\{i,j\}}$$

$X_{\{i,j,o,m,s,l\}}$: $Binary\ variable, 1\ if\ patient\ j\ is\ assigned\ to\ RC\ i\ using\ vehicle\ o\ in\ area\ m\ at\ time\ l\ and\ severity\ s$
$D_{\{i,j\}}$: $Distance\ between\ RC\ i\ and\ patient\ j$

2. Z_2: $\boldsymbol{Minimize\ Total\ Cost}$

$$min\ Z_2: \sum_{\{M\}} A_i \cdot Q_{\{i,m\}} + \sum_{\{I\}} \sum_{\{O\}} \sum_{\{L\}} C_o \cdot N_{\{i,o,l\}} + m \sum_{\{I\}} Y_i \cdot CA_i$$

$Q_{\{i,m\}}$: *Rescuers used at RC i for area m*
A_i: *RF training cost in* i^{th}*RC*
C_o: *Transportation Cost of the vehicle o*
$N_{\{i,o,l\}}$: *Number of vehicles o in* i^{th}*RC during* l^{th}*period*
Y_i: *Binary Variable which gets 1 if RC is active*
CA_i: *the cost of activating the* i^{th}*RC*

Constraints:

$$\sum_{\{I\}} \sum_{\{J\}} \sum_{\{M\}} \sum_{\{O\}} \sum_{\{S\}} \sum_{\{L\}} X_{\{i,j,o,m,s,l\}} \geq F_m\ \forall m \tag{1}$$

Each area m *must receive at least as many rescue assignments as the number of patients* F_m *located there.*

$$L \leq \sum Y_i \leq U \tag{2}$$

The number of active rescue centers should be between a lower limit L *and an upper limit* U

$$\sum_{\{M\}} A_i \cdot Q_{\{i,m\}} + \sum_{\{I\}} \sum_{\{O\}} \sum_{\{L\}} C_o \cdot N_{\{i,o,l\}} + m \sum_{\{I\}} Y_i \cdot CA_i \leq \boldsymbol{B} \tag{3}$$

The total cost (rescuer cost + vehicle cost + activation cost)must be within the buget b

$$\sum_{\{M\}} \sum_{\{J\}} \sum_{\{S\}} X_{\{i,j,o,m,s,l\}} \leq N_{\{i,o,l\}} \times CP_{\{o\}}\ \forall o,i,l \tag{4}$$

The total number of patients assigned per vehicle must not exceed the vehicle capacity

$$\sum_{\{I\}} \sum_{\{J\}} \sum_{\{M\}} \sum_{\{O\}} \sum_{\{S\}} \sum_{\{L\}} X_{\{i,j,o,m,s,l\}} = 1\ \forall j \tag{5}$$

Every patient j *must be assigned to exactly one rescue plan*

$$\sum_{\{S\}} X_{\{i,j,o,m,s,l\}} = 1\ \forall i,j,m,o,l \tag{6}$$

For each assignment, exactly one severity level s *must be chosen*

$$\sum_{\{I\}} \sum_{\{O\}} \sum_{\{M\}} \sum_{\{L\}} X_{\{i,j,o,m,s,l\}} = N_s\ \forall j,s \tag{7}$$

The number of rescuers assigned must match the required number for each severity level.

$$\sum_I Q_{\{i,m\}} \geq \alpha_m\ \forall m \tag{8}$$

Each area m *must receive at least* α_m *rescuers based on priority (e.g., MCDM score).*

Model Assumptions:

1. **All patients are assigned to a relief centre (RC)** to ensure complete rescue coverage.
2. **Patient data is synthetic**, and severity is predicted using a trained ML model, reflecting real-world uncertainty.
3. **Each patient is limited to their 3 nearest RCs**, simulating realistic mobility constraints.
4. **Severe patients must be rescued earlier**, with time limits based on severity levels to reflect medical urgency.

5. Synthetic Scenario Evaluation

To test the proposed methodology in the absence of real-world disaster data, a synthetic scenario was constructed for the state of Mizoram, India. The scenario simulates a hypothetical earthquake event and evaluates disaster response strategies using machine learning, MCDM, and bi-objective optimization.

Mizoram was selected as the case study region because it lies in **Seismic Zone V**, the highest earthquake risk category in India, making it **highly vulnerable to frequent and severe seismic events**. This vulnerability provides a realistic and relevant setting to demonstrate the effectiveness of the proposed framework.

5.1 District Data Preparation

Eleven districts of Mizoram were considered, and key attributes such as population, area size, hazard factor (earthquake risk), and accessibility were assigned to each district. These values were derived from the 2011 census and extrapolated using estimated growth probabilities to reflect more current population scenarios.

The criteria were normalized and ranked using MCDM techniques.

5.2 Multi Criterion Decision Making (MCDM)

Two methods were used:

- **Best-Worst Method (BWM):** To compute the relative importance (weights) of criteria based on expert input or synthetic pairwise comparisons.
- **WASPAS Method:** To aggregate the normalized values using both additive and multiplicative components, providing a ranking of districts by priority.

The final scores were used as area priority weights (α⍰) in the optimization model

District	Area_ID	Population	Area Size	Hazard Factor	Accessibility	WASPAS_Score	Rank
Aizawl	1	400309	3577.00	7	10	0.781367	1
Champhai	3	125745	3185.83	9	7	0.702890	2
Lunglei	2	161428	4536.00	9	6	0.679851	3
Mamit	5	86364	3025.00	8	7	0.636324	4
Serchhip	6	64937	1421.00	7	8	0.631177	5
Saiha	8	56574	1399.00	10	3	0.607730	6
Kolasib	4	83955	1382.00	6	8	0.597058	7
Lawngtlai	7	117894	2557.00	8	4	0.573286	8
Hnahthial	9	28500	1133.00	8	5	0.572594	9
Saitual	11	30000	1500.00	7	7	0.569012	10
Khawzawl	10	28500	1152.00	6	6	0.510333	11

5.3 Machine Learning for Severity Prediction

Synthetic patients were then **randomly generated** across Mizoram by sampling geographical coordinates within the state boundary.
Each patient was also assigned to a district (Area) and described by medically relevant attributes including:

- **Age**, **Gender**, **Blood Pressure**, **Pulse Rate**
- **Injury Type** (e.g., bleeding, fracture, burn)
- **Trapped Duration**, **Consciousness Status**

These features were input to a pre-trained **Decision Tree Classifier** to predict the **severity level** (Very Low: 0, Low: 1, Medium: 2, High: 3, Very High: 4), which then influenced the number of rescuers required per patient in the model.

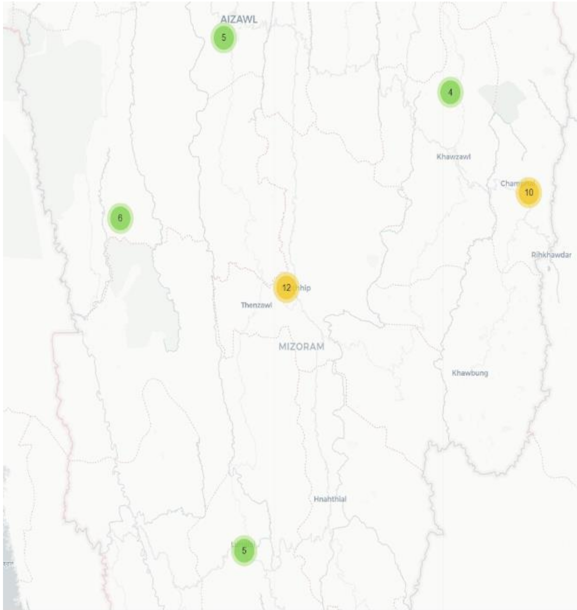
Age	Gender	Pregnancy_Status	Consciousness_Level	Severe_Bleeding	Fractures	Pulse_Rate	Mobility	Trapped_Duration_Hours	Blood_Pressure	Area ID	Condition_Label	AreaName
47	0	1	1	0	0	61	1	5	133	7	1	Lawngtlai
30	0	1	0	1	0	88	0	9	133	4	4	Kolasib
17	0	0	1	0	0	55	1	7	80	4	1	Kolasib
45	0	1	1	1	0	81	1	5	176	3	2	Champhai
25	0	0	1	0	0	57	1	7	91	1	1	Aizawl
33	0	1	1	0	0	58	1	5	139	3	1	Champhai
34	1	0	1	0	0	58	1	9	138	6	0	Serchhip
38	1	0	1	0	0	59	1	5	132	4	0	Kolasib
48	1	0	1	0	0	61	1	9	180	2	0	Lunglei
18	0	0	1	0	1	55	0	11	108	4	3	Kolasib
26	1	0	1	1	0	77	1	6	147	5	1	Mamit
49	0	0	0	1	0	91	0	12	152	7	3	Lawngtlai
17	0	0	1	0	0	55	1	9	120	1	1	Aizawl
39	0	0	1	0	0	59	1	2	141	3	0	Champhai
48	1	0	1	0	0	61	1	4	173	7	0	Lawngtlai
47	1	0	1	0	0	61	1	11	125	7	0	Lawngtlai
41	0	0	1	1	0	80	1	9	135	7	2	Lawngtlai
27	0	0	1	1	0	77	1	1	132	7	1	Lawngtlai
38	1	0	1	0	0	59	1	10	141	2	0	Lunglei
27	0	0	1	0	0	57	1	6	104	6	1	Serchhip
36	0	0	1	0	0	59	1	1	139	7	0	Lawngtlai
3	1	0	1	0	0	52	1	1	80	5	1	Mamit
14	0	0	1	0	0	54	1	5	114	2	0	Lunglei
37	1	0	1	0	0	59	1	8	135	1	0	Aizawl
52	0	1	1	0	0	62	1	5	172	3	2	Champhai
37	0	0	0	1	1	89	0	8	155	1	4	Aizawl
54	1	0	0	1	0	92	1	11	171	7	2	Lawngtlai
40	1	0	1	1	0	80	1	10	155	4	1	Kolasib

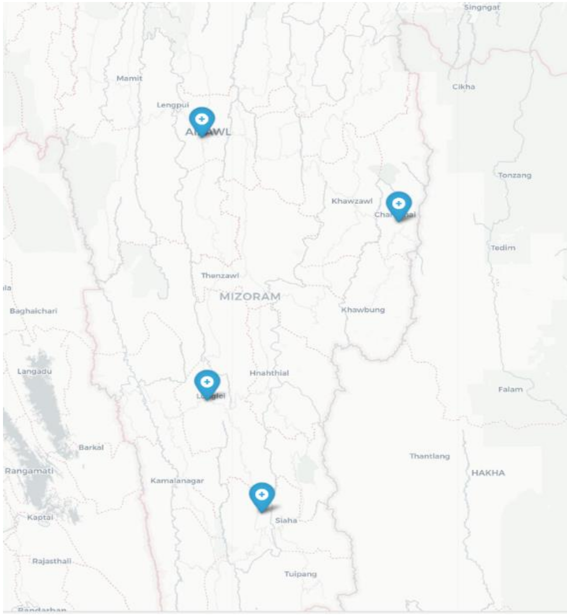
5.4 Bi-Objective Model

To evaluate the emergency response planning, a bi-objective mixed-integer programming model was built using **Pyomo** and solved using Gurobi optimizer.

Four Relief Centres (RCs) were predefined at key district capitals:

- **Aizawl**, **Lunglei, Champhai**, and **Lawngtlai**
- Their real-world latitude and longitude coordinates were used as fixed RC locations.





The optimization model aimed to:

- **Minimize rescue distance (Z_1)**
- **Minimize total operational cost (Z_2)**
- **Optimize trade-off via LP-Metric (Z_3)**

A **combined objective function** (**Z_3**) was tested to balance Z_1 and Z_2 using **LP-Metric**:

The **LP-metric (Z_3)** measures the Euclidean distance between the current solution and the **ideal point** (Z_1*, Z_2*). It is calculated as:

$$Z_3 = W_1 \times \frac{[z_1^* - z_1]}{[z_1^* - z_1^{-1}]} + W_2 \frac{[z_2^* - z_2]}{[z_1^* - z_2^{-2}]}$$

where:

- Z_1*, Z_2* = Best possible values (ideal)
- Z_1^{-1}, Z_2^{-2} = Worst observed values

This metric helps **compare trade-offs** between cost and distance in a unified way.

Patient–RC assignments, rescuer planning, and vehicle deployment were optimized under constraints related to:

- **District-level demand** (based on MCDM-prioritized area needs),

- **Budget availability** for RC activation, training, and transportation,
- **Vehicle capacities** based on type and assigned routes,
- **Rescuer availability and limits per RC**,
- **Minimum and maximum number of active RCs**,
- **Severity-dependent rescuer requirement per patient**,
- **RC accessibility restricted to 3 nearest RCs per patient**, and
- **Binary and integer enforcement for all decision variables** (e.g., RC activation, assignments, rescuer counts).

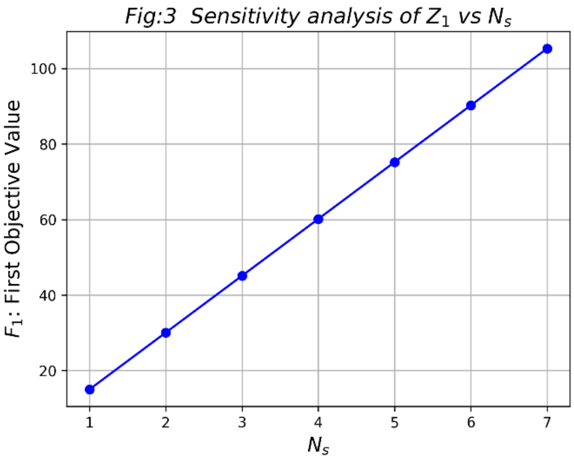
The LP-metric (Z_3) was calculated using normalized Z_1 and Z_2 values across multiple test problems with increasing distance between patients and relief centers in order to compare trade-offs between cost and distance.

	Z1* (×10 m)	Z1_worst (×10 m)	Z2* (×10^3 ₹)	Z2_worst (×10^3 ₹)	Z1_combined (×10 m)	Z2_combined (×10^3 ₹)	Z3
0	2.2755	3.1985	13.6397	50.2551	3.1985	13.6397	0.500000
1	863.6355	864.9230	185.9846	219.9271	864.9125	185.9825	0.495891
2	1725.9345	1727.2130	358.4426	392.3869	1727.2130	358.4426	0.500000
3	2588.2345	2589.5130	530.9026	564.8469	2589.5130	530.9026	0.500000
4	3450.5350	3451.8125	703.3625	737.3070	3451.8125	703.3625	0.500000
5	4312.8335	4314.1125	875.8225	909.7667	4314.1125	875.9225	0.501473
6	5175.1330	5176.4105	1048.3821	1082.2266	5176.4105	1048.2821	0.498523

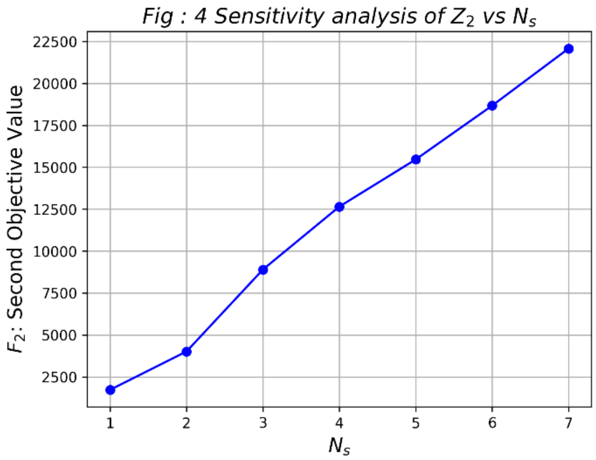
However, because Z_1 was calculated using simplified Euclidean distances rather than actual road networks, Z_1_combined stayed close to Z_1_worst in this artificial setup. Because of this, Z_3 exhibited little change across test problems, staying at or near 0.5. This emphasizes the significance of improved distance modeling and objective scaling in real-world applications by showing that the LP-metric may become less informative when one objective lacks dynamic range.

6. Sensitivity Analysis

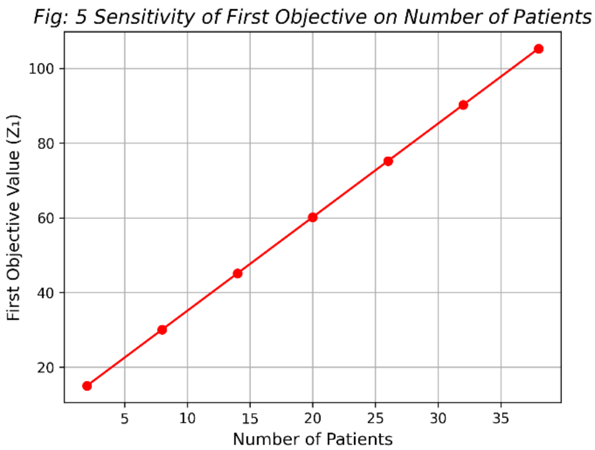
To assess the robustness and responsiveness of the proposed optimization model, sensitivity analysis was performed by varying key parameters and observing their impact on the objectives (Z_1: distance, Z_2: cost) and resource allocation (vehicles and rescuers). The following scenarios were analyzed:



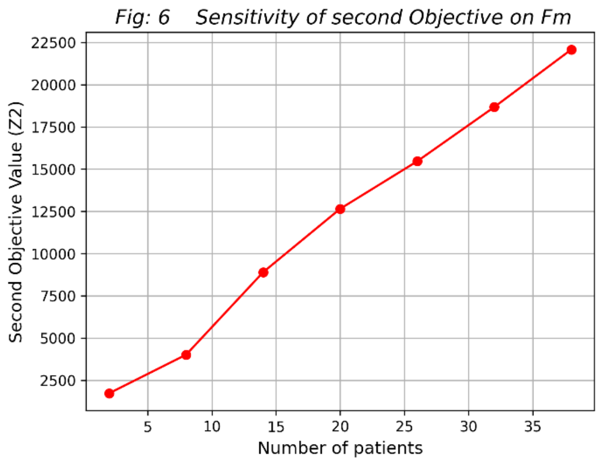
Z_1 vs N_s – Rescue distance increases as more rescuers are required per patient severity



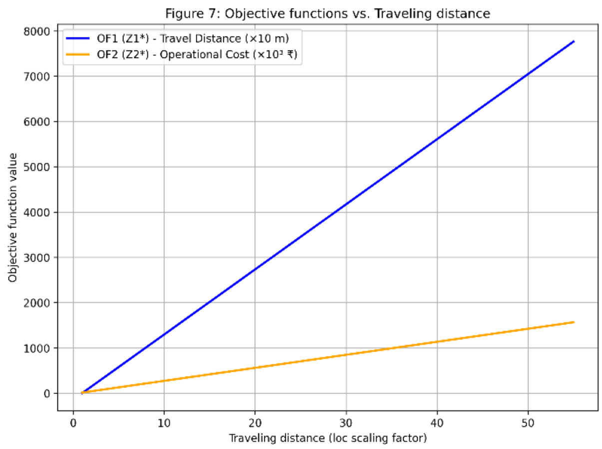
Z_2 vs N_s – Operational cost rises with increasing rescuer demand per severity level.



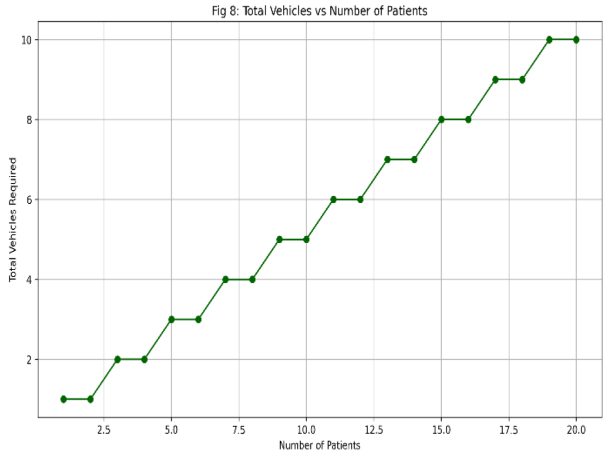
Z_1 vs Number of Patients – Rescue distance increases with more patients to serve.



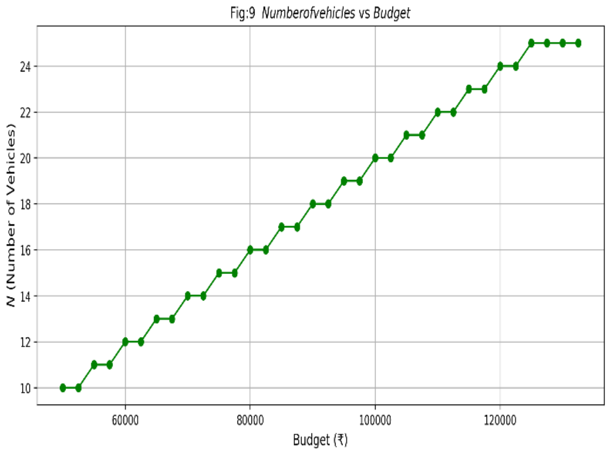
Z_2 vs Number of Patients – Total operational cost rises with increasing patient count.



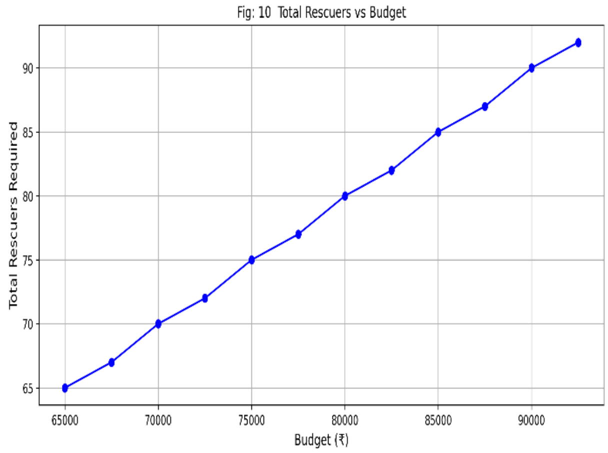
Z_1 and Z_2 vs Patient–RC Distance – Both distance and cost increase as travel distance to patients grows.



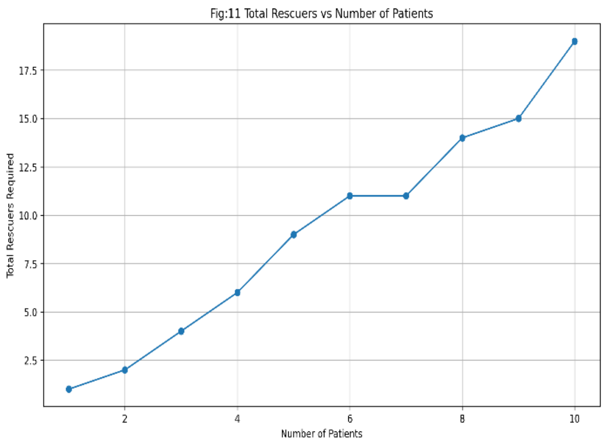
Total Vehicles vs Number of Patients – More patients require a proportional increase in deployed vehicles.



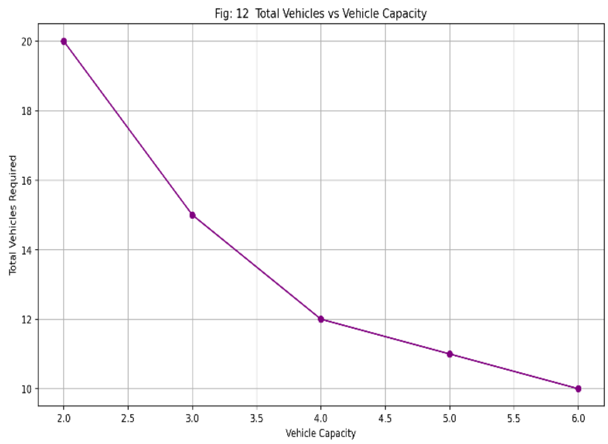
Total Vehicles vs Budget – Higher budgets enable deployment of more vehicles for rescue operations.



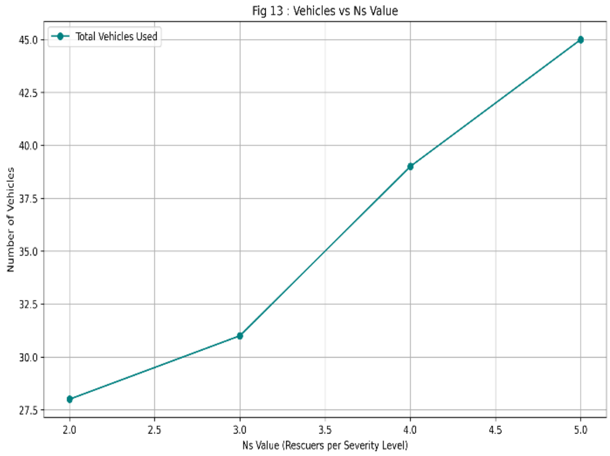
Total Rescuers vs Budget – The number of rescuers increases with available budget, enhancing service coverage.



Total Rescuers vs Number of Patients – More patients require a larger rescuer workforce to meet demand.



Total Vehicles vs Vehicle Capacity – Fewer vehicles are needed as vehicle capacity increases.



Total Vehicles vs N? – As rescuer requirements per severity rise, more vehicles are deployed to meet transport constraints.

Figure Summary – Sensitivity Analysis

FIGURE	PLOT TITLE	DESCRIPTION
FIG:3	Z_1 vs N_s	Rescue distance increases with more rescuers required per patient severity.
FIG:4	Z_2 vs N_s	Operational cost rises as rescuer demand per severity level increases.
FIG:5	Z_1 vs Number of Patients	More patients lead to longer total rescue distances.
FIG:6	Z_2 vs Number of Patients	Total cost grows with increasing number of injured individuals.
FIG:7	Z_1 & Z_2 vs Patient–RC Distance	Both distance and cost increase as travel distance to patients increases.
FIG:8	Total Vehicles vs Number of Patients	More patients require a proportional increase in deployed vehicles.
FIG:9	Total Vehicles vs Budget	Higher budgets allow more vehicles to be used.
FIG:10	Total Rescuers vs Budget	Additional budget enables deployment of more rescuers.
FIG:11	Total Rescuers vs Number of Patients	More patients lead to higher rescuer requirements.
FIG:12	Total Vehicles vs Vehicle Capacity	Fewer vehicles are needed as each vehicle's capacity increases.
FIG:13	Total Vehicles vs N_s	As rescuer need per severity increases, more vehicles are dispatched.

7.Conclusion and Future Work

This study combined machine learning, bi-objective optimization, and multi-criteria decision-making (BWM and WASPAS) to present an integrated decision-support framework for post-disaster humanitarian logistics. For Mizoram, synthetic scenarios were developed that simulated resource allocation and rescue operations using patient data, including severity levels predicted by a decision tree classifier, and district priority scores. Under real-world-inspired constraints such as budgetary limitations, vehicle capacity, and district-level rescue demand, the optimization model effectively reduced rescue distance and operational cost.

We used sensitivity analysis to examine the effects of important factors on overall distance, cost, vehicle use, and rescuer allocation, including the number of patients, severity profiles, and budget. The findings revealed consistent patterns, with resource requirements increasing in tandem with patient severity or volume. But some indicators, like the LP-metric (Z_3), were less sensitive because of the simplified synthetic setup (e.g., Euclidean distance instead of road networks), underscoring the significance of precise spatial modeling.

Future improvements include incorporating real-world geospatial data via GIS, using dynamic and uncertain parameters such as injury progression and blocked roads, and expanding the model to support multiple vehicle types and routes. Integrating fairness constraints and real-time updates could enhance equity and responsiveness, making the model more suitable for actual disaster response systems. As a potential extension, patient and logistics data from real disaster events—such as **Cyclone Remal**, which impacted Mizoram in 2024—could be used to validate and calibrate the model under realistic conditions.

References

Behl, A. and Dutta, P. (2019). Humanitarian supply chain management: a thematic literature review and future directions of research. *Annals of Operations Research*, 1001–1044.

Brintrup, A. P. (2020). Supply chain data analytics for predicting supplier disruptions: a case study in complex asset manufacturing. *International Journal of Production Research*, 3330–3341.

Budak, A. K. (2020). Real-time location systems selection by using a fuzzy MCDM approach: an application in humanitarian relief logistics. *Applied Soft Computing*, 106322.

Choudhary, A. G. (2023). Designing a post-disaster humanitarian supply chain using machine learning and multi-criteria decision-making techniques. *Kybernetes*.

Gurobi Optimization, L. (n.d.). *Gurobi Optimizer Version 11.0*. Retrieved from https://www.gurobi.com

Hart, W. L.-P. (2017). *Pyomo – Optimization Modeling in Python.* Springer.

India, C. (2011, June). *Mizoram Population (2011)*. Retrieved from https://censusindia.gov.in/2011census/dchb/DCHB.html

Oloruntoba, R., Gray, R. (2006). Humanitarian aid: an agile supply chain? *Supply Chain Management: An International Journal*, 115–120.

Pedregosa, F. e. (2011, June 30). *Scikit-learn: Machine Learning in Python*. Retrieved from https://scikit-learn.org

Sarma, D. D. (2020). An optimal redistribution plan considering aftermath disruption in disaster management. *Soft Computing*, 65–82.

Wikipedia. (n.d.). *Mizoram Population Projection (2024)*. Retrieved from https://en.wikipedia.org/wiki/Mizoram