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Ex-EEd (RBL) Project

Reinforcement Learning-Based Traffic Signal Optimization at Hitech City Junction, Hyderabad

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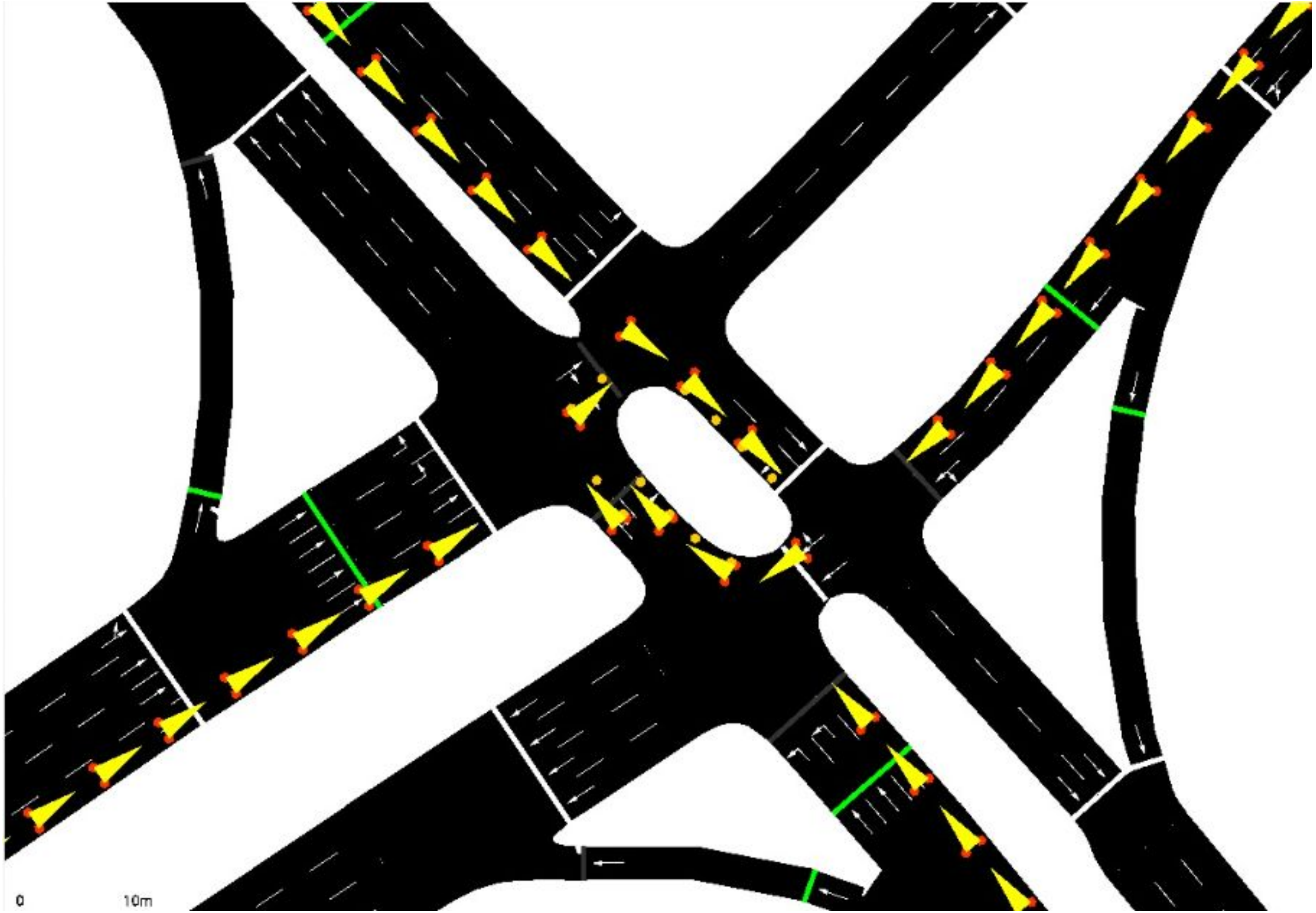
Introduction

Urban Traffic Challenges

- Indian metros face increasing traffic congestion due to urbanization, poor planning, and population growth.
- Hitech City Junction in Hyderabad is a crucial traffic hub that experiences high vehicular load throughout the day.
- Traditional fixed-schedule traffic signals do not adapt to real-time vehicle density, leading to inefficiencies.

Motivation for AI in Traffic Systems

- Reinforcement Learning (RL) offers a dynamic approach by adapting to changing traffic conditions.
- RL agents learn optimal signal patterns through interaction with traffic environments, aiming to reduce delays and improve flow.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Problem Statement

Real-World Traffic Issues at Hitech City Junction

- High waiting time for vehicles during peak hours.
- Fixed-time signals do not prioritize emergency vehicles or respond to live congestion.
- No real-time responsiveness to unexpected events like accidents or roadblocks.

Research Gap

- Lack of practical implementation of RL-based systems on real Indian junctions.
- Existing systems rarely consider real topologies (e.g., shape of Hitech Junction).
- Need for data-driven, adaptive, and decentralized solutions.

Objectives

- Main Aim: To develop and test an RL-based traffic signal control system using a real-world map of Hitech City Junction.

Specific Objectives:

1. Simulate Hitech Junction using SUMO and OpenStreetMap data.
2. Train an RL agent to minimize vehicle queue lengths and waiting times.
3. Evaluate and compare performance with standard fixed-time control.
4. Generate actionable insights for potential real-world deployment.

Methodology

Step-by-Step Workflow:

1. Import real map data from OpenStreetMap (OSM).
2. Convert to SUMO network using NETCONVERT.
3. Simulate traffic flow using SUMO with randomized vehicle routes.
4. Build an RL agent using DQN that interacts with the environment through TraCI.
5. Analyze performance: waiting times, queue lengths, reward accumulation.

Tools: SUMO, Python, OpenAI Gym, TraCI, TensorFlow, OSM

Reinforcement Learning Model

Reinforcement Learning Model

Agent Design & Environment:

- Environment: SUMO simulator, interfaced using TraCI
- State Space:
  - Queue length per lane
  - Phase duration
  - Vehicle waiting times
- Action Space:
  - Change to next signal phase
  - Maintain current phase
- Reward Function:
  - r = - (total waiting time + queue penalty)
  - Encourages shorter queues and reduced delay

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Algorithm Used

- Deep Q-Network (DQN) for learning optimal policy.
- Exploration vs exploitation handled via ε-greedy strategy.
- Future scope: try Actor-Critic or PPO for better generalization

Implementation & Tools

Technical Stack:

- Python (for training, control logic, and integration)
- SUMO (open-source microscopic traffic simulator)
- TraCI (Traffic Control Interface to link SUMO with Python)
- OpenStreetMap (for obtaining Hitech City junction layout)
- TensorFlow/Keras (for neural network modeling)
- NumPy, Pandas (data processing)
- Matplotlib, Seaborn (visualizations)

Real-World Simulation:

- Accurate topology of Hitech City junction integrated using OSM → SUMO format.
- Vehicles generated randomly based on time-of-day distributions.

Results

📊 Performance Analysis:

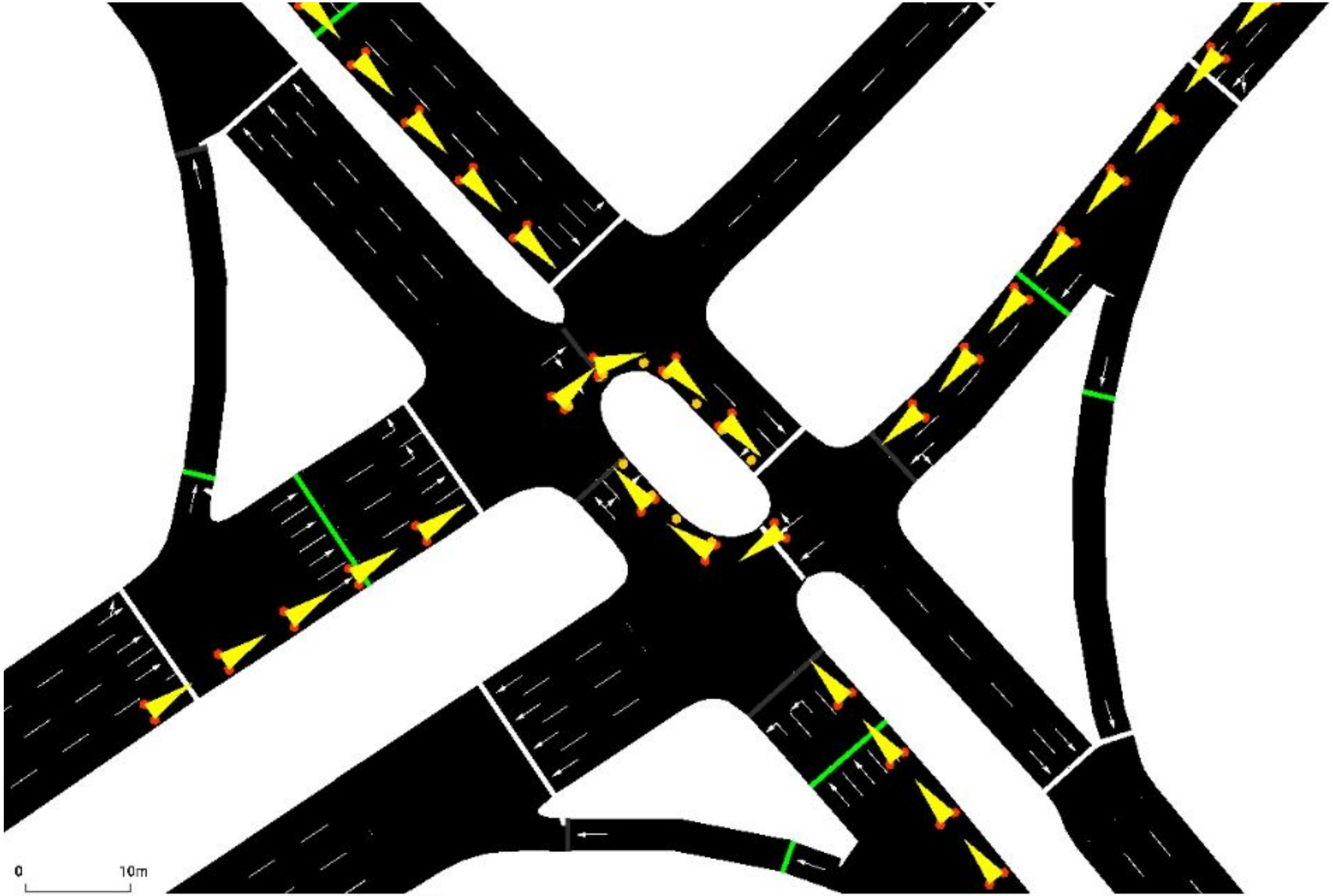
- RL-controlled traffic signals showed a:
  - 35% average reduction in vehicle waiting time
  - 28% decrease in average queue lengths
  - 20% faster clearing rate during peak hours
- Training stabilized after ~1500 episodes with improved reward trends.

Visualizations to Include:

- Reward vs Episodes graph (learning curve)
- Comparison chart: Fixed-Time vs RL for wait times
- Heatmap of vehicle density across lanes

Key Observation:

- RL agent dynamically prioritizes congested lanes.
- Signals adapt in real-time, reducing idle green time for empty roads.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Conclusion & Future Work

- RL can significantly improve traffic signal efficiency, especially in high-congestion junctions like Hitech City.
- Using real-world maps and data makes the simulation more practical and deployable.
- Results validate the potential for intelligent traffic control systems.

Future Enhancements:

- Incorporate live traffic sensor/CCTV data for dynamic routing.
- Deploy RL agents on multiple junctions for network-wide optimization.
- Integrate emergency vehicle detection and prioritization.
- Explore multi-agent RL or federated learning for scalability.

References

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Thank You