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

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# 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.

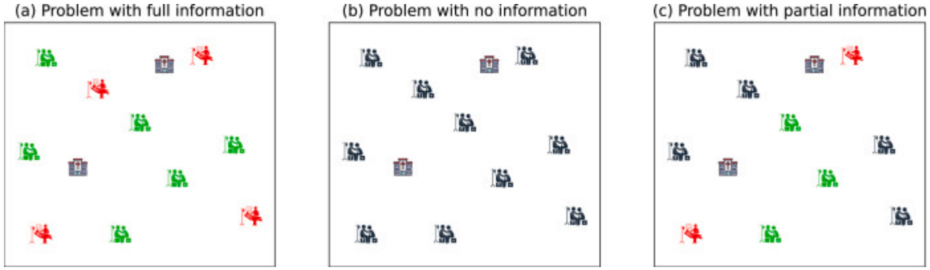


Figure 5: Triage Problem [10]

## Efficient

- 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).

## Scalable

- 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.

## Realistic

- Incorporate real-world population density and hospital data from OSMnx for accurate modeling.
- Simulate road damage using spatial smoothing techniques.

## Safe

- 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

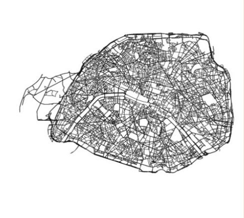


*Figure 10 :Paris Road Network created by Student using OpenStreetMap*

### SUBURBAN

Soreang, Indonesia

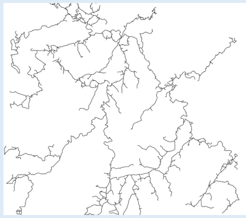


*Figure 11 :Soreang Road Network created by Student using OpenStreetMap*

Plano, Texas

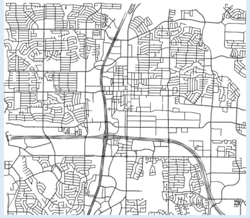


*Figure 12: Plano Road Network created by Student using OpenStreetMap*

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

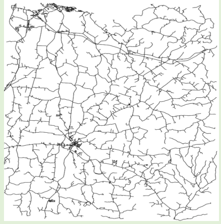


*Figure 16: Mason Road Network created by Student using OpenStreetMap*

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

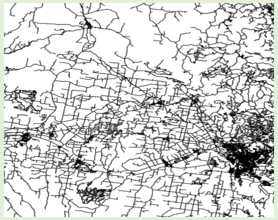


*Figure 20: Boonah Road Network created by Student using OpenStreetMap*

# ROAD DAMAGE CONDITION

## Minor Road Damage

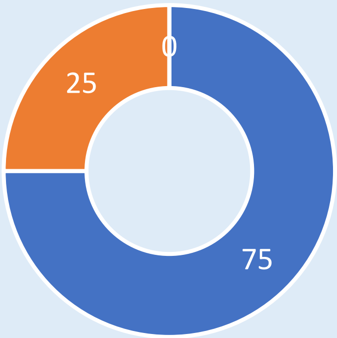
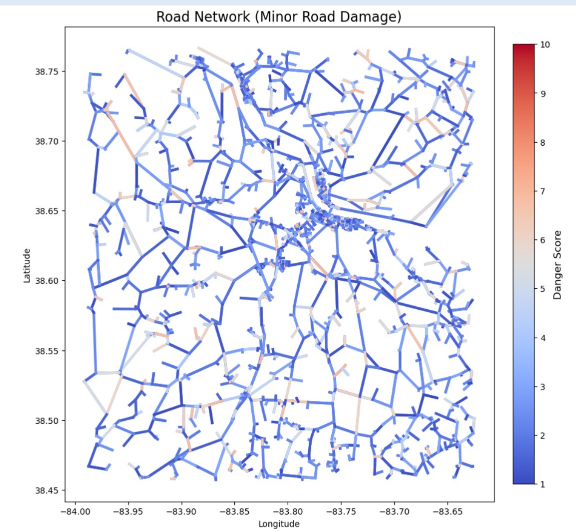



*Figure 21a: Percentage of Road Scores based on Road Damage Type. Graph created by student, 2025*




## Medium Road Damage

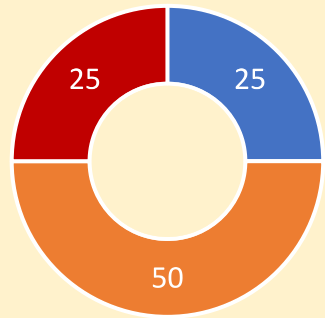
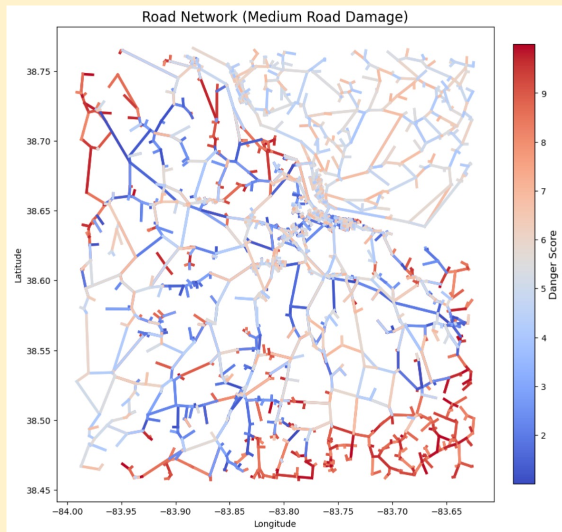



*Figure 21b: Percentage of Road Scores based on Road Damage Type. Graph created by student, 2025*




## Major Road Damage

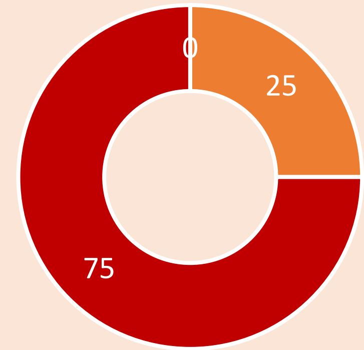



*Figure 21c: Percentage of Road Scores based on Road Damage Type. Graph created by student, 2025*

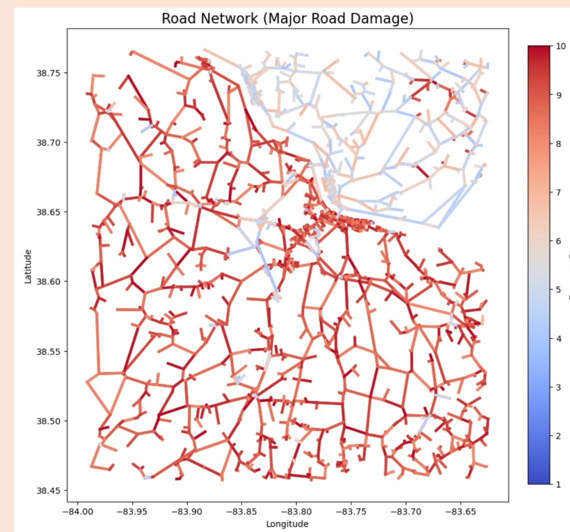
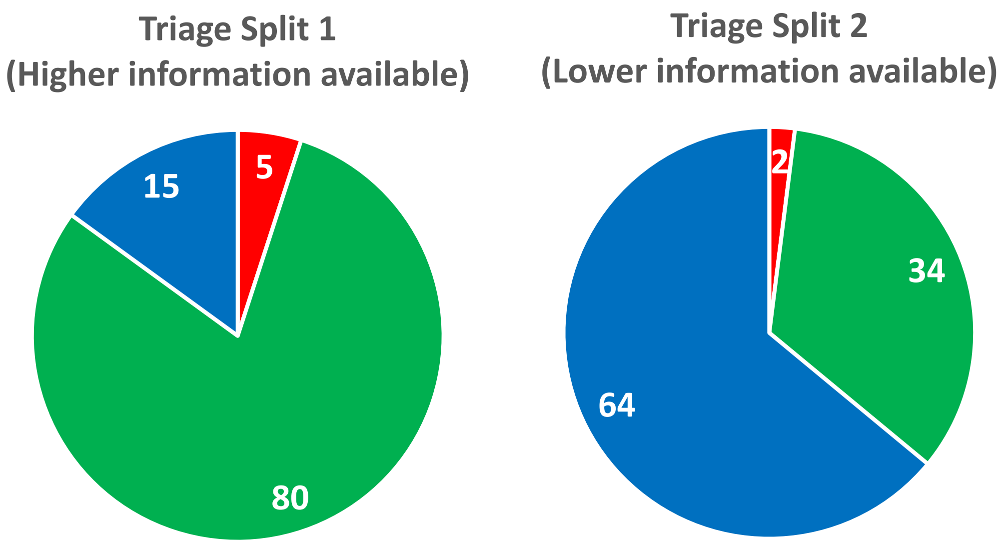



*Figure 22: Road Networks for County. Graph created by student using OpenStreetMaps, 2025*

- 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.

# VICTIM TRIAGE STATUS




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

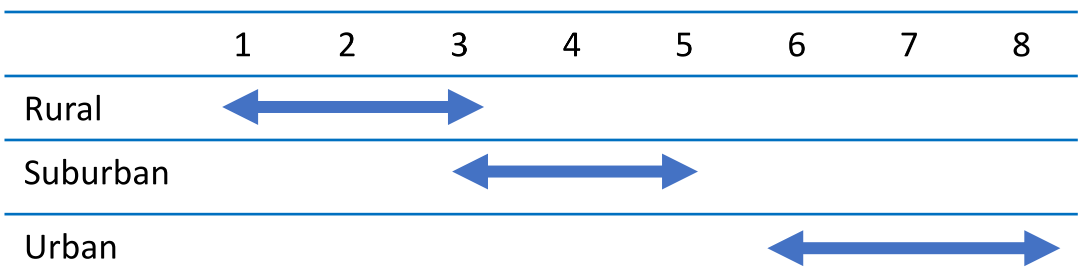



*Figure 24. Temporary Hospitals Count in each location type*
(Patient capacities: 10-15 at each temporary hospital)
*Created by Student, 2025*

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

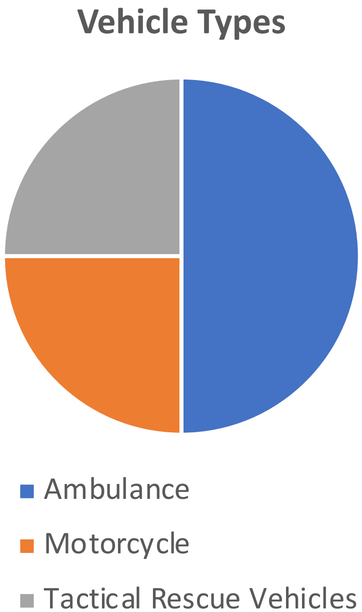



*Figure 28: Vehicle Types Split*
*Graph created by student, 2025*

| | AMBULANCE  Figure 25: Ambulance [5] | Motorcycle Ambulance (MRVs)  Figure 26: Motorcycle Ambulance [11] | Tactical Rescue Vehicles  Figure 27:Tactical Rescue Vehicles [6] |
|---|---|---|---|
| **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.**

## Flowchart steps

Location Data → Identify Hospitals/ Temporary Medical Stations → Identify Victim Information → Road Damage Score → Allocate Vehicles →

## 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**

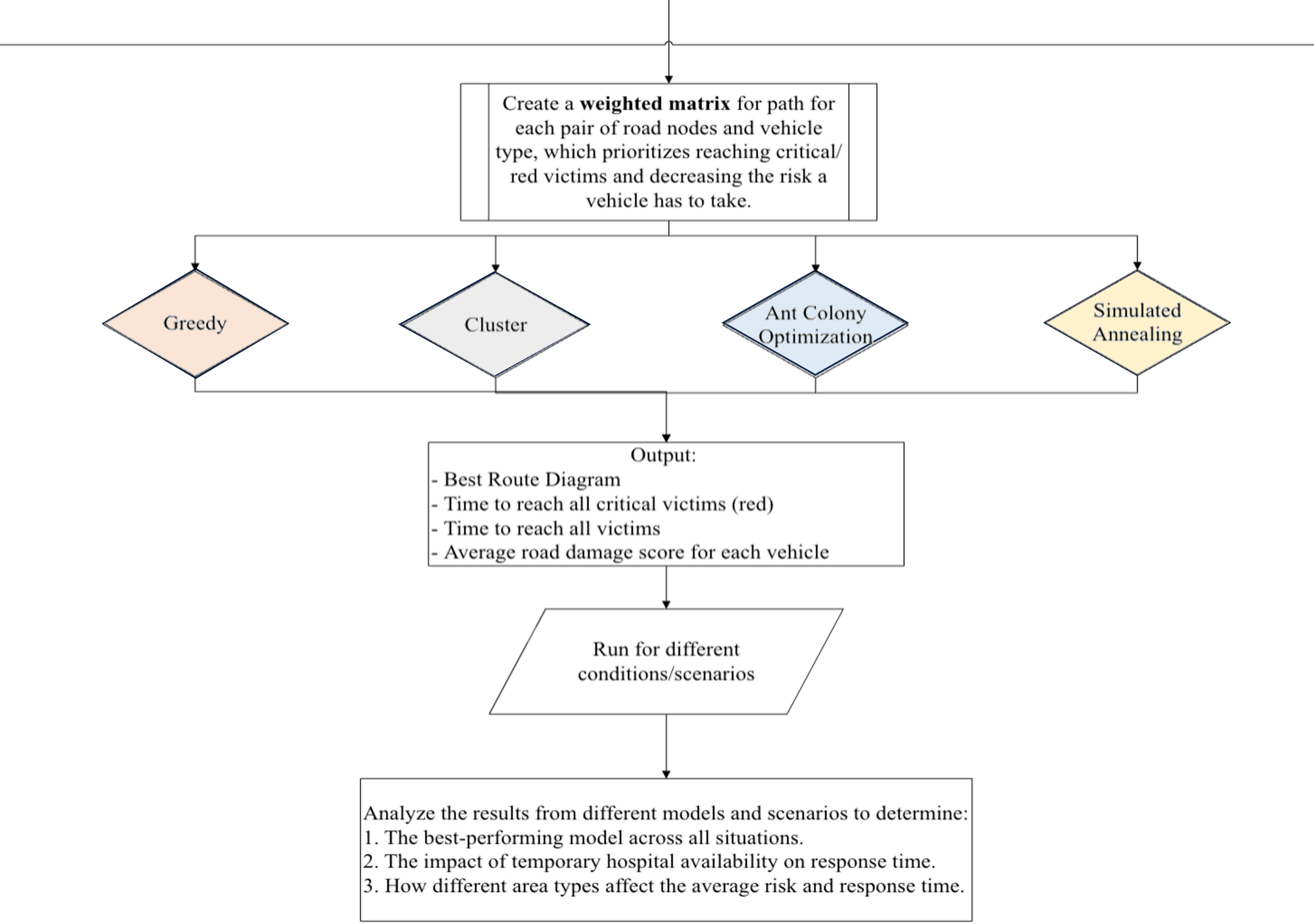



*Figure 29 : Flowchart of Process*
*Flowchart created by Student using Visio, 2025*

# FUNCTION DEFINITIONS

## Path Cost Function

The score for a given pair of nodes $i$ and $j$, and a vehicle is defined as:

$$\text{Score}(i, j, \text{vehicle}) = \frac{T(P, \text{vehicle}) + 1.5 \cdot R(P, \text{vehicle})}{3 \cdot R_j + 2 \cdot U_j + G_j}$$

*Equation 1: Path Cost Function*
*Equation created by student using Overleaf, 2025*

where:

- $P$ 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.

## Time Function

The travel time for a given path $P$ and vehicle is defined as:

$$T(P, \text{vehicle}) = \frac{\sum_{e \in P} d(e)}{\text{vehicle.speed()}}$$

*Equation 2: Time Function*
*Equation created by student using Overleaf, 2025*

where:

- $d(e)$ is the length of edge $e$.
- vehicle.speed is the speed of the vehicle.

## Road Damage Function

For a given path $P$ and vehicle:

$$R(P, \text{vehicle}) = \frac{\sum_{e \in P} S(e, \text{vehicle})}{d_{\text{total}}}$$

*Equation 3: Road Damage Function*
*Equation created by student using Overleaf, 2025*

where $S(e, \text{vehicle})$ is defined as:

$$S(e, \text{vehicle}) = \begin{cases} 999999, & \text{if vehicle.road\_damage\_capacity} < \text{road\_damage}(e) \\ r(e) \cdot d(e), & \text{if vehicle.road\_damage\_capacity} \geq \text{road\_damage}(e) \end{cases}$$

where:

- $r(e)$ 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.

## Objective Function

$$\text{Current}(v) = \begin{cases} \sum_i \text{Victims assigned to vehicle } v_i, & \text{while en route (before drop-off)} \\ 0, & \text{after delivering victims to hospital } h \end{cases}$$

$$\text{Curr}(h) \leq \text{cap}(h), \quad \forall h \in H$$

where $H$ is the set of all hospitals, and $\text{cap}(h)$ is the capacity of hospital $h$.

$$\text{Total victims} = \sum_{h \in H} \text{cap}(h)$$

*Equation 4: Objective Function*
*Equation created by student using Overleaf, 2025*

$$\text{Main goal:} \quad \min\left(\text{time\_red} + \text{time\_all}\right) + 1.5 \cdot (R_{\text{avg}})$$

where:
- time_red is the time to reach red/critical victims,
- time_all is the time to reach all victims,
- $R_{\text{avg}}$ 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 unreached 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
$\mu_i$ = 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.

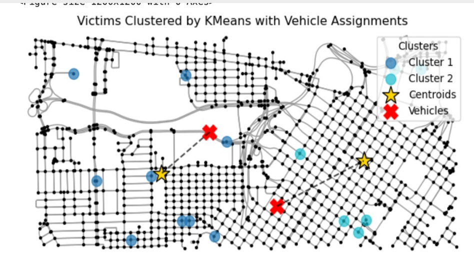



*Figure 30 : Example of K-Means Clustering and Hungarian Algorithm*
*Graph created by student using Python, 2025*

## 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:

$$P(\text{accept}) = e^{\left(\frac{-\Delta E}{T}\right)}$$

*Equation 7: Acceptance Probability*
*Equation created by student using Overleaf, 2025*

where $\Delta E$ 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:

$$T_{\text{new}} = T_{\text{old}} \cdot \text{cooling\_rate}$$

*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

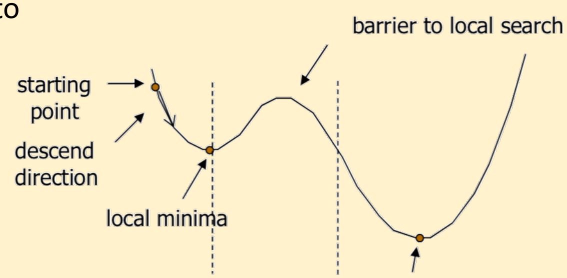



*Figure 31: Graphic of Simulated Annealing*
*Note. From* ResearchGate. (2025, February 14). *Research on logistics distribution vehicle path optimization based on simulated annealing algorithm - Scientific figure.* Retrieved from https://www.researchgate.net/figure/Principle-of-the-simulated-annealing-algorithm_fig5_360434054

## 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:**

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 $j$
- $\tau_{ij}$ = Pheromone level on $(i, j)$
- $\eta_{ij}$ = Heuristic value for $(i, j)$
- $\alpha, \beta$ = 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 $t$
- $\rho$ = 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*

**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.

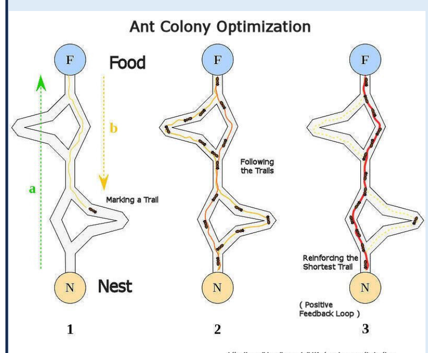



*Figure 32: Ant Colony Optimization*
*Note. From* 1Hive Forum. (n.d.). *Image of Ant Colony.* Retrieved January 3, 2025, from https://forum.1hive.org/uploads/default/original/2X/7/7448c9ae3fce8c5fcb21f2f404ebde21805adb95.jpeg

# EXAMPLE RESULTS

| Location: Rural | Triage: 5/80/15 | Temporary Hospital: 3 | Road Damage: Medium |
|---|---|---|---|

## Greedy Algorithm

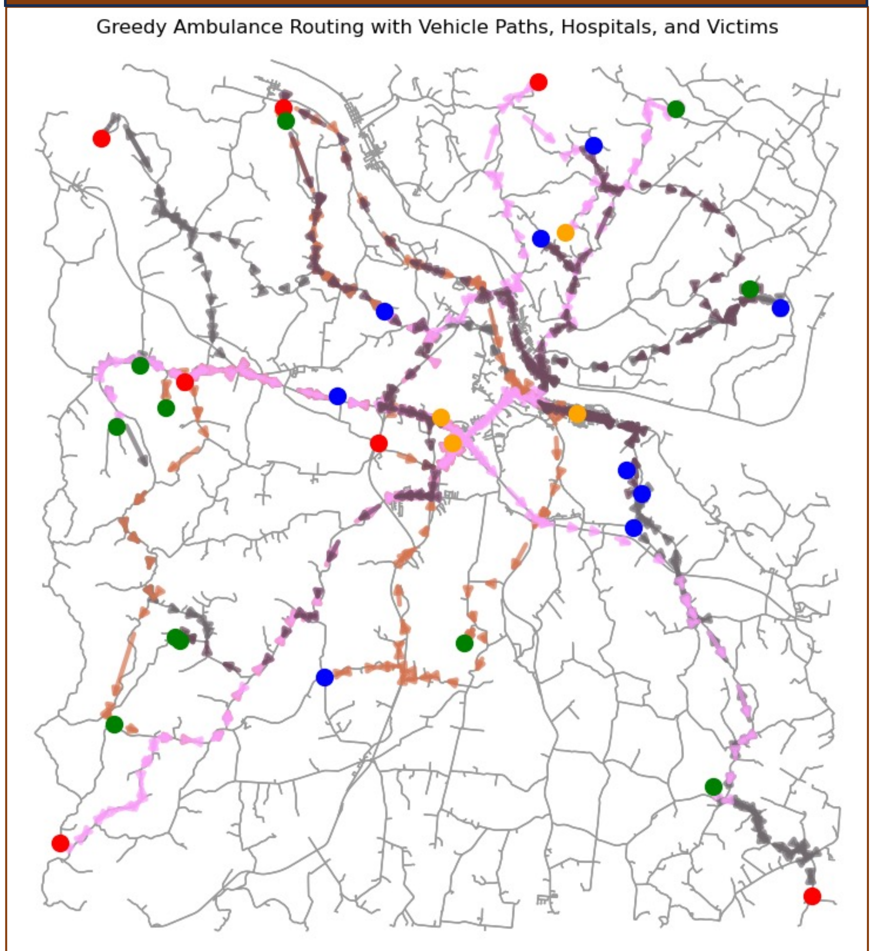



*Figure 33: Greedy Optimization Vehicle Routing*
*Graph created by student using Python, 2025*

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

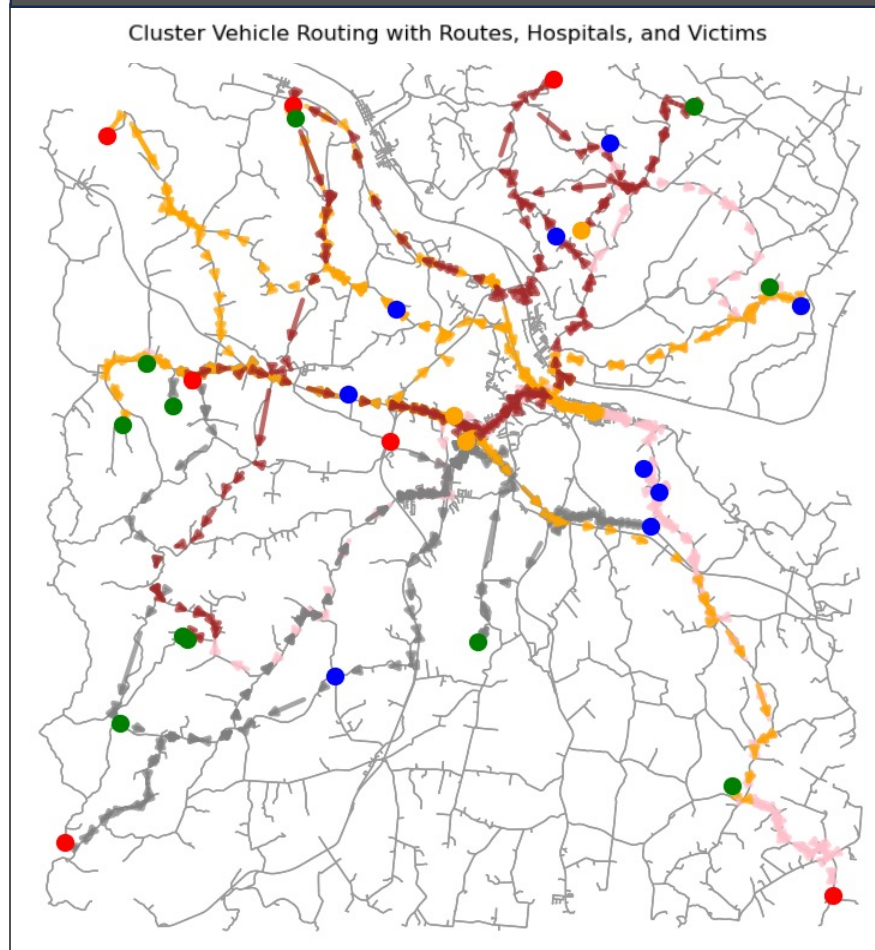



*Figure 34: Cluster Optimization Vehicle Routing*
*Graph created by student using Python, 2025*

## Simulated Annealing

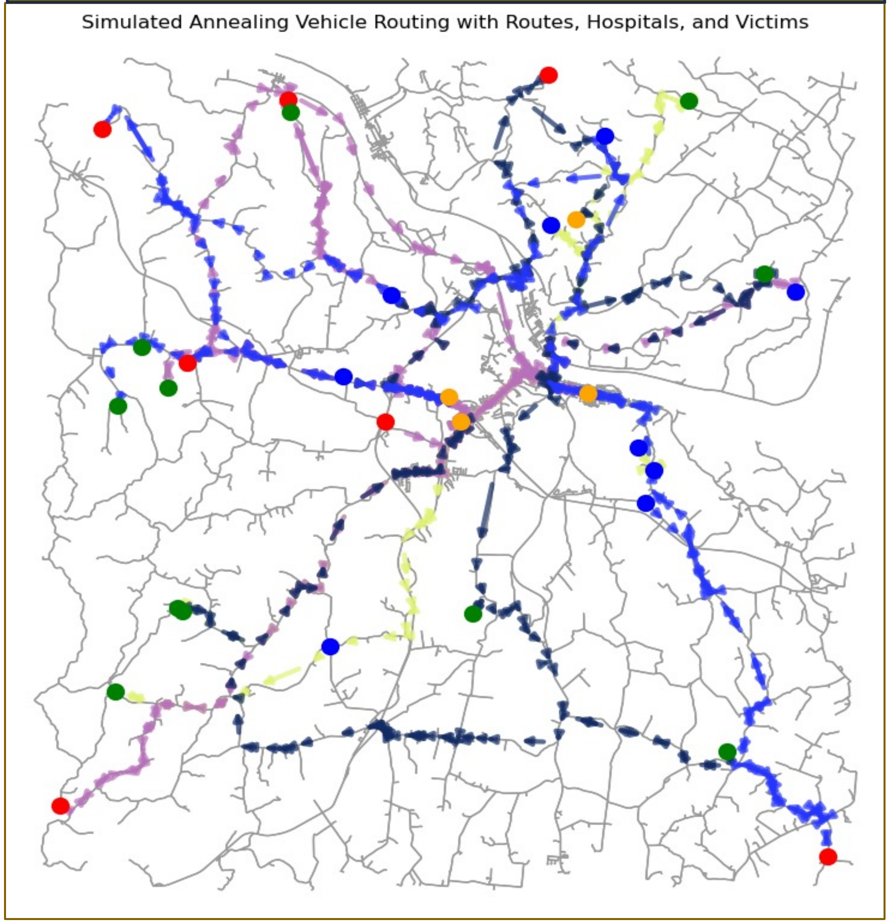



*Figure 35: Simulated Annealing Vehicle Routing*
*Graph created by student using Python, 2025*

## Ant Colony Optimization

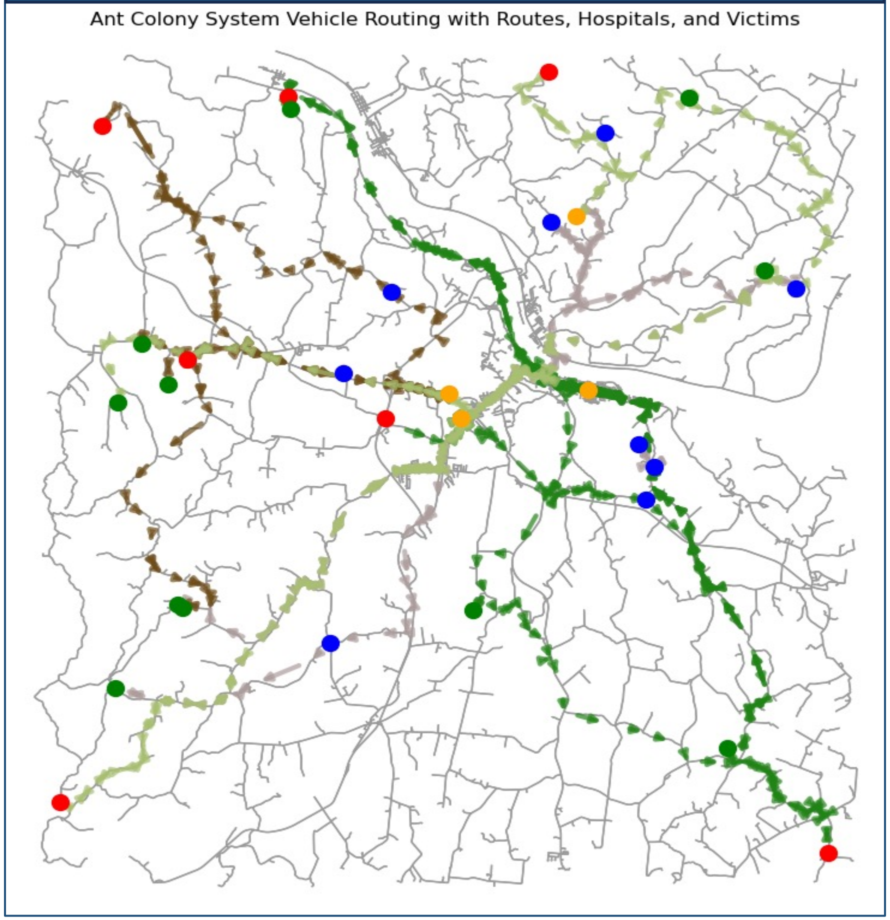
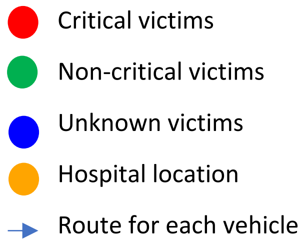



*Figure 36: Ant Colony Optimization Vehicle Routing*
*Graph created by student using Python, 2025*

| | 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 |

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



# RESULT

## ALGORITHM PERFORMANCE PER LOCATION TYPE

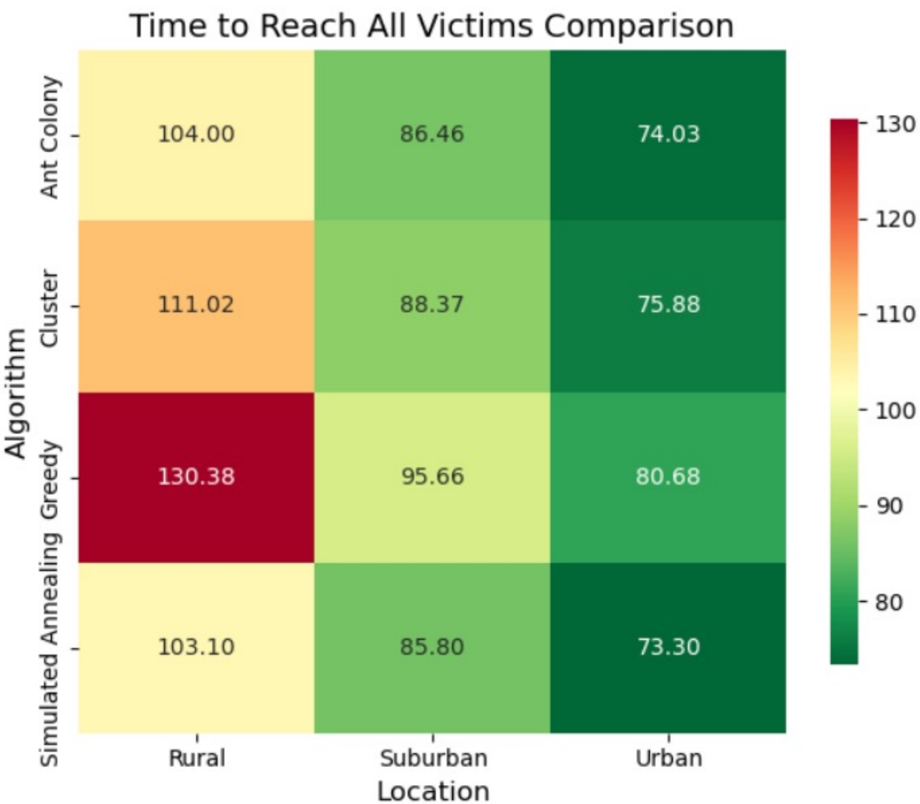



*Figure 37: Time to Reach All Victims*
*Graph created by student using Python, 2025*

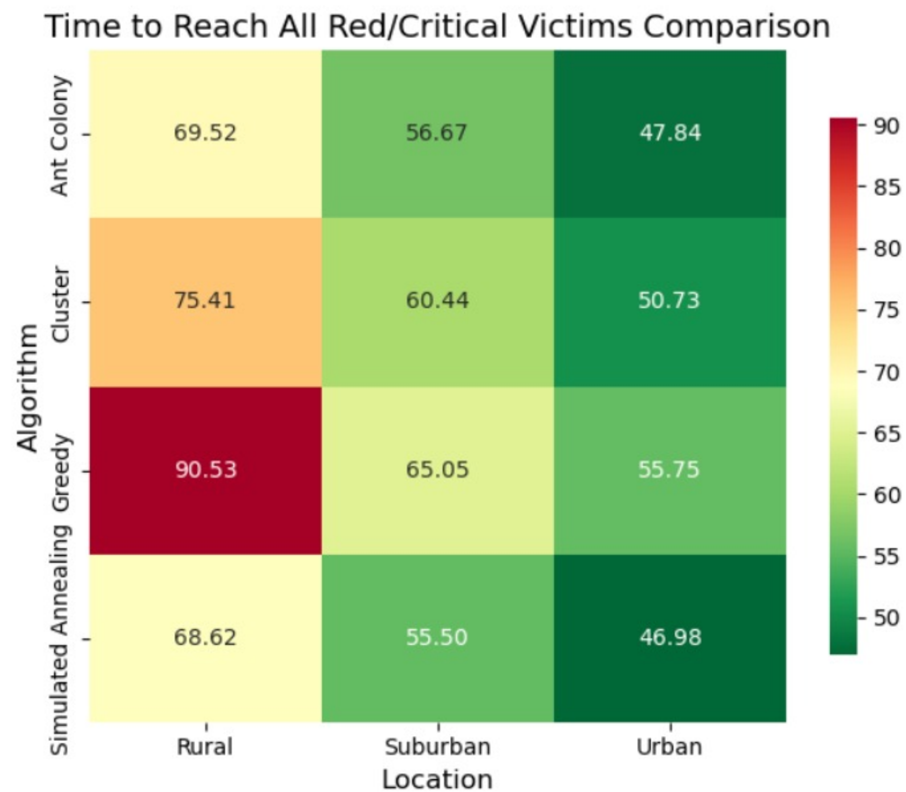



*Figure 38: Time to Reach All Red/Critical Victims*
*Graph created by student using Python, 2025*

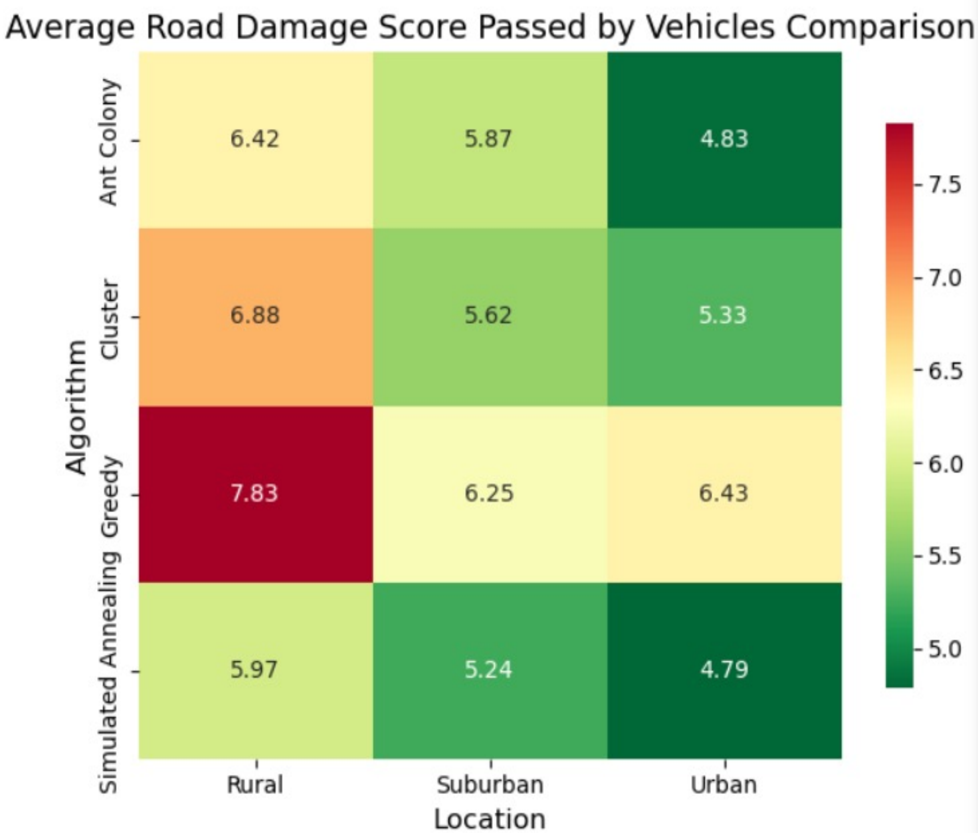



*Figure 39: Average Road Damage Score Passed by Vehicles*
*Graph created by student using Python, 2025*

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)*

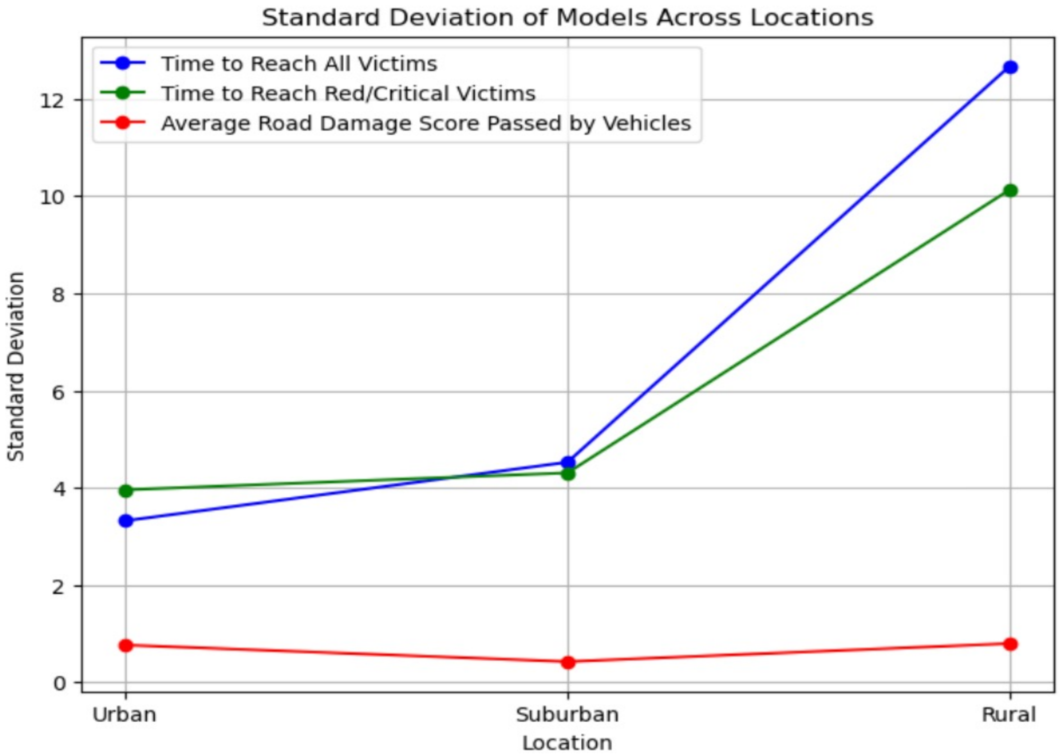



*Figure 40: Plot of Standard Deviation of Models Across Locations*
*Made by Student, 2025*

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)*

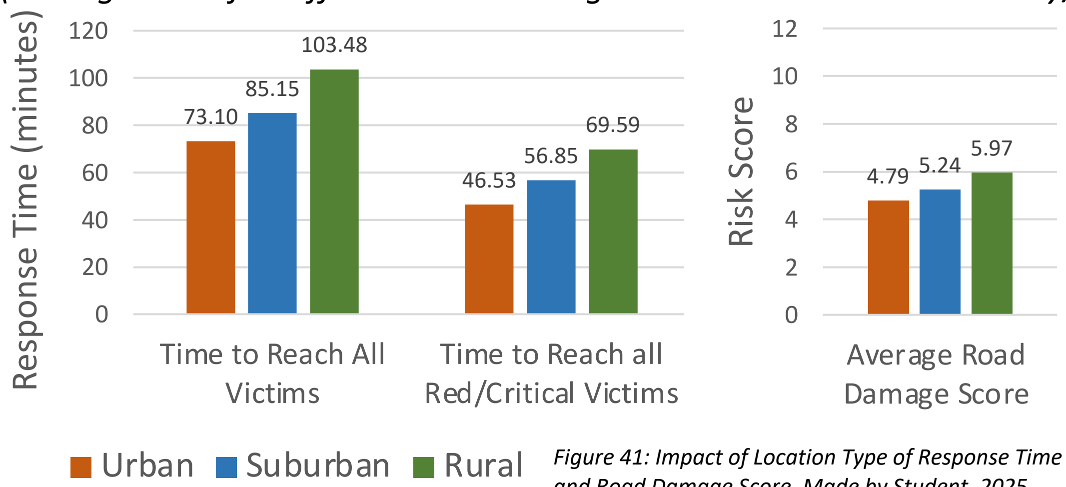



*Figure 41: Impact of Location Type of Response Time and Road Damage Score, Made by Student, 2025*

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)*

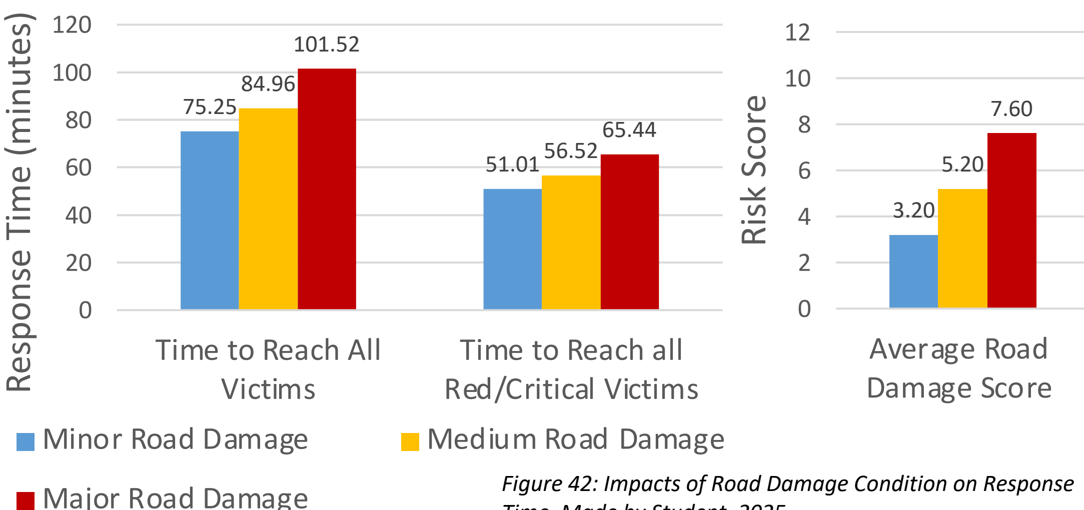



*Figure 42: Impacts of Road Damage Condition on Response Time, Made by Student, 2025*

**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

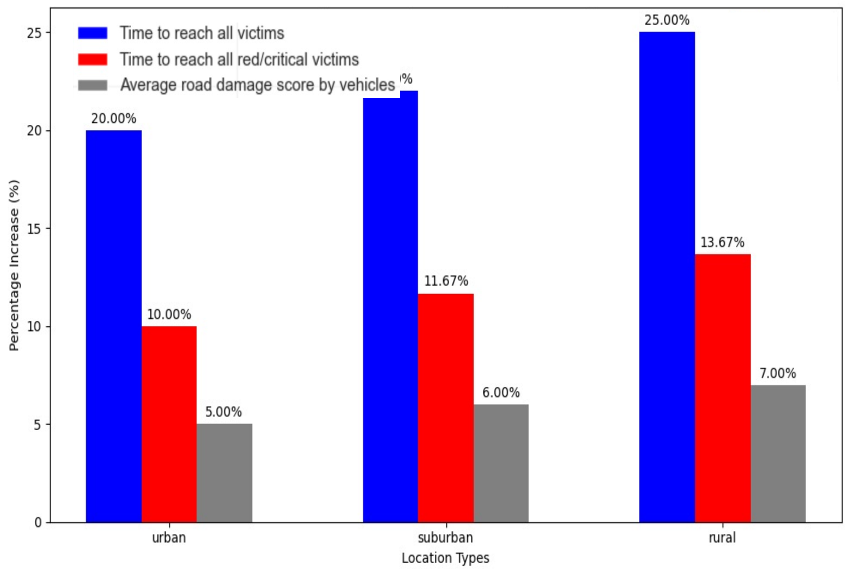



*Figure 43: Impacts of Triage Splits by Location*
*Made by Student, 2025*

### Average percentage increase for Road Damage Condition

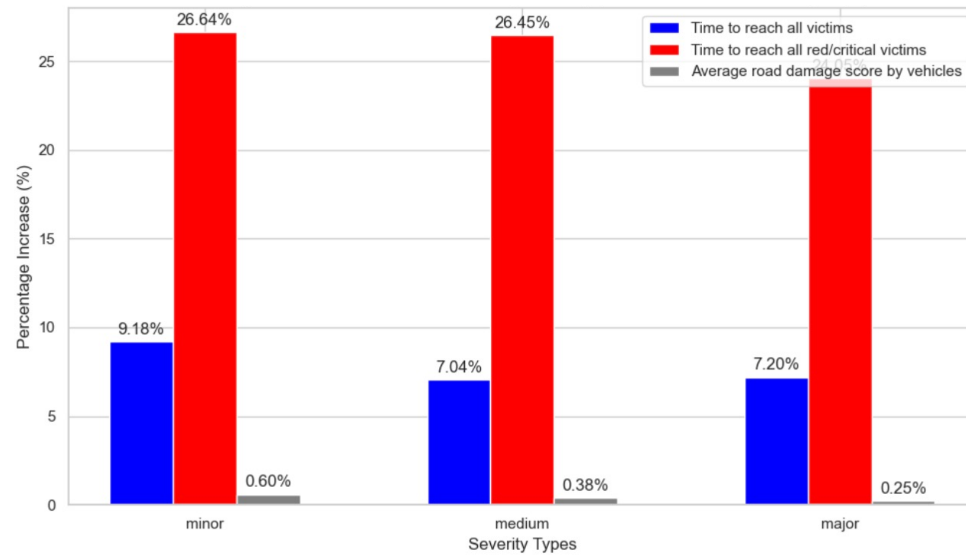



*Figure 44: Impacts of Triage Splits by Road Damage Condition*
*Made by Student, 2025*

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)*

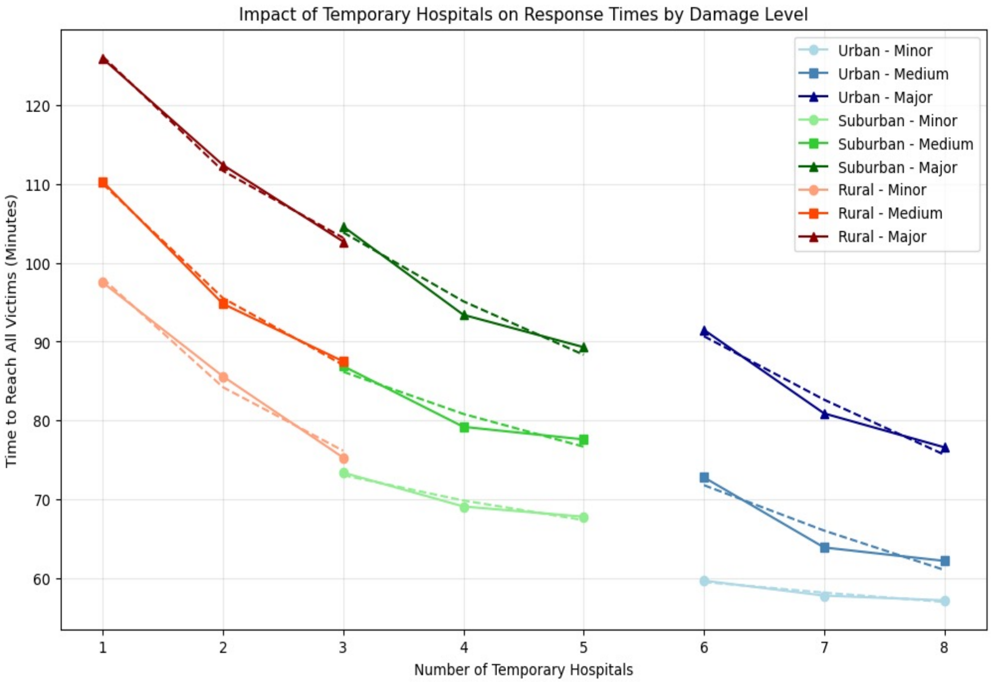



*Figure 45: Impact of Temporary Hospital Count on Response Time*
*Graph created by student, 2025*

| 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)*

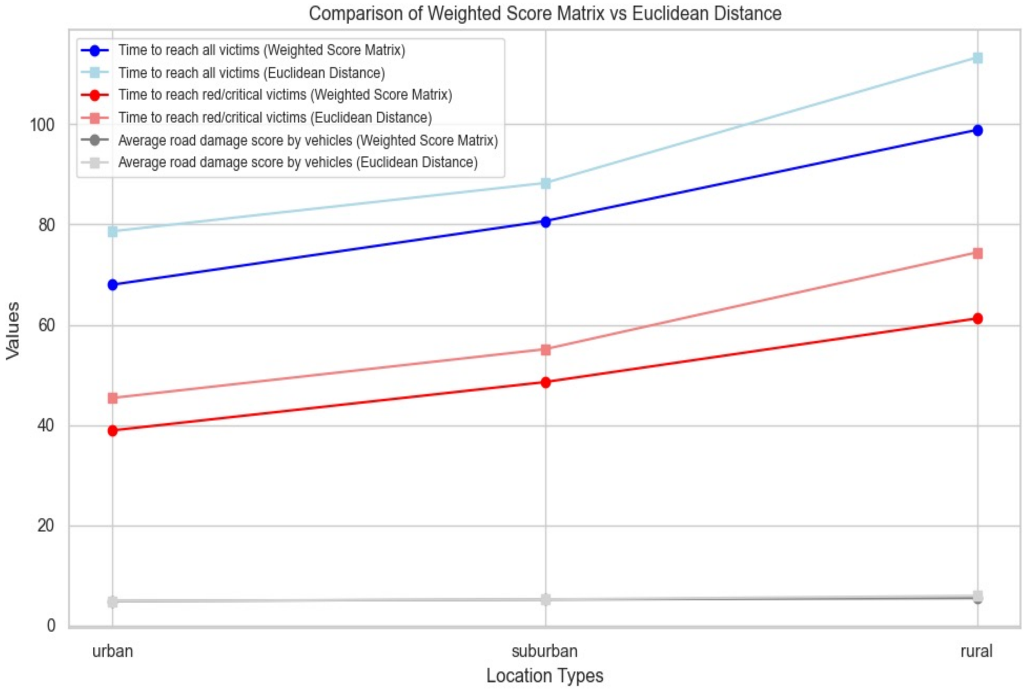



*Figure 46: Comparison of Weighted Score Matrix vs Euclidean Distance*
*Made by Student, 2025*

| 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


- Evaluates the effectiveness of temporary hospitals and resource allocation during the disaster, providing insights for future improvements.

- 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.

### 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.

### 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.

### 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.

### 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.

### 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.

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