Lloyd Expressway Traffic Signal Logic Optimization

Research Question:

How can a change to the algorithm used by traffic control systems along the Lloyd expressway affect the average trip speed in Evansville, Indiana along the road system per $10,000 spent annually?

Subject: Sciences, Computer Science

Word Count: 4000

1. Introduction

Driving a motor vehicle is a commonplace means of transportation for the majority of United States residents, with a reported 239.24 million people holding a drivers license (Hedges Company, n.d.). This number is projected to grow steadily at a 2.5% rate over the next decade (Rudy & Dempster, 2024), raising concerns about the ability of road networks to accommodate such large traffic volumes in the future. A survey conducted by HNTB, an infrastructure contractor with hundreds of clients nationwide, shows an inability to handle current traffic volumes, highlighting that 84% of Americans experience traffic congestion during their regular commutes (HNTB Corporation, 2023). Traffic congestion can have many adverse effects, such as lost time, physical and mental strain and fatigue (Abdul Fattah et al., 2022, 6-7), and significantly increased carbon dioxide emissions (Barth & Boriboonsomsin, 2008, 18).

The problem of traffic congestion is particularly prevalent in Evansville Indiana, where the Indiana Department of Transportation expects a 3% growth in traffic volumes over the next decade (Indiana Department of Transportation & Midwestern Software Solutions LLC, 2024) along the junction that connects Indiana State Route 62 and 66, commonly known as the Lloyd expressway. The city plans to address this between summer of 2024 and fall of 2027 by investing over $105 million, sourced from taxes and federal and state grants, into the physical road infrastructure through various projects such as repaving and expanding the road (Indiana Department of Transportation, n.d.). This large expenditure, however, may not fully address the problem In a world where computers are ubiquitous, one must consider if the algorithms employed by traffic control signals are a source of inefficiency and congestion as well, creating an intriguing question which may guide future transportation infrastructure investment in Evansville, IN, and provide a framework to help guide infrastructure investment nationwide:

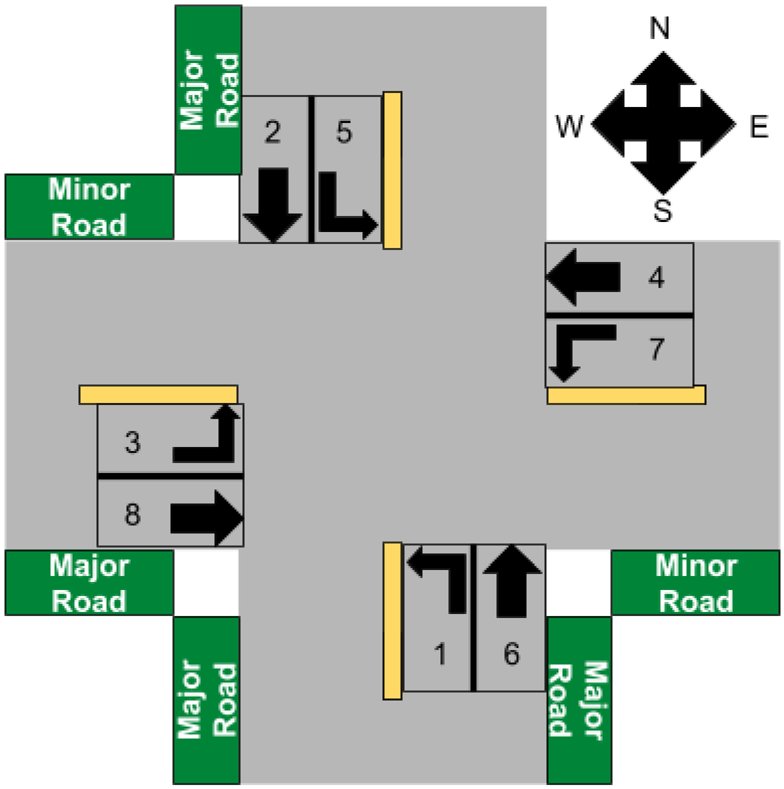
How can a change to the algorithm used by traffic control systems along the Lloyd expressway affect the percentage of traffic congestion in Evansville, Indiana along the road system per $10,000 spent annually?

2 . Literature Review

2.1 Background

2.1A Traffic Control Logic

To understand differences in traffic control models, one must first understand how traffic signals operate. Traffic signals operate by selecting phases. A phase is “a timing unit associated with the control of one or more indications” (U.S. Department of Transportation Federal Highway Administration, 2008), which is made up of potential movements cars can take through the intersection. An example of a phase, as shown in the diagram, is a car going south along the major road, as denoted with the phase number two. Phases can be concurrent or conflicting, and concurrent phases are often placed together in what is called a phase cycle, a grouping of phases that can be called simultaneously, like phases 2 and 6 in the diagram. The role of a traffic control model is to identify which phase cycle is allowed to proceed through the intersection and the time frame they are allotted to proceed through the intersection. For better optimization, most traffic control models are given upper and lower boundaries to parameters such as green time and phase cycles. The nuance in traffic control models comes from the inputs and methods they use to determine which phase cycle is allowed to proceed through the intersection and for how long. To understand different traffic control models reviewed and the nuances between them, see Appendix A.



[1]

[1] Two lane intersection with phases listed

2.2 Reinforcement Learning for Traffic Control

Machine-learning-based traffic control models can provide traffic control at a higher efficiency than currently implemented models. Wade Genders[2] and Saideh Razavi[3] highlight this difference in their 2019 study in which they developed a “framework for developing and evaluating different adaptive traffic signal controller models in [a] simulation” (Genders & Razavi, 2019, 1). To test their framework, Genders and Razavi tested multiple models, including the Deep-Q-Network model, the Deep Deterministic Policy Gradient model, and a Uniform model, on a road network composed of two four-way intersections placed next to each other; the SUMO simulated network experienced dynamic traffic volumes for three simulated hours (Genders & Razavi, 2019, 6). The study found that the DQN and DDPG models were able to similarly cut down travel time along the road network by 11% as compared to the uniform, however, the gap in the models becomes apparent when observing vehicle queue length and delay; the DQN model was able to undercut the DDPG model’s queue length by nearly 50% and outperformed the Uniform model’s queue length by 66%, however, the DQN model seemed to maximize delay when the DDPG and Uniform models minimized it and vice versa (Genders & Razavi, 2019, 8). Similarly, a study by Hrishit Chaudhuri[4], Vibha Masti[5],

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[2] Dr. Wade Genders received a Ph.D. from “the Department of Civil Engineering, McMaster University” (Genders & Razavi, 2019, 1) and is currently the machine learning lead at Flow Labs, a company that offers “comprehensive data to analyze and diagnose … transportation problems” (Flow Labs, 2023).
[3] Dr. Saiedeh Razavi received a Ph.D. from the Sharif University of Technology (McMaster University, 2020), and is currently “an Associate Professor, Chair in Heavy Construction and Director of McMaster Institute for Transportation & Logistics at the Department of Civil Engineering, McMaster University, Hamilton, Ontario, Canada” (Genders & Razavi, 2019, 1).
[4] Hrishit Chaudhuri is “a grad student in computer science” that is “currently pursuing an MSCS [Masters of Science in Computer Science] at the Courant Institute at NYU” with a research focus in “compilers and programming languages” (Chaudhuri, n.d.).
[5] Vibha Masti is a “Master’s student at the Language Technologies Institute, Carnegie Mellon University” (Masti, 2024).

Vishruth Veerendranath[6], and S Natarajan[7] observed the efficiency of reinforcement learning models, like the DQN and Advantage Actor-Critic models, and tested them against a Round Robin Scheduler (RR) in order to compare different methods of intelligent traffic signal control (Chaudhuri et al., 2022, 271). The study used SUMO to simulate a single lane four-way intersection for 5400 timestops. The study found that the two reinforcement-learning based models, the DQN and A2C models, were unable to consistently outperform the currently implemented RR model at similar computing power (Chaudhuri et al., 2022, 284). The data suggests, however, that the model's performance would significantly improve with increase in available processing power (Chaudhuri et al., 2022, 282-283), suggesting that varying levels of efficiency can be achieved at different costs. Developing upon the gaps of the reinforcement-learning-based DQN model, research by Xiaoyuan Liang[8], Xusheng Du[9], Guiling Wang[10], and Zhu Han[11] developed a new model which combines different aspects of existing machine learning techniques, consequently named the Double Dueling Deep Q Network (D3QN). Liang et Al simulated their D3QN model in SUMO on a three-lane four-way intersection scenario for one simulated hour (Liang et al., 2018, 8), and found that the model was able to significantly improve itself between measured intervals in the simulated hour, suggesting that reinforcement-learning based models have potential to significantly grow that cannot be properly evaluated in a short-term experiment (Liang et al., 2018, 10). Looking at the

[6] Vishruth Veerendranath is a "masters student at Carnegie Mellon University's Language Technologies Institute (LTI) specializing in Machine Learning (ML) and Natural Language Processing (NLP)" (Veerendranath, 2024).
[7] "Dr. S. Natarajan has five decades of experience spanning research and development and teaching. He has 140+ research articles in reputed conferences and journals" and is a "review of journal articles of IEEE, Springer and Elsevier" (PES University, n.d.).
[8] "X. Liang" is "with the Department of Computer Science, New Jersey Institute of Technology, Newark, NJ, 07102 USA" (Liang et al., 2018, 1).
[9] "X. Du" is "with [the] Department of Electrical and Computer Engineering, University of Houston, Houston, TX 77004 USA" (Liang et al., 2018, 1).
[10] "G. Wang" is "with the Department of Computer Science, New Jersey Institute of Technology, Newark, NJ, 07102 USA" (Liang et al., 2018, 1).
[11] "Z. Han" is "with [the] Department of Electrical and Computer Engineering, University of Houston, Houston, TX 77004 USA" (Liang et al., 2018, 1).

three sources and how they converse with each other suggests that current research into optimizing traffic control algorithms could provide large insights into optimizing traffic control when applied to lesser known, real-world scenarios like complex highways with varying traffic levels. Additionally, there isn't much research into the cost effectiveness of different algorithms. If cost were to be measured as a factor, then it could also account for the inconsistency in data between these sources caused by a difference in computing power.

2.3 Simple Algorithms

Simple algorithm-based traffic control models can provide traffic control at a higher efficiency than currently implemented models. This difference is exemplified in the results from a study conducted by Hao Mei[12], Xiaoliang Lei[13], Longchao Da[14], Bin Shi[15], and Hua Wei[16]. In the study, researchers aimed to test LibSignal, a library developed by the researchers "for cross-simulator comparison of reinforcement learning models in traffic signal control tasks" (Mei et al., 2023, 1). They utilized a benchmark test in which they simulated different traffic control models on a 4 x 4 grid network composed of two-lane four-way intersections, and compared the performances of the models with their expected performance and performance on existing evaluation libraries (Mei et al., 2023, 6). Focusing on the results of the simple algorithms like the Max-Pressure model and Self-Organizing Traffic Lights model, as compared to the baseline fixed time algorithm, the simple algorithms performed significantly better; on average, the max-pressure model cut down average road network travel time by 44.7% and the SOTL model cut down average road network travel time by 36.1%, meaning a 291 second average travel time on the baseline fixed time algorithm was cut down to 186 seconds by the SOTL model and 161 seconds by the max-pressure model (Mei et al., 2023, 7-8). While this

[12] Hao Mei is "a Ph.D. student currently studying at [the] New Jersey Institute of Technology" with a research interest in "Deep Reinforcement Learning for Traffic Signal Control, Spatio-temporal Data Mining, and Learning to Simulate" (Mei, 2022).

[13] No bio was found for Xiaoliang Lei, however, the researcher has been cited in 11 papers dating back to 2019, with a majority of papers relating to machine learning applications with a specialization in neural networks (dblp: computer science bibliography, 2024).

[14] Longchao Da is "a Ph.D. student at the Computer Science Department [at] Arizona State University" with an interest in "LLMs, Reinforcement Learning, Data Mining, and Trustworthy Policy Evaluation & Deployment" (*About*, 2024).

[15] No bio was found for Bin Shi, however, the researcher has been cited in 53 papers dating back to 2014, with a majority of papers relating to machine learning and computer engineering topics (Google Scholar, 2024).

[16] Dr. Hua Wei received a Ph.D. from Penn State University and currently is "an Assistant Professor at Arizona State University" with research interests in "reinforcement learning, data mining, and urban computing, with a focus on trustworthy reinforcement learning, multi-agent reinforcement learning, and spatio-temporal data mining" (*Hua Wei | ASU Search*, 2023).

study may not completely accurately reflect real-world travel times due to its use of a completely hypothetical simulation space, its results retain credibility due to their use of triangulation and involvement of multiple different simulators such as SUMO and CityFlow. This study's trend of a significant difference between simple algorithms and currently implemented models is further developed in a study conducted by Wade Genders[17] and Saiedeh Razavi[18]. In their 2016 paper, the researchers developed a "framework for developing and evaluating different adaptive traffic signal controller models in [a] simulation" (Genders & Razavi, 2019, 1) and tested it by using SUMO to simulate multiple models on a two-lane road network with two four-way intersections. Two of the models tested, the SOTL and max-pressure models, were simple algorithm-based models that were also tested in Mei, however, Genders and Razavi tested the models against a Uniform model as a baseline. The researchers' results highlighted how a simple algorithm-based model was able to outperform a currently implemented model, similar to the results of Mei et al., but varied significantly in the relative performance of the two simple algorithm-based models. The study found that the max-pressure model was able to reduce average travel time along the road network by 27.0% as compared to travel time along the road network with the implementation of a Uniform model, whereas the SOTL model actually increased travel time along the road network by 14.9%, suggesting that the SOTL model may be better suited for more complex road networks and is less effective on simpler traffic networks, suggesting that the SOTL model could outperform currently implemented models in an urban environment whereas a max-pressure model could outperform

[17] Dr. Wade Genders received a Ph.D. from "the Department of Civil Engineering, McMaster University" (Genders & Razavi, 2019, 1) and is currently the machine learning lead at Flow Labs, a company that offers "comprehensive data to analyze and diagnose … transportation problems" (Flow Labs, 2023).

[18]Dr. Saiedeh Razavi received a Ph.D. from the Sharif University of Technology (McMaster University, 2020) and is currently "an Associate Professor, Chair in Heavy Construction and Director of McMaster Institute for Transportation & Logistics at the Department of Civil Engineering, McMaster University, Hamilton, Ontario, Canada" (Genders & Razavi, 2019, 1).

currently implemented models in both an urban and a suburban environment (Genders & Razavi, 2019, 8). The discrepancy in the findings of the two studies can be explained by the differences in road networks, or the differences in processing hardware and versions of SUMO traffic simulator used. Similarly, a study by Gurcan Comert[19], Mecit Cetin[20], and Negash Begashaw[21] further develops the trend of a simple algorithm-based model outperforming a currently implemented traffic control solution. The researchers aimed to test a traffic signal control model they made and compared their model, hereby referred to as the queue length (QL) model, with the currently implemented fully actuated model on a one-lane four-way intersection and road network. The study found that the QL model was able to reduce average delay in the road network by 6.3% as compared to the fully actuated model (Comert et al., 2020, 11). The credibility of the QL model is negatively impacted by the fact that it has only been tested on hypothetical networks. Nonetheless, all of the mentioned simple algorithm-based models, the SOTL, max-pressure, and QL, are able to significantly outperform current traffic signal control methods requiring very few additional inputs, suggesting that they would have a potentially low cost of implementation.

[19] Dr. Gurcan Comert received a Ph.D in "civil engineering from [the] University of South Carolina, Columbia" and is "currently an associate professor in physics and engineering" at the university of Illinois Urbana-Champaign with a research interest in "intelligent transport systems particularly on connected vehicles, resilient transportation networks, and statistical modeling of different problems for traffic signals and freeway monitoring" (University of Illinois Urbana-Champaign, 2024).
[20] Dr. Mecit Cetin received a "Ph.D. in Transportation Engineering" from the Rensselaer Polytechnic Institute, and is currently "the director of the Transportation Research Institute" at Old Dominion University with a research interesting "Intelligent Transportation Systems (ITS), connected and automated vehicles, system-state prediction, traffic flow theory and simulation, big data analytics, and congestion pricing" (Old Dominion University, 2024).
[21] Dr. Negash Begashaw received "a Ph.D. degree in Mathematics from Washington State University" and is currently "an Associate Professor in the department of Computer Science, Physics, and Engineering at Benedict College" with a research interest in "mathematical foundations, modeling algorithms, and applications in Machine Learning and Data Science and modeling, design, analysis, and computational study of algorithms, applications in optimization/Operations" (“Reflections From Virtual Undergraduate Summer Research Experience With Interdisciplinary Teams,” 2021, 1).

2.4 Complex Algorithms

Complex algorithm-based traffic control models can provide traffic control at a higher efficiency than currently implemented models. This is exemplified in a study conducted by Zhuoxiao Meng[22], Anibal Siguenza-Torres[23], Mingyue Gao[24], Margherita Grossi[25], Alexander Wieder[26], Xiaorui Du[27], and Stefano Bortoli[28]. The researchers aimed to test the "Discrete-Event, Aggregating, and Relational Control Interfaces framework" (Meng et al., 2023, 1) they created "for achieving efficient traffic management simulations" (Meng et al., 2023, 1). The researchers tested their DAR-CI model on "a grid road network with 100 interactions and 5000 lanes," (Meng et al., 2023, 7) and compared it against a baseline simulation of the same traffic network without any traffic control logic. The researchers found that the DAR-CI model on average was able to speed up travel time throughout the network by 21% through more efficient signal phase executions, with the performance difference increasing as traffic volume increased (Meng et al., 2023, 9). The credibility of the findings of the paper are negatively impacted due to the comparison metric used; the baseline model that the DAR-CI model was compared to is extremely rudimentary and is not an extremely conventionally

[22] Zhuoxiao Meng "is a Ph.D. student at the Technical University of Munich and Huawei Munich Research Center. His research interests are controllability and interoperability of large-scale simulations" (IEEE Xplore, 2024).
[23] Anibal Siguenza-Torres "is a Ph.D. student at the Technical University of Munch and Huawei Munich Research Center. His work is centered on parallel large-scale microscopic traffic simulations" (Du et al., 2023, 12).
[24] No bio was found for Mingyue Gao, however the original paper affiliates them with the Intelligent Cloud Technologies Laboratory at the Huawei Munich Research Center (Meng et al., 2023, 1) and the researcher's ORCID page is attributed with three papers each dealing with traffic simulation interfaces (ORCID, 2024).
[25] Dr. Margherita Grosser received a Ph. D. from the Ludwig-Maximilians-University and Max Planck Institute for Astrophysics in "Probing Early Dark Energy and primordial Non-Gaussianity with cosmological simulations" and has a research interest in "Machine Learning, Deep Learning, Computer Vision, [and] Generative AI" (Grossi, 2023).
[26]No bio was found for Alexander Weider, however the researcher's ACM Digital Library page is attributed with 14 publications dating back to 2010, centered around machine learning and simulations (Association for Computing Machinery, 2024).
[27] Xiaorui Du is a Ph.D. student at the Technical University of Munich with a research interest in exploring "high-performance, scalable streaming data processing systems" (Du, 2024).
[28] Dr. Stefano Bortoli received a Ph.D. from the Universitá di Trento in Information and Communication Technology, and is currently the "Chief Technology Architect in the AI and Simulation R&D lab of Huawei Cloud at Munich Research Center" (Bortoli, 2025).

applied model in the modern day. Nonetheless, the complex nature of DAR-CI makes it a promising option to fill the gap between simple algorithm-based models and machine learning models. The promising performance of complex algorithm-based traffic control models is expanded on in a study by Hrishit Chaudhuri[29], Vibha Masti[30], Vishruth Veerendranath[31], and S Natarajan[32] which aimed to test the efficiency of different reinforcement learning based traffic control models by comparing them against many different hypothetical and currently implemented models. One such complex algorithm-based model, the MONOPOLY model, significantly outperformed the conventionally used Round Robin model, on average cutting down peak vehicle queue length by 14.6% (Chaudhuri et al., 2022, 284). The two studies can be analyzed together in their respective contexts to discern that complex algorithm-based traffic control models serve as a middle ground between simple algorithm-based models and machine learning based models. Their median performance dissuades real-world application unless other factors are considered, primarily cost. If the cost of these models can be quantified and their efficiency can be reported as a function of cost, one could determine optimal traffic control methods for different applications at different price points, ultimately maximizing traffic efficiency in constrained budgets, and the gap this paper seeks to fill is to derive this model for the Lloyd Expressway in Evansville Indiana.

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[29] Hrishit Chaudhuri is "a grad student in computer science" that is "currently pursuing an MSCS [Masters of Science in Computer Science] at the Courant Institute at NYU" with a research focus in "compilers and programming languages" (Chaudhuri, n.d.).
[30] Vibha Masti is a "Master's student at the Language Technologies Institute, Carnegie Mellon University" (Masti, 2024).
[31] Vishruth Veerendranath is a "masters student at Carnegie Mellon University's Language Technologies Institute (LTI) specializing in Machine Learning (ML) and Natural Language Processing (NLP)" (Veerendranath, 2024).
[32] "Dr. S. Natarajan has five decades of experience spanning research and development and teaching. He has 140+ research articles in reputed conferences and journals" and is a "review of journal articles of IEEE, Springer and Elsevier" (PES University, n.d.).

3. Methodology

3.1 Design

In order to establish a causal relationship between traffic efficiency and control method, an independent measure experimental design was employed. This design is used by the majority of the literature that has been reviewed before conducting the experiment, and proves the most effective in establishing a relationship between the identified variables while generating quantitative data. As is the case with all experiments, however, the design cannot account for one hundred percent of confounding variables, and in this case specifically fails to account for the uniqueness of a human driver. The experimental design holds key driver behaviors constant, such as speed, vehicle size, and rate of acceleration, and does not attempt to address what would happen if aggressive driving behaviors were to be employed. That said, a correlation can still be drawn between road network efficiency with traffic model selection in a reliable manner similar to that which drives metropolitan investment into alternative traffic control models.

3.2 Setup

3.2A Hardware

The experiment was run on an M3 model Macbook Pro. The specific model has 18 Gigabytes of LPDDR5 SDRAM, a 12-core M3 pro CPU rated at a maximum clock rate of 4.05 Gigahertz, and an 18-core M3 pro GPU rated at a maximum 150 Gigabytes per second memory bandwidth (*MacBook Pro (14-Inch, M3, Nov 2023) - Tech Specs*, n.d.). Background processes were limited throughout the simulation process and CPU, GPU, and RAM usage was recorded. The laptop was connected to power throughout the simulation.

3.2B Virtual Machine

In order to reduce confounding variables and utilize the most currently optimized release of the SUMO traffic simulator, a virtual machine was employed. A free personal license of VMware Fusion Pro was used to establish a 64-bit Windows 11 Home Arm, and installed SUMO on that machine. The virtual machine was able to successfully utilize 11 of the CPU cores and 12 Gigabytes of RAM. Bloatware was uninstalled on the virtual machine and background processes were minimized. CPU, RAM, GPU, disk, and network speed was monitored through Stats, an open source macOS system monitor (*Exelban/stats: MacOS System Monitor in Your Menu Bar*, n.d.). VMware fusion pro offers the highest performance virtual machines of all free and open source options. Compared to tools that require licenses, VMware fusion pro ranks second (Mendelson, 2022).

3.2C Simulator

The traffic simulator used was Simulation of Urban MObility, “an open source, microscopic, multi-modal traffic simulation” (*SUMO at a Glance - SUMO Documentation*, 2024). SUMO operates by simulating each vehicle independently and the traffic lights in a manner that reflects how traffic lights operate in the real world, and amalgamating the data and experiences of each of the vehicles.

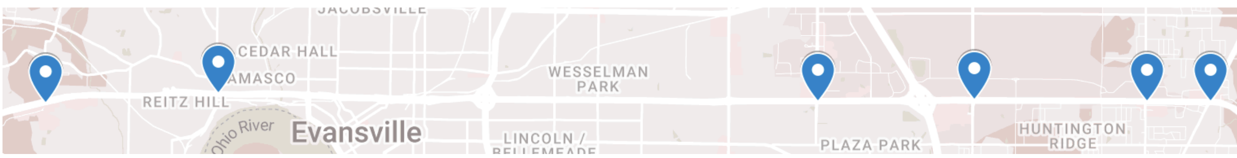
The utilization of SUMO comes with both advantages and disadvantages. SUMO has been used in hundreds of similar and different experiments to mine due to its accurate portrayal of traffic light operations. A traffic light in SUMO operates exactly how a traffic light would in the real world, meaning any experiment involving SUMO has high external validity when it comes to traffic light behavior. Problems arise, however, when trying to model driver behavior in SUMO as all drivers operate in a uniform and safe manner, rendering SUMO inaccurate in the face of aggressive driving behaviors and road incidents, as shown in a paper written by Michael Behrisch[33], Laura Bieker[34], Jakob Erdmann[35], and Daniel Krajzewicz[36] (Behrisch et al., 2011, 64).

[33]“Michael Behrisch is an Assistant Professor for Visual Analytics at the Utrecht University, Netherlands” (Behrisch, 2022).
[34] Laura Bieker-Walz, Laura Bieker at the time of publishing, is a “Professor of Computer Science with a focus on Software Engineering” at Bremerhaven University of Applied Sciences (Hochschule Bremerhaven, n.d.).
[35] “Jakob Erdmann is the lead developer of the open source traffic simulation software SUMO, which is used world-wide by academia and consultancies. He received his Ph.D. at the Friedrich Schiller University Jena, Germany. After that, he has been involved in the development of SUMO since 2010 and has used it for research in various areas with a focus on traffic signal optimization” (IEEE Xplore, 2024).
[36] Daniel Krajzewicz is a “scientific coworker at the German Aerospace Center” that has “contributed to the development of … SUMO… TAPAS…UrMoAC” and has written “publications about different sub-topics of mobility and traffic” (*Daniel Krazjewicz*, 2024).

3.2D Model Source Code

Code for each of the tested traffic control models was sourced from their respective repositories. None of the code for models was adapted in any way to prevent any misrepresentation of the model in the data set. All repositories were cited to the respective databases in which they were found.

3.2E Simulated Areas



The simulated road network spans 13.4 miles across the greater Evansville Area. The road network was exported from OpenStreetMap with the following boundaries: -87.64103 (West), 37.97959 (North), -87.38821 (East), and 37.97465 (South). To see the utilized flows file containing the traffic volumes simulated hour by hour as generated with data from the Indiana Department of Transportation Traffic Count Database System, see appendix B. To see the simulated network, see appendix C. The network includes the following traffic signals:

- Indiana State Road 66 and Indiana State Road 261
- Indiana State Road 66 and County Road 850 W
- Indiana State Road 66 and Epworth Road
- Indiana State Road 66 and Burkhardt Road
- Indiana State Road 66 and St. Joseph Avenue
- Indiana State Road 66 and Red Bank Road

The intersections were selected to represent the greater road network of Indiana State Road 66 as it cuts through Evansville Indiana, commonly known as the Lloyd Expressway.

3.3 Variables

3.3A Independent Variable

The independent variable in the experiment was the traffic model employed to control the traffic signal. The following traffic models were tested:

- Reinforcement Learning
  - Deep Deterministic Policy Gradient (sourced from Genders and Razavi)
  - Advantage Actor-Critic (sourced from Chaudhuri Et al.)
  - Double Dueling Deep Q Network (sourced from Liang Et al.)
- Complex Algorithm
  - MONOPOLY Feedback Control Mechanism (sourced from Chaudhuri Et al.)
- Simple Algorithms
  - Max Pressure (sourced from Mei Et al.)
  - Self-Organizing Traffic Lights (sourced from Mei Et al.)
  - Round Robin (sourced from Chaudhuri Et al.)

3.3B Control Group

To establish a baseline, the control group was the currently employed methods of traffic signal control in Evansville. Currently, the traffic signals along the Lloyd Expressway are owned by the state of Indiana and operate on their procedures. The state of Indiana utilizes a model from the *Highway Capacity Manual* as issued by the Transportation Research Board, which operates in a fixed cycle and uses the following equation: $C = 1900 * \frac{g}{t_1} * N$ (US Department of Transportation Federal Highway Administration, 2017, 16), where C = capacity in vehicles per hour per lane, g = effective green time in seconds per cycle, t_1= total signal cycle length in seconds, and N = number of lanes. Using collected data on traffic volume and a tool called Synchro Studio, the state of Indiana defines cycle length and adjusts signal timing for other factors such as heavy vehicle disruptions and lane usage, which will be ignored in this experiment.

3.3C Dependent Variable

The dependent variable, efficiency per $10,000 spent, is composed of multiple components. Efficiency is derived from the vehicle queue length of individual intersections, the average travel time of vehicles through the network, and the average wait time at each intersection. Cost of running the models is derived from examination of each of their source codes and their computing costs to be run for a year, defined as 365.25 days.

3.3D Constants

- Simulation time - 86,400 seconds
- Vehicle length - 2 meters
- Vehicle acceleration 2.6 meters per second squared
- Simulation data recording interval 1 time per second
- Computing demand recording interval 1 time per second

3.4 Data Analysis

The following data points were collected: vehicle queue length, average trip speed, average wait time by car, average wait time by intersection, simulation delay, and second-by-second position data for each car.

Furthermore, the cost of running the models for a year will be calculated by using the average RAM, CPU, and GPU usage of the model during its simulation, identifying a virtual machine on Microsoft Azure's cloud computing platform that meets those requirements, and using the monthly costs Microsoft Azure provides to determine the yearly costs of operation. While comparing computing costs to Microsoft Azure may not be the exact computing method employed by cities to run their traffic lights, it reflects a similar cost to employing cloud computing like is currently employed, and presents a slightly inflated recurring cost as compared to a scenario in which the city would establish the computing infrastructure themselves. In the event that implementing a new model requires cities to install new hardware, the cost will not be factored in as municipalities purchase this hardware with federal grants awarded specifically for them.

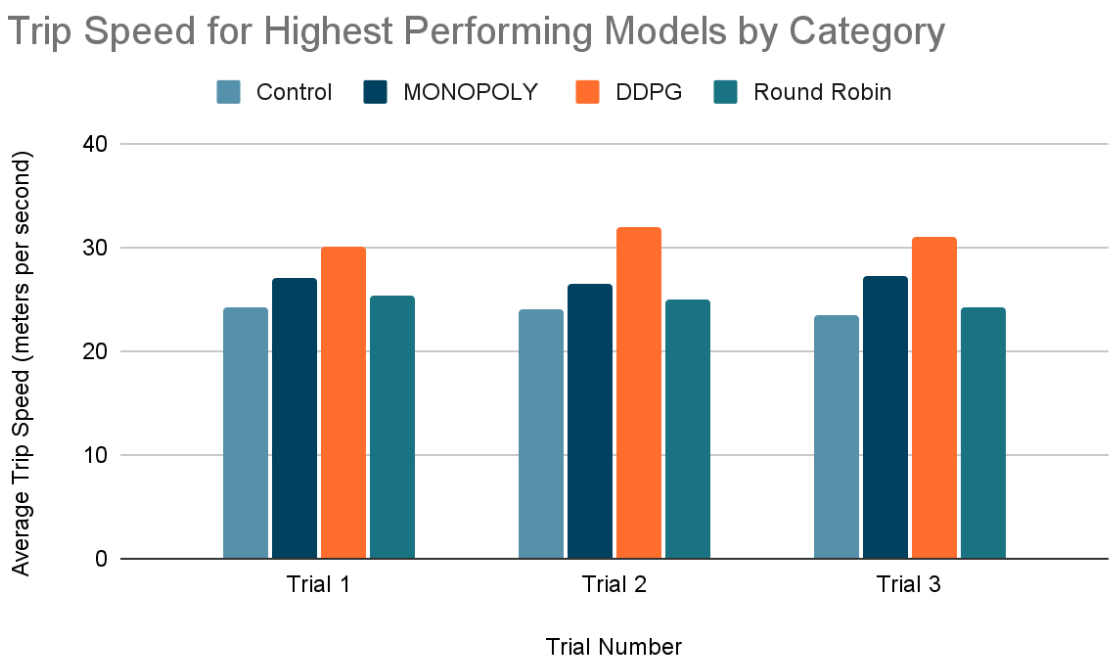
4. Results

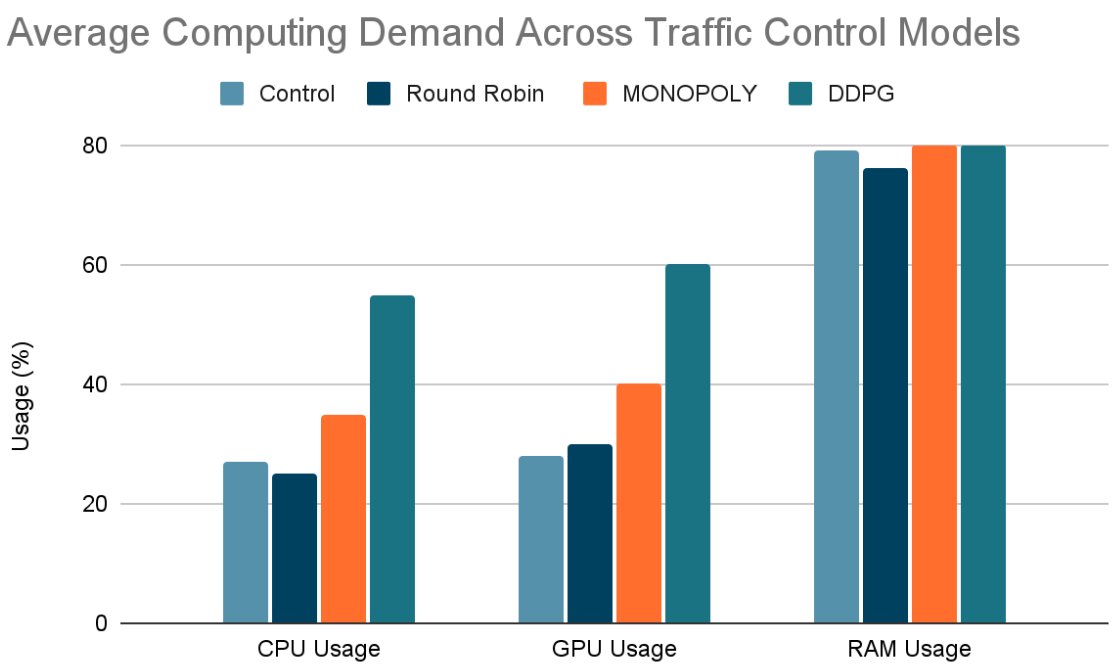
An average of 12.6 gigabytes of data was collected across vehicle state output and computing power usage for each model.

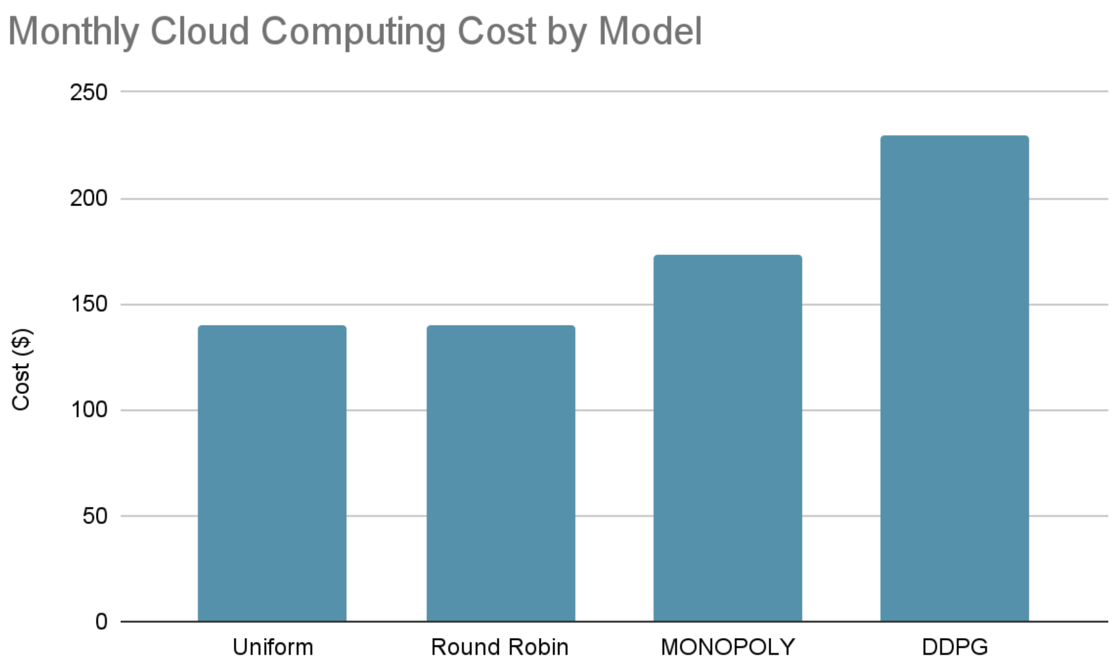
The experiment found that across every trial there were frontrunners in each of the three classifications of logic: the MONOPOLY model for complex algorithms, the Round Robin model for simple algorithms, and the DDPG model for reinforcement learning. The control was outperformed by almost all models, with the performance difference relating directly with the computing demand.

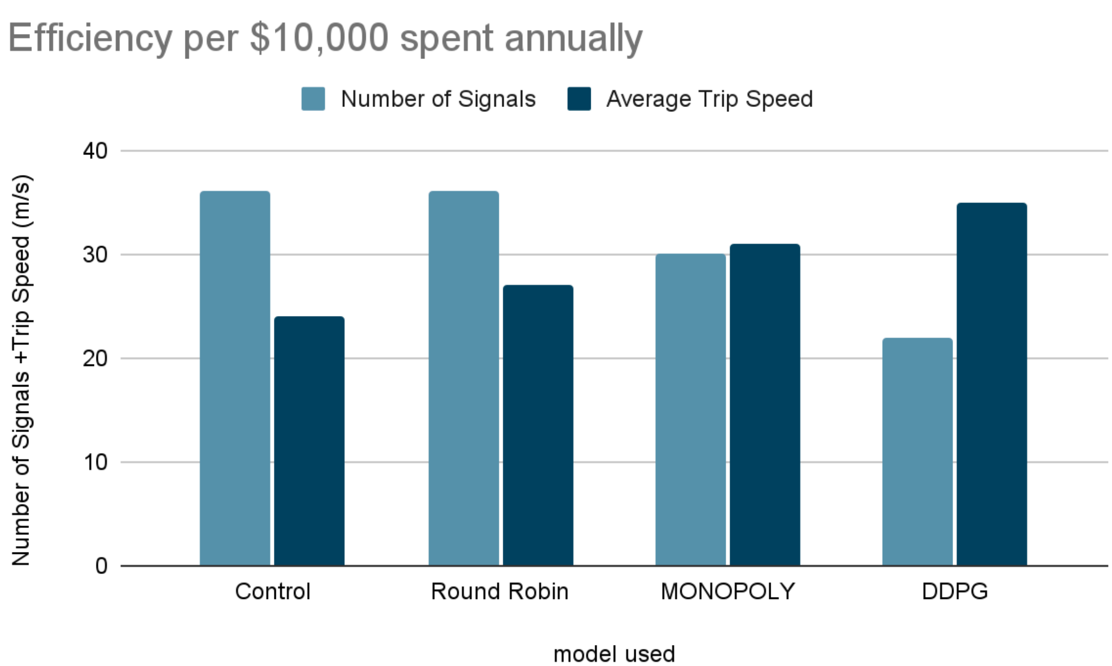
The experiment found that the simple algorithm-based and complex algorithm-based traffic control models required a similar amount of computing power to the control, with the complex algorithm-based model requiring slightly more, suggesting that the simple algorithm-based model can be run at no additional cost to the control and the complex can be run at a slight additional cost, while the reinforcement learning model requires significant investment into hardware for operation.

Returning to the research question, the experiment found that different numbers of traffic signals can be run at different efficiencies, with the most balanced option being the MONOPOLY model, which can operate 30 traffic signals within $10,000 at an average trip speed of 31.3 meters/second.


Trip Speed for Highest Performing Models by Category
Control
MONOPOLY
DDPG
Round Robin
Average Trip Speed (meters per second)
40
30
20
10
0
Trial 1
Trial 2
Trial 3
Trial Number


Average Computing Demand Across Traffic Control Models
Control
Round Robin
MONOPOLY
DDPG
Usage (%)
80
60
40
20
0
CPU Usage
GPU Usage
RAM Usage


Monthly Cloud Computing Cost by Model
250
200
150
100
50
0
Cost ($)
Uniform
Round Robin
MONOPOLY
DDPG


Efficiency per $10,000 spent annually
Number of Signals
Average Trip Speed
40
30
20
10
0
Number of Signals +Trip Speed (m/s)
Control
Round Robin
MONOPOLY
DDPG
model used

[37]

Groups	*Count*	*Sum*	*Average*	*Variance*
Control	3	71.52371134	23.84123711	0.1498437666
MONOPOLY	3	80.7	26.9	0.21
DDPG	3	93	31	1
Round Robin	3	74.5	24.83333333	0.3233333333

[38]

Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	90.5227952	3	30.17426507	71.70787926 [39]	0.000004008266487[40]	4.066180557
Within Groups	3.3663542	8	0.420794275			
Total	93.8891494	11				

[37] Summary table made with XLMiner Analysis ToolPak
[38] ANOVA table made with XLMiner Analysis ToolPak
[39] The F value exceeds the F value, therefore the null hypothesis can be rejected
[40] The p value is less than the alpha of .05, so the data is significant

5. Conclusion

5.1 Limitations

The experiment fails to account for a multitude of factors which could influence its applicability. Firstly, driver behavior is homogenized and all vehicles along the road network are the same dimension, which reduces the external validity of the experiment, but cannot be accounted for due to a lack of research on the driving psychology of residents of Evansville, IN. Furthermore, each vehicle along the road network was programmed to travel along the entirety of the road network, which was done in order to acquire a significant sample size for the experiment. The experiment cannot be modeled after the real-life driving habits of Evansville residents without further research into Lloyd Expressway commuting. Additionally, the experiment does not account for the effect of dynamic and sudden traffic incidents which may affect the flow of traffic, such as accidents and emergency vehicle preemption systems. This was done due to a lack of research on the matter and an inability to properly simulate the delay. Finally, the experiment does not account for systemic traffic delays that arise from construction. These factors mean that the results generated by the simulation under approximate travel times along the network, and do not account for sudden or systemic causes of traffic delays. However, these factors affect all experimental conditions equally, meaning the relative performance of the models can still be examined effectively.

5.2 Implications

The findings of the experiment can serve as a framework to guide future investment into Evansville, IN road networks, with budgets in mind. The findings of the experiment provide different efficient solutions at different price points for the city of Evansville and State of Indiana to invest into Lloyd Expressway traffic management. Additionally, the findings of the experiment contradicts the existing notion that traffic control methods created for research become antiquated quickly, instead suggesting that different traffic control models have specific circumstances under which they thrive, cost of operation being one of them. Due to the lack of information on the Indiana Department of Transportation's budget for fiscal year 2026 and its allocation, an optimal model cannot be currently suggested for the road network.

Appendices

Appendix A

2.1 B Currently Implemented Traffic Control Models

The currently implemented models reviewed were: the Fully Actuated Signal Control model, the Fixed Time or Uniform model, and the Round Robin Scheduler. The Fully Actuated Signal Control Model operates by receiving a simple binary input from vehicle detectors, typically from an induction loop - a coil of wire with current flowing through it which detects the presence of a large metal object above it- or a radar detector, which extends green phases and brings importance to red phases, while remaining in a set phase cycle (Comert et al., 2020, 9). The Fixed Time model, also known as the Uniform model, operates by running through a set phase cycle, giving each phase a green for a set amount of time and not taking any inputs in the process (Genders & Razavi, 2019, 2). The Round Robin Scheduler operates in a similar manner to the Fixed Time model, except instead of a fixed phase time it operates on a fixed relative interval of time called a timestep, with 30 timesteps of green and 3 timesteps of yellow making up a full phase (Chaudhuri et al., 2022, 4-5.) The low number of inputs and minimal logic allows these traffic control models to run at a very low cost.

2.1C Machine Learning-Based Traffic Control Models

The machine learning-based traffic control models reviewed were: the Deep Q Network (DQN) model, the Deep Deterministic Policy Gradient (DDPG) model, the Advantage Actor-Critic (A2C) model, and the Double Dueling Deep Q Network (D3QN) model. The Deep Q Network model operates without a phase cycle, instead it uses an artificial intelligence model which uses density and queue length of incoming and oncoming lanes to determine the next green phase, and is rewarded to optimize the system (Genders & Razavi, 2019, 4). The Deep Deterministic Policy Gradient model operates by giving an artificial intelligence model queue length and density of the incoming and outgoing lanes of an intersection and using this information to dynamically define green phase timings in a set phase cycle (Genders & Razavi, 2019, 5). The Advantage Actor-Critic model operates by using vehicle queue length and lane density information to suggest a phase, specifically by feeding this information into multiple artificial intelligence agents which attempt to predict actions that will maximize rewards, and an agent which will evaluate the actions to define future rewards (Chaudhuri et al., 2022, 8). The Double Dueling Deep Q Network model operates by combining aspects of Q Network models like utilizing two networks for evaluation and action selection as well as complex reward modeling to determine phase selection and duration through analysis of vehicle speed, vehicle queue length, and lane density (Liang et al., 2018, 5-7). The additional inputs as well as the high processing power required for decision making makes machine learning-based models very expensive to operate.

2.1D Simple Algorithm-Based Traffic Control Models

The simple algorithm-based traffic control models reviewed were: the Max-Pressure model, Self-Organizing Traffic Lights (SOTL) model, and the Queue Length model. The Max-Pressure model operates by assigning each phase a pressure value, which correlates to the amount of traffic waiting on the phase as well as the time the traffic has waited (Genders & Razavi, 2019, 3). The model selects the phase with the highest pressure phase after phase for preset phase timings. The Self-Organizing Traffic Lights model operates by setting phase lengths dynamically. The model checks the number of vehicles affected by the green phase and compares it to the number of vehicles affected by the red phase, and adjusts the phase length to favor the side with more vehicles (Genders & Razavi, 2019, 3). The Queue Length model operates through a function that groups phases and establishes a maximum and minimum green time for them based on queue lengths on concurrent and conflicting phases (Comert et al., 2020, 3). The low number of inputs and relatively low processing power requirements allow simple algorithm-based traffic control models to run at a cost slightly higher than currently implemented models.

2.1E Complex Algorithm-Based Traffic Control Models

The complex algorithm-based traffic control models reviewed were the MONOPOLY Feedback mechanism model and the Discrete-Event, Aggregating, and Relational Control Interfaces (DAR-CI) model. The MONOPOLY feedback mechanism model operates by attaching a reward function - a component which selects phases by estimating a reward for each phase based on the number of cars it allows to pass through, and activates the phase with the highest reward value - to the round robin scheduler model, with multiple agents analyzing lane state, time, queue length, and average speed to determine phase selection and length (Chaudhuri et al., 2022, 4-6). The Discrete-Event, Aggregating, and Relational Control Interfaces model operates by using trends in vehicle queue length and lane density over time and taking decisions from the perspective of an entire road network rather than one intersection (Meng et al., 2023, 4). The relatively intermediate number of inputs and processing power requirements allow complex algorithm-based traffic control models to run at a cost higher than simple algorithm-based models, but lower than machine learning-based models.

Appendix B - Traffic Flow Representation

```xml
<routes xmlns:xsi="http://www.w3.org/2001/XMLSchema-instance" xsi:noNamespaceSchemaLocation="http://sumo.dlr.de/xsd/routes_file.xsd">


    <vType id="car" accel="2.6" decel="4.5" sigma="0.5" length="5.0" maxSpeed="30" />


    <flow id="flow_0" from="864210428" to="1120039256#1" begin="0" end="3600" vehsPerHour="84.61" />
    <flow id="flow_1" from="864210428" to="1120039256#1" begin="3600" end="7200" vehsPerHour="42.30" />
    <flow id="flow_2" from="864210428" to="1120039256#1" begin="7200" end="10800" vehsPerHour="42.30" />
    <flow id="flow_3" from="864210428" to="1120039256#1" begin="10800" end="14400" vehsPerHour="42.30" />
    <flow id="flow_4" from="864210428" to="1120039256#1" begin="14400" end="18000" vehsPerHour="84.61" />
    <flow id="flow_5" from="864210428" to="1120039256#1" begin="18000" end="21600" vehsPerHour="253.82" />
    <flow id="flow_6" from="864210428" to="1120039256#1" begin="21600" end="25200" vehsPerHour="592.25" />
    <flow id="flow_7" from="864210428" to="1120039256#1" begin="25200" end="28800" vehsPerHour="846.07" />
    <flow id="flow_8" from="864210428" to="1120039256#1" begin="28800" end="32400" vehsPerHour="1184.49" />
    <flow id="flow_9" from="864210428" to="1120039256#1" begin="32400" end="36000" vehsPerHour="1015.28" />
    <flow id="flow_10" from="864210428" to="1120039256#1" begin="36000" end="39600" vehsPerHour="846.07" />
    <flow id="flow_11" from="864210428" to="1120039256#1" begin="39600" end="43200" vehsPerHour="676.85" />
    <flow id="flow_12" from="864210428" to="1120039256#1" begin="43200" end="46800" vehsPerHour="507.64" />
    <flow id="flow_13" from="864210428" to="1120039256#1" begin="46800" end="50400" vehsPerHour="423.03" />
    <flow id="flow_14" from="864210428" to="1120039256#1" begin="50400" end="54000" vehsPerHour="592.25" />
    <flow id="flow_15" from="864210428" to="1120039256#1" begin="54000" end="57600" vehsPerHour="846.07" />
    <flow id="flow_16" from="864210428" to="1120039256#1" begin="57600" end="61200" vehsPerHour="1184.49" />
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    <flow id="flow_18" from="864210428" to="1120039256#1" begin="64800" end="68400" vehsPerHour="846.07" />
    <flow id="flow_19" from="864210428" to="1120039256#1" begin="68400" end="72000" vehsPerHour="676.85" />
    <flow id="flow_20" from="864210428" to="1120039256#1" begin="72000" end="75600" vehsPerHour="507.64" />
    <flow id="flow_21" from="864210428" to="1120039256#1" begin="75600" end="79200" vehsPerHour="338.43" />
    <flow id="flow_22" from="864210428" to="1120039256#1" begin="79200" end="82800" vehsPerHour="169.21" />
    <flow id="flow_23" from="864210428" to="1120039256#1" begin="82800" end="86400" vehsPerHour="84.61" />
```
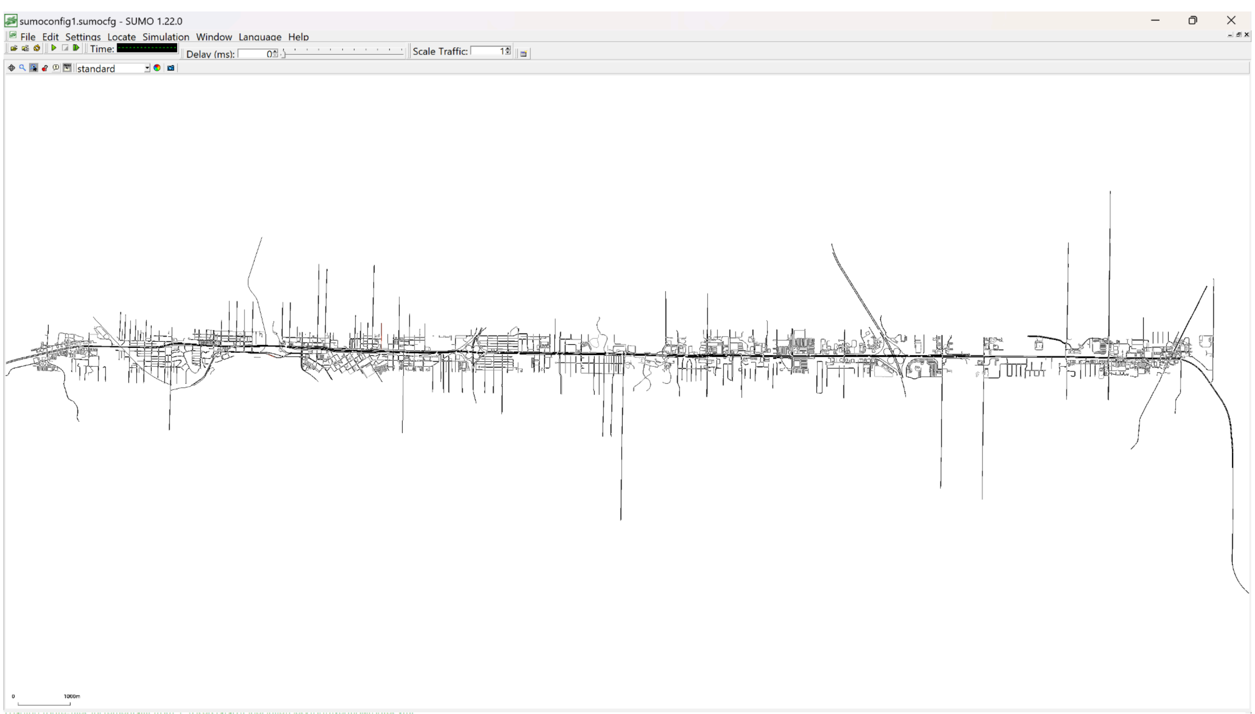

Appendix C - Network Representation



References

Abdul Fattah, M., Morshed, S. R., & Al Kafy, A. (2022). Insights into the socio-economic impacts of traffic congestion in the port and industrial areas of Chittagong city, Bangladesh. *Transportation Engineering*, *9*, 1-12. Science Direct. https://doi.org/10.1016/j.treng.2022.100122

About. (2024). Longchao Da. Retrieved January 15, 2025, from https://longchaoda.github.io/LongchaoHere/

Association for Computing Machinery. (2024, May). *Alexander Wieder*. ACM Digital Library. Retrieved January 22, 2025, from https://dl.acm.org/profile/81466646827

Barth, M., & Boriboonsomsin, K. (2008, March 31). Real-World CO2 Impacts of Traffic Congestion. *Transportation Research Record*, 1-23. https://escholarship.org/content/qt4fx9g4gn/qt4fx9g4gn_noSplash_0fd1f0095e8174e3515ae7f9ead2626a.pdf?t=lnrm6k

Behrisch, M. (2022, July). *Michael Behrisch*. Michael Behrisch. Retrieved December 2, 2024, from https://mbehrisch.github.io/

Behrisch, M., Bieker, L., Erdmann, J., & Krajzewicz, D. (2011). SUMO - Simulation of Urban MObility An Overview. *SIMUL 2011: The Third International Conference on Advances in System Simulation*, *XX*(XX), 63-68. https://sumo.dlr.de/docs/SUMO_at_a_Glance.html#:~:text=%22Simulation%20of%20Urban%20MObility%22%2C,through%20a%20given%20road%20network

Bortoli, S. (2025, January). *Stefano Bortoli*. LinkedIn. Retrieved January 22, 2025, from https://www.linkedin.com/in/stefano-bortoli/?originalSubdomain=de

Chaudhuri, H. (n.d.). *Hrishit Chaudhuri*. Hrishit Chaudhuri. Retrieved December 3, 2024, from https://hrishitchaudhuri.github.io/

Chaudhuri, H., Masti, V., Veerendranath, V., & Natarajan, S. (2022). A Comparative Study of Algorithms for Intelligent Traffic Signal Control. *Springer, Singapore, Machine Learning and Autonomous Systems*, *X*(X), 271-286. arXiv. https://doi.org/10.48550/arXiv.2109.00937 Focus to learn more

Comert, G., Cetin, M., & Begashaw, N. (2020, June 11). A Simple Traffic Signal Control Using Queue Length Information. *arXiv*, 1-17. https://doi.org/10.48550/arXiv.2006.06337

Daniel Krazjewicz. (2024, July 7). dkrajzew — Main. Retrieved December 2, 2024, from https://krajzewicz.de/

dblp: computer science bibliography. (2024). *Xiaoliang Lei* [Researcher Profile].

Du, X. (2024, November). *Xiaorui Du*. LinkedIn. Retrieved January 22, 2025, from https://www.linkedin.com/in/xiaoruipython/?originalSubdomain=de

Du, X., Meng, Z., Siguenza-Torres, A., Knoll, A., Piccione, A., Bortoli, S., Pimpini, A., & Pellegini, A. (2023). Autonomic Orchestration of In-Situ and In-transit Data Analytics for Simulation Studies. *2023 Winter Simulation Conference*, 1-12. https://www.alessandropellegrini.it/publications/DuX23.pdf

exelban/stats: macOS system monitor in your menu bar. (n.d.). GitHub. Retrieved November 17, 2024, from https://github.com/exelban/stats

Flow Labs. (2023). *Team*. Flow Labs. Retrieved January 15, 2025, from https://www.flowlabs.ai/about/team

Genders, W., & Razavi, S. (2019, Sep 1). An Open-Source Framework for Adaptive Traffic Signal Control. *JOURNAL OF TRANSACTIONS ON INTELLIGENT*

TRANSPORTATION SYSTEMS, *X*(X), 1-11. arXiv. https://doi.org/10.48550/arXiv.1909.00395

Google Scholar. (2024). Bin Shi [Researcher Profile]. In *Google Scholar*. Google Scholar. Retrieved January 15, 2025, from https://scholar.google.com/citations?user=RnCxzuYAAAAJ&hl=zh-CN

Grossi, M. (2023, September). *Margherita Grossi*. LinkedIn. Retrieved January 22, 2025, from https://www.linkedin.com/in/margherita-grossi-6299572b/?originalSubdomain=de

Hedges Company. (n.d.). *How Many Licensed Drivers Are There In The US?* Hedges Company. Retrieved December 4, 2024, from https://hedgescompany.com/blog/2024/01/number-of-licensed-drivers-us/

HNTB Corporation. (2023, August 23). *HNTB survey: Increasing congestion has Americans willing to pay additional fees to maintain road quality and reduce commute time*. HNTB. Retrieved December 4, 2024, from https://www.hntb.com/press_release/hntb-survey-increasing-congestion-has-americans-willing-to-pay-additional-fees-to-maintain-road-quality-and-reduce-commute-time/

Hochschule Bremerhaven. (n.d.). *Prof. Dr. rer. nat. Laura Bieker-Walz*. Hoschule Bremerhaven. Retrieved December 2, 2024, from https://www.hs-bremerhaven.de/laura-bieker-walz

Hua Wei | ASU Search. (2023). ASU Search. Retrieved January 15, 2025, from https://search.asu.edu/profile/3095662#nav-group-research

IEEE Xplore. (2024). *Zhuoxiao Meng*. IEEE Xplore. Retrieved January 22, 2025, from https://ieeexplore.ieee.org/author/358007023048972

IEEE Xplore. (2024, Jan 31). *Jakob Erdmann*. Author details. Retrieved December 2, 2024, from https://ieeexplore.ieee.org/author/37085678119

Indiana Department of Transportation. (n.d.). *INDOT - Next Level Roads*. IN.gov. Retrieved December 4, 2024, from https://entapps.indot.in.gov/dotmaps/nlri/

Indiana Department of Transportation. (2024, November 15). *INDOT Trafficwise Map*. Trafficwise. Retrieved February 5, 2025, from https://511in.org/@-88.5498,40.29978,6?show=incidents,normalCameras,stationsAlert,weatherWarningsAreaEvents,plowCameras,flooding

Indiana Department of Transportation & Midwestern Software Solutions LLC. (2024). *Traffic Count Database System*. Transportation Data Management System. Retrieved December 4, 2024, from https://indot.public.ms2soft.com/TCDS/tsearch.asp?loc=Indot&mod=TCDS

Liang, X., Wang, G., & Han, Z. (2018, Mar 29). Deep Reinforcement Learning for Traffic Light Control in Vehicular Networks. *IEEE TRANSACTIONS ON VEHICULAR TECHNOLOGY*, *XX*(XX), 1-11. arXiv. https://doi.org/10.48550/arXiv.1803.11115

MacBook Pro (14-inch, M3, Nov 2023) - Tech Specs. (n.d.). Apple Support. Retrieved November 17, 2024, from https://support.apple.com/en-us/117735

Masti, V. (2024). *Vibha Masti*. Vibha Masti. Retrieved December 2, 2024, from https://vibhamasti.github.io/

McMaster University. (2020). *Dr. Saiedeh Razavi*. Engineering Faculty. Retrieved January 15, 2025, from https://www.eng.mcmaster.ca/civil/faculty/dr-saiedeh-razavi/

Mei, H. (2022). *Hao Mei*. Academic. Retrieved January 15, 2025, from https://derekmei233.github.io/

Mei, H., Lei, X., Da, L., Shi, B., & Wei, H. (2023, November 29). LibSignal: An Open Library for Traffic Signal Control. *Conference on Neural Information Processing Systems 2022*, *36*(Reinforcement Learning for Real Life Workshop), 1-17. arXiv. https://doi.org/10.48550/arXiv.2211.10649

Mendelson, E. (2022, June 24). *VMware Fusion Review*. PCMag. Retrieved November 18, 2024, from https://www.pcmag.com/reviews/vmware-fusion

Meng, Z., Sommer, C., Knoll, A., Siguenza-Torres, A., Gao, M., Grossi, M., Wieder, A., Du, X., & Bortoli, S. (2023, June 21). Towards Discrete-Event, Aggregating, and Relational Control Interfaces for Traffic Simulation. *ACM International Conference on Principles of Advanced Discrete Simulation (PADS 2023)*, *XX*(XX), 1-11. ACM Digital Library. https://doi.org/10.1145/3573900.3591116

Old Dominion University. (2024). *Mecit Cetin*. Old Dominion University. Retrieved January 16, 2025, from https://www.odu.edu/directory/mecit-cetin

ORCID. (2024, June 19). *Mingyue Gao*. ORCID. Retrieved January 22, 2025, from https://orcid.org/0009-0009-7312-4710

PES University. (n.d.). *Dr. Natarajan S*. PES University. Retrieved December 3, 2024, from https://staff.pes.edu/nm1090/

Reflections from Virtual Undergraduate Summer Research Experience with Interdisciplinary Teams. (2021). *American Society for Engineering Education*, *2021*(35162), 1-15.

Rudy, L. J., & Dempster, M. (2024, January 24). How Many People Drive in the U.S.? 2024 | ConsumerAffairs®. *Consumer Affairs*. https://www.consumeraffairs.com/automotive/number-of-drivers-in-us.html

SUMO at a Glance - SUMO Documentation. (2024, January 6). Eclipse SUMO - Simulation of Urban MObility. Retrieved November 17, 2024, from https://sumo.dlr.de/docs/SUMO_at_a_Glance.html

Thomson, I. (2000, October). Traffic Congestion: Its Economic and Social Consequence. *Bolletin*, *FAL*(70), 1-6. https://www.cepal.org/sites/default/files/publication/files/36298/FAL_Bulletin170_en.pdf

University of Illinois Urbana-Champaign. (2024). *Gurcan Comert*. The Grainger College of Engineering Information Trust Institute. Retrieved January 16, 2025, from https://iti.illinois.edu/people/profile/gcomert

U.S. Department of Transportation Federal Highway Administration. (2008, June). Traffic Signal Timing Manual. In *Office of Operations*. U.S. Department of Transportation Federal Highway Administration. Retrieved January 23, 2025, from https://ops.fhwa.dot.gov/publications/fhwahop08024/chapter5.htm#:~:text=Traffic%20signals%20operate%20in%20either,cycle%20length%20for%20the%20intersection.

US Department of Transportation Federal Highway Administration. (2017). *Simplified Highway Capacity Calculation Method for the Highway Performance Monitoring System*. US Department of Transportation Federal Highway Administration. https://www.fhwa.dot.gov/policyinformation/pubs/pl18003/hpms_cap.pdf

Veerendranath, V. (2024). *Vishruth Veerendranath*. Vishruth Veerendranath. Retrieved December 2, 2024, from https://vishruth-v.github.io/