

# Emergen-Sim : Data Analysis and Simulation Modeling for Optimizing Urban Emergency Response Systems

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## Abstract

This project is centered on developing an advanced framework for optimizing emergency response strategies in urban settings, grounded in sophisticated data analysis and simulation modeling. The project commenced with a comprehensive preprocessing of the 'Emergency Response' dataset that was given. This involved transforming incident timestamps into actionable insights, including the extraction of temporal features such as the day of the week and categorized time slots (morning, afternoon, evening, and night). I then calculated incident probabilities for each grid cell, incorporating a temporal dimension to reflect the likelihood of incidents at different times and days.

In the EmergencyResponseEnv simulation, I meticulously modeled a 30x30 urban grid to simulate diverse emergency scenarios with varying severity. The simulation is influenced by two key inputs: incident probabilities, dynamically generated for each grid cell based on the specific time chunk (e.g., morning, afternoon) and day of the week, and configurations of emergency resources, each with unique types and initial stationing.

**Simulation Execution:** Each step of the simulation executes a decision cycle within the EmergencyResponseEnv. Incident occurrences are stochastically determined by comparing randomly sampled values against the predefined probabilities for each grid cell, reflecting historical incident data and temporal patterns. When a sampled value falls below the cell's threshold probability, an incident is generated. Concurrently, each incident's severity is assigned by random sampling, adhering to predefined likelihoods of severity levels. This methodical yet randomized approach ensures a realistic and varied simulation landscape, echoing the unpredictability of real-world emergency events.

**Resource Constraints:** A key aspect of the simulation is the realistic constraints placed on resources. Each resource type (e.g., 'A', 'B') has specific capabilities and operational limits. For instance, a resource might only be effective within a certain distance from its station, or it may be specialized to handle particular severity levels of incidents. These constraints necessitate careful planning and strategy in resource allocation, echoing the complexities of real-world emergency response.

The reward function of the model is designed to measure the efficiency of emergency responses and is given

by the following equation:

$$\begin{aligned} \text{Reward} = & - \sum (\text{Severity of Unaddressed Incidents}) \\ & + \sum_{r \in \text{Responded}} \left( \text{Severity}_r \times \left( 1 - \frac{\text{TravelTime}_r}{\text{Max Permissible Response Time}} \right) \right) \end{aligned} \quad (1)$$

This function balances the urgency of addressing severe incidents against the efficiency of resource deployment, with the Max Permissible Response Time serving as a normalizing factor.

The state space is a vector representing the grid, with each element indicating the severity of incidents at that location. The action space is defined by the grid cell numbers for each available resource. Decisions involve choosing which grid cell each resource should be deployed to.

At the end of each episode, the model calculates key performance metrics, including total incidents responded to, cumulative response time, total incidents recorded, average response time, and resolution rate. These metrics offer a comprehensive evaluation of the strategy’s effectiveness.

In summary, this project provides a nuanced and robust simulation tool for urban emergency scenarios. It offers valuable insights into optimizing resource allocation and response strategies, with temporal variability and resource constraints that closely mimic real-world emergency management challenges. This project significantly enhances urban planning and public safety, contributing to the preparedness and efficacy of emergency services in urban environments.

## Outcomes from a Sample Simulation Run

In the provided simulation setup, ten ambulances—each defined by a specific type ('A' or 'B') and station coordinates—are inputted into the EmergencyResponseEnv environment. The simulation is configured to represent an urban grid during a particular time slot, set to 'Afternoon', and on a specific day, which in this case is 'Saturday'.

```
# Create an instance of the environment
resource_types = ['A', 'B', 'A', 'B', 'A', 'B', 'A', 'B', 'A', 'B']
stations = [(5, 5), (10, 10), (15, 15), (20, 20), (25, 25), (5, 15), (10, 25), (15, 5), (20, 15), (25, 25)]
env = EmergencyResponseEnv(interpolated_data, resource_types, stations)

# Number of steps for the simulation
num_steps = 1 # or more, as needed

# Run the simulation
env.reset(time='Afternoon', day='Saturday')
```

Figure 1: Image 1 (The Inputs given to the simulator)

