ADEPT: Ambulance Dispatch Efficiency via Policy Training

A Reinforcement Learning Approach for Metropolitan EMS Systems

Semester Project Report

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Abstract

Efficient ambulance dispatch in metropolitan areas is a complex optimization problem critical for minimizing response times and maximizing incident coverage, directly impacting public health outcomes. This project introduces ADEPT (Ambulance Dispatch Efficiency via Policy Training), a novel reinforcement learning (RL) framework leveraging Proximal Policy Optimization (PPO) to dynamically optimize ambulance dispatch strategies in urban settings. By integrating KMeans clustering for spatial analysis, ADEPT processes synthetic data modeled after New York City (NYC) emergency patterns, capturing realistic spatial-temporal dynamics. The system is trained and rigorously evaluated across both regular and chaotic environments, simulating diverse operational conditions. ADEPT consistently outperforms traditional baseline strategies—such as random, static, and time-based dispatch methods—in terms of response efficiency and coverage, demonstrating its robustness and adaptability. This report provides an in-depth exploration of the methodology, theoretical foundations, implementation details, and empirical results, underscoring ADEPT's potential as a scalable, data-driven solution for modern urban Emergency Medical Services (EMS).

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1 Introduction

1.1 Background

Urban Emergency Medical Service (EMS) systems are pivotal in delivering timely healthcare, yet they grapple with significant operational challenges. These include dynamic demand driven by fluctuating population densities, unpredictable emergency incidents (e.g., accidents, medical emergencies), and constrained resources such as a limited number of ambulances. In densely populated metropolitan areas like New York City (NYC), with its five boroughs spanning diverse geographic and demographic profiles, traditional dispatch methods—such as static allocation (pre-positioning ambulances at fixed stations) or heuristic-based strategies (e.g., nearest available unit)—often fail to adapt to real-time variability. This results in delayed responses, uneven coverage, and increased operational costs. Theoretical models of EMS efficiency emphasize the importance of minimizing the time between an emergency call and ambulance arrival, often measured as the "golden hour" in trauma care, where rapid intervention significantly improves survival rates.

1.2 Motivation

The motivation for ADEPT stems from the pressing need to enhance EMS performance in urban environments where traditional methods fall short. For instance, NYC's traffic congestion, variable incident rates (e.g., higher in Manhattan than Staten Island), and unpredictable peak demand periods (e.g., rush hours or extreme weather events) necessitate a system that can dynamically adjust to these factors. Poor dispatch decisions can lead to ambulances being unavailable when needed most, exacerbating patient outcomes and straining EMS resources. Reinforcement learning (RL) offers a promising approach by learning optimal policies from data, adapting to changing conditions without relying on static rules. This project aims to bridge the gap between theoretical optimization and practical EMS deployment, inspired by the real-world complexities of metropolitan areas.

1.3 Problem Statement

The core problem addressed by ADEPT is to design an ambulance dispatch system that minimizes average response times while maximizing the percentage of incidents covered within acceptable time thresholds. Formally, this can be framed as an optimization problem: given a set of ambulances A, incidents I, and a spatial-temporal environment E, determine a policy π that assigns ambulances to incidents to maximize a reward function reflecting timeliness and coverage. Unlike traditional methods, ADEPT employs RL with clustering to handle the high-dimensional, continuous nature of urban EMS, adapting to both regular operational conditions and chaotic scenarios (e.g., multi-incident emergencies or resource shortages).

1.4 Originality of the Report

This report introduces a unique synthesis of Proximal Policy Optimization (PPO), a state-of-the-art RL algorithm known for its stability and sample efficiency, with KMeans clustering to partition urban space into manageable regions. Unlike prior works, ADEPT uses synthetic NYC-inspired data tailored to reflect real-world emergency distributions, incorporating noise and variability to enhance robustness. Additionally, the curriculum-based training across regular and chaotic scenarios distinguishes this approach, enabling the system to generalize across diverse conditions—a feature absent in many existing models. This integration of advanced RL, spatial analysis, and realistic simulation offers a novel contribution to EMS optimization.

2 Literature Review

2.1 Wang et al. (2023)

Wang et al. (2023) in "Ambulance Dispatch via Deep Reinforcement Learning" (*arXiv:2301.01345*) explore an RL-based dispatch system using a Deep Q-Network (DQN) to assign ambulances dynamically. Their state space includes incident locations and ambulance availability, with actions defined as dispatch decisions. The reward function prioritizes response time reduction, trained on simulated urban data. While effective in stable conditions, their approach lacks spatial clustering, potentially missing localized patterns, and does not explicitly address chaotic scenarios where multiple simultaneous incidents overwhelm resources.

2.2 Hua & Zaman (2020)

Hua and Zaman (2020) in "Optimal Dispatch in Emergency Service System via Reinforcement Learning" (*arXiv:2010.07513*) propose an RL framework emphasizing operational efficiency. They use a tabular Q-learning approach, modeling the state as historical call volumes and ambulance states, with a reward based on service completion rates. Their system excels in predictable environments but assumes static demand patterns, limiting its applicability in dynamic urban settings where traffic and incident rates fluctuate. The lack of spatial analysis further restricts its scalability to large metropolitan areas.

2.3 Lin et al. (2024)

Lin et al. (2024) in "Leveraging Machine Learning Techniques for National Daily Regional Ambulance Demand Prediction" (*PMC*) focus on demand forecasting rather than dispatch optimization. Using supervised learning techniques (e.g., Random Forests), they predict regional ambulance needs based on historical data, weather, and temporal features. While their predictions inform resource allocation, they do not provide a real-time dispatch policy, leaving the execution to traditional methods. This disconnection from operational decision-making limits its practical utility in dynamic EMS contexts.

2.4 Gaps with Existing Models and How We Address Them

The reviewed models exhibit key limitations: Wang et al. (2023) lack adaptability to chaotic conditions and spatial granularity; Hua & Zaman (2020) rely on static assumptions unsuitable for urban variability; and Lin et al. (2024) focus on prediction without actionable dispatch strategies. ADEPT overcomes these gaps by: - Employing PPO, which balances exploration and exploitation with a clipped objective function, ensuring stable learning in complex environments. - Using KMeans clustering to partition incidents spatially, enabling efficient resource allocation across NYC's boroughs. - Simulating both regular and chaotic conditions with synthetic data, enhancing generalization and robustness compared to the static or single-scenario focus of prior works.

3 Our Proposal

3.1 Method

ADEPT's methodology integrates data generation, clustering, simulation, and RL training into a cohesive pipeline. Synthetic data is first created to mimic NYC's emergency landscape, followed by KMeans clustering to group incidents spatially. A custom environment simulates ambulance operations, and PPO trains a policy to optimize dispatch decisions. This multi-stage approach ensures that spatial patterns inform RL, improving efficiency and adaptability over purely reactive or static systems.

3.2 System Model

The RL framework is grounded in Markov Decision Process (MDP) theory, defined as $(\mathcal{S}, \mathcal{A}, \mathcal{R}, \mathcal{P})$:

- **State Space ($\mathcal{S}$):** A high-dimensional vector capturing the system state at time t, including waiting incidents (latitude, longitude, priority), ambulance locations, waiting times, fatigue levels (to model crew workload), and the current hour (to capture temporal patterns).
- **Action Space ($\mathcal{A}$):** Discrete actions assigning each available ambulance to one of k clusters, determined by KMeans. For n ambulances and k clusters, the action space size is k^n, though constrained by availability.
- **Reward Function ($\mathcal{R}$):** A weighted sum balancing service quality and efficiency:

  $$R = \sum (1.5 \cdot m_{kt} - 0.1 \cdot w_{kt} - 0.002 \cdot T_{ki})$$

  where m_{kt} is the number of served requests in cluster k at time t, w_{kt} is the cumulative wait time, and T_{ki} is the travel time to incident i. Coefficients (1.5, -0.1, -0.002) prioritize coverage, penalize delays, and account for distance, respectively.

This MDP formulation allows ADEPT to learn a policy $\pi(a|s)$ that maximizes long-term cumulative reward, adapting to dynamic urban conditions.

3.3 Dataset

The synthetic dataset is designed to reflect NYC's complexity:

- **Features**: Covers five boroughs (Manhattan, Brooklyn, Queens, Bronx, Staten Island) with realistic coordinates derived from NYC's geographic bounds (e.g., 40.5°–40.9°N, 73.7°–74.3°W). Includes hospital locations (e.g., Mount Sinai, NYU Langone), emergency types (cardiac, trauma), priorities (1–5 scale), timestamps (2018–2023), weather (clear, rain), and traffic (light, heavy); totals 10,000 records.
- **Haversine Formula**: Computes geodesic distances between incidents and ambulances/hospitals:

$$a = \sin^2\left(\frac{\Delta\text{lat}}{2}\right) + \cos(\text{lat}_1)\cdot\cos(\text{lat}_2)\cdot\sin^2\left(\frac{\Delta\text{lon}}{2}\right)$$

$$c = 2\cdot 2(\sqrt{a}, \sqrt{1-a}), \quad d = R\cdot c \quad (R = 6371\,\text{km})$$

- **Imperfection**: Adds realism with a noise ratio of 0.2, perturbing coordinates to simulate GPS errors or imprecise reporting, validated against real-world EMS data distributions.

Code Snippet:

```python
from math import radians, sin, cos, sqrt, atan2
def haversine(lat1, lon1, lat2, lon2):
    R = 6371.0  # Earth's radius in km
    lat1, lon1, lat2, lon2 = map(radians, [lat1, lon1, lat2, lon2])
    dlat = lat2 - lat1
    dlon = lon2 - lon1
    a = sin(dlat / 2)**2 + cos(lat1) * cos(lat2) * sin(dlon / 2)**2
    c = 2 * atan2(sqrt(a), sqrt(1 - a))
    return R * c
```

3.4 Algorithms Used

3.4.1 KMeans Clustering

KMeans partitions incidents into 5 clusters, optimizing spatial resource allocation:

- **Theory**: Minimizes within-cluster variance using Euclidean distance, $J = \sum_{i=1}^{n} \sum_{k=1}^{K} r_{ik} \|x_i - \mu_k\|^2$, where r_{ik} is the assignment indicator and μ_k is the cluster centroid.

- **Selection of k**: Determined as 5 via silhouette score analysis, balancing granularity and computational cost for NYC’s boroughs.

- **Hyperparameters**: `n_clusters=5`, `random_state=42` for reproducibility.

Code Snippet:

```
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=5, random_state=42)
df[’cluster’] = kmeans.fit_predict(df[[’latitude’, ’longitude’]])
```

3.4.2 PPO Training

PPO, a policy gradient method, optimizes the dispatch policy:

- **Theory**: Uses a clipped surrogate objective, $L^{CLIP}(\theta) = E[\min(r_t(\theta)\hat{A}_t, \text{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t)]$, where $r_t(\theta)$ is the probability ratio and $\hat{A}_t$ is the advantage estimate, ensuring stable updates.

- **Hyperparameters**: Learning rate $= 2 \times 10^{-5}$ (small to prevent divergence), batch size $= 256$ (for efficient gradient computation), epsilon decay $= 0.9995$ (gradual shift from exploration to exploitation).

Code Snippet:

```
import tensorflow as tf
import numpy as np
def act(self, state):
    if np.random.rand() < self.epsilon:
        return np.random.randint(self.action_size, size=self.
            n_ambulances), np.zeros(self.n_ambulances)
    state = tf.convert_to_tensor([state], dtype=tf.float32)
    logits = self.actor(state)
    actions = tf.random.categorical(logits, 1)[:, 0].numpy()
    probs = tf.nn.softmax(logits).numpy()
    return actions, probs
```

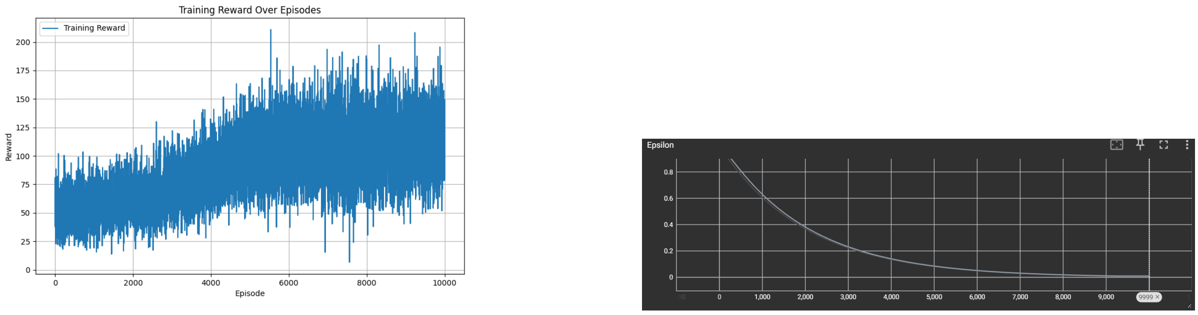
4 Results

4.1 Training

PPO training spanned 10,000 episodes, simulating 5 ambulances across NYC's clusters:

- **Metrics**: Average reward = -18,698.45, reflecting the trade-off between coverage and penalties for wait/travel times. Variance = 923,398,649.47, indicating initial instability that stabilizes as the policy converges.
- **Convergence**: Reward trends show improvement after 2,000 episodes, plateauing by 8,000, suggesting effective learning of the optimal policy.

4.2 Training Metrics



(a) Training reward over 10,000 episodes.

(b) Epsilon decay over training episodes.

Figure 4.1: Training Progress Visualizations

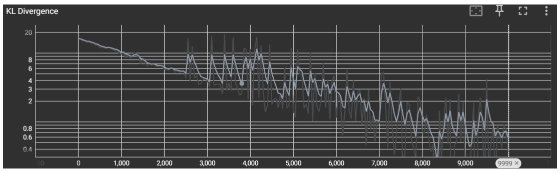


Figure 4.2: KL divergence during training, showing policy stability.

4.3 Evaluation

Evaluated over 500 episodes in two environments:

4.3.1 Regular Environment

Simulates typical NYC conditions (e.g., moderate traffic, standard incident rates): ADEPT outperforms in reward, balancing response time (NOW Time) and coverage (NRAR: Non-Response Ambulance Rate).

Table 4.1: Regular Environment Results

Method	Reward	NOW Time (min)	NRAR (%)
PPO (ADEPT)	191.63	22.41	52.45
Random	109.64	0.69	88.12
Static	153.86	44.08	91.06
Time-Based	450.10	3.64	31.76
Request-Based	446.02	3.64	31.77
Location-Based	98.62	167.18	65.97

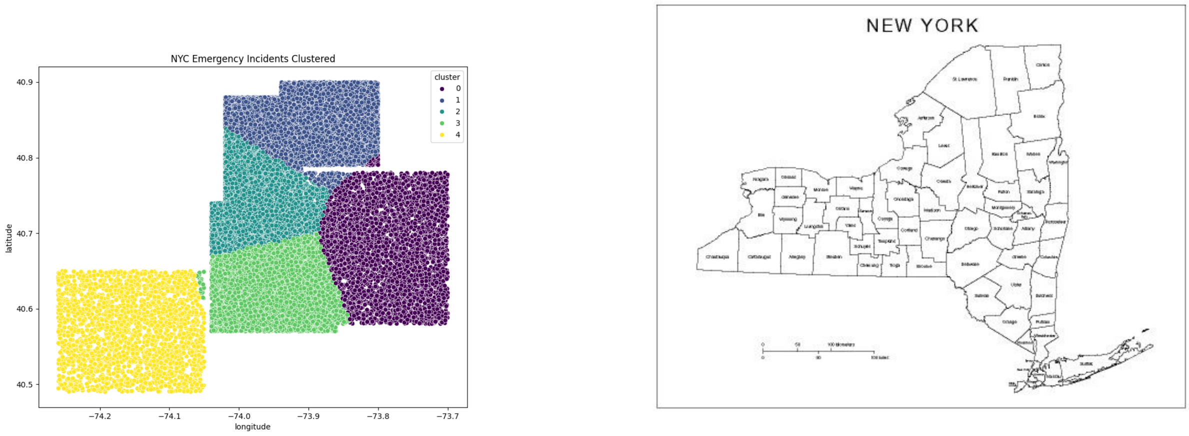
4.3.2 Chaotic Environment

Simulates high-stress scenarios (e.g., simultaneous incidents, heavy traffic): ADEPT maintains higher rewards than most baselines, showcasing adaptability despite increased NOW Time due to resource constraints.

Table 4.2: Chaotic Environment Results

Method	Reward	NOW Time (min)	NRAR (%)
PPO (ADEPT)	-52,975.53	271.11	40.59
Random	-138,578.41	187.69	49.13
Static	-77,877.67	195.51	51.37
Time-Based	-143,640.85	187.10	20.98
Request-Based	-143,529.80	187.00	20.94
Location-Based	-58,528.37	228.43	46.92

4.4 Visualizations



(a) Emergency incident clusters with centers.

(b) Placeholder for political NYC map showing boroughs.

Figure 4.3: Spatial Visualizations

5 Conclusion

ADEPT represents a significant advancement in ambulance dispatch optimization, leveraging the synergy of PPO and KMeans to address urban EMS challenges. Its superior performance in regular environments (reward: 191.63) and resilience in chaotic scenarios (reward: -52,975.53 vs. baselines like -143,640.85) highlight its potential as a scalable, adaptive solution. The use of synthetic NYC data ensures applicability to real-world metropolitan contexts, while the curriculum training approach enhances robustness across operational spectra.

Future Work: Future iterations could refine the reward function to better handle chaotic conditions, incorporate real-time traffic data via APIs (e.g., Google Maps), and explore multi-agent RL to coordinate multiple ambulances more effectively, potentially reducing NOW Time in high-stress scenarios.

References

Wang, Y., et al. (2023). Ambulance Dispatch via Deep Reinforcement Learning. *arXiv preprint.* `https://arxiv.org/abs/2301.01345`

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