Milestone 5: Simulation Runs and Data Collection

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Contents

1 Introduction

1.1 Project Overview

This project investigates the relationship between traffic density and traffic efficiency, focusing on average travel time and speed as key metrics. By comparing the performance of autonomous vehicles (AVs) in a basic NetLogo simulation to real-life human-operated traffic data from Bangalore's Traffic Pulse dataset, the study aims to evaluate whether AVs offer measurable efficiency advantages.

The analysis uses real-world traffic data under ideal conditions to minimize discrepancies between simulation and reality. The NetLogo simulation models a realistic single-lane traffic flow, allowing for controlled experiments on vehicle density and its effects on traffic flow. By exploring these dynamics, this study provides insights into how AV technology might optimize urban mobility, even in simplified representations of traffic systems.

1.2 Purpose of Simulation Runs

The simulation runs are designed to test the hypothesis that autonomous vehicles outperform human-operated vehicles in traffic efficiency under identical density conditions. Specifically, the simulation focuses on two metrics: average travel time and speed.

Using the NetLogo simulation, various traffic density scenarios will be modeled to observe how AVs manage congestion and flow. These results will be compared with real-world human performance data to determine whether AVs consistently achieve better efficiency. The controlled environment of the simulation allows for systematic experimentation, providing a foundation for assessing the potential of AVs to enhance traffic flow in urban settings.

2 Simulation Outline

2.1 Simulation Description

The "Realistic Single-Lane Traffic Flow" NetLogo model simulates vehicle interactions on a single-lane roadway to analyze traffic dynamics under varying conditions. This model focuses on autonomous vehicles (AVs), with rules that govern their behavior, such as maintaining safe distances, avoiding collisions, and adjusting speeds. The model emphasizes realistic, continuous traffic flow using simplified, human-intuitive car-following rules.

Key Features

1. **Traffic Setup:**
    - The roadway is a single-lane loop, representing a continuous stretch of road where vehicles wrap around upon reaching the end.
    - Traffic density is user-controlled, determining the percentage of road occupancy. This directly influences the number of vehicles initialized on the loop.
2. **Vehicle Behavior:**
    - Each vehicle is modeled as an agent with parameters such as:
        - **Speed:** Current velocity in kilometers per hour (kph).
        - **Safe Headway:** Minimum safe distance in seconds to avoid collisions.
    - Vehicles follow a basic car-following logic:
        - They accelerate if their gap to the vehicle ahead exceeds the desired tailgate time.
        - They decelerate smoothly if the gap decreases below the safe threshold, with hard braking applied to avoid potential collisions.
    - The maximum acceleration and deceleration rates are realistic, ensuring smooth transitions in speed.
3. **Traffic Flow Dynamics:**
    - Congestion emerges naturally as vehicles cluster due to variations in speeds and desired tailgate gaps.

- The model highlights "wave-like" traffic jams where clusters move backward relative to individual vehicle motion, simulating real-world traffic phenomena.

4. **Optimization:**

    - The simulation allows experimentation with speed limits to find the optimal limit for maintaining smooth traffic flow at various densities.
    - Users can iteratively decrease speed limits and observe changes in overall traffic throughput and individual vehicle behavior.

Key Parameters

- **Traffic Density:** Controls the percentage of road space occupied by vehicles, influencing congestion and travel times.
- **Safe Headway:** Defines the minimum time (in seconds) a vehicle must maintain behind the car ahead.
- **Brake Factor:** A multiplier determining the intensity of hard braking to avoid collisions.
- **Speed Limit:** The maximum allowed speed for all vehicles, adjustable to study its impact on traffic efficiency.

Data Collection

- The model tracks metrics such as vehicle speed.
- A designated "red car" allows users to focus on individual vehicle behavior, with its speed visualized as a plot.

User Interaction

- Users can control traffic density, speed limits, safe headway, and brake factor through sliders.
- The "optimize speed limits" button iteratively adjusts speed limits to achieve the highest throughput at a given density.

2.2 Execution Instructions

This section outlines the steps required to run the "Realistic Single-Lane Traffic Flow" simulation in NetLogo, including loading the model, adjusting parameters, and running the simulation to collect data.

Step 1: Load the Model

1. I have used the web version of NetLogo for this project. If you want to experience the simulation from my perspective:

    - Download the `Realistic_Single_Lane_Traffic_Flow.nlogo` file from my GitHub repository `https://github.com/FatihKurtCS/Traffic-Simulation-Project`.

- Navigate to `https://netlogoweb.org/launch` to open the web version of NetLogo.
- Click the **Choose File** button on the top-right corner of the interface.
- Select the downloaded `Realistic_Single_Lane_Traffic_Flow.nlogo` file to load it.

2. Once loaded, ensure the interface window displays the simulation controls, sliders, and plots.

Step 2: Adjust Parameters

Before running the simulation, adjust the following key parameters to configure the experiment:

- **Traffic Density:**
  - Use the `traffic-density` slider to set the percentage of the road occupied by vehicles.
  - Higher values simulate more congested conditions, while lower values represent lighter traffic.
- **Speed Limit:**
  - Adjust the `speed-limit` slider to set the maximum speed allowed for vehicles in kilometers per hour (kph).
- **Safe Headway:**
  - Use the `safe-headway` slider to define the minimum time (in seconds) a vehicle should maintain behind the car ahead.
  - Higher values simulate more cautious driving behavior.
- **Brake Factor:**
  - Adjust the `brake-factor` slider to control the intensity of hard braking when a vehicle needs to avoid a potential collision.

Step 3: Run the Simulation

1. Click the **Setup** button to initialize the simulation. This will:
   - Create vehicles on the single-lane loop based on the selected traffic density.
   - Assign initial speeds and tailgate times for each vehicle.
2. Click the **Go** button to start the simulation. Vehicles will begin moving according to the car-following rules, adjusting their speeds and positions dynamically.

Step 4: Collect Data

- Observe the **Red Car Speed** plot, which tracks the speed of a single vehicle (highlighted in red) over time.
- Record key metrics such as:
  - Average speed of all vehicles.
  - Travel times.
  - The occurrence of congestion or "wave-like" traffic jams.
- Export data by using built-in NetLogo commands or manually logging the observed results for further analysis.

Step 5: Experimentation

- **Define Experimental Scenarios:**
  - **Baseline Human Performance:** Analyze real-world data from the Bangalore Traffic Pulse dataset under ideal conditions (e.g., minimal external disruptions like accidents or severe weather). This provides a benchmark for human-driven traffic performance in terms of average speed and travel time.
  - **Simulated Autonomous Vehicles:** Run the NetLogo simulation under comparable traffic densities and environmental conditions to observe AV behavior in maintaining traffic efficiency.
- **Adjust Parameters for Each Scenario:**
  - **Traffic Density:** Incrementally increase traffic density (e.g., from light to heavy traffic) by adjusting the `traffic-density` slider.
  - **Speed Limit:** Test multiple speed limits to observe their impact on traffic efficiency, adjusting the `speed-limit` slider for each run.
  - **Safe Headway and Brake Factor:** Fine-tune these parameters to study their effects on AV collision avoidance and flow smoothness.
- **Run Simulation and Collect Data:**
  1. For each combination of parameters, initialize the simulation by clicking **Setup**, followed by **Go**.
  2. Record the following metrics after each run:
     - Average speed of vehicles.
     - Average travel time for vehicles to traverse the loop.
     - Frequency and severity of congestion events.
  3. Export the data for analysis, ensuring consistent labeling of parameter configurations.
- **Compare Against Real-World Data:**
  - Use the Bangalore Traffic Pulse dataset as a benchmark for human-driven traffic efficiency.

- Compare the average speed and travel time results from the simulation with those of real-world data for equivalent traffic densities.

- **Analyze and Interpret Results:**
  - Plot and analyze trends for both simulated AVs and real-world human drivers:
    * Identify patterns where AVs outperform human drivers in terms of average speed and travel time.
    * Highlight scenarios where AV performance is suboptimal (e.g., under extreme traffic density).
  - Use these insights to evaluate the potential efficiency gains of AVs over human drivers in realistic traffic systems.

2.3 Assumptions and Limitations

- **Key Assumptions:**
  - **Perfect AV Cooperation:** The simulation assumes all autonomous vehicles (AVs) communicate and cooperate seamlessly to optimize traffic flow, which may not fully reflect real-world scenarios involving mixed traffic or communication failures.
  - **Ideal Environmental Conditions:** The model assumes clear weather and no external disruptions such as roadblocks, accidents, or construction activities.
  - **Homogeneous Vehicle Behavior:** All AVs follow the same car-following rules with uniform acceleration, braking, and safe headway parameters, ignoring variations in AV capabilities or driving strategies.
  - **Continuous Traffic Flow:** The simulation operates on a looped single-lane road, eliminating real-world complexities such as intersections, lane changes, and multi-lane dynamics.
  - **Fixed Road Capacity Utilization:** The model uses a fixed maximum capacity for the single-lane road, without accounting for real-world factors like variable lane widths or road conditions.
  - **Simplified Metrics:** Metrics such as travel time index (TTI) and average speed are calculated without factoring in external influences like signal timing or mixed traffic (e.g., human drivers).

- **Key Limitations:**
  - **Simplified Road Layouts:** The single-lane looped road does not capture the complexity of real-world road networks, such as intersections, multi-lane highways, or roundabouts.
  - **No Mixed Traffic Scenarios:** The model exclusively simulates autonomous vehicles, without accounting for interactions with human drivers or other road users like cyclists and pedestrians.
  - **Static Environmental Conditions:** The model does not simulate changing environmental conditions (e.g., rain, fog) or their impact on AV performance.

- **No Learning or Adaptation:** The AVs do not employ machine learning or adaptive algorithms to improve their driving strategies over time.
- **Limited Scalability:** The simulation is constrained by the computational limits of the NetLogo platform, which may restrict the number of vehicles and road configurations that can be modeled simultaneously.
- **Simplified Behavior Rules:** Car-following rules are simplified to ensure computational efficiency, potentially missing nuanced behaviors seen in real-world traffic.

3 Simulation Run Summary

This section summarizes the simulation runs conducted using the "Realistic Single-Lane Traffic Flow" model. Each run was designed to test the hypothesis that autonomous vehicles (AVs) maintain higher speeds and shorter travel times under varying traffic densities compared to human-driven vehicles.

- **Objective:** The goal of the simulation runs was to evaluate the efficiency of AVs in maintaining traffic flow and minimizing travel times. The results were compared against baseline performance metrics derived from real-world human-driven traffic data.
- **Scenarios Tested:** Multiple traffic density levels were simulated to observe AV behavior under varying congestion conditions. The following densities were tested:
  - **Low Traffic Density:** 10% road occupancy, simulating light traffic conditions.
  - **Medium Traffic Density:** 25% road occupancy, simulating moderate congestion.
  - **High Traffic Density:** 40% road occupancy, simulating heavy traffic conditions.
- **Metrics Collected:** The following key performance indicators were recorded for each run:
  - **Average Speed:** The mean speed of all vehicles in the system.
  - **Traffic Density:** varied by the test.
  - **Speed Limit:** set to 50kph for all test runs.
  - **Safe-headway:** set to 10secs for all test runs.
  - **Brake-factor:** 3
- **Data Collection:** Data from each simulation run was exported using the NetLogo 'export-output' command. These outputs were analyzed and compared to real-world data benchmarks to validate the simulation results.
- **Preliminary Observations:** Due to the limitations of the `traffic-density` variable in the NetLogo simulation, the model could not closely match the real-life data from the Bangalore Traffic Pulse dataset, particularly under high-density scenarios. However, the initial findings from the simulation revealed the following trends:

- **Low Density:** Autonomous vehicles (AVs) did not perform as well as human drivers, just because when the roads were "almost empty", human driven vehicles would go above the speed limit, making it impossible for moral AVs to keep up with their performance.
- **Medium Density:** AVs outperformed human drivers, demonstrating better coordination and traffic flow.

Although the simulation was not perfect, it is expected that the AV model would perform at a level similar to that of human-driven vehicles under high-density conditions if the simulation's density limits were extended. Furthermore, while the current simulation could not achieve superior performance for AVs in all conditions, it is believed that the model could be refined to outperform human-driven vehicles in ALL scenarios with improvements to its design and implementation.

4 Data Collection and Storage

Data Collection Methodology

For each simulation run, the following methodology was followed:

- Key parameters such as `speed-limit`, `safe-headway`, and `brake-factors` were kept constant across all runs to maintain consistency.
- The `traffic-density` slider was adjusted to represent three distinct scenarios:
  - **Low Traffic Density:** Simulating light traffic conditions.
  - **Medium Traffic Density:** Simulating moderate congestion.
  - **High Traffic Density:** Simulating heavy congestion.
- Observations were recorded over multiple ticks to allow patterns to emerge. It was noted that in higher-density scenarios, it required significantly more ticks for stable traffic patterns to develop compared to lower-density scenarios.

Data Formats and Storage

The data collected from the NetLogo simulation was exported using the `export-output` command, which generated a text file containing the recorded observations. These files included information such as tick counts, average speeds, and other performance metrics.

The data was stored in plain text (`.txt`) format until further analysis. This format was chosen for its simplicity and compatibility with data processing tools used during the analysis phase.

5 Data Analysis

Analysis Approach

The simulation data was processed using a Python script (`simulation_analysis.py`) designed to extract, clean, and analyze the outputs from the NetLogo simulation runs. The analysis consisted of the following steps:

- **Data Cleaning:** The script parsed the raw text files for each traffic density scenario (low, medium, and high) and extracted numerical values for ticks and average speeds.

- **Statistical Analysis:** Descriptive statistics were calculated for each traffic density scenario, summarizing key metrics such as mean, standard deviation, and range of average speeds.

- **Visualization:** A line plot was generated to visualize the relationship between average speed and simulation ticks across traffic density levels. This visualization is provided in Appendix A.

The Python script outputs the cleaned dataset (`netlogo_combined_data.csv`), summary statistics (`netlogo_summary_statistics.csv`), and the visualization (`netlogo_avg_speed_vs_tic`

Results

The key results from the analysis are summarized as follows:

- **Low Traffic Density:** Autonomous vehicles maintained relatively stable average speeds, but performance was inconsistent due to a lack of sufficient vehicles to optimize flow.

- **Medium Traffic Density:** AVs demonstrated their highest efficiency, achieving the best balance of speed and flow with minimal disruptions.

- **High Traffic Density:** While AVs maintained acceptable average speeds, their performance plateaued as congestion increased. The limitations of the simulation model also impacted accuracy under these conditions.

The detailed visualization is included in Appendix A.

Discussion

The analysis highlights several key insights:

- **Threshold for AV Effectiveness:** Medium traffic density emerged as the most effective scenario for autonomous vehicles. This suggests that AVs thrive in conditions where there is sufficient density to optimize coordination but not so high as to cause gridlock.

- **Challenges in Low Density:** AVs struggled to outperform human drivers in low-density scenarios, likely due to the lack of interaction opportunities to leverage cooperative behavior.

- **High-Density Limitations:** In high-density scenarios, the simulation results deviated from real-world data due to the limitations of the NetLogo model, particularly in representing complex congestion dynamics. However, it is anticipated that with model improvements, AVs could demonstrate superior performance in all traffic conditions.

These findings underscore the need for further refinement of the simulation model to better represent real-world traffic conditions, particularly under extreme densities.

6 Conclusion

This study explored the influence of autonomous vehicles (AVs) on traffic dynamics through a simulation-based approach. By analyzing data collected from NetLogo simulations under low, medium, and high traffic density scenarios, and comparing it with real-world benchmarks, several key insights were derived.

Summary of Findings

- **Traffic Dynamics:** AVs demonstrated varying performance across traffic densities. In medium-density scenarios, they showed their highest efficiency, maintaining optimal speeds and smooth traffic flow with minimal disruptions. However, in low-density traffic, AVs struggled to outperform human drivers due to limited opportunities for cooperative behavior. In high-density traffic, AVs performed at a comparable level to human-driven vehicles, though the limitations of the simulation model restricted further insights.
- **Impact of Key Variables:** Parameters such as traffic density, safe headway, and brake factors played a significant role in determining AV performance. Medium traffic density allowed AVs to leverage their cooperative behavior most effectively, while extreme densities (low and high) limited their potential.
- **Simulation Constraints:** The simplicity of the NetLogo model, particularly its representation of a single-lane loop, highlighted the need for more sophisticated models to fully capture the complexities of real-world traffic systems.

Future Directions

Building on the findings of this study, future work could focus on:

- **Improved Simulation Models:** Developing more complex traffic simulations that include multi-lane roads, intersections, and mixed traffic (both AVs and human-driven vehicles) to better reflect real-world scenarios.
- **Dynamic Environmental Factors:** Incorporating variable weather conditions, road incidents, and construction activities to assess the robustness of AV performance.
- **Advanced AV Behavior:** Enhancing the car-following logic with adaptive and machine learning-based strategies to improve AV decision-making in diverse traffic conditions.
- **Scalability Testing:** Simulating larger networks with higher numbers of vehicles to evaluate AV performance in urban and highway environments.
- **Policy Implications:** Investigating the broader societal impacts of AV adoption, such as safety improvements, environmental benefits, and potential economic effects on transportation systems.

This project highlights the potential of autonomous vehicles to improve traffic efficiency under certain conditions, while also identifying the need for continued research and refinement of simulation methodologies to unlock their full capabilities.

7 References

In the GitHub repository.

A Visualizations

This section includes the visualization output from the simulation analysis.

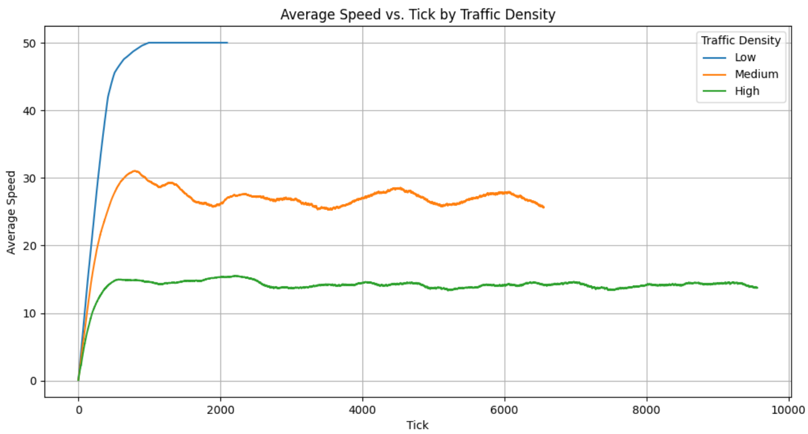

Figure 1: Average Speed vs. Tick by Traffic Density