

RESCUE: Real world
Emergency Solutions for
Crisis Response Vehicle
and Urgent Evacuation
Routing

PROBLEM

DAMAGED ROADS Block EMS Access



Figure 1: Japan 2011 Earthquake [1]

- After the Arasbaran twin earthquakes in Iran, **damaged roads caused severe EMS delays, preventing timely medical response.**
- In Japan's 2011 earthquake, **70% of roads were damaged** within the first 24 hours, making it nearly impossible for ambulances to reach victims

RESOURCE SHORTAGE Force Prioritization



Figure 2: Ontario Emergency Responders [8]

- Longer EMS response times significantly increase fatality rates in disaster scenarios.
- Disaster response teams often lack clear information on victim severity (unknown triages), leading to inefficient ambulance dispatch.

HOSPITAL OVERCROWDING Delays Care



Figure 3: Overcrowded Hospital [2]

- Hospital **bed occupancy reaches 80%** during disasters, leading to severe overcrowding for at least **72 hours^[4]**.
- An Australian study found that emergency department overcrowding directly increases mortality, estimating **13 preventable deaths per year** due to overwhelmed hospitals^[9].

LIMITED SPECIFIC Vehicle Routing



Figure 4: Dutch Ambulance Motorcycle [3]

- A study evaluating 1664 patients, with 468 from motorcycle response vehicles, found that **MRVs reduced response times by 54 seconds^[12]** on average.
- **Over 10 countries** use motorcycle ambulances but are **often ignored in routing**.

OBJECTIVES

Develop an optimized pathway-finding solution for multiple emergency vehicles, designed to minimize risk and maximize response speed in realistic disaster environments.

The research focused on:

- evaluating the performance of various routing algorithms to determine the most effective ones for different realistic scenarios
- assessing the impact of key realistic parameters and conditions on response time efficiency to enhance the planning and preparation of resources and responses.

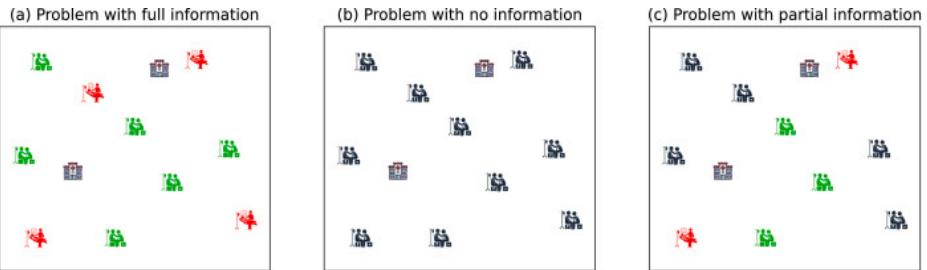


Figure 5: Triage Problem [10]

Efficient	Scalable	Realistic	Safe
<ul style="list-style-type: none">• Minimize response time while accounting for road damage, vehicle capabilities, and hospital capacities.• Prioritize critical (red) patients while adapting to unknown victim conditions (partial triages).	<ul style="list-style-type: none">• Perform effectively in various locations.• Handle varying numbers of victims, emergency vehicles, road damage levels, and temporary hospital placements.• Compute optimal routing solutions within minutes to enable real-time disaster response.	<ul style="list-style-type: none">• Incorporate real-world population density and hospital data from OSMnx for accurate modeling.• Simulate road damage using spatial smoothing techniques.	<ul style="list-style-type: none">• Reduce vehicle breakdown risks by avoiding severely damaged roads.• Optimize routes by balancing response time with road safety and vehicle durability.

Disaster Response Vehicle Routing Solution

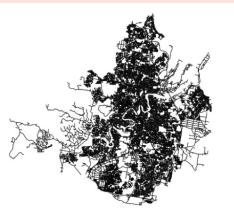
INPUT VARIABLES

LOCATION

URBAN

Brisbane,
Australia

Figure 6:Brisbane Road Network created by Student using OpenStreetMap



Chicago,
Illinois

Figure 7:Chigago Road Network created by Student using OpenStreetMap



Guadalajara,
Mexico

Figure 8:Guadalajara Road Network created by Student using OpenStreetMap



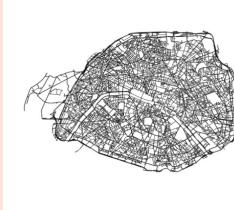
Phoenix,
Arizona

Figure 9 :Phoenix Road Network created by Student using OpenStreetMap



Paris,
France

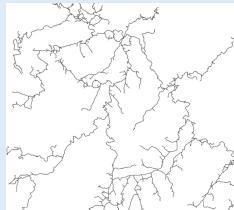
Figure 10 :Paris Road Network created by Student using OpenStreetMap



SUBURBAN

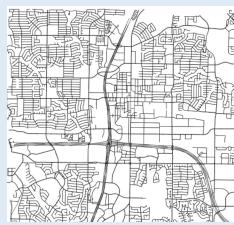
Soreang,
Indonesia

Figure 11 :Soreang Road Network created by Student using OpenStreetMap



Plano, Texas

Figure 12: Plano Road Network created by Student using OpenStreetMap



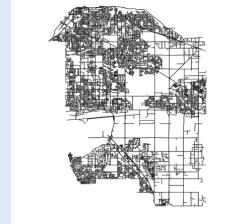
Reading, UK

Figure 13: Reading Road Network created by Student using OpenStreetMap



Surrey, British Columbia, Canada

Figure 14: Surrey Road Network created by Student using OpenStreetMap



Petaling Java,
Malaysia

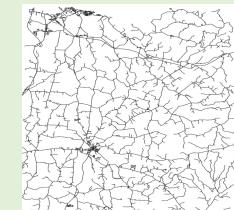
Figure 15: Petaling Java Road Network created by Student using OpenStreetMap



RURAL

Mason County,
Kentucky

Figure 16: Mason Road Network created by Student using OpenStreetMap



Dawson County,
Alaska

Figure 17: Dawson Road Network created by Student using OpenStreetMap



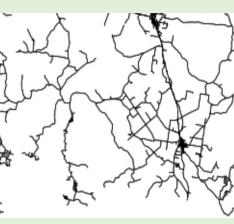
Westlake, Florida

Figure 18: Westlake Road Network created by Student using OpenStreetMap



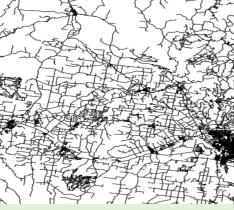
Nova Scotia,
Canada

Figure 19: Nova Scotia Road Network created by Student using OpenStreetMap



Boonah,
Australia

Figure 20: Boonah Road Network created by Student using OpenStreetMap



ROAD DAMAGE CONDITION

Minor Road Damage

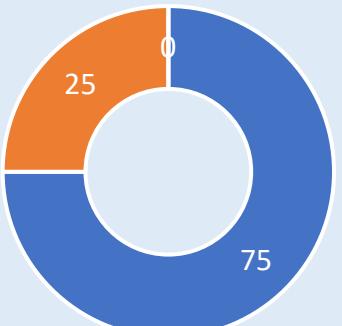


Figure 21a: Percentage of Road Scores based on Road Damage Type. Graph created by student, 2025

Medium Road Damage

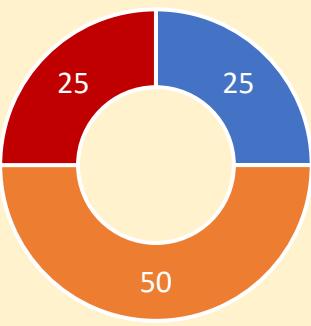


Figure 21b: Percentage of Road Scores based on Road Damage Type. Graph created by student, 2025

Major Road Damage

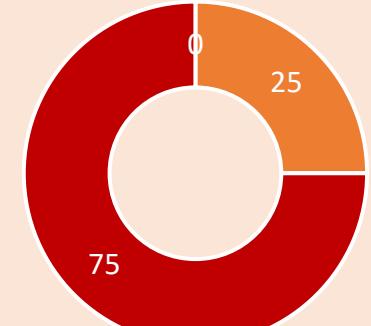
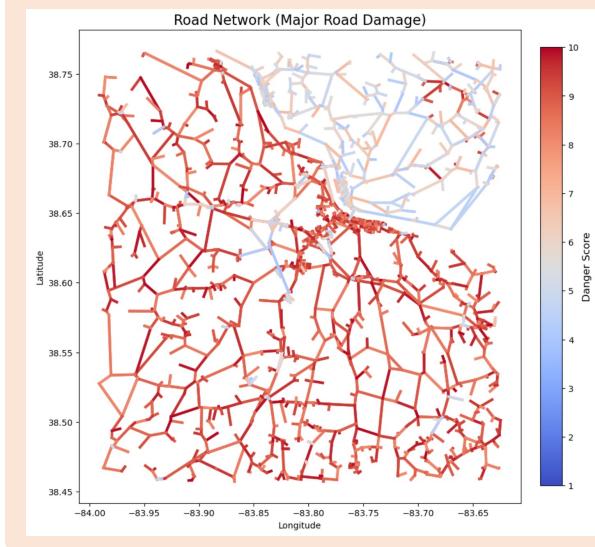
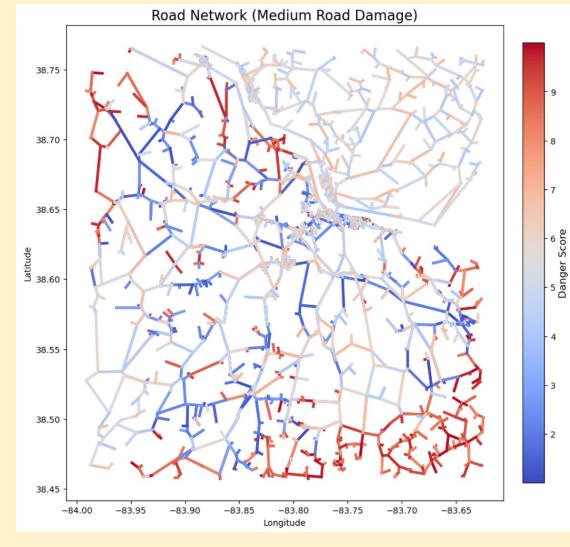
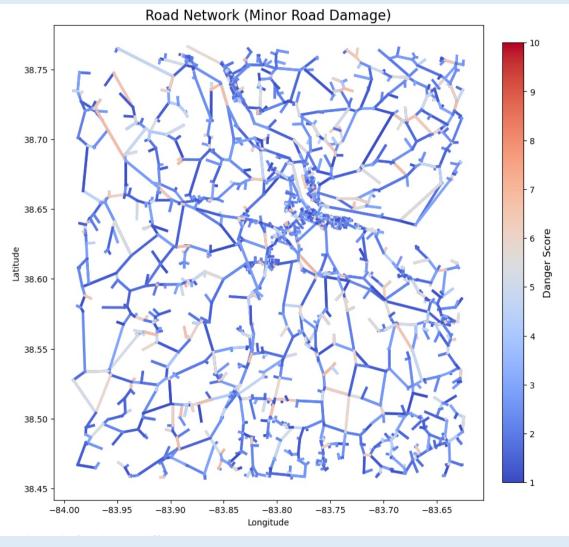


Figure 21c: Percentage of Road Scores based on Road Damage Type. Graph created by student, 2025



█ Roads with scores 1-3, little to no road damage.

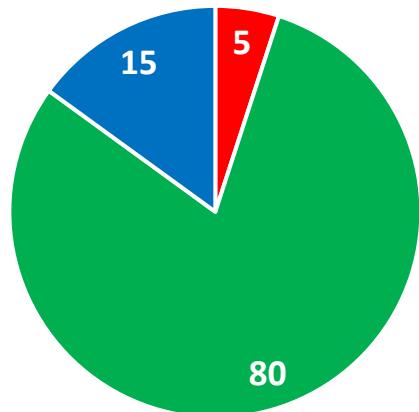
█ Roads with scores 4-7, moderate amount of road damage.

█ Roads with scores 8-10, unpassable by certain vehicles and unsafe.

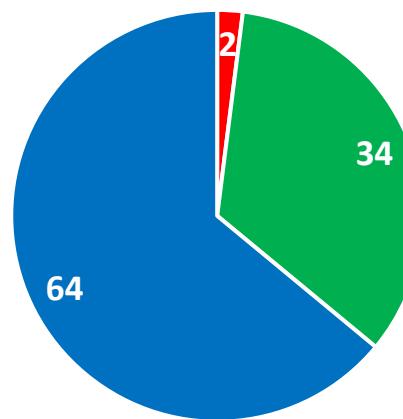
Figure 22: Road Networks for County. Graph created by student using OpenStreetMaps, 2025

VICTIM TRIAGE STATUS

Triage Split 1
(Higher information available)



Triage Split 2
(Lower information available)



- Red (Critical) Victims %: These victims must be transported to a hospital immediately for treatment.
- Green Victims %: These victims can either receive treatment on-site within 5 minutes or can be transported to a hospital at a later time, as their condition is not immediately life-threatening
- Unknown Victims %

Figure 23: Triage Splits Considered
Graph created by student, 2025

TEMPORARY HOSPITAL COUNT

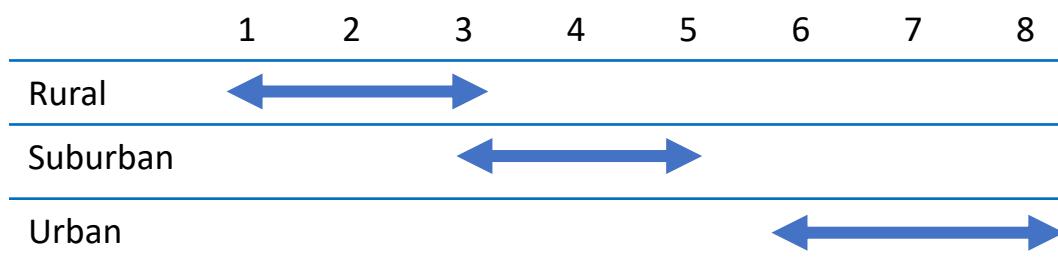


Figure 24. Temporary Hospitals Count in each location type
(Patient capacities: 10-15 at each temporary hospital)
Created by Student, 2025

These temporary hospitals are integrated into the existing healthcare network alongside permanent hospitals to reduce patient overload and minimize ambulance rerouting delays.

EMERGENCY VEHICLE TYPES

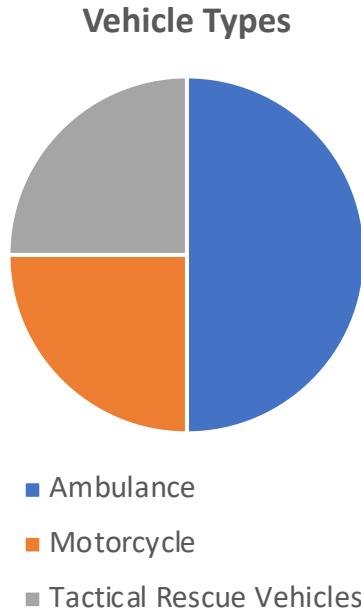


Figure 28: Vehicle Types Split
Graph created by student, 2025

	AMBULANCE	Motorcycle Ambulance (MRVs)	Tactical Rescue Vehicles
Speed (m/s)	15	25	10
Road Damage Capacity	5	10	7
Patient Capacity	6	1	8

Table 1: Information about Each Vehicle Type
Table created by student, 2025

FLOWCHART

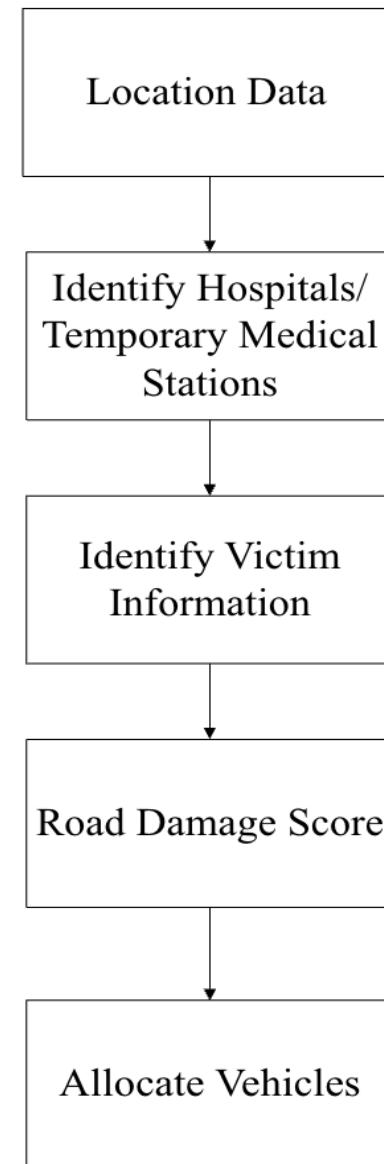
REAL-WORLD

- Check EMS and hospital systems for capacity, and use government/NGO data.
- Utilize GIS, crowdsourcing, and field reports for real-time tracking.
- Integrate APIs to monitor hospital and temporary medical station capacities.

Use **911 calls and in-person emergency responder reports** for victim locations and triage/severity (red, green, unknown).
Supplement with drone imagery if necessary.

Use **UAV/drone imagery** to assess road damage.
Incorporate **reports from disaster response teams** to evaluate road damage scores.

Check with hospitals and emergency responders for **vehicle information**.
Gather details on vehicle types, capacities, speeds, and maximum passable damage scores.



SIMULATED REAL-WORLD

Select 15 random areas covered by OpenStreetMap:
- 5 Urban Areas
- 5 Suburban Areas
- 5 Rural Areas

- Pull permanent hospital location data from OpenStreetMap.
- Randomly assign locations for temporary hospitals and map them to the nearest road node.
- Assign capacity values to each hospital.

- Set the number of victims as **0.1% of the population**.
- Split victims into three triage categories: red, green, and unknown.
- Randomly assign each victim a location.

- Assign each road a random damage score from **1 to 10**.
- Apply a smoothing filter five times to simulate realistic disaster conditions.

- Randomly assign a set number of vehicles.
- The 3 vehicle types are: **ambulances, motorcycles, and tactical rescue vehicles**.
- Each vehicle has specific attributes:
 - Maximum road damage score
 - Speed
 - Capacity

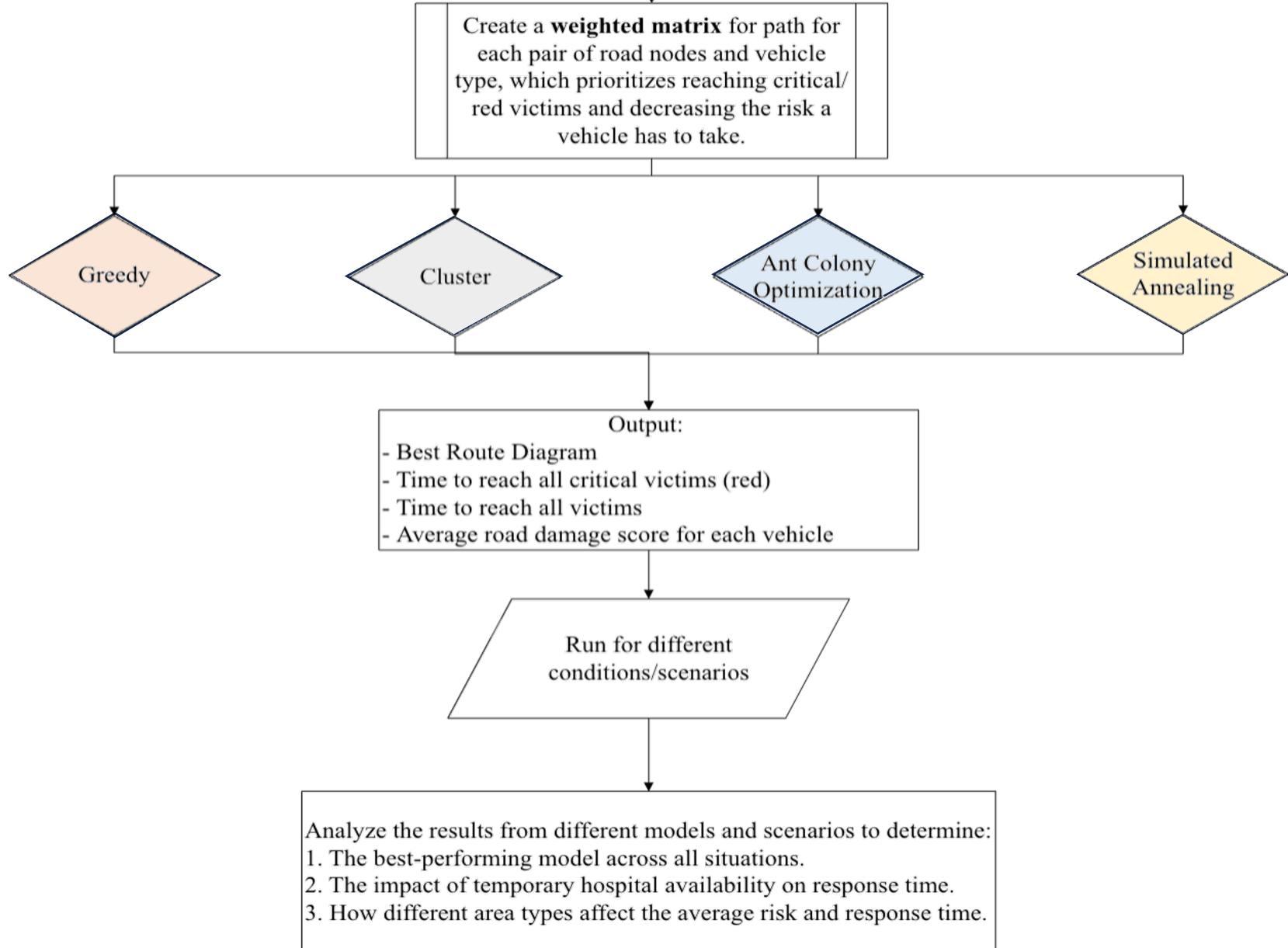


Figure 29 : Flowchart of Process
Flowchart created by Student using Visio, 2025

FUNCTION DEFINITIONS

Path Cost Function	Time Function
<p>The score for a given pair of nodes i and j, and a vehicle is defined as:</p> $\text{Score}(i, j, \text{vehicle}) = \frac{T(P, \text{vehicle}) + 1.5 \cdot R(P, \text{vehicle})}{3 \cdot R_j + 2 \cdot U_j + G_j} \quad \begin{array}{l} \text{Equation 1: Path Cost Function} \\ \text{Equation created by student} \\ \text{using Overleaf, 2025} \end{array}$ <p>where:</p> <ul style="list-style-type: none"> • P is the path from node i to node j. • $T(P)$ is the travel time for path P. • $R(P, \text{vehicle})$ is the road damage score for path P and the vehicle. • R_j, U_j, and G_j are the numbers of red, unknown, and green victims at node j, respectively. 	<p>The travel time for a given path P and vehicle is defined as:</p> $T(P, \text{vehicle}) = \frac{\sum_{e \in P} d(e)}{\text{vehicle.speed}()} \quad \begin{array}{l} \text{Equation 2: Time Function} \\ \text{Equation created by student} \\ \text{using Overleaf, 2025} \end{array}$ <p>where:</p> <ul style="list-style-type: none"> • $d(e)$ is the length of edge e. • vehicle.speed is the speed of the vehicle.
Road Damage Function	Objective Function
<p>For a given path P and vehicle:</p> $R(P, \text{vehicle}) = \frac{\sum_{e \in P} S(e, \text{vehicle})}{d_{\text{total}}} \quad \begin{array}{l} \text{Equation 3: Road Damage} \\ \text{Function} \\ \text{Equation created by student} \\ \text{using Overleaf, 2025} \end{array}$ <p>where $S(e, \text{vehicle})$ is defined as:</p> $S(e, \text{vehicle}) = \begin{cases} 999999, & \text{if } \text{vehicle.road_damage_capacity} < \text{road_damage}(e) \\ r(e) \cdot d(e), & \text{if } \text{vehicle.road_damage.capacity} \geq \text{road_damage}(e) \end{cases}$ <p>where:</p> <ul style="list-style-type: none"> • $r(e)$ is the road damage score of edge e. • $d(e)$ is the length of edge e. • $d_{\text{total}} = \sum_{e \in P} d(e)$ is the total path distance. 	<p>Current(v) = $\begin{cases} \sum_i \text{Victims assigned to vehicle } v_i, & \text{while en route (before drop-off)} \\ 0, & \text{after delivering victims to hospital } h \end{cases}$</p> <p>Curr($h$) $\leq \text{cap}(h), \quad \forall h \in H$</p> <p>where H is the set of all hospitals, and $\text{cap}(h)$ is the capacity of hospital h.</p> $\text{Total victims} = \sum_{h \in H} \text{cap}(h) \quad \begin{array}{l} \text{Equation 4: Objective Function} \\ \text{Equation created by student using} \\ \text{Overleaf, 2025} \end{array}$ <p>Main goal: $\min (\text{time_red} + \text{time_all}) + 1.5 \cdot (R_{\text{avg}})$</p> <p>where:</p> <ul style="list-style-type: none"> - time_red is the time to reach red/critical victims, - time_all is the time to reach all victims, - R_{avg} is the average risk score for all vehicles.

ROUTING ALGORITHMS

Greedy Algorithm

What it is: A heuristic approach that makes locally optimal choices at each step. Prioritizes victims with the smallest score (a weighted average of risk on that path and time it takes). Drops off victims at the nearest hospital with capacity when hitting a red victim or reaching vehicle capacity. Updates hospital and vehicle capacities dynamically.

Key Formula:

For a given vehicle v , the greedy algorithm selects the next node j^* such that the score is minimized:

$$j^* = \min_{j \in \text{UnvisitedNodes}} \text{Score}(i, j, \text{vehicle})$$

Equation 5: Greedy Formula
Equation created by student using Overleaf, 2025

Incorporation:

- Implemented as the baseline routing system.
- Vehicles iteratively select the nearest victim based on the score formula, update routes, and drop off at hospitals when necessary.

Cluster-Based Routing

(K-Means + Hungarian Algorithm)

What it is: Combines K-Means clustering (Euclidean distance) and the Hungarian Algorithm. Victims are grouped into clusters, and hospitals are assigned to clusters using the Hungarian Algorithm. Greedy routing is applied within each cluster. If a cluster finishes early, vehicles assist other clusters by targeting the lowest-score unreachd victim.

Key Formulas:

K-Means Clustering: Minimizes the sum of squared Euclidean distances between victims and cluster centroids:

$$\text{Cost} = \sum_{i=1}^k \sum_{x \in C_i} |x - \mu_i|^2$$

Equation 6: K-Means Clustering
Equation created by student using Overleaf, 2025

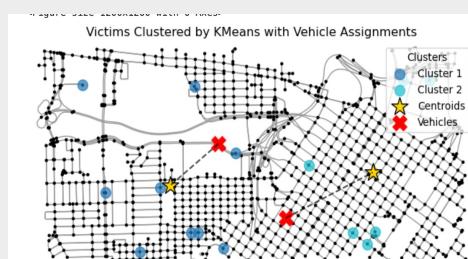
C_i = Cluster i
 μ_i = Centroid of cluster i

Hungarian Algorithm: Optimally assigns hospitals to clusters by minimizing the total assignment cost.

Incorporation:

- Used K-Means to partition victims into clusters.
- Applied the Hungarian Algorithm to assign hospitals to clusters optimally.
- Ran Greedy routing within each cluster and added logic for inter-cluster assistance.

Figure 30 : Example of K-Means Clustering and Hungarian Algorithm
Graph created by student using Python, 2025



Simulated Annealing

What it is: A metaheuristic optimization algorithm that starts with a Greedy solution. Explores the solution space by swapping routes, reordering victims, or moving victims between routes. Minimizes total score by accepting worse solutions probabilistically (based on temperature) to escape local optima.

Key Formulas:

Acceptance Probability: A worse solution is accepted with probability:

$$P(\text{accept}) = e^{\left(\frac{-\Delta E}{T}\right)} \quad \text{Equation 7: Acceptance Probability}$$

Equation created by student using Overleaf, 2025

where ΔE is the change in energy (or cost) between the new and old solutions, and T is the current temperature.

Cooling Schedule: The temperature is updated according to the formula:

$$T_{\text{new}} = T_{\text{old}} \cdot \text{cooling_rate} \quad \text{Equation 8: Cooling Schedule}$$

Equation created by student using Overleaf, 2025

Incorporation:

- Started with Greedy solution as the initial state.
- Defined three neighborhood operations:

swap_routes: Swap routes between vehicles.

swap_order: Reorder victims within a route.

victim_change: Move a victim to a different route.

- Repeated for 1,000 iterations with cooling rate and temperature decay to

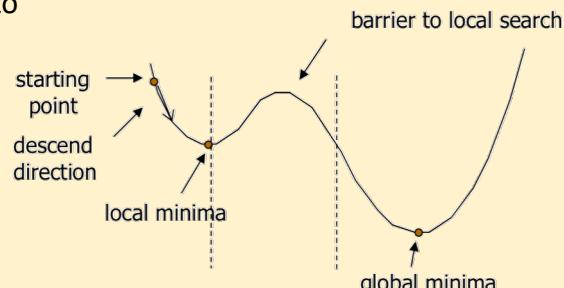


Figure 31: Graphic of Simulated Annealing

Note. From ResearchGate. (2025, February 14). Research on logistics distribution vehicle path optimization based on simulated annealing algorithm - Scientific figure. Retrieved from https://www.researchgate.net/figure/Principle-of-the-simulated-annealing-algorithm_fig5_360434054

Ant Colony Optimization

What it is: A bio-inspired optimization algorithm mimicking ant foraging behavior. Ants (vehicles) probabilistically construct routes based on pheromone trails and heuristic information (e.g., victim scores). Pheromones are updated based on route quality, reinforcing better solutions over iterations.

Key Formulas:

Incorporation:

Implemented pheromone matrices for each vehicle type.

Defined probabilistic victim selection based on pheromone levels and heuristic information. Updated pheromones after each iteration to reinforce high-quality routes.

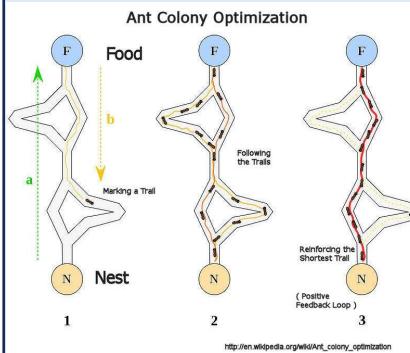


Figure 32: Ant Colony Optimization

Note. From 1Hive Forum. (n.d.). Image of Ant Colony. Retrieved January 3, 2025, from <https://forum.1hive.org/uploads/default/original/2X/7/7448c9ae3fce8c5fc21f2f404ebde21805adb95.jpeg>

1. Transition Probability:

$$P_{ij} = \frac{\tau_{ij}^\alpha \cdot \eta_{ij}^\beta}{\sum_{k \in N_i} \tau_{ik}^\alpha \cdot \eta_{ik}^\beta}$$

Where:

- P_{ij} = Probability of moving from i to j
- τ_{ij} = Pheromone level on (i, j)
- η_{ij} = Heuristic value for (i, j)
- α, β = Influence factors for pheromone and heuristic
- N_i = Set of neighbors of node i

2. Heuristic Information:

$$\eta_{ij} = \frac{1}{\text{Score}(i, j, v_k)}$$

3. Pheromone Update (Evaporation):

$$\tau_{ij}(t+1) = (1 - \rho) \cdot \tau_{ij}(t) + \Delta\tau_{ij}(t)$$

Where:

- $\tau_{ij}(t)$ = Pheromone on (i, j) at time t
- ρ = Evaporation rate
- $\Delta\tau_{ij}(t)$ = Pheromone deposit on (i, j) at time t

4. Pheromone Deposit:

$$\Delta\tau_{ij}(t) = \begin{cases} \frac{Q}{L_k} & \text{if edge } (i, j) \text{ is in ant's tour} \\ 0 & \text{otherwise} \end{cases}$$

Where:

- Q = Constant pheromone amount
- L_k = Path length of ant k

5. Global Update Rule:

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \Delta\tau_{ij}^{\text{global}}$$

Where:

- $\Delta\tau_{ij}^{\text{global}}$ = Pheromone from best solution

Equation 9: Ant Colony Optimization Formulas
Equation created by student using Overleaf, 2025

EXAMPLE RESULTS

Location: Rural

Triage: 5/80/15

Temporary Hospital: 3

Road Damage: Medium

Greedy Algorithm

Greedy Ambulance Routing with Vehicle Paths, Hospitals, and Victims

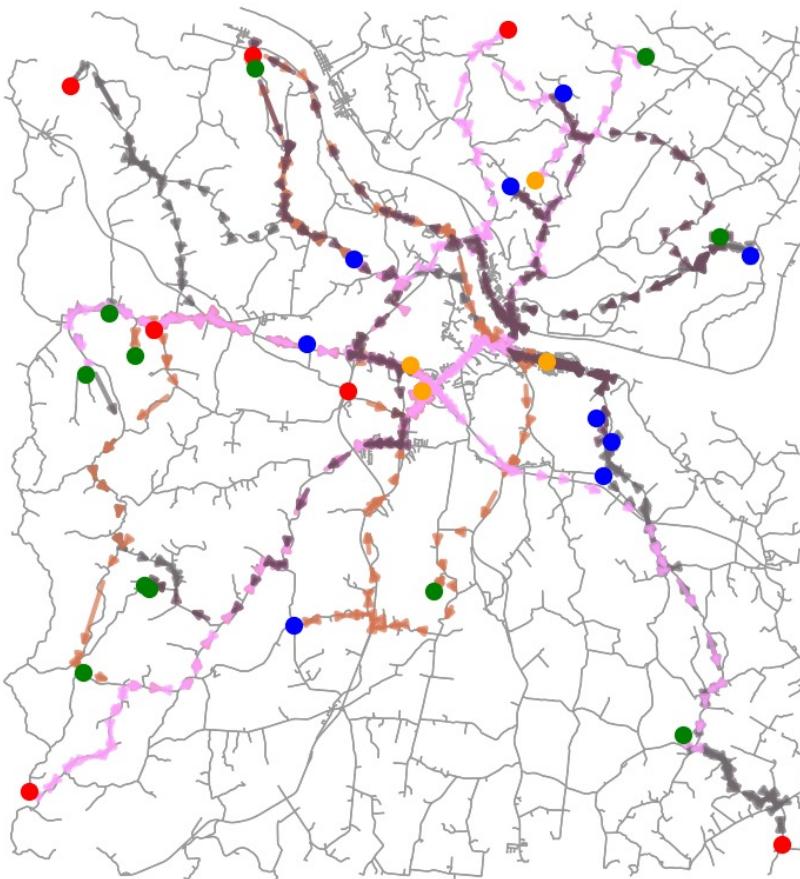


Figure 33: Greedy Optimization Vehicle Routing
Graph created by student using Python, 2025

Cluster-Based Routing (K-Means + Hungarian Algorithm)

Cluster Vehicle Routing with Routes, Hospitals, and Victims

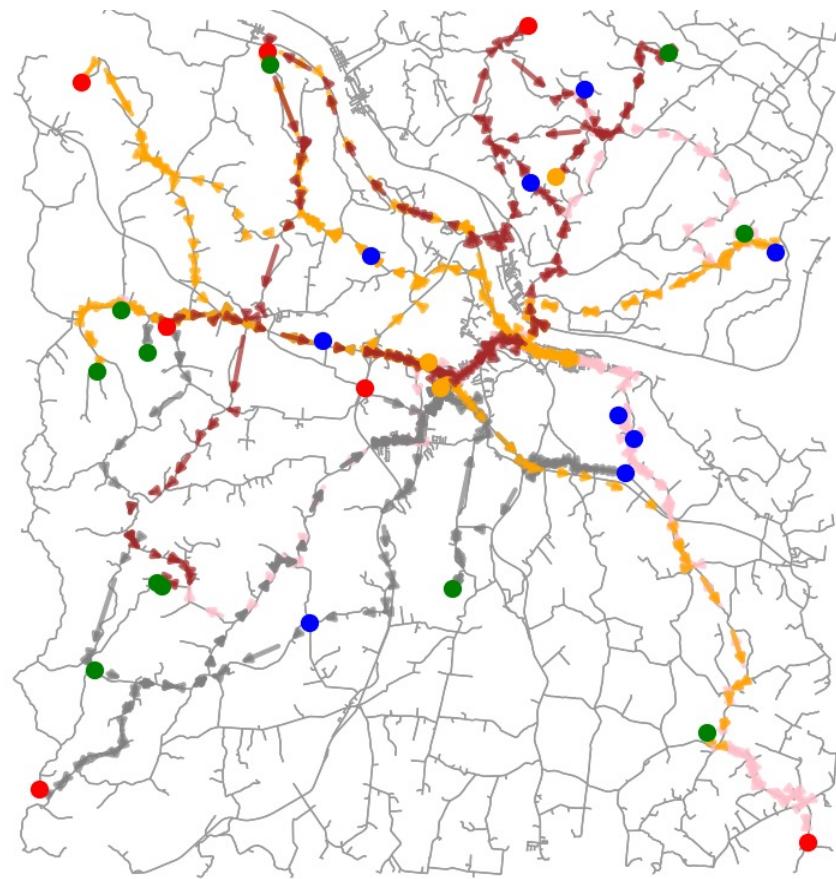


Figure 34: Cluster Optimization Vehicle Routing
Graph created by student using Python, 2025

Simulated Annealing

Simulated Annealing Vehicle Routing with Routes, Hospitals, and Victims

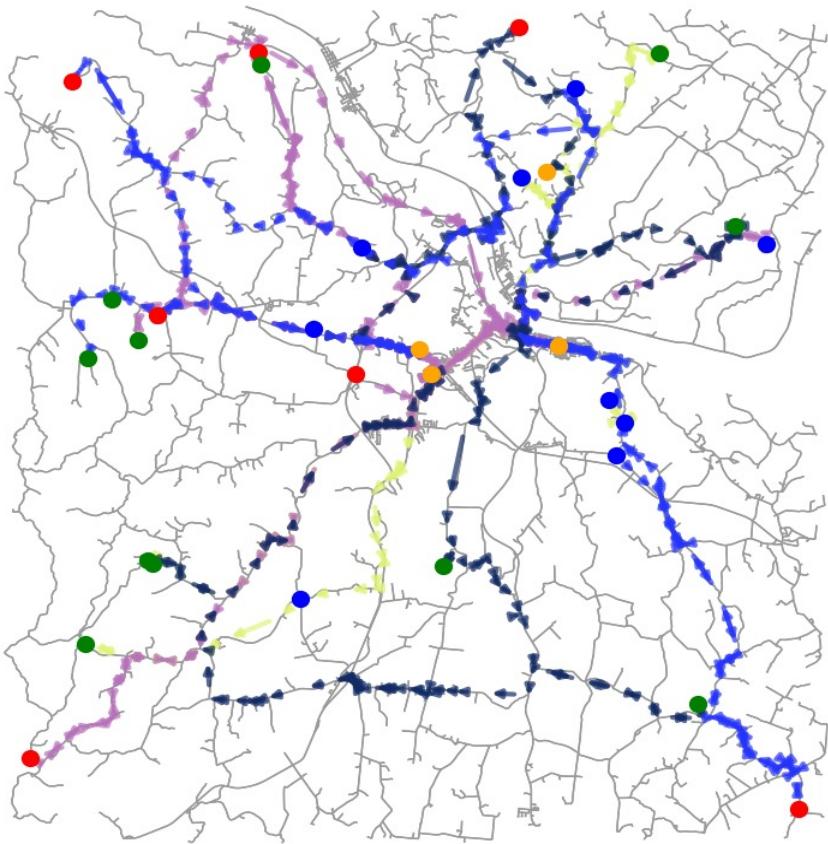


Figure 35: Simulated Annealing Vehicle Routing
Graph created by student using Python, 2025

Ant Colony Optimization

Ant Colony System Vehicle Routing with Routes, Hospitals, and Victims

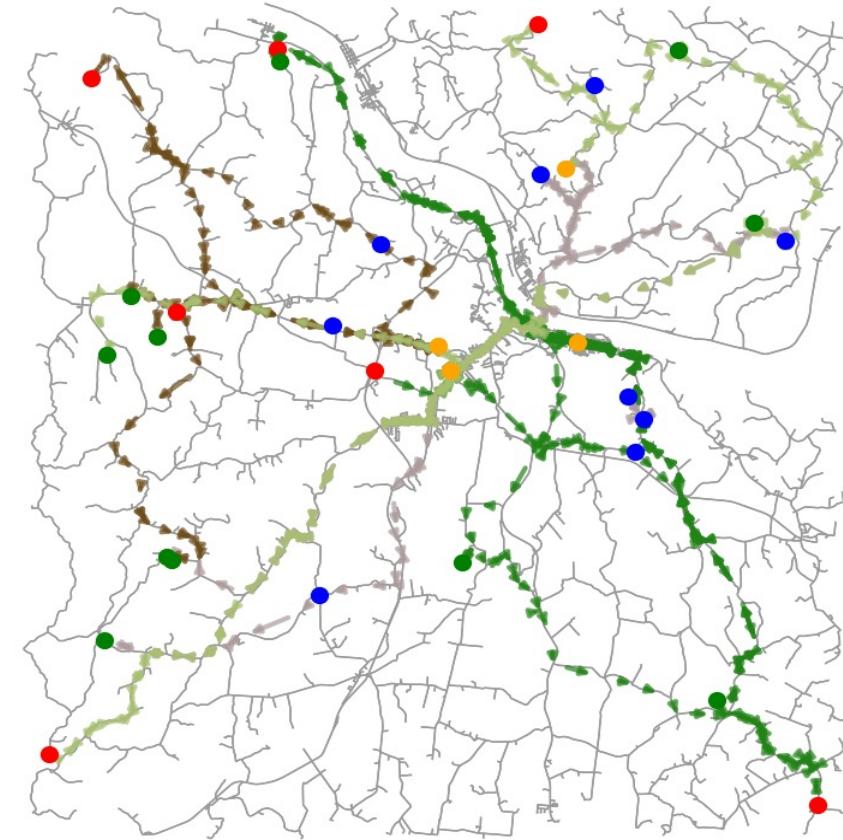


Figure 36: Ant Colony Optimization Vehicle Routing
Graph created by student using Python, 2025

	Greedy	Cluster	Simulated Annealing	Ant Colony
Time to Reach All Victims (minutes)	86.9	85.9	84.0	84.3
Time to Reach All Critical Victims (minutes)	54.8	54.0	54.1	53.9
Average Risk Score	5.32	5.23	5.13	5.39

- Critical victims
- Non-critical victims
- Unknown victims
- Hospital location
- Route for each vehicle

Table 2 : Results for different algorithm for example case, Table created by student, 2025

RESULT

ALGORITHM PERFORMANCE PER LOCATION TYPE

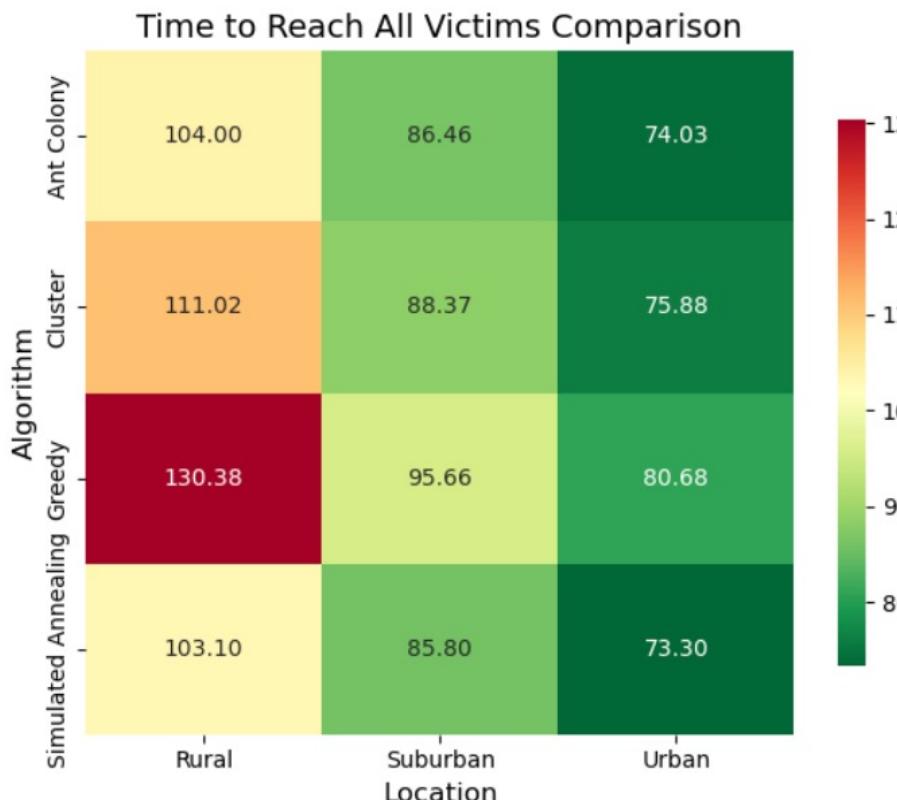


Figure 37: Time to Reach All Victims
Graph created by student using Python, 2025

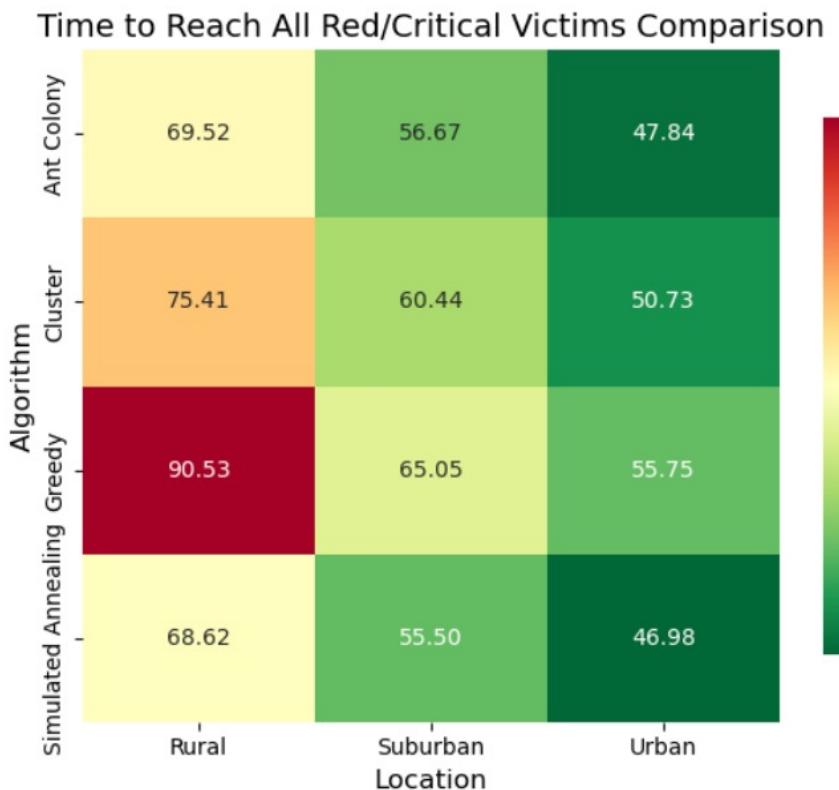


Figure 38: Time to Reach All Red/Critical Victims
Graph created by student using Python, 2025

Average Road Damage Score Passed by Vehicles Comparison

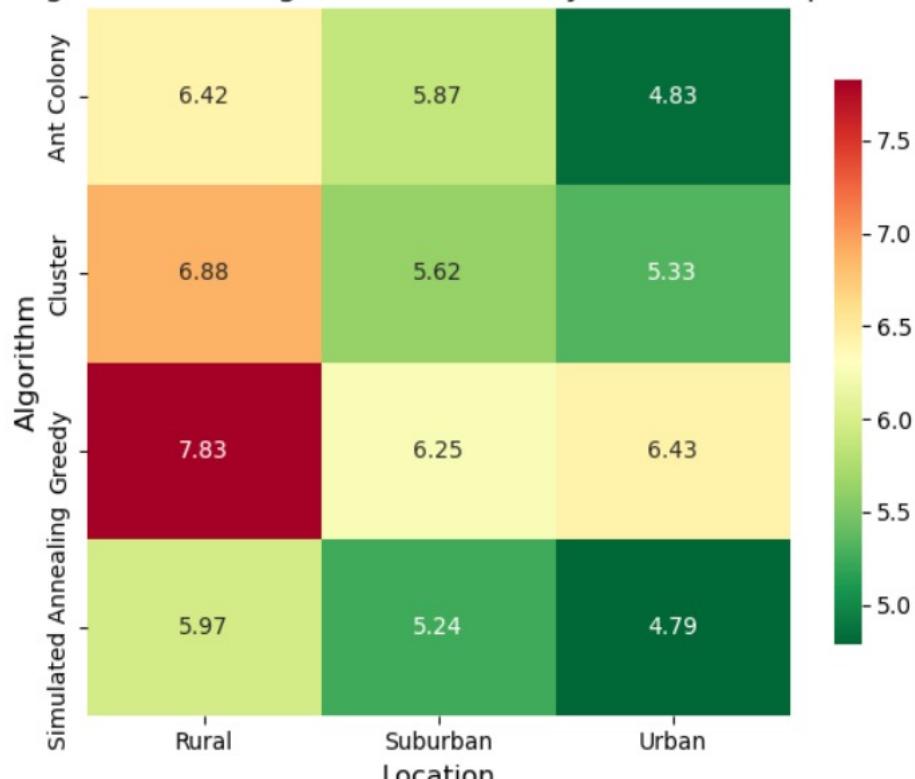


Figure 39: Average Road Damage Score Passed by Vehicles

Graph created by student using Python, 2025

Simulated Annealing performed the best overall, achieving the shortest time to reach all victims, the fastest response to critical (red) victims, and the lowest average road damage score.

Compared to the worst-performing algorithm, Greedy, Simulated Annealing reduced the time to reach all victims by 14.51%, decreased the time to reach critical victims by 19.04%, and lowered the average road damage score by 21.99%.

The second best, Ant Colony, had a 0.87% increase in time to reach all patients, a 1.71% increase in time to reach all critical victims, and a 7.63% increase in road damage score.

ALGORITHM'S PERFORMANCE VARIATION PER LOCATION

(averaged score across triage, road damage condition, and count of temporary hospital)

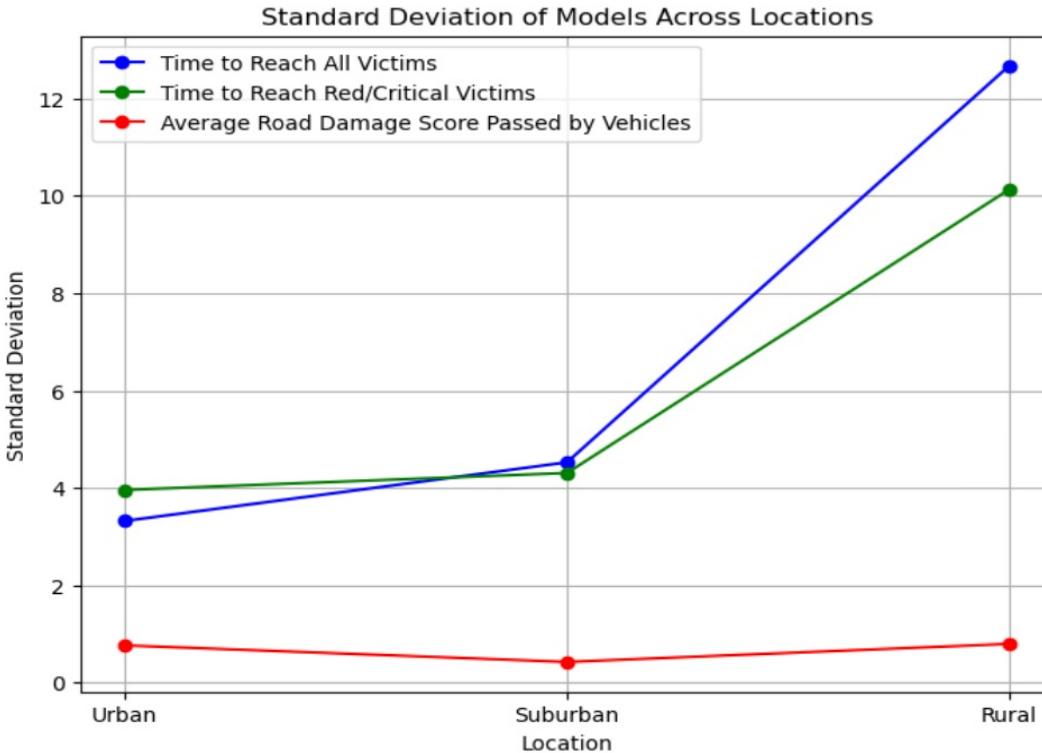


Figure 40: Plot of Standard Deviation of Models Across Locations

Made by Student, 2025

The models show greater variability in rural areas compared to urban and suburban areas. This is likely due to the fact that urban and suburban areas have more roads and connections, which means that even if the models take different paths, they tend to lead to similar results. In contrast, rural areas have fewer routes, causing more variability in the model outcomes.

IMPACT OF LOCATION TYPE

(average score for different road damage condition and victim severity/triage)

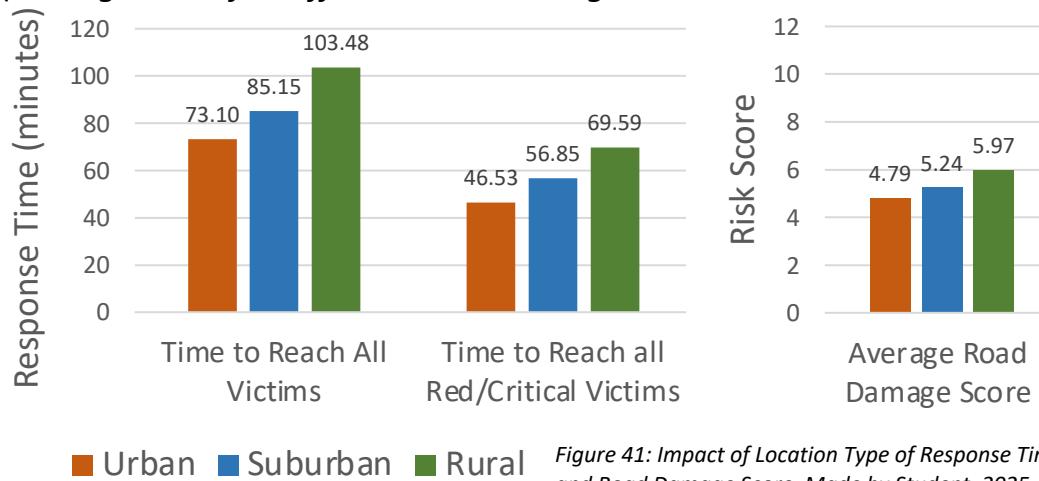


Figure 41: Impact of Location Type of Response Time and Road Damage Score, Made by Student, 2025

Typically, urban regions demand less time and exhibit lower risk scores than rural regions, despite having a greater number of victims. In rural areas, there is an **average increase of 41.56% in the time taken to reach all victims following a disaster**. This observation is consistent with research from non-disaster Emergency Medical Services (EMS): a study published in *JAMA Surgery*^[7] indicates that response times in rural locations can be **twice that of urban areas** during normal, non-disaster circumstances.

IMPACT OF ROAD DAMAGE CONDITION

(average score for different location and victim severity/triage)

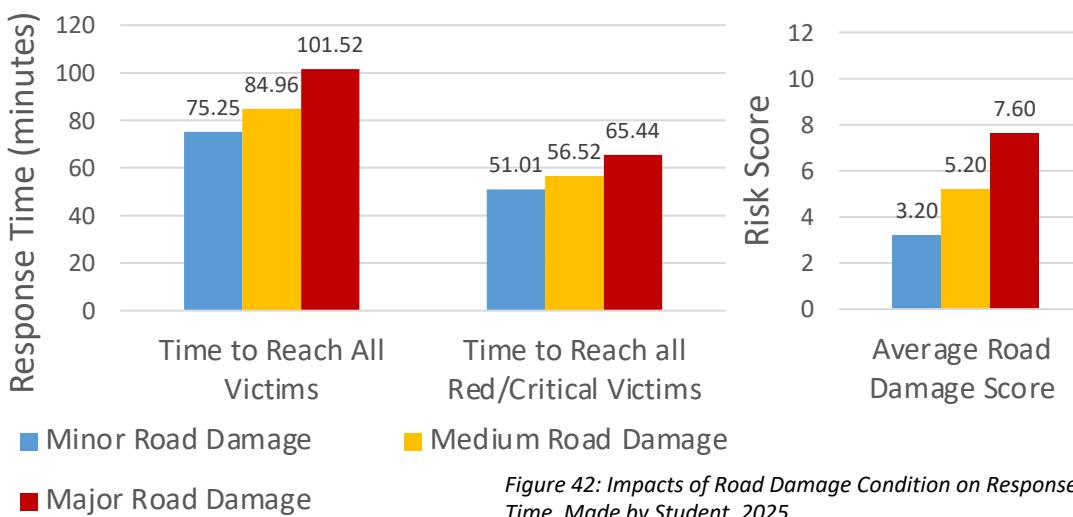


Figure 42: Impacts of Road Damage Condition on Response Time, Made by Student, 2025

From Minor to Medium Road Damage:

- Time to reach all victims up by **12.90%**.
- Time to reach red/critical victims up by **10.80%**.

From Medium to Major Road Damage:

- Time to reach all victims up by **19.49%**.
- Time to reach red/critical victims up by **15.78%**.

This is because red/critical victims are prioritized during routing, ensuring they are reached as quickly as possible even under worsening road conditions. Vehicles are routed more directly or given priority access to clearer roads for critical cases, which minimizes the increase in time to reach them.

ANALYSIS

IMPORTANCE OF TRIAGE INFORMATION

(percentage increase for each metric from 5/80/15 (more information) triage split to 2/34/64 (less information) split)

Average percentage increase by location type

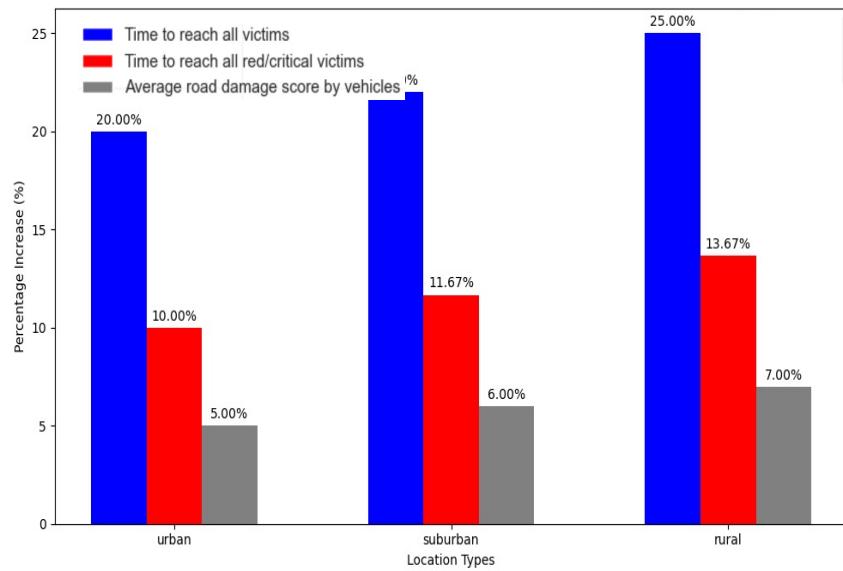


Figure 43: Impacts of Triage Splits by Location
Made by Student, 2025

Average percentage increase for Road Damage Condition

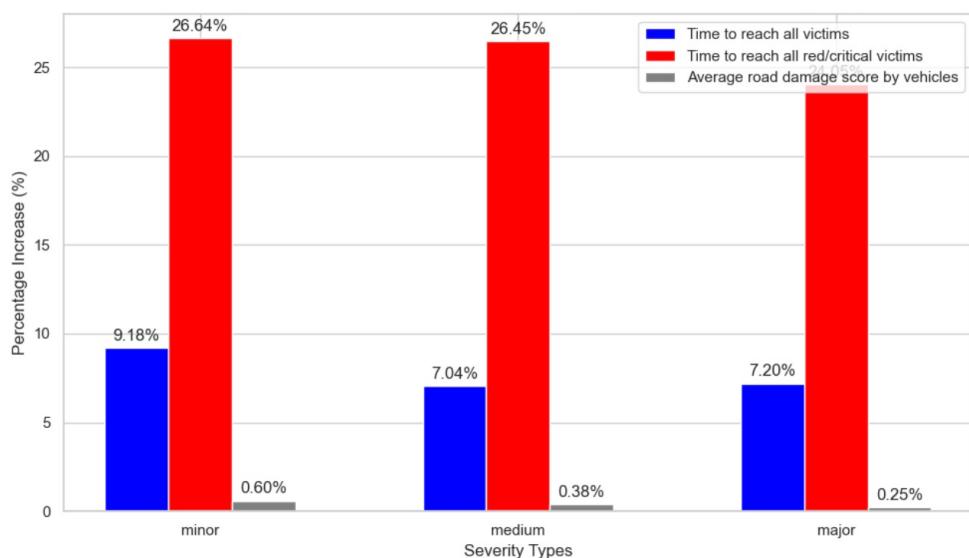


Figure 44: Impacts of Triage Splits by Road Damage Condition
Made by Student, 2025

The amount of known triage information significantly impacts the time to reach all victims, with rural areas being more affected due to fewer roads and paths. The lack of information has a greater effect in areas with minor road damage, as more accessible routes make response times variable. These findings highlight the importance of accurate triage information, especially in rural areas and regions with minor damage, to minimize delays in reaching critical victims.

VALUE OF TEMPORARY HOSPITAL COUNT

(for different location and road damage condition)

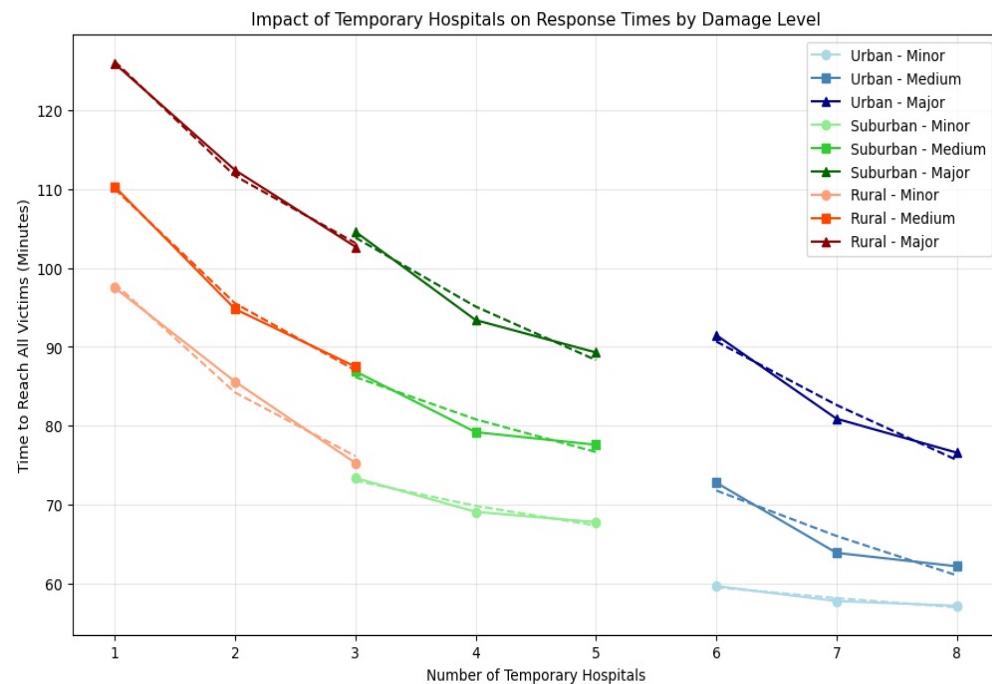


Figure 45: Impact of Temporary Hospital Count on Response Time
Graph created by student, 2025

Location	Average MAE	Observation
URBAN	5.07	The law of diminishing returns is strongest in urban areas because the model fits the data well (low MAE). Additional hospitals initially reduce response times significantly, but the marginal improvements taper off consistently.
SUBURBAN	7.66	The effect of diminishing returns is moderately strong in suburban areas, but higher MAE reflects some variability in the data.
RURAL	14.01	The law of diminishing returns is weakest in rural areas due to higher MAE. Sparse populations and infrastructure variability contribute to inconsistent reductions in response times with additional temporary hospitals.

Table 3: Average MAE values for Location Types regarding Law of Diminishing Returns
Made by Student, 2025

EUCLIDEAN DISTANCE VS WEIGHTED SCORE MATRIX

(average score for different road damage condition and victim severity/triage)

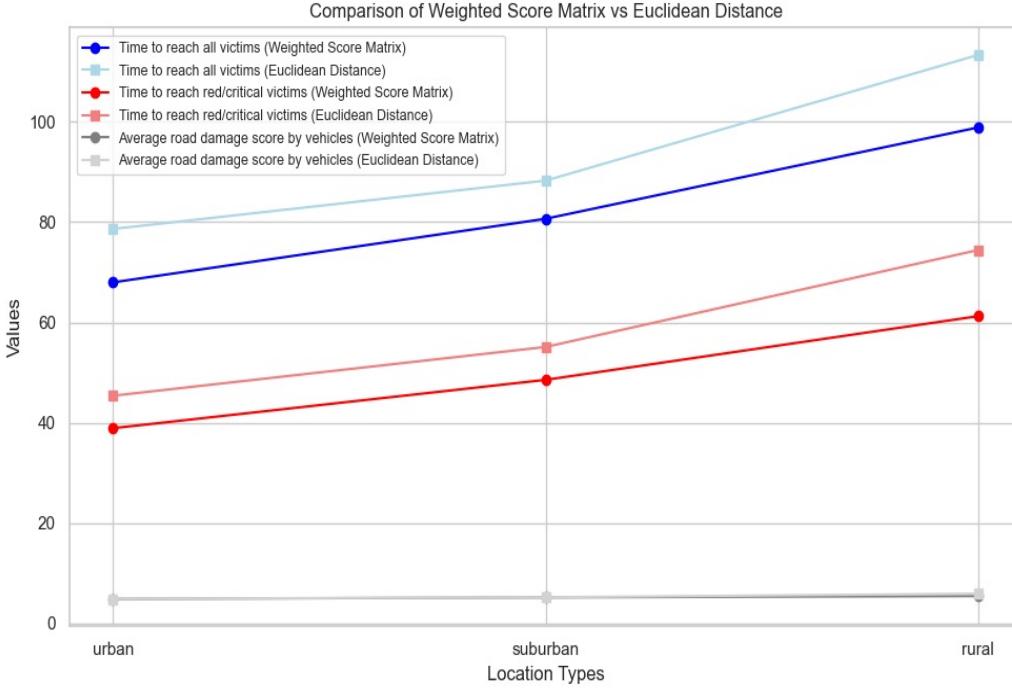


Figure 46: Comparison of Weighted Score Matrix vs Euclidean Distance
Made by Student, 2025

Metric	t-statistic	p-value	Interpretation
Time to reach all victims	-6.07	0.0017	Statistically significant difference ($p < 0.05$)
Time to reach red-level victims	-5.17	0.0036	Statistically significant difference ($p < 0.05$)
Risk score	-1.89	0.1171	No significant difference ($p > 0.05$)

Table 4: Statistical Analysis of Weighted Score Matrix vs Euclidean Distance
Made by Student, 2025

Performance Comparison of Routing Strategies Using Paired t-Test

In this analysis, a paired t-test was conducted to compare the performance of two routing strategies, Weighted Score and Euclidean, on key metrics such as time to reach all victims, time to reach red-level victims, and risk score.

- Time to Reach All Victims:** The paired t-test produced a t-statistic of -6.07 and a p-value of 0.0017, which is less than the significance threshold of 0.05. This indicates a statistically significant difference between the two methods, suggesting that the Weighted Score and Euclidean models perform differently in terms of the total time taken to reach all victims.
- Time to Reach Red-Level Victims:** Similarly, the test for this metric resulted in a t-statistic of -5.17 and a p-value of 0.0036, which is also less than 0.05. This suggests that there is a significant difference between the two models in terms of the time it takes to reach red-level victims, further reinforcing the difference in performance between the two strategies.
- Risk Score:** For the risk score comparison, the t-test produced a t-statistic of -1.89 and a p-value of 0.1171, which is greater than 0.05. This indicates that there is no statistically significant difference in the risk scores generated by the two models, suggesting that both methods yield similar results when assessing the risk associated with the victim locations.

LEARNINGS AND CONCLUSIONS

- **Algorithm Performance:**
 - **Simulated Annealing:** Achieved the fastest response time, averaging 87.4 minutes to reach all victims.
 - **Ant Colony Optimization:** Had slightly higher response times but maintained competitive risk scores.
 - **Cluster Algorithm:** Balanced speed and risk effectively, averaging 91.8 minutes with moderate risk scores.
 - **Greedy Algorithm:** Had the slowest response time (102.2 minutes) and the highest risk scores, demonstrating its inefficiency in complex disaster scenarios.
- **Impact of Road Damage Conditions:** As road damage severity and area type transition from urban to suburban to rural, both risk damage scores and response times for reaching all victims and red (critical) victims increase. However, the percentage increase in response time due to worsening road damage is consistently greater for reaching all victims compared to reaching red (critical victims), highlighting prioritization of critical cases from the models during disaster response.
- **Impact of Unknown Triage Statuses:** The percentage of unknown triage statuses had a significant impact on the time to reach all patients, particularly red (critical) patients. In scenarios where communication systems are compromised (e.g., in rural areas), the lack of triage information can drastically increase response times, underscoring the need for robust communication infrastructure during disasters.
- **Temporary Hospitals and Diminishing Returns:** A slight “law of diminishing returns” was observed for temporary hospitals. As the number of temporary hospitals increased, the marginal benefit in response time and resource allocation decreased significantly. This suggests that beyond a certain threshold, adding more temporary hospitals provides limited improvements in disaster response efficiency.
- **Impact of Distance Metrics:** Using Euclidean distance versus the score matrix showed marginal differences in urban areas. However, disparities between models became more pronounced in suburban and rural areas, highlighting the importance of accurate road metrics in non-urban environments.

This research reveals that the choice of routing algorithm, consideration of real-world road damage conditions, triage status, and the strategic placement of temporary hospitals significantly influence the efficiency and risk levels of emergency vehicle response during disasters. Simulated Annealing emerged as the most effective algorithm, while the Greedy Algorithm proved inefficient in complex scenarios. Furthermore, the findings underscore the importance of robust communication infrastructure and accurate road metrics, especially in rural areas. Effective disaster response planning must balance the benefits of temporary hospitals and prioritize reaching critical victims to optimize overall response time and minimize risk.

REAL WORLD APPLICATION AND BENEFITS

- Informs public health policy makers by identifying trends and vulnerabilities that can be addressed to build more resilient communities.



- Simulates different disaster scenarios to help emergency planners develop robust preparedness strategies.
- Can be used to identify optimal locations for temporary hospitals and how many/what types of vehicles should be there

- Optimizes emergency vehicle routing by analyzing road conditions, and hospital capacities to provide fastest possible response times.
- Provides real-time data on temporary hospital capacities to guide patient distribution and reduce overcrowding in permanent facilities.

FUTURE RESEARCH AND ENHANCEMENTS

Incorporating Helicopter and Boat Vehicles

- Add **helicopters** and **boats** as additional vehicle types to improve response times in disaster scenarios.
- **Helicopters** can bypass road congestion and damage, especially in urban environments or where roadways are impassable.
- **Boats** can be used in flood-prone areas, providing vital access when roadways are submerged.
- Future research will focus on integrating both vehicle types into the routing model, optimizing their use based on infrastructure, weather conditions, road status, and hospital capacity.

Modifying Road Damage in Real-Time

- Currently, road conditions are assumed to be static once routing begins, but **real-time road updates** can enhance model accuracy.
- As roads are repaired or cleared of debris, the system will automatically adjust, enabling rerouting and reducing response times.
- This dynamic approach will ensure vehicles are always using the most efficient available routes.

Further Scalability and Disaster-Type Specialization

- The model will be expanded to test on a broader range of **disaster zones** and **geographical settings** (e.g., coastal areas, mountainous regions).
- This includes addressing different types of disasters (earthquakes, floods, wildfires), each presenting unique challenges.
- Tailoring the model to specific disaster scenarios will ensure optimized and specialized routing for each situation.

Dynamic Patient Information

- Real-world disaster situations are constantly changing, and **dynamic patient data** will be incorporated to reflect evolving conditions.
- The system will update routes based on new data, such as worsening patient conditions, additional victims, or changes in hospital status.
- Real-time data integration will allow the system to continuously adjust priorities and optimize response efforts.

Integration of Real-Time Traffic and Weather Data

- Disasters are often compounded by **traffic congestion** and **severe weather**.
- Incorporating real-time traffic and weather data will improve the routing system's adaptability.
- The system will adjust routes based on weather events (e.g., storms, floods) and traffic patterns, ensuring efficient vehicle movement.

Collaboration with Emergency Response Teams

- Future research will involve **collaborating with emergency responders** to refine the model and validate its real-world applicability.
- Feedback from responders will help adjust assumptions, improve model parameters, and test its effectiveness in real disaster situations.
- Collaboration will ensure the developed strategies are practical and actionable for emergency teams.

References

Graphic Reference List

1. CNN. (2016, April 17). Damage from Japan earthquake [Photograph]. CNN. <https://i2.cdn.cnn.com/cnnnext/dam/assets/160417120013-04-japanquake-0417-super-169.jpg>
2. Salvation Army NZFTS. (2025). Response to flooding in Canadian provinces - The Salvation Army NZFTS. The Salvation Army NZFTS. <https://www.salvationarmy.org.nz/news/response-flooding-canadian-provinces/>
3. Curtis, J. (2018, March 27). Shocking pictures show overcrowded A&E department in NHS winter crisis. Mail Online. <https://www.dailymail.co.uk/news/article-5548277/Shocking-pictures-overcrowded-E-department-peak-NHS-winter-crisis.html>
4. Staff, F. E. (2013, May 30). Can motorcycle paramedics be used effectively in Western EMS? Fire Engineering: Firefighter Training and Fire Service News, Rescue. <https://www.fireengineering.com/firefighting/can-motorcycle-paramedics-be-used-effectively-in-western-ems/>
5. Shiri, D., Akbari, V., & Tozan, H. (2023). Online optimization for ambulance routing in disaster response with partial or no information on victim conditions. Computers & Operations Research, 159, 106314. <https://doi.org/10.1016/j.cor.2023.106314>
6. Greenwood Emergency Vehicles. (2024). Lexington, MA – Horton | Ford F550 Type I Ambulance. Greenwood Emergency Vehicles. <https://www.greenwoodev.com/lexington-ma-horton-ford-f550-type-i-ambulance/>
7. Dutch emergency photos. (2025, February 14). Dutch ambulance BMW R1200rt [Photograph]. Flickr. <https://www.flickr.com/photos/dutchemergencyphotos/32622623617>
8. International Armored Group (IAG). (2020, September 17). Sentinel tactical response vehicle (TRV) - IAG armored rescue vehicles. IAG Home. <https://www.interarmored.com/products/sentinel-trv/>
9. Mell, H. K., Mumma, S. N., Hiestand, B., Carr, B. G., Holland, T., & Stoprya, J. (2017). Emergency Medical Services Response Times in Rural, Suburban, and Urban Areas. JAMA surgery, 152(10), 983–984. <https://doi.org/10.1001/jamasurg.2017.2230>
10. Feizolahzadeh, S., Vaezi, A., Taheriniya, A., Mirzaei, M., Vafaeenabab, M., & Khorasani-Zavareh, D. (2019). The Feasibility of Increasing Hospital Surge Capacity in Disasters through Early Patient Discharge. Bulletin of emergency and trauma, 7(2), 105–111. <https://doi.org/10.29252/beat-070203>
11. Sartini, M., Carbone, A., Demartini, A., Giribone, L., Oliva, M., Spagnolo, A. M., Cremonesi, P., Canale, F., & Cristina, M. L. (2022). Overcrowding in Emergency Department: Causes, Consequences, and Solutions-A Narrative Review. Healthcare (Basel, Switzerland), 10(9), 1625. <https://doi.org/10.3390/healthcare10091625>
12. van der Pols, H., Mencl, F., & de Vos, R. (2011). The impact of an emergency motorcycle response vehicle on prehospital care in an urban area. European journal of emergency medicine : official journal of the European Society for Emergency Medicine, 18(6), 328–333. <https://doi.org/10.1097/MEJ.0b013e32834624e8>

Key Literature Review

1. Anuar, W. K., Lee, L. S., Pickl, S., & Seow, H.-V. (2021). Vehicle routing optimisation in humanitarian operations: A survey on modelling and optimisation approaches. Applied Sciences, 11(2), 667. <https://doi.org/10.3390/app11020667>
2. Luan, S., & Jiang, Z. (2024). Does the priority of Ambulance Guarantee no delay? A MIPSSTW model of emergency vehicle routing optimization considering complex traffic conditions for highway incidents. PLOS ONE, 19(4). <https://doi.org/10.1371/journal.pone.0301637>
3. Shiri, D., Akbari, V., & Salman, F. S. (2024). Online algorithms for ambulance routing in disaster response with time-varying victim conditions. OR Spectrum, 46(3), 785–819. <https://doi.org/10.1007/s00291-024-00744-4>
4. Tili, T., Abidi, S., & Krichen, S. (2018). A mathematical model for efficient emergency transportation in a disaster situation. The American Journal of Emergency Medicine, 36(9), 1585–1590. <https://doi.org/10.1016/j.ajem.2018.01.039>
5. ZIDI, I., Al-Omani, M., & Aldhafeeri, K. (2019). A new approach based on the hybridization of simulated annealing algorithm and tabu search to solve the static ambulance routing problem. Procedia Computer Science, 159, 1216–1228. <https://doi.org/10.1016/j.procs.2019.09.291>