



ABSTRACT

We optimize urban road systems using evolutionary algorithms and reinforcement learning, interfacing with the Simulation of Urban Mobility (SUMO) package. Our models adjust traffic signal timings, speed limits, and lane access to maximize throughput and minimize congestion, waiting time, and crashes. The reinforcement learning models use reward signals based on traffic efficiency metrics, while evolutionary algorithms iteratively refine configurations through performance-based selection. Evaluated on travel time, speed variation, and throughput, our models outperform real-world-inspired baselines, demonstrating the effectiveness of these approaches for traffic optimization.

INTRODUCTION

- We chose to tackle traffic management in urban planning due its contribution to fuel waste, emissions, and decrease in safety
- Urban road systems require intricate planning, time, and funding to ensure safe and effective transportation. Due to this, many cities suffer from terrible traffic, affecting the quality of life of the people
- ML Algorithms can drastically reduce the time and money required to create effective road systems.
- But the use of ML algorithms in this field has focused on prediction, not optimization.

METHODOLOGY

- This study optimizes traffic configurations using two computational approaches: a genetic algorithm, which evolves high-performing solutions, and an actor-critic model, which learns optimal changes via reinforcement learning.
- Simulations were run on snapshots of 10 cities from OpenStreetMaps, incorporating speed limits and signals.
- Each simulation featured 1,000 vehicles with randomized routes spawning over 1,800 steps (30 simulated minutes) to maintain constant traffic flow.
- The effectiveness of each approach was evaluated based on metrics such as average travel time, congestion time, and throughput

SIMULATIONS WERE RUN ON THE FOLLOWING CITIES:

- Lisbon, Portugal
- Boston, USA
- Shanghai, China.
- Los Angeles, USA
- Mumbai, India
- Rio de Janeiro, Brazil
- Monaco, Monaco
- Manila, Philippines
- Johannesburg, South Africa
- Cairo, Egypt

EXPERIMENTAL CONFIGURATION

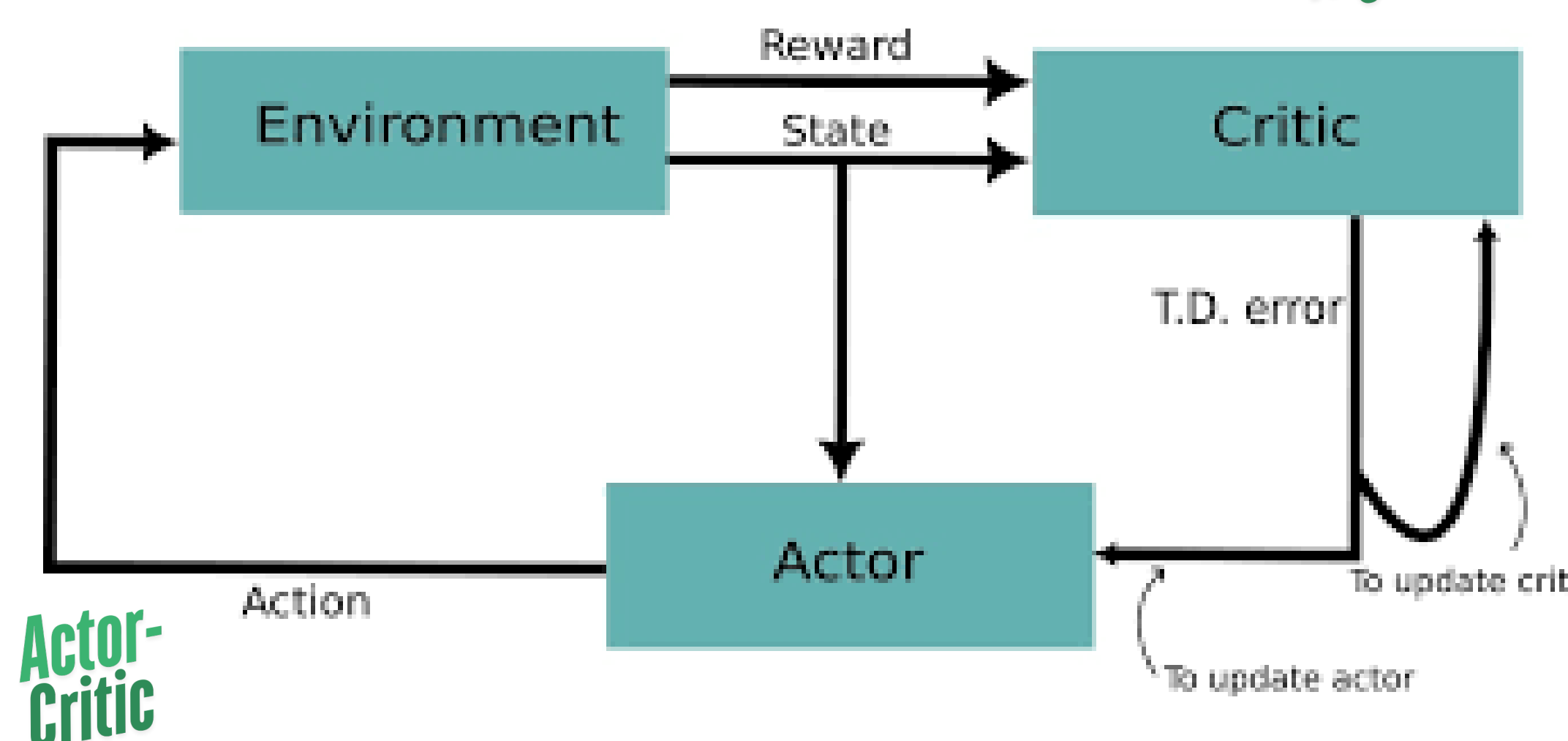
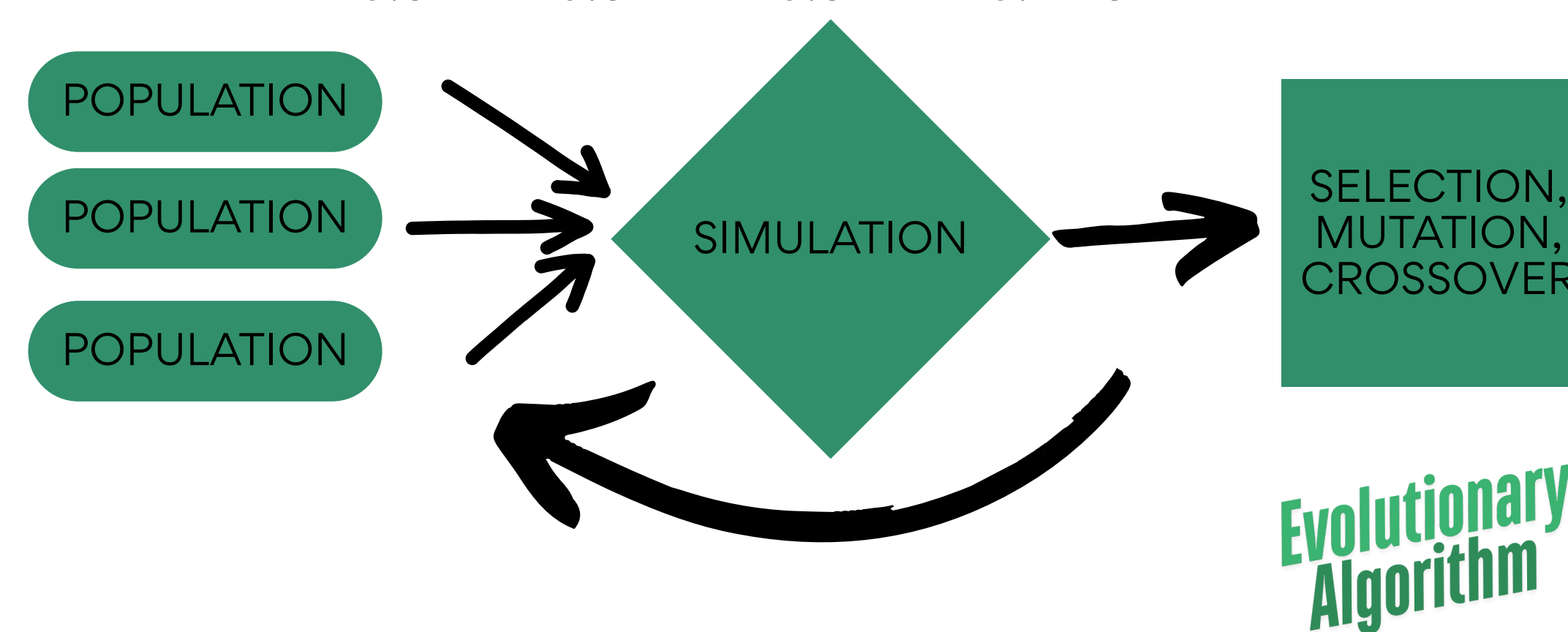
Parameters:

- **Speed limits:** Randomly changed from 15-50 mph
- **Traffic signals:** Randomly changed from 10 to 60 seconds per signal light cycle.
- **Lane accessibility:** Lane restrictions allowing only carpool vehicles or HOV were added.

Evaluation Metrics:

- **Total Travel Time:** The average time taken per vehicle to complete it's intended route.
- **Total Waiting Time:** The total amount of time each vehicle is currently at a traffic intersection
- **Vehicle Throughput:** How many vehicles can enter or exist the system per second
- **Speed Variation:** Represents how much each car changes it's speed relative to the maximum speed of the lane.

$$= -0.3 \times T - 0.3 \times W + 0.3 \times P - 0.1 \times S$$



MAPS



BOSTON, USA



LISBON, PORTUGAL

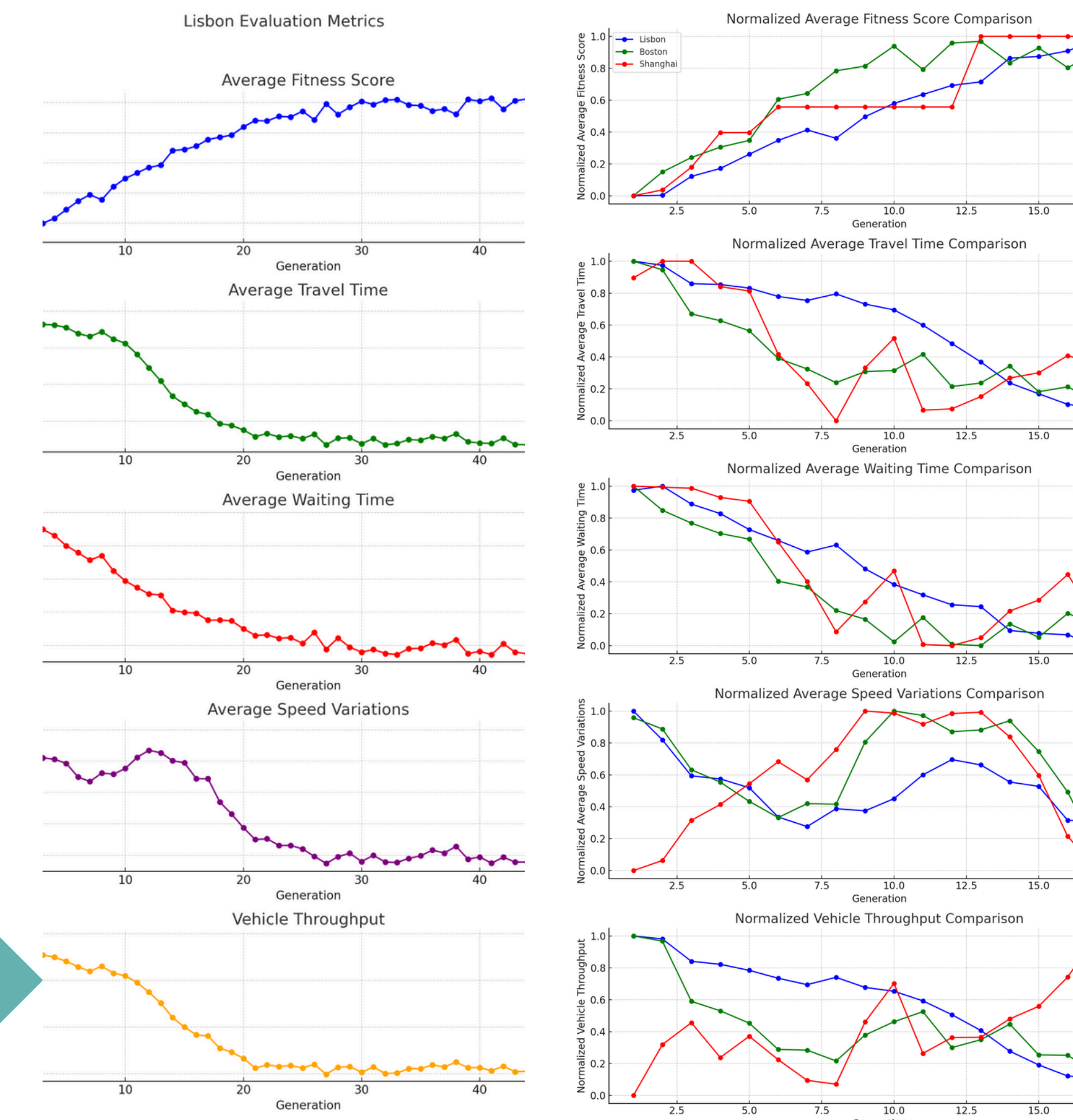


SHANGHAI, CHINA

RESULTS

- Cities with a gridded layout tended to work best, with concentric layouts performing second and unstructured cities improving at varying rates.
- Speed variations would often increase when making other changes, which required more refactoring to bring down again
- Throughput proved to be a poor metric at measuring efficiency, possibly due to how the simulation measures it.

The following graphs show Shanghai, Boston, and Lisbon. These cities showed the most improvement.



CONCLUSION

This study highlights three key contributions:

1. The integration of simulation-based approaches to derive optimal traffic configurations
2. The evidence that these models can more effectively mitigate congestion and reduce collision points compared to manual strategies
3. The necessity for further research to validate the robustness of simulation metrics in real-world urban environments.

ACKNOWLEDGEMENTS:

- DA, L., CHU, C., ZHANG, W., & WEI, H. (2024). CITYFLOWER: AN EFFICIENT AND REALISTIC TRAFFIC SIMULATOR WITH EMBEDDED MACHINE LEARNING MODELS. ARXIV.
- FHWA. (2011). TRAFFIC SIMULATION RUNS: HOW MANY NEEDED?
- FATTAH, M. A., MORSHED, S. R., & KAFY, A. (2022). SOCIO-ECONOMIC IMPACTS OF TRAFFIC CONGESTION IN CHITTAGONG. TRANSPORTATION ENGINEERING, 9, 100122.
- GALVAN, B. ET AL. (2003). PARALLEL EVOLUTIONARY COMPUTATION FOR CFD OPTIMIZATION. ELSEVIER, 573-604.
- KASURA, K. ET AL. (2023). BENCHMARKING ACTOR-CRITIC DRL FOR ROBOTICS CONTROL. IEEE ROBOTICS & AUTOMATION LETTERS, 8(8), 4449-4456.
- KIKUTA, D. ET AL. (2024). ROUTEEXPLAINER: A FRAMEWORK FOR VEHICLE ROUTING PROBLEMS. ARXIV.
- KONDA, V. & TSITSIKLIS, J. (1999). ACTOR-CRITIC ALGORITHMS.
- ZANETTE, A., WAINWRIGHT, M. J., & BRUNSKILL, E. (2021). PROVABLE BENEFITS OF ACTOR-CRITIC METHODS FOR OFFLINE REINFORCEMENT LEARNING. ARXIV.
- FHWA. (N.D.). WORK ZONE SYSTEM PLANNING & DESIGN.
- FHWA. (N.D.). TRAFFIC CONGESTION & MITIGATION STRATEGIES.
- WANG, M. ET AL. (2024). LLM-ASSISTED TRAFFIC SIGNAL CONTROL IN URBAN ENVIRONMENTS. ARXIV.