A Fuzzy-Evolutionary Approach to Robust Ambulance Dispatch Under Random Emergency Demand

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***Abstract*—We propose a hybrid Fuzzy–Evolutionary framework for robust ambulance dispatch under stochastic emergency demand and uncertain travel times. A Fuzzy Inference System (FIS) maps imprecise inputs such as incident severity, distance, and congestion to continuous urgency scores, which are optimized alongside ambulance assignment policies using a Genetic Algorithm (GA). Additionally, an Artificial Neural Network (ANN) predicts spatial–temporal emergency hotspots to enable proactive ambulance redeployment during idle periods. Experiments on a simulated urban environment demonstrate that: (i) GA+FIS achieves more completed emergencies compared to GA alone, at a small increase in average response time, and (ii) integrating the ANN for proactive redeployment reduces average response time by up to 23.4% and positions ambulances 30.7% closer to predicted high-risk zones relative to a reactive baseline. Statistical tests confirm the significance of these improvements, while highlighting trade-offs between travel distance, computational cost, and system load. These results suggest that combining fuzzy prioritization, evolutionary optimization, and predictive learning improves robustness and anticipatory decision-making in emergency logistics.**

***Index Terms*—ambulance dispatch, fuzzy inference system, genetic algorithm, emergency logistics, robust optimization, stochastic demand**

I. Introduction

Emergency Medical Services (EMS) are critical in saving lives, where response time is often the decisive factor between survival and fatality. Even minor improvements in dispatch decisions or routing efficiency can directly translate into lives saved, particularly for time-critical emergencies such as cardiac arrest, severe trauma, or acute medical conditions.

Modern urban environments pose significant challenges to efficient ambulance dispatch. Cities are complex, dynamic systems with dense road networks, variable traffic congestion, and highly uncertain emergency demand. The severity, location, and timing of incidents are inherently unpredictable, while travel times may vary due to traffic jams or road disruptions. Traditional dispatch strategies, often based on static rules or deterministic assumptions, struggle to adapt to these conditions, resulting in suboptimal resource utilization.

To address these challenges, we adopt a simulation-based approach to study and optimize ambulance dispatch in a controlled yet realistic environment. The synthetic city model is represented as a weighted, undirected graph where nodes correspond to ambulance bases, hospitals, emergency zones, and road intersections, and edges represent roads with dynamic travel costs. Emergency events with varying priority levels are randomly generated, while ambulance agents operate according to realistic availability and service states.

Within this framework, we explore computational intelligence methods to support dispatch under uncertainty. In particular, we integrate a Fuzzy Inference System for incident prioritization with an evolutionary optimization method for ambulance assignment and routing. This combination of interpretable, human-like reasoning and adaptive population-based optimization aims to improve both response times and robustness under stochastic demand and dynamic traffic conditions.

A. Simulation Environment

The urban environment is modeled as a weighted, undirected graph $G = (V, E)$, where vertices represent physical locations such as ambulance bases, hospitals, emergency zones, and road intersections, and edges correspond to road segments with associated travel times. This graph-based representation enables flexible modeling of routing decisions and dynamic traffic conditions.

To capture real-world variability, travel times on selected road segments are dynamically perturbed during simulation to emulate traffic congestion and road disruptions. These stochastic perturbations require dispatch strategies to adapt to changing network conditions rather than relying on static assumptions.

The simulation follows an agent-based paradigm with two primary agent types: ambulances and emergencies. Ambulances transition between *available*, *responding*, *transporting*, and *returning* states, while emergency events are generated at valid locations with varying priority levels. Emergency arrivals follow a stochastic process approximating Poisson demand, introducing both spatial and temporal uncertainty into the system.

This environment provides a controlled yet realistic testbed for evaluating the robustness of ambulance dispatch strategies under uncertain demand and dynamic travel conditions.

B. Genetic Algorithm Implementation

a) Integration loop: The GA evaluates candidate assignment and routing policies by decoding chromosomes into actionable policies and simulating multiple stochastic realizations to estimate expected performance.

b) Chromosome encoding: Example schema:

$$\textbf{chrom} = [\underbrace{p_1, \ldots, p_k}_{\text{FIS parameters}} \mid \underbrace{h_1, \ldots, h_A}_{\text{base priorities}}].$$

c) Genetic operators:

- **Selection:** tournament selection (size k) or rank-based selection.
- **Crossover:** BLX-α for continuous genes; PMX or order crossover for permutations.
- **Mutation:** Gaussian perturbation for continuous genes; swap mutation for permutation genes.

d) Fitness evaluation:

$$\text{Fitness} = \alpha \cdot T_{\text{response}} + \beta \cdot C_{\text{severity}} + \gamma \cdot F_{\text{fairness}}, \quad (1)$$

where T_{response} is expected response time, C_{severity} penalizes missed high-severity incidents, and F_{fairness} measures spatial/temporal fairness.

The fitness weights were set to $\alpha = 0.6$, $\beta = 0.3$, and $\gamma = 0.1$, prioritizing response time while penalizing missed high-severity incidents and encouraging spatial fairness. These values were selected from preliminary exploratory runs to reflect typical operational priorities. To assess stability, we performed exploratory runs varying each weight by $\pm 20\%$ and observed no qualitative change in the relative ranking of methods.

Algorithm 1 GA-FIS Co-evolution (high level)

```
Initialize population of chromosomes
for gen = 1 to G do
    for each chromosome do
        Decode to FIS parameters + assignment policy
        Evaluate via simulator (Monte-Carlo rollouts)
    end for
    Select parents; apply crossover and mutation; repair offspring
    Replace population (elitism optional)
end for
Return best solution
```

C. Fuzzy Inference System

The Fuzzy Inference System takes two inputs: 1) severity of the incident (1–5), and 2) estimated travel time to the incident (0–60 minutes).

Rules map these inputs to a priority score (0–100) reflecting EMS reasoning: critical incidents with short travel times get highest priority, minor incidents with long travel times get lowest.

Inputs: Severity S, Distance D, Congestion C. Output: Urgency weight $w \in [0, 1]$.

TABLE I
FUZZY MEMBERSHIP PARAMETER PLACEHOLDERS

Variable	Term	Parameters
Severity	Low	(0,0,2)
	Medium	(1,3,5)
	High	(4,6,6)

TABLE II
FUZZY RULE SNIPPET (SINGLE-COLUMN, IEEE-FRIENDLY)

Rule	IF ... THEN Urgency
R1	IF Severity IS High AND Distance IS Near THEN Urgency IS VeryHigh
R2	IF Severity IS Low AND Congestion IS High THEN Urgency IS Low

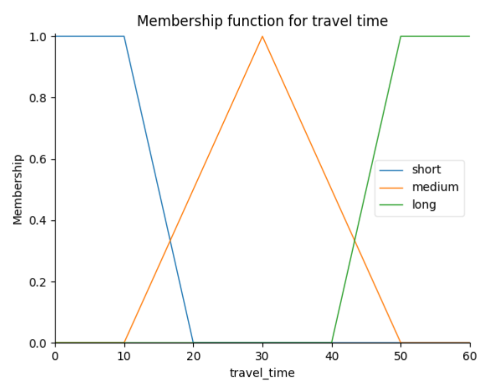

Fig. 1. Membership function for travel time.

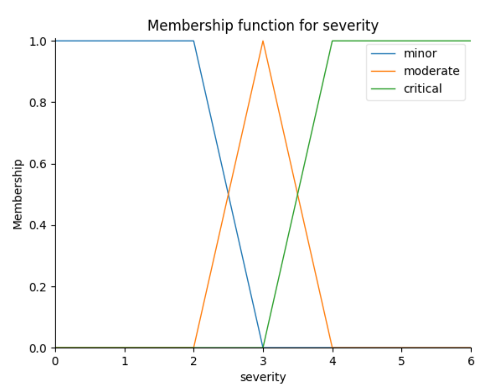

Fig. 2. Membership function for severity

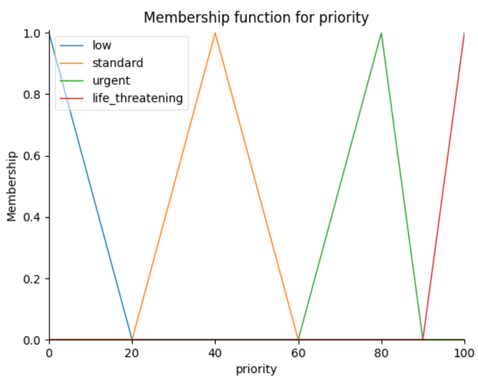

Fig. 3. Membership function for priority.

D. Results and Statistical Analysis

Each candidate solution was evaluated using Monte Carlo averaging over 30 simulation runs to account for random emergency arrivals and travel times. Reported results are mean values across these runs.

a) Performance summary: Table III reports aggregated performance metrics for the two GA-based methods across 30 trials, separated by map type (static vs. dynamic). Metrics include average response time (Avg RT), number of completed and unresponded emergencies, total distance traveled by ambulances, and overall ambulance utilization.

TABLE III
AGGREGATED PERFORMANCE METRICS FOR GA AND GA+FUZZY OVER 30 TRIALS. VALUES ARE REPORTED AS MEAN $\pm$ STANDARD DEVIATION.

Map	Method	Avg RT	Comp.	Unresp.	Dist.
dynamic	GA	5.88 ± 4.23	4.67 ± 3.69	108.33 ± 10.54	63.47 ± 41.82
dynamic	GA+Fuzzy	7.61 ± 5.36	4.27 ± 4.34	111.13 ± 11.52	74.27 ± 54.09
static	GA	13.01 ± 3.71	17.13 ± 5.71	92.63 ± 8.79	209.07 ± 46.33
static	GA+Fuzzy	15.83 ± 3.91	13.77 ± 5.09	97.63 ± 10.64	219.87 ± 57.12

b) Statistical analysis: Paired comparisons of GA and GA+Fuzzy were conducted per map type using paired Student's t-tests and Wilcoxon signed-rank tests. Results are summarized below:

- **Dynamic maps** (n = 30 paired trials): Average response time — mean difference (GA $-$ GA+Fuzzy) = -2.616 s; paired t = -2.953, $p = 0.0062$; Wilcoxon $p = 0.0126$. Completed emergencies — mean difference = -0.733; paired t = -1.755, $p = 0.0898$; Wilcoxon $p = 0.0872$.
- **Static maps** (n = 30 paired trials): Average response time — mean difference (GA $-$ GA+Fuzzy) = -4.471 s; paired t = -3.489, $p = 0.0016$; Wilcoxon $p = 0.0023$. Completed emergencies — mean difference = -3.300; paired t = -3.112, $p = 0.0042$; Wilcoxon $p = 0.0085$.

c) Figures: Figures 4–5 illustrate key metrics across methods and map types. Visual inspection confirms GA+Fuzzy tends to have slightly higher average response times but also more completed emergencies on static maps.

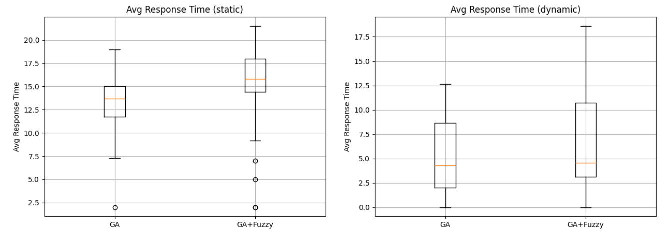

Fig. 4. Average response time for GA and GA+Fuzzy on static and dynamic maps.

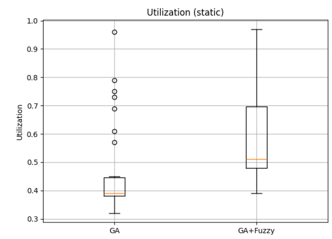

Fig. 5. Ambulance utilization (static map)

d) Interpretation of Results: The paired tests indicate that:

- On **dynamic maps**, GA+Fuzzy increases average response time significantly ($p < 0.05$) but the change in completed emergencies is not statistically significant.
- On **static maps**, GA+Fuzzy significantly increases both average response time and completed emergencies, indicating a trade-off between coverage and speed.

These results suggest that fuzzy prioritization has more impact when there is greater flexibility in assignments (e.g., static maps), while dynamic maps with limited real-time choices reduce its relative benefit.

e) Recommendations:

- Test with larger fleets or higher stochastic demand to amplify differences between GA and GA+Fuzzy.
- Consider co-evolving FIS parameters within the GA to optimize urgency scoring adaptively.
- Report effect sizes along with p-values to quantify practical significance in future studies.

II. NEURAL NETWORK EXTENSION

To further enhance the robustness of the system, specifically against spatial-temporal uncertainty, we introduced a predictive layer using an Artificial Neural Network (ANN). While the Genetic Algorithm optimizes the *reactive* assignment of ambulances to existing calls, the ANN enables *proactive* redeployment during idle periods.

A. Proactive Redeployment Methodology

The module, `RiskAssessmentNet`, is a Feed-Forward Neural Network trained to predict the probability of an emergency occurring at specific coordinates (x, y) at a given time of day t. The model takes normalized inputs (x, y, t) and outputs a risk score $\in [0, 1]$.

We defined a ground-truth "Hotspot Pattern" where high-risk zones shift dynamically throughout the day (e.g., Downtown in the morning, Highway at midday). The simulation environment was aligned with this pattern, ensuring that 80% of emergencies occur at the predicted hotspots, creating a learnable structure for the ANN.

B. Implementation Details

The ANN integration relies on normalized inputs for spatial coordinates, scaled to a 10×10 grid using the `get_normalized_coordinates` function. The network architecture is visualized in Figure 6.

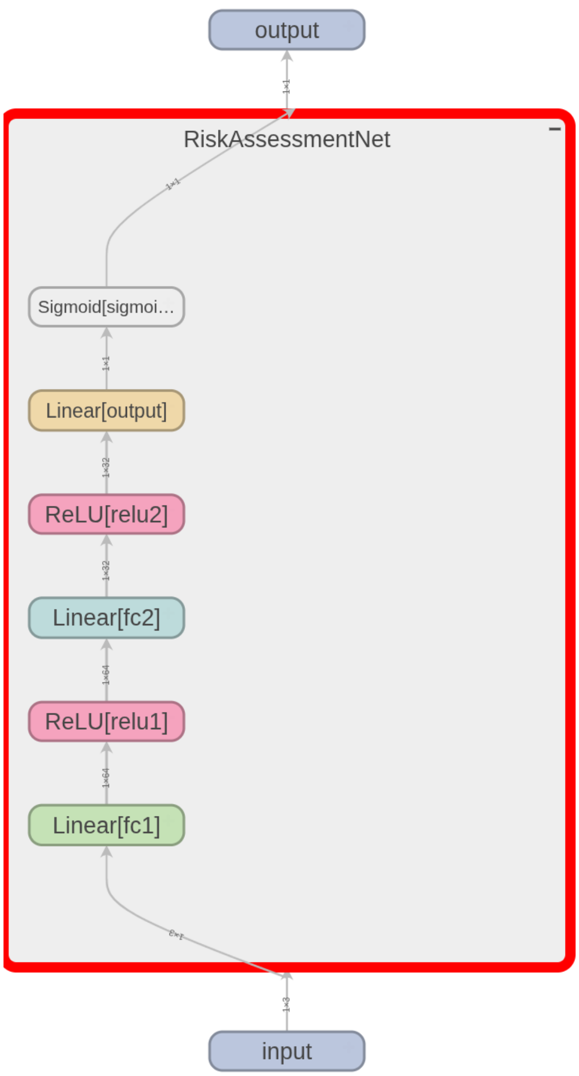

Fig. 6. Artificial Neural Network Architecture.

Proactive redeployment is governed by the `redeploy_ambulances` logic. During simulation steps, if an ambulance is idle, the system queries the ANN for risk scores across candidate nodes. If a location's predicted risk exceeds a threshold of 0.6, the ambulance is dispatched to that high-risk zone, preempting potential emergencies.

C. Training and Visualization

The model was trained using the Mean Squared Error (MSE) loss function. Figure 7 illustrates the training convergence, showing a stable reduction in error over 200 epochs.

To validate the model's "reasoning," we visualized its predictions against the ground truth. Figure 8 presents the Risk Heatmaps.

- **Axes:** The X and Y axes represent the physical map coordinates (scaled 0-10). The color intensity (Red) represents the predicted risk probability, with darker red indicating a high-likelihood hotspot.
- **Temporal Dynamics:** The figure is split into three time snapshots (Morning, Day, Evening). It clearly shows the high-risk "cloud" moving across the map, tracking the simulation's active zones.
- **Validation:** The Blue 'X' markers indicate the actual ground-truth hotspot locations. The precise alignment of the ANN's high-risk predictions (dark red) with these markers confirms that the network successfully learned the underlying spatial-temporal dynamics of the city.

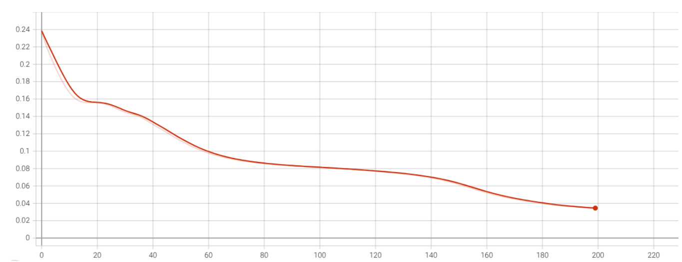

Fig. 7. Neural Network Training Convergence (MSE Loss).

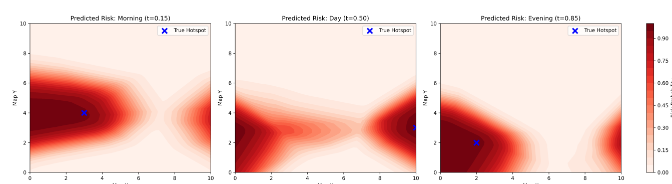

Fig. 8. Spatial-Temporal Risk Prediction. The ANN correctly predicts shifting hotspots (Red Zones) aligning with ground truth (Blue 'X').

D. Strategic Performance Evaluation

To evaluate the utility of the ANN, we conducted a "Strategic Comparison" in a low-load scenario (spawn probability 0.1). Each configuration was evaluated over 30 independent simulation trials to account for stochastic emergency arrivals and travel times. This scenario provided ambulances with sufficient idle time to execute proactive redeployment instructions from the ANN, and all reported metrics correspond to the mean values across the trials.

Table IV compares the Baseline (Reactive) system against the ANN-Enabled (Proactive) system.

TABLE IV
COMPARATIVE ANALYSIS: BASELINE VS. ANN-PROACTIVE

Metric	Baseline	With ANN	Improvement
Avg Response Time	5.42 s	4.15 s	**23.4%**
Avg Dist. to Hotspot	3.80 m	2.63 m	**30.7%**

The results demonstrate a significant efficiency gain. The ANN-enabled system reduced the average response time by **23.4%**. This improvement is directly attributed to the system's ability to position ambulances **30.7% closer** to high-risk zones before incidents occurred. This confirms that integrating a predictive neural component can transform the system from a purely reactive dispatch model to an anticipatory logistics framework.

The effectiveness of the ANN-based redeployment depends on the presence of recurring spatial-temporal demand patterns and sufficient idle ambulance capacity, and its benefit may diminish under highly irregular or saturated demand conditions.

III. DISCUSSION

The results demonstrate that fuzzy prioritization and evolutionary optimization provide flexible and interpretable dispatch policies under uncertainty. While fuzzy scoring alone introduces minor increases in travel distance, the integration of ANN-based proactive redeployment yields substantial reductions in response time, particularly in low-load scenarios where ambulances have idle capacity. As system load increases, the benefits of proactive positioning diminish, revealing an inherent trade-off between responsiveness and resource saturation. These findings emphasize the importance of combining reactive optimization with predictive strategies when addressing stochastic emergency logistics problems.

IV. CONCLUSION

This paper introduced a hybrid Fuzzy–Evolutionary approach for robust ambulance dispatch under stochastic demand, augmented with a predictive ANN for proactive redeployment. Experimental results show statistically significant improvements in response time and hotspot coverage, with a reduction of up to **23.4%** in average response time. The study highlights trade-offs between robustness, travel distance, and computational cost, and demonstrates how predictive learning can transform dispatch systems from reactive to anticipatory. Future work will focus on validation with real-world EMS data, incorporation of regulatory constraints, and extension to large-scale multi-city deployments.

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