# Enhancing Traffic using Ant Colony Optimisation Final Reports

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November 11, 2024

Report submitted for **4439 MATHS 7097B Data Science Research Project B** at the School of Mathematical Sciences, University of Adelaide

Project Area: **Heuristic Techniques for solving Constraint Optimization Problem**
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# Abstract

Considering the ever-changing traffic patterns and intricate intersection designs in city environments, alongside the shortcomings of current traffic signal optimization methods, this study introduces a new approach. By conceptualizing the traffic network as a directed acyclic graph, we developed an innovative Q-learning-based ant colony optimization (Q-ACO) algorithm, inspired by reinforcement learning principles. This algorithm adjusts to real-time traffic variations by dynamically updating the Q-matrix, guided by a reward function that takes into account traffic density and waiting times. This updated Q-matrix forms the foundational pheromone level for the ant colony algorithm, which then employs a pseudo-random proportional rule to refine signal timing. Through simulations across various traffic conditions, our algorithm has demonstrated a significant reduction in average vehicle waiting times and an enhancement in traffic flow efficiency. When compared with traditional methods like ACO and Q-Learning alone, our Q-ACO algorithm consistently reduces waiting times, presenting a robust solution for managing dynamic traffic scenarios.



## Keywords

• Optimisation • Ant Colony Optimisation (ACO) • Traffic Signal Timing • Q-Learning • Pheromone

# 1 Introduction

In urban environments, traffic signals play a crucial role in managing vehicle movements to mitigate congestion, enhance safety, and implement strategies aimed at reducing delays and improving environmental conditions [**1**]. The growth in vehicle numbers and industrial development has made the optimization of traffic signal parameters increasingly critical to maximize network capacity. Over the past decade, advancements in communications and information technologies have significantly evolved classical methods of optimizing traffic signal timings, paving the way for more intelligent solutions.

By effectively regulating traffic demand at each intersection, the objective is to prevent traffic conflicts and minimize queue lengths at stoplights. Researchers have proposed numerous approaches to the traffic signal control problem over the years. Some of the pioneering large-scale adaptive traffic signal control systems include TRANSYT (Traffic Network Study Tool) [**2**], SCOOT (Split, Cycle, and Offset Optimization Technique) [**3**], and SCATS (Sydney Coordinated Adaptive Traffic System) [**4**], which utilize pre-calculated offline timing plans for signal cycles tailored to current traffic conditions. More contemporary advancements in traffic signal control have embraced artificial intelligence technologies such as neural networks and fuzzy logic [**5**], with recent investigations exploring the use of algorithms based on Petri nets and Markov decision control [**6**].

The Ant Colony algorithm is a meta-heuristic approach designed to tackle complex combinatorial optimization problems. This algorithm draws inspiration from the foraging behavior observed in natural ant colonies [**7**]. In this multi-agent system, each individual agent is modeled as an artificial ant, contributing to one of the most successful applications of swarm intelligence. The algorithm has been effectively applied to a variety of challenges, including the classical traveling salesman problem, path planning, and network routing [**8**].

In their natural environment, ants initially search for food in a random pattern. Upon locating food, they return to their colony while depositing pheromones, chemicals that serve as a communication medium within the colony [**9**]. These pheromone trails help guide other ants to the food source. Over time, as more pheromones are deposited, the paths of the ants become increasingly targeted, favoring routes with higher pheromone concentrations, thus reducing randomness.

Mimicking this natural mechanism, the ant colony algorithm uses artificial ants that explore the solution space in a probabilistic manner, generating potential solutions. These solutions are evaluated, and the results influence the updating of pheromone concentrations on the paths. As the algorithm progresses, pheromone on less successful paths evaporates, leaving only the paths that are frequently reinforced with pheromone, thus optimizing the search for the most effective solutions [**9**].

Ant Colony Optimization (ACO) has demonstrated remarkable success in addressing a range of NP-hard combinatorial optimization challenges, including problems like the traveling salesman [**10**], graph partitioning [**11**], and the generalized spanning tree [**12**]. Within the ACO framework, each artificial ant explores potential solutions in a probabilistic manner. These potential solutions are assessed based on a performance criterion analogous to the pheromone concentrations left by biological ants. While ACO does not always guarantee convergence to the global optimum, it is highly effective at finding near-optimal solutions within a feasible computational timeframe.

The use of ACO in traffic engineering has also garnered interest among researchers. Recent studies have applied ACO to complex vehicle routing problems where travel costs are uncertain [**12**]. Moreover, traffic signal optimization at intersections, particularly those with bidirectional traffic flows requiring only two-phase controllers [**13**], has been explored using ACO. However, contemporary traffic networks and control systems demand more advanced signal configurations to manage the diverse traffic flows across various directions and road links.

The project aims to alleviate traffic congestion and improve traffic signal efficiency by implementing an intelligent ant colony strategy enhanced by Q-learning (ACOQ). Experimental findings affirm that this algorithm delivers exceptional results, rendering it ideal for heterogeneous computing environments and demanding computational tasks. The adoption of a Q-Learning based Intelligent Ant Colony Optimization (ACO) strategy for traffic signal optimization brings manifold advantages that significantly boost traffic management efficacy. This adaptive learning model enables the system to independently learn from real-time traffic data and refine its operational strategies accordingly. By optimizing traffic flow at intersections, the system minimizes wait times at signals and ensures smoother transitions, thereby reducing overall journey durations—a significant benefit for commuters. Moreover, the enhanced traffic flow markedly reduces fuel usage and vehicle emissions, supporting environmental sustainability objectives. The system's scalability and adaptability allow it to expand across larger traffic light networks and adjust to diverse traffic conditions, including unplanned disruptions like road construction or accidents. Furthermore, this strategy not only enhances road safety by decreasing the likelihood of congestion-induced accidents but also offers a cost-effective solution by reducing the necessity for manual traffic control and diminishing the economic impacts of traffic congestion. Thus, implementing a Q-Learning based Intelligent ACO system promises to transform urban traffic management into a more efficient, safer, and environmentally conscious operation.

## 1.1 Motivation Behind the Research

The traffic signal problem is addressed very naturally as a combinatorial optimization problem. As traffic networks grow, the complexity of the finding an optimal solution becomes much more difficult. Total enumeration of all solutions becomes intractable very quickly, so advanced methods must be used [9]. ACO algorithms have successfully been applied to many computationally complex combinatorial problems, making ACO a good choice for solving the traffic signal problem. The ACO ability to incorporate heuristic information about traffic networks makes it more efficient. For example, in the isolated traffic signal problem the maximum queue length currently at the signal is accounted for. On more complicated traffic topologies, other heuristic measures can be incorporated, such as distances between signals. Ant colony optimization has successfully been applied to other traffic related problems, such as the vehicle routing problem (VRP), with positive results. Although the VRP has a different setup and objectives, similar heuristics and objective functions are used in both cases. As will be discussed later in this section, the ACO can be used to optimize rolling horizon control. Rolling horizon control has successfully been used in traffic signal control [13]. Some of the advantages of this approach were discussed in Chapter Two. Additionally, ACO requires very few restrictions on the cost function. For example, many optimization techniques rely on computing a gradient. This requires the existence of a gradient and can be computationally expensive. ACO algorithms are not dependant on the form of objective function; if the objective function is changed the algorithm works the same. This allows the heuristic information, intersection topology, and vehicle arrival rates to be easily changed. Thus, the ACO robustly conforms to new situation

# 2 Background

The research by (Renfrew & Yu, 2012)[**15**] explores a novel application of the Ant Colony Optimization (ACO) algorithm to develop optimal signal timing plans for traffic intersections, aiming to minimize average vehicle delay times. The effectiveness of the ACO algorithm, enhanced by a heuristic local search mechanism with weighted pheromone levels, was rigorously tested through simulations at intersections experiencing varied vehicle arrival rates, ranging from 400 to 850 vehicles per hour per movement. Performance comparisons were drawn against traditional fully actuated control algorithms adhering to the National Electrical Manufacturers Association (NEMA) standards. Various configurations of the ACO algorithm were explored, using 10, 25, and 50 ants, to study their effectiveness as demonstrated in convergence graphs. Additionally, a rank-based ant system algorithm incorporating local search and heuristic strategies was specifically applied to manage traffic signals, significantly reducing vehicle waiting times even under conditions of high traffic demand. Results confirm that this method surpasses conventional control systems, with the added advantage of being sufficiently rapid for real-time implementation in traffic management systems.

Jinjian et al.[**16**] proposed a traffic control system for isolated intersections that eliminates traditional traffic lights and phases. Using a Vehicle-to-Infrastructure (V2I) communication framework, vehicles dynamically share their information upon entering a communication zone. The system allocates right-of-way based on real-time data, optimizing the passing sequence with the Artificial Bee Colony (ABC) optimization algorithm. This approach minimizes delays by aligning vehicle speeds with the optimized sequence, allowing for near free-flow travel speeds. Simulation results highlight the system's efficiency in reducing delays and improving traffic flow without relying on conventional signals. The study of (Haldenbilen, Baskan, and Ozan, 2013)[**17**], addresses area traffic control problem using the ACOTRANS using an Ant Colony Optimization (ACO)-based algorithm known as ACORSES, designed to optimize signal parameters in coordinated signalized networks for a fixed set of link flows. One of the key advantages of ACO, and specifically ACORSES, is its ability to optimize signal timings with less computational complexity compared to traditional methods. By leveraging a reduced search space, the algorithm avoids being trapped in poor local optima, enabling it to converge quickly to a global or near-global optimum. During its progression, the algorithm searches for optimal signal timings within this limited space, mimicking the way ants find efficient routes. Using the Performance Index as a metric, the results demonstrate that ACORSES outperforms other optimization methods such as genetic algorithms and hill-climbing techniques.

Rutgar et al. [**18**] introduced an Ant Colony Optimization (ACO) algorithm designed to address challenges in distributed systems, particularly traffic congestion. The proposed method employs intelligent systems and future estimations to avoid congestion by enabling cooperation among ants representing vehicles. Through shared pheromone trails, ants exchange general knowledge to improve route-finding. A simulation of this cooperative ACO algorithm was conducted to evaluate its effectiveness compared to a non-cooperative version, measuring both the quality of calculated routes and the number of iterations required to reach optimal solutions. The results indicate that while the cooperative approach reduces the number of iterations needed to find solutions, the overall improvement in route quality and computational speed is minimal, especially for smaller networks. However, the reduction in iterations is significant in scenarios where inter-agent communication is a limiting factor. This highlights the adaptability of ACO algorithms in traffic routing by allowing ants to share information across multiple routing problems within a distributed traffic graph. Despite its modest advantages, the cooperative variant demonstrates the potential for ACO algorithms to incorporate generalized information-sharing in addressing complex traffic management issues.

# 3 Methods

## 3.1 Ant Colony Optimisation

Ant Colony Optimization (ACO) is a metaheuristic specifically designed to tackle computationally challenging combinatorial optimization problems. Initially developed to address the Traveling Salesman Problem, ACO has since proven effective for a variety of NP-hard problems, including routing issues, quadratic assignment, and scheduling dilemmas. The inspiration for ACO comes from the foraging behaviors observed in ant colonies. [**19**]

In their natural environment, ants initially wander randomly near their nests in search of food. Upon discovering a food source, an ant assesses its quality and quantity before heading back to the nest. During this return journey, the ant leaves behind a pheromone trail—a chemical means of communication among ants. The strength of the pheromone trail depends on the food's quality and quantity, guiding other ants to the source. Over time, as more ants follow and reinforce this trail, their paths become more direct, concentrating on routes with stronger pheromone signals. However, pheromones also evaporate over time, which means that less-traveled paths gradually lose their trail markers unless continuously reinforced. [**20**]

This process not only helps ants locate the most abundant food sources but also the shortest routes to them. Shorter routes get traversed more frequently, leading to quicker and more substantial pheromone deposits, thus accelerating the path-finding process. [**20**]

A famous illustration of this behavior is the Double Bridge Experiment[**21**] shown in Figure 3, where an ant colony is provided with two equal-length bridges between their nest and a food source. Initially, ants select either path at random, but as time passes, one path may begin to accumulate more pheromones due to random fluctuations. This increased pheromone level attracts more ants, who add their own pheromones to the path, thus reinforcing a positive feedback loop. Eventually, this can lead to all ants favoring and using one bridge exclusively.

In a subsequent trial of this experiment, the lengths of the two bridges were varied—one was made twice as long as the other. Despite initial random usage of both bridges, the shorter bridge quickly accumulated more pheromones, eventually directing all traffic along its route. This experiment illustrates how ACO leverages these natural efficiencies to optimize route selection in computational tasks.

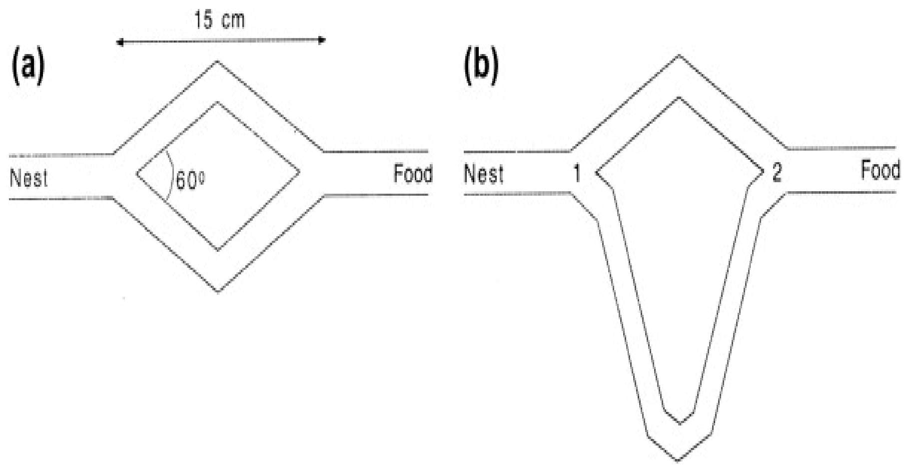


Figure 1: The double bridge experiment features two setups: (a) both bridges of equal length, and (b) bridges of varying lengths[**22**].

**Algorithm 1** Generic Ant Colony Algorithm

**Step 1: Initialization**
    Initialisation of pheromone trail
**Step 2: Construction of the Solution**
**for** each ant **do**
        Construct the solution using the pheromone trail
**end for**
**Step 3: Updation of the Pheromone Trail**
    Update the pheromone trails
    Repeat until stopping criteria are met

The basic workflow of the Ant Colony Optimization (ACO) algorithm is outlined above. Initially, a pheromone path is established to direct the simulated ants. During each iteration, these ants develop potential solutions by tracing the paths previously laid out, thus effectively navigating and utilizing the available search area. After forming the solutions, adjustments are made to the pheromone levels depending on the quality of these solutions. This process is repeated until a predetermined endpoint is reached, aiming to discover the optimal or a near-optimal solution.

## 3.2 Q-Learning Algorithm

Q-learning is a type of model-free reinforcement learning algorithm that determines the value of an action in a specific state without needing a model of the environment. This approach is capable of addressing problems characterized by stochastic transitions and rewards, and it adapts without any additional modifications. [**23**]

In the context of traffic signal control, Q-learning operates by developing a policy that guides an agent—here, a traffic light controller—on which actions to take in various traffic situations. Essentially, it learns to associate the state of the environment, such as the current traffic conditions at an intersection, with actions that adjust traffic light phases. The goal is to maximize a cumulative reward, which could involve minimizing vehicle waiting times at intersections[**23**].

Implementing traffic signal control using a Q-learning approach involves a series of carefully structured steps. Initially, the states are defined to represent various traffic conditions at an intersection, such as the number of vehicles on each approach, the current traffic light phase, or the time since the last phase change. Actions are then defined, typically as transitions between different traffic light phases. Each of these transitions is considered a potential action within the system. The reward function, which is vital for guiding the learning algorithm, is designed to minimize waiting times by penalizing longer delays, thus incentivizing the system to find solutions that reduce wait times[**23**].

The Q-table, an essential element of this setup, is initialized with values for each state-action pair, which are often set to zero or a small random number to kickstart the learning process. The learning process itself involves observing the current state of traffic at each time step, then selecting and performing actions based on an $\epsilon$-greedy policy. This policy allows the agent to mostly exploit the best-known action as per the Q-table but occasionally explore new actions with a probability determined by $\epsilon$. This approach helps balance the need to exploit known good actions with the need to explore potentially better options[**23**].

This cycle of observation, action selection, and execution is repeated until the Q-values converge, indicating that the algorithm has learned a stable and effective policy for controlling traffic signals. Through these steps, the Q-learning algorithm is equipped to effectively optimize traffic flow and reduce waiting times at intersections, improving overall traffic management. [**23**]

## 3.3 Q-Learning Algorithm combined with ACO

In my research, I adapted the innovative methodology proposed by Li et al. (2021)[**24**], which initially applied a combination of Q-Learning with Ant Colony Optimization (ACO) to address scheduling challenges, reconfiguring it to tackle the complexities of traffic signal optimization. The original study demonstrated the potential of merging these two robust algorithms to enhance decision-making processes in heterogeneous systems. By pivoting this approach to traffic management, I redefined the nodes to represent intersections or pivotal decision points within urban traffic networks. Paths in this adapted model symbolize the possible routes or directional flows that can be taken at each intersection, where metaphorical 'ants' traverse these paths. These paths are influenced by the effectiveness of the signal timings, which are in turn dictated by the Q-values generated from a sophisticated reinforcement learning process.

By intelligently integrating initial pheromone concentrations with these Q-values, the algorithm is endowed with a heuristic advantage from the onset. This initial bias helps accelerate the convergence process, directing the early stages of exploration towards more promising and effective pathways. This strategic approach effectively combines the strengths of ACO in identifying optimal paths through historical performance data (pheromone trails) with the adaptive, dynamic capabilities of Q-learning, which updates and refines strategies based on real-time data about traffic flow and congestion patterns. The convergence of these methodologies not only enhances the efficiency of traffic signal management but also provides a scalable model that can adapt to varying traffic conditions and continuous changes within urban traffic networks. This hybrid model thus represents a significant advancement in applying intelligent algorithms to solve real-world problems, specifically in the domain of urban traffic control, by leveraging historical insights and real-time adaptive learning to optimize traffic flows and reduce congestion systematically. [**24**]

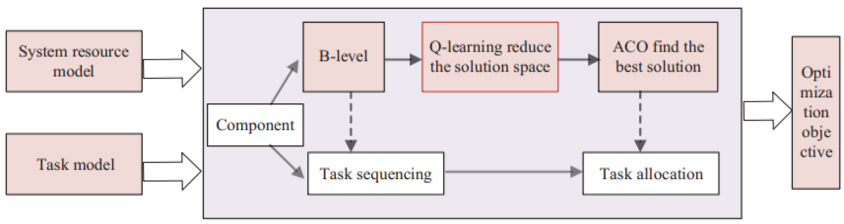


Figure 2: Design Framework of the Proposed Algorithm[**24**]

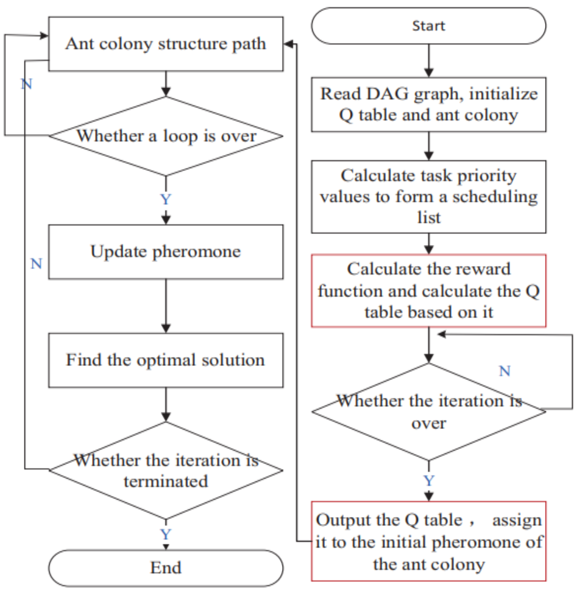


Figure 3: Flow Chart of the Proposed Algorithm[**24**]

In the system design framework for optimizing traffic signals, the metaphorical use of "ants" and "intersections" forms the cornerstone of the approach. In this setup, each "ant" embodies a series of strategic decisions designed to manage the traffic signals across a comprehensive network of intersections. The paths that these ants follow represent various sequences or adjustments in the timing of traffic light changes, each path offering a potential solution to traffic congestion.

To ensure thorough optimization, the system completes what is referred to as a "cycle," during which all traffic lights within the network undergo a full program of changes. This cycle is meticulously designed to optimize traffic flow by adjusting to current traffic conditions dynamically. To achieve robust outcomes, the system employs a parallel search strategy where multiple decision-making sequences, or "ants," are executed simultaneously. Each ant tests different traffic management strategies in parallel, allowing for a diverse exploration of possible solutions and enabling the system to identify the most effective strategies quickly.

The strategic use of a Q-table to set initial pheromone levels is particularly significant in this model. This initial setup provides the system with baseline knowledge of potentially effective traffic management strategies, based on historical data and prior simulations. Over time, as the system encounters real-world traffic conditions, it continuously refines and adapts its strategies. This learning process is driven by ongoing adjustments based on actual traffic patterns and outcomes, enhancing the system's ability to respond dynamically to changes and improve traffic flow efficiently.

Through this sophisticated approach, the traffic signal optimization system not only increases its efficiency but also its adaptability, making it capable of handling complex traffic scenarios and improving overall traffic management in urban environments.

In the stage of traffic task sorting, the priority of each intersection is determined recursively using the B-level method, which incorporates the above equations (1) and (2). The intersections are then organized into a scheduling list based on the descending order of their priority values.[**24**]

$$\text{priority}(v_i) = w_i + \max_{v_j \in \text{succ}(v_i)} \left(\bar{c}_{i,j} + \text{priority}(v_j)\right) \tag{1}$$

$$\bar{c}_{i,j} = \left(\sum_{m=1}^{n-1} \sum_{s=m+1}^{n} \frac{c_{i,j}}{q_{m,s}}\right) \bigg/ \left(p \times \frac{p-1}{2}\right) \tag{2}$$

$q_{m,s}$ denotes the number of communication paths between processor $m$ and $s$, $\bar{c}_{i,j}$ represents the average communication overhead between intersections $v_i$ and $v_j$, $\text{succ}(v_i)$ refers to the succeeding intersections in the task.

## 3.4 Design of the Algorithm

The traffic management simulation was developed using Python and Numpy to effectively manage Q-table and pheromone levels for addressing real-world traffic flow problems. Configured with five intersections, each allowing three actions: no change, change to green, or change to red, the simulation integrates essential constants such as pheromone decay and initial Q-table values to model behavior over time. The `TrafficEnvironment` class centralizes management of intersections and pheromone synchronization, featuring a reset method that aligns pheromone levels with Q-table updates. The `get_traffic_metrics` function plays a crucial role by simulating traffic delays and rewarding strategies that minimize waiting times.

In the second phase, introducing "Ant Agents," the simulation employs the `Environment` and `Ant` classes to explore ant colony optimization (ACO). Ants make probabilistic decisions influenced by pheromone levels at each intersection, navigating from one intersection to the next, and recording their paths. Each cycle allows ants to reset and prepare for new decisions, enhancing route optimization through continuous interaction with the environment.

The third phase focuses on simulation loops and pheromone updates, essential for refining ACO strategies. The `update_pheromones` function adjusts pheromone levels based on ant decisions, encouraging exploration of new paths. The simulation runs across multiple epochs, with ants influencing pheromone distribution and adapting their paths accordingly, allowing for iterative improvements in traffic management.

Finally, the simulation incorporates TraCI control scripts to link the ACO framework with SumoLink. Verifying the `SUMO_HOME` variable ensures proper tool access, and the `run_simulation` function oversees the simulation through SUMO's GUI, managing real-time steps and updating traffic lights based on ant decisions. The simulation concludes with `traci.close()`, demonstrating the efficacy of ant colony optimization in a dynamic urban traffic setting.

**Algorithm 2** Pseudo Code for Traffic Simulation using the proposed ACO

1: **Step 1: Setup**
Define the number of intersections and possible actions (no change, change to green, change to red). Initialize constants for simulation (pheromone influence, heuristic influence, decay factor).

2: **Step 2: Define Environment and Ants**
Create a TrafficEnvironment class to handle intersections and their pheromone levels. Create an Ant class where each ant can make decisions based on pheromone levels.

3: **Step 3: Simulation Process**
Define a function to run simulations over a specified number of epochs.
Each ant starts at a random intersection and moves through the environment making decisions.
After each move, update pheromones based on the ants' decisions and the traffic conditions they experience.

4: **Step 4: Pheromone Update Mechanism**
Apply a decay to reduce all pheromone levels gradually. Increase pheromones on paths that yield better traffic conditions (e.g., less delay).

5: **Step 5: Reward Function**
Define a reward function that evaluates the effectiveness of actions taken by ants based on traffic metrics like delay.

6: **Step 6: Integration with SUMO**
Set up the path to SUMO tools and ensure necessary environment variables are set.
Run the simulation in SUMO using a configuration file (e.g., simulation.cfg).
Use Traci to interact with the SUMO simulation, allowing ants to influence traffic light phases based on their decisions.
Update pheromones based on simulation feedback and repeat until the simulation ends.

7: **Step 7: Conclusion**
Each epoch of simulation provides insights into better traffic management through the use of pheromones influenced by ant decisions.
Debug output to track pheromone levels after each epoch to monitor and adjust strategies.

### 3.5 Simulation Using Sumo

In this research, I employed the Simulation of Urban Mobility (SUMO) tool, an open-source and versatile traffic simulation package. The chosen route for this study was located within the Kamppi district of Helsinki, Finland. Given SUMO's ability to manage large road networks and perform detailed microscopic traffic simulations, it was perfectly suited for analyzing the complexities of urban traffic.

I configured the simulation environment by constructing a custom network that covered a specific section of Kamppi, featuring multiple intersections complete with traffic signals to mirror the unique traffic patterns of the area accurately. The ".osm" file for the map obtained is attached in the GitHub named as "map.osm". The geographical details of Kamppi were sourced from OpenStreetMaps; the data was exported into an .osm file and then transformed using SUMO's 'netedit' tool. To add variability to the traffic flows, I utilized 'Random.py', a Python script, to create diverse traffic routes.[**25**]

Due to the computational constraints of my system, I set the simulation time to 30 minutes and capped the number of moving vehicles at 100. This configuration was selected to maintain manageability and ensure consistent performance during the simulation process.

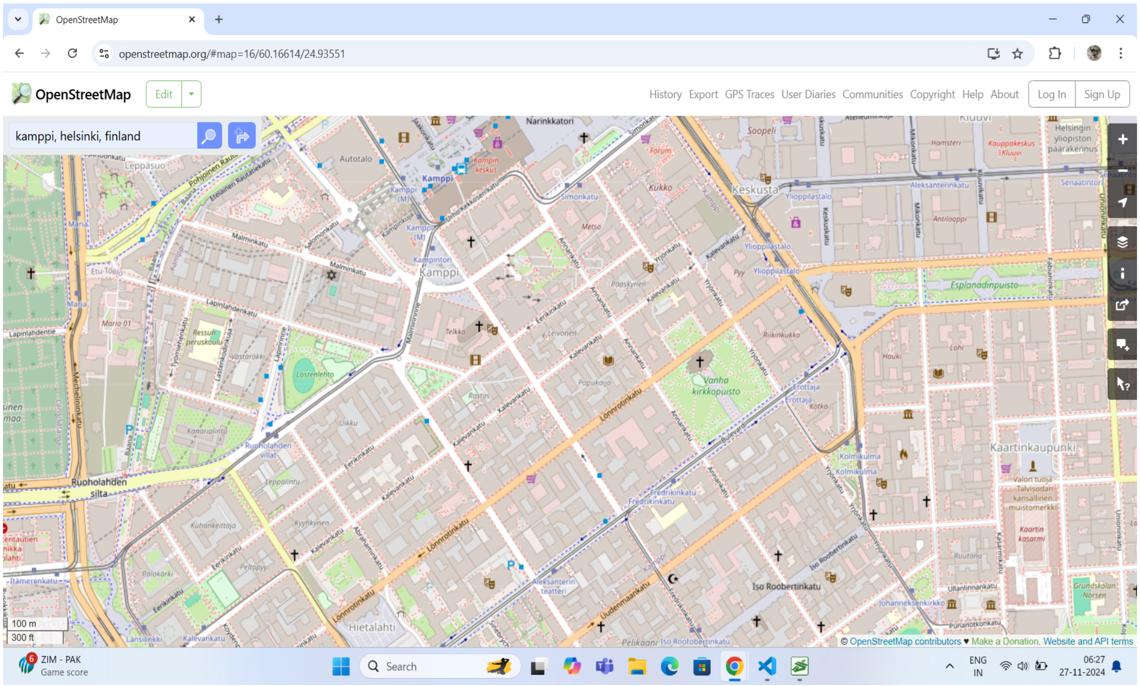


Figure 4: OpenStreet Map of Kamppi

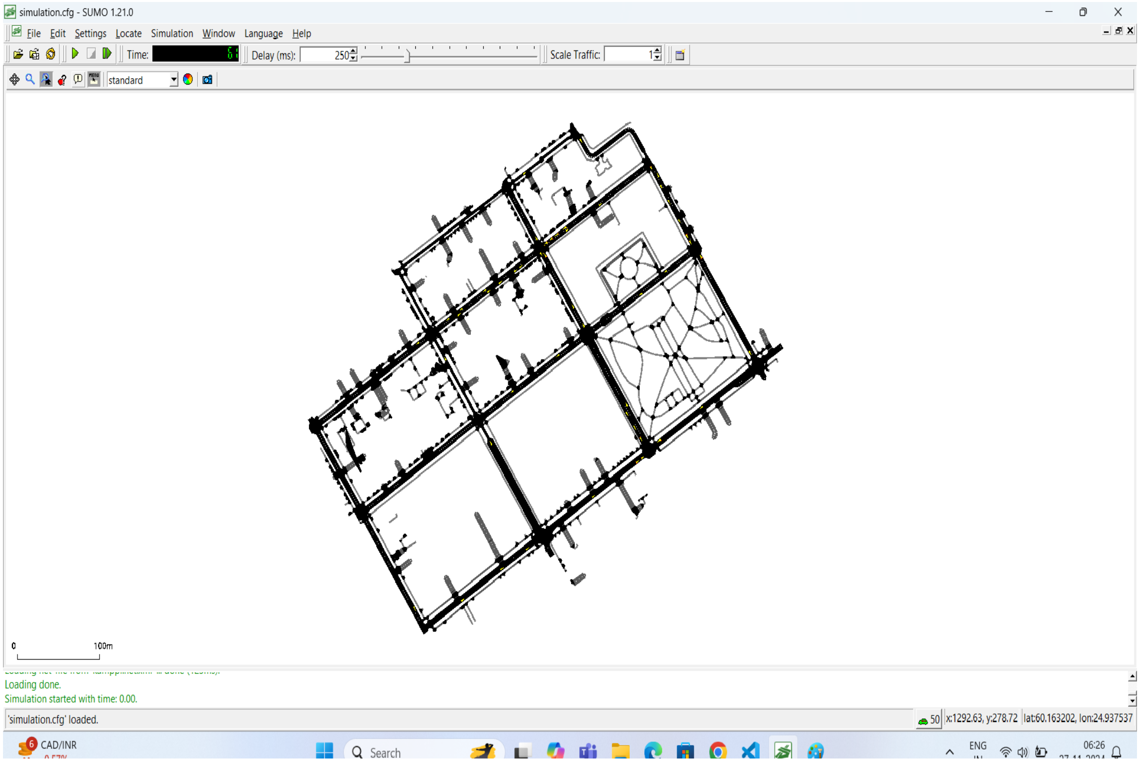


Figure 5: Road Network from Sumo for the proposed Algorithm

I successfully executed the code by connecting Python to Sumo using the TraCI API, which proved to be a valuable tool for controlling simulation parameters with Python. A '.cfg' configuration file is essential for initiating the simulation[**25**]. There are two methods to conduct the simulation:

**Using GUI**: This method utilizes a graphical user interface within the application known as 'sumo-gui'. It provides a visual representation of the simulation, making it user-friendly but computationally intensive.

**Non-GUI Python Simulation**: Alternatively, Python can run the simulation without the GUI, which is a more streamlined option as it simplifies the process and reduces computational demands.

During the simulation, key data points were targeted for collection:

**Traffic Light Phases:** We recorded the state and duration of each traffic light phase at every simulation step, providing detailed insights into traffic signal behavior.

**Vehicle Waiting Times:** Data collection focused specifically on peak periods, previously identified from preliminary simulation runs, which exhibited the highest levels of congestion. This method facilitated an understanding of critical impact points and aided in optimizing traffic light phases.

The simulation was meticulously designed to capture a broad spectrum of data under varying traffic conditions, including peak times, off-peak times, and weekends. The goal was to thoroughly understand the dynamics at these critical moments, focusing on:

- The behavior of traffic lights during periods of high vehicle congestion to better understand their impact on traffic flow.
- The detailed waiting times for each vehicle, which are crucial for assessing the effectiveness of current traffic light timings and identifying areas for potential improvement.

Given the complexity of the network and the demands on computing resources, and considering the specifications of my personal system, I focused on a specific junction with the ID "3228733111". This junction ID was retrieved from the '.net.xml' file associated with the '.cfg' file. Both a '.net.xml' and a '.rou.xml' file are necessary to conduct the simulation. An illustration of the junction is presented below.

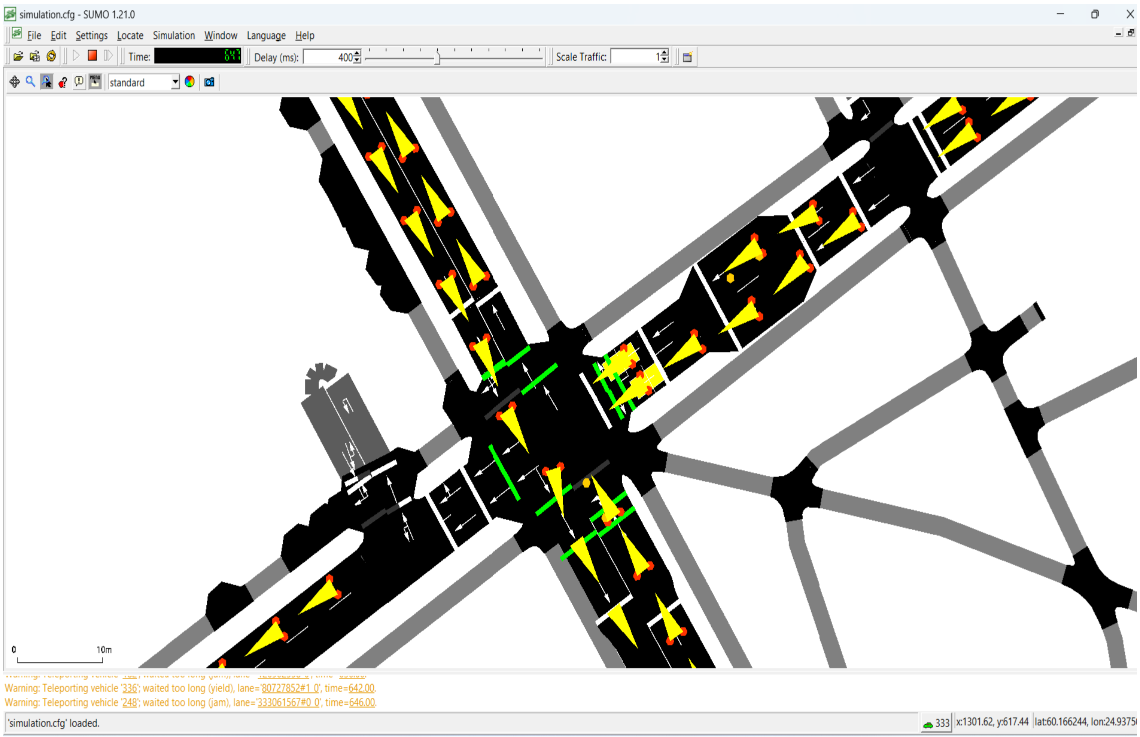


Figure 6: Road Network from Sumo for the proposed Algorithm

The 'run simulation' function was pivotal in this process. It initiated the SUMO simulation, systematically collected the necessary data, and terminated the simulation once data gathering was complete. It produced a well-organized dictionary that included timestamps, corresponding traffic light phases, and individual vehicle waiting times. This methodical approach not only streamlined the analysis but also increased the precision and relevance of the results[**25**]. All pertinent files have been made available on the GitHub repository.

# 4 Results

## 4.1 Data Preprocessing

In the development of the traffic optimization system, I initially searched for an appropriate dataset but was unsuccessful. This challenge directed me to the insightful paper "Microscopic traffic simulation using sumo" [**25**], which provided a methodology for generating custom datasets using Python and SUMO. Employing this approach, I crafted several datasets tailored for analyzing the algorithm, encompassing vehicle emissions and waiting times across various traffic scenarios, all formatted in 'xml' [**25**]. I chose this method because utilizing historical data to establish initial conditions and validate simulation outcomes seemed to offer a straightforward and effective strategy.

These are the datasets generated using SUMO:

- `emmisionpeak.xml` - Emission of vehicles in peak traffic
- `emmisionoffpeak.xml` - Emission of vehicles in off-peak traffic
- `emmisionweekend.xml` - Emission of vehicles during weekend traffic
- `queuepeak.xml` - Waiting time for vehicles in peak traffic
- `queueoffpeak.xml` - Waiting time for vehicles in off-peak traffic
- `queueweekend.xml` - Waiting time for vehicles during weekend traffic

In the development of the traffic optimization system, my initial search for an appropriate dataset was unsuccessful. This challenge directed me to the influential paper, "Microscopic traffic simulation using SUMO" [**25**], which provided a comprehensive guide on generating custom datasets using Python and SUMO. Inspired by this approach, I generated several datasets tailored for algorithm analysis, including emissions and vehicle waiting times under various traffic conditions, formatted in 'xml' [**25**]. I opted for this method because using historical data to establish initial conditions and validate the simulation results simplifies the process. Moreover, this approach ensures that the simulation begins under realistic scenarios, enhancing the validity and applicability of the outcomes.

## 4.2 Evaluation and Performance

**Table 1:** Parameter and Values used in the experiment

| **Parameters** | **Value** |
|---|---|
| Sumo Version | 1.21.0 |
| Python Version | 3.10.0 |
| Simulation Steps | 500s |
| Road Network | Kamppi, Helsinki, Finland |
| Number of Intersections | 5 |
| Pheromone Evaporation Rate | 1.0 |
| Beta | 1.0 |
| Decay | 0.1 |
| `Q_INIT_VALUE` | 0.2 |

To assess the program's compatibility, a traffic simulation was conducted using the TraCI module from SUMO. The process initiates with the `run_simulation()` function, which starts SUMO's graphical user interface via `traci.start(['sumo-gui', '-c', 'simulation.cfg'])`, using `simulation.cfg` for essential simulation settings. The simulation operates within a while loop, continuing as long as there are vehicles on the network, monitored by `traci.simulation.getMinExpectedNumber() > 0`. Simulation steps are processed using `traci.simulationStep()`, and traffic light controls are dynamically adjusted every minute to test various traffic management strategies; specifically, traffic lights are reset to phase 0 every 60 seconds if divisible by 60. Upon completion, `traci.close()` terminates the simulation and clears resources, ensuring a smooth shutdown. This setup allows for evaluating different traffic light configurations and their impacts on urban traffic flow, showcasing the dynamic capabilities of the SUMO traffic simulator.

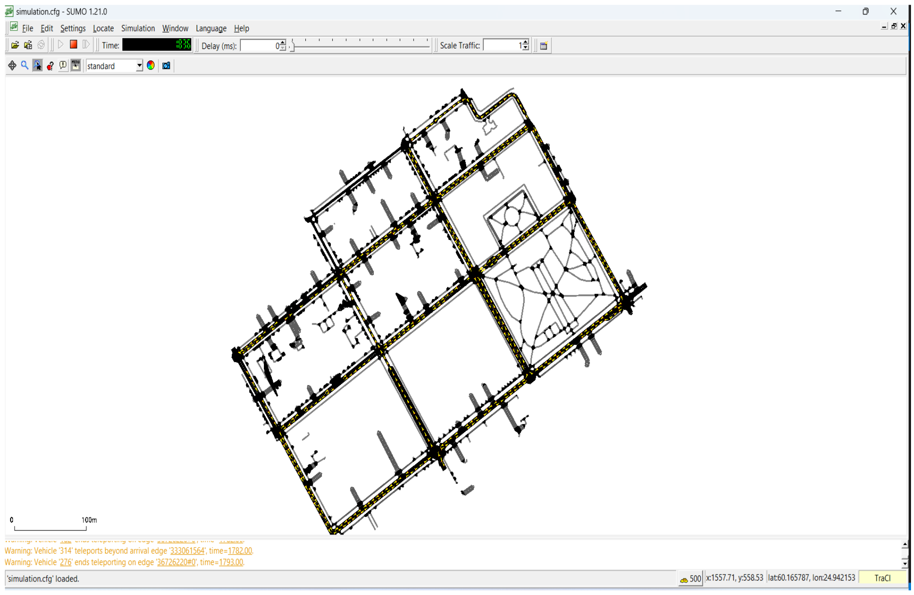


Figure 7: Simulation Time Step Analysis

Table 2: Outputs from the Simulation

| Metric | Value |
|---|---|
| Total number of stops | 24 |
| Average speed (m/s) | 3.361 |
| Average delay (s) | 52.194 |

To effectively monitor and manage the variability in traffic light phases due to route generation via Random.py, the TraCI module was employed to scrutinize changes at the intersection. Initial observations highlighted frequent and irregular phase changes, exemplified by a phase change to 1 at 0.083 seconds, with a similarly brief interval since the last change, raising concerns about the unexpected brevity of these intervals.

Further analysis revealed several critical adjustments made to enhance system consistency and efficiency:

Adjustments for Consistency: The system is configured to enforce minimum durations for main phases, setting a standard of no less than 30 seconds for phases that do not involve transitions. This adjustment is crucial for ensuring intersections clear safely, particularly during high-traffic periods.

Maintained Transitions: To keep traffic flowing smoothly, the script actively maintains short durations for transition phases, particularly those involving yellow lights. This approach effectively minimizes downtime and ensures quick transitions between traffic signals.

Comprehensive Control: The diversity in traffic light configurations, such as 'Gr', 'GGrrrG', and 'GGGrrr', demonstrates the system's capacity to handle complex traffic scenarios. This includes managing different traffic directions and accommodating pedestrian movements, which are essential for urban traffic networks.

These measures illustrate the system's refined approach to traffic light management, ensuring both safety and efficiency at busy intersections. Each element of the control strategy serves to enhance the overall functionality and responsiveness of the traffic management system.

To gain a comprehensive understanding of the traffic flow at our focal point, which is the junction identified by the ID "3228733111", we analyzed the detector data. The following observations were obtained:

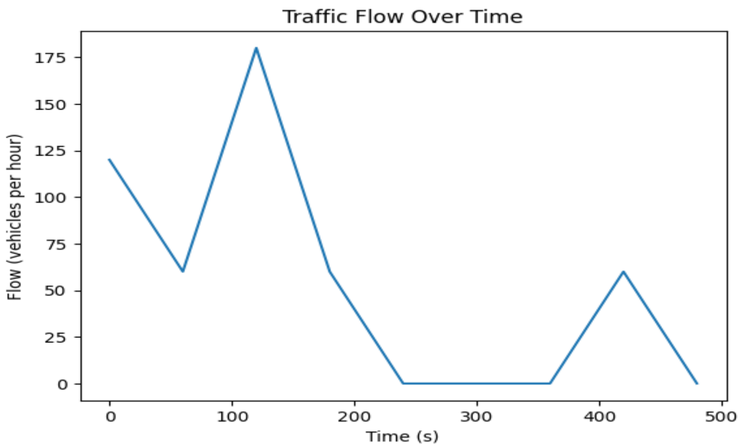


Figure 8: Time Flow over time from Detector 1

Figure 8 displays the variation in vehicle flow rates across a span of 500 seconds, measured in vehicles per hour. It starts with a relatively low traffic volume, which sharply peaks to just over 175 vehicles per hour around the 200-second mark, before dropping significantly. A secondary, smaller peak occurs after 300 seconds, followed by another decrease. This fluctuating pattern suggests intermittent changes in traffic conditions, potentially due to factors like traffic signal cycles or emerging congestion. This visualization is instrumental in identifying critical points of high and low traffic flow, providing valuable insights for traffic pattern analysis and the development of effective traffic management strategies.

Table 3: Summary Statistics for Detector Data 1

| Statistic | Flow | Speed (m/s) | Occupancy (%) |
|---|---|---|---|
| Count | 9.000000 | 9.000000 | 9.000000 |
| Mean | 53.333333 | 0.702222 | 62.986667 |
| Std Dev | 63.245553 | 2.510706 | 39.271967 |
| Min | 0.000000 | -1.000000 | 0.000000 |
| 25% | 0.000000 | -1.000000 | 46.300000 |
| 50% | 60.000000 | 0.020000 | 72.850000 |
| 75% | 60.000000 | 0.250000 | 100.000000 |
| Max | 180.000000 | 5.850000 | 100.000000 |

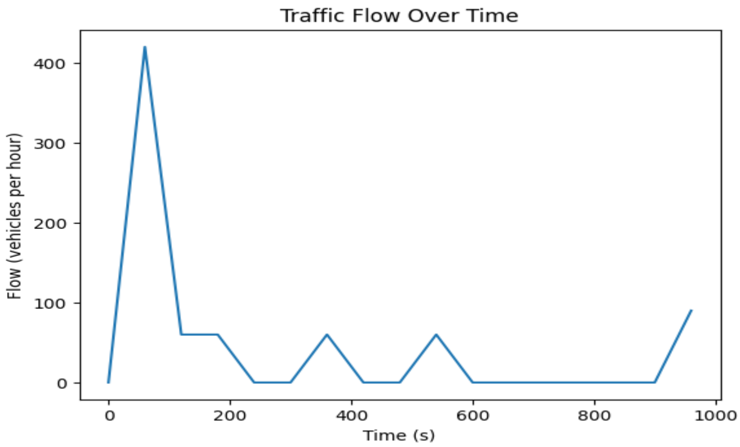


Figure 9: Time Flow over time from Detector 2

Figure 9 presents the changes in vehicle flow rates over a period of 1000 seconds, depicted in vehicles per hour. Initially, the graph shows a dramatic spike in traffic flow, reaching up to 400 vehicles per hour within the first 200 seconds, followed by a sharp decline. Subsequently, the traffic volume remains relatively low and stable with minor fluctuations until a gradual increase is observed again as the period approaches 1000 seconds. This pattern of traffic flow suggests sporadic bursts of high volume, potentially influenced by external factors such as traffic signal timings or nearby events, which intermittently affect the number of vehicles passing through. This visualization aids in understanding the distribution and timing of traffic peaks and lows, crucial for optimizing traffic management and planning interventions.

The summary statistics from both Detector Data sets show significant variability in traffic flow, speed, and occupancy, influenced by peak and off-peak traffic periods. Notably, the large standard deviations, particularly where traffic flow peaks at 480 vehicles per hour, indicate a need for dynamic signal control to manage these fluctuations effectively. The presence of negative speed values and a wide speed range suggests possible data collection errors or anomalies that warrant further investigation. These conditions suggest that traffic signals may be adapting to real-time data, which could be crucial for managing the observed variability and ensuring efficient traffic flow during periods of heavy use. This adaptive approach, potentially involving actuated signal control, could significantly enhance road safety and traffic efficiency, making it a valuable strategy for these locations.

Table 4: Summary Statistics for Detector Data 2

| Statistic | Flow | Speed (m/s) | Occupancy (%) |
|---|---|---|---|
| Count | 9.000000 | 9.000000 | 9.000000 |
| Mean | 73.333333 | 0.583333 | 10.787778 |
| Std Dev | 155.241747 | 2.554662 | 18.410417 |
| Min | 0.000000 | -1.000000 | 0.000000 |
| 25% | 0.000000 | -1.000000 | 0.000000 |
| 50% | 0.000000 | -1.000000 | 0.000000 |
| 75% | 60.000000 | 0.260000 | 11.840000 |
| Max | 480.000000 | 5.900000 | 50.480000 |

The insights gained from the simulation play a crucial role in identifying congestion bottlenecks and critical issues within the transportation network. These findings enable the strategic implementation of measures aimed at improving traffic flow and reducing congestion. The use of such simulations significantly aids in creating smoother, safer, and more sustainable urban traffic systems. This is particularly vital in urban centers that are facing increasing challenges related to vehicular activity and rapid urbanization.

Table 5: Traffic Control Results

| Metric | Value |
|---|---|
| Vehicle Throughput | 348 vehicles |
| Average Delay | 0.0058 seconds (approx) |
| Average Queue Length | 0.0 vehicles |
| Average Travel Time | 200.47 seconds (approx) |

Below are the key metrics used to evaluate traffic performance at intersections:

- **Vehicle Throughput**: The number of vehicles passing through an intersection in a given period.
- **Average Delay**: The average time that vehicles are delayed at the traffic lights.
- **Queue Length**: The average and maximum length of vehicle queues at the intersection during red phases.
- **Travel Time**: The average time it takes for a vehicle to travel through the intersection or across the network.

The analysis of traffic light phase durations and states at this intersection demonstrates a sophisticated approach to traffic management. The system adeptly handles complex traffic flows, as evidenced by a variety of signal patterns and transitions. Green phases vary substantially from 42 to 82 seconds, specifically tailored to manage fluctuating traffic volumes, with longer durations supporting heavier flows on main arterial routes. Transition phases are uniformly maintained at approximately 3 seconds for yellow and all-red signals, enhancing safety by providing sufficient time for vehicles and pedestrians to clear the intersection safely before the next traffic phase begins.

Moreover, the consistency and synchronization of these signals, especially the repeated 82-second green phases, indicate a structured strategy to optimize traffic flow and alleviate congestion. However, while the fixed timing schedules are effective, there is potential for further improvement through adaptive traffic control systems. Such systems could dynamically adjust signal timings based on real-time traffic data, thus improving throughput and reducing delays. Implementing these adaptive measures would not only boost the network's efficiency but also contribute to safer and more predictable driving conditions. This thorough approach to traffic signal management highlights the intersection's ability to effectively manage complex traffic situations, though it also points to opportunities for further refinement as traffic patterns evolve and technology advances.

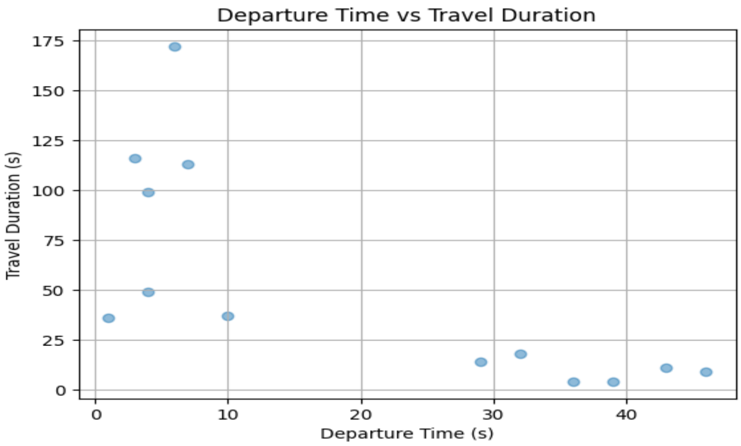


Figure 10: Scatter Plot for Peak Traffic

The scatterplot of Peak Traffic illustrates a clear relationship between when vehicles depart and how long their journeys take. Vehicles departing in the initial seconds show a wide range of travel times, indicating variable early conditions. As departure time extends, travel duration consistently decreases, suggesting conditions improve over time. The clustering of data points around specific times and noticeable gaps in longer durations as time advances suggest departures are staggered and delays lessen. This information is valuable for traffic management, indicating that optimizing departure times and adjusting traffic signals could greatly improve flow and reduce peak period congestion.

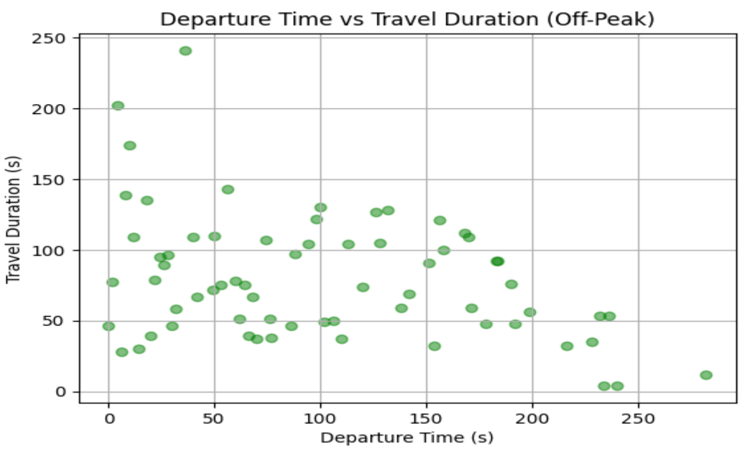


Figure 11: Scatterplot for Off Peak Traffic

The scatterplot for Off Peak Traffic presents a diverse range of travel durations early on, with some journeys taking up to 250 seconds. As departure time progresses, the plot shows a descending trend, indicating shorter travel durations as the period extends beyond 100 seconds. This pattern suggests that conditions likely improve, leading to faster travel times as the off-peak period progresses. Notably, there's a concentration of shorter travel durations around the 150-second mark, followed by an increase and another gradual decrease. This distribution indicates that travel times are generally less variable and more predictable during off-peak hours, which could influence transportation planning strategies aimed at smoothing traffic flow and reducing overall travel times.

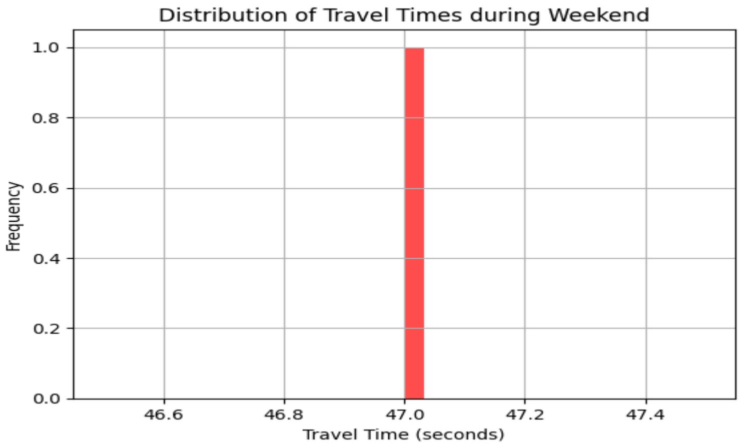


Figure 12: Histogram for Weekend

The histogram for Weekend illustrates a remarkably consistent travel time pattern, with the vast majority of trips clustered tightly around 47 seconds. This uniformity suggests that weekend traffic conditions are stable and predictable, likely due to reduced commuter flows and lighter overall traffic. The lack of variability indicates minimal congestion, enabling nearly uniform travel times across the observed interval. This consistency is particularly useful for traffic management, highlighting that during weekends, travel times can be reliably forecasted, which may reduce the necessity for adaptive traffic control measures typically employed during busier weekday periods.

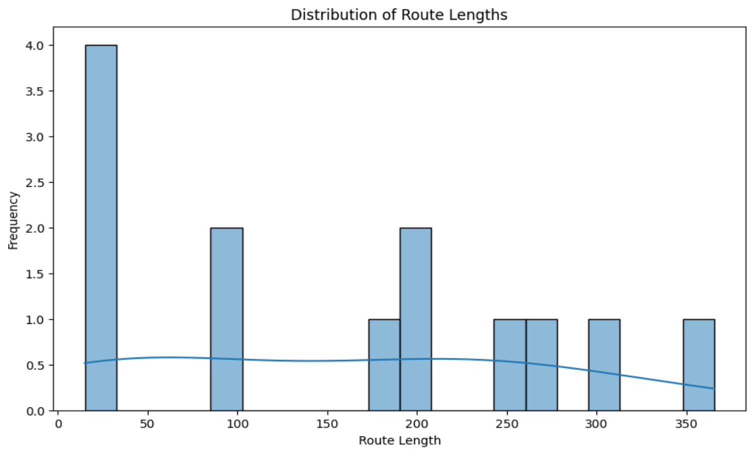


Figure 13: Distribution of Route Length

Figure 13 shows a right-skewed distribution, indicating that shorter routes are more common than longer ones, with the most frequent route lengths concentrated at the lower end of the scale. There are noticeable gaps in the distribution around route lengths of 100 and 200, suggesting these specific lengths are less commonly used. The trend line on the graph further supports the prevalence of shorter routes, as it shows a general decrease in frequency as route length increases, highlighting the rarity of longer routes.

Below is the cost matrix derived from trip data, representing the transition costs between trips:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | $\infty$ | 39 | 42 | 42 | 46 | 49 | 52 | 53 | 54 | 102 | 118 | 119 | 177 |
| 1 | 71 | $\infty$ | 7 | 21 | 63 | 22 | 81 | 18 | 19 | 131 | 149 | 142 | 202 |
| 2 | 74 | 7 | $\infty$ | 24 | 66 | 25 | 84 | 15 | 16 | 134 | 152 | 145 | 205 |
| 3 | 64 | 11 | 14 | $\infty$ | 56 | 21 | 74 | 25 | 26 | 124 | 142 | 135 | 195 |
| 4 | 45 | 30 | 33 | 33 | $\infty$ | 40 | 55 | 44 | 45 | 105 | 123 | 116 | 176 |
| 5 | 67 | 8 | 11 | 17 | 59 | $\infty$ | 77 | 22 | 23 | 127 | 145 | 138 | 198 |
| 6 | 39 | 36 | 39 | 39 | 43 | 46 | $\infty$ | 50 | 51 | 99 | 117 | 116 | 174 |
| 7 | 78 | 11 | 8 | 28 | 70 | 29 | 88 | $\infty$ | 12 | 138 | 156 | 149 | 209 |
| 8 | 81 | 14 | 11 | 31 | 73 | 32 | 91 | 14 | $\infty$ | 141 | 159 | 152 | 212 |
| 9 | 39 | 36 | 39 | 39 | 43 | 46 | 49 | 50 | 51 | $\infty$ | 117 | 116 | 174 |
| 10 | 38 | 37 | 40 | 40 | 44 | 47 | 50 | 51 | 52 | 100 | $\infty$ | 117 | 175 |
| 11 | 42 | 33 | 36 | 36 | 40 | 43 | 52 | 47 | 48 | 102 | 120 | $\infty$ | 173 |
| 12 | 41 | 34 | 37 | 37 | 41 | 44 | 51 | 48 | 49 | 101 | 119 | 114 | $\infty$ |

The cost matrix presented above was generated from data parsed from the tripinfo.xml file, which contains detailed trip information including departure times, durations, waiting times, time losses, and route lengths. Each entry in the matrix represents the cost associated with transitioning from one trip to another, calculated as the sum of the duration of one trip and the waiting time of the next. The diagonal entries of the matrix, marked as "inf", indicate the prohibitive cost of a trip transitioning to itself, effectively disallowing such movements. This matrix is crucial for understanding the travel dynamics and will be used to optimize routing strategies through methods such as the Ant Colony Optimization algorithm, enhancing the efficiency of traffic management systems.

# Cost Matrix

Below is the cost matrix derived from trip data, representing the transition costs between trips:

| | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | $\infty$ | 39 | 42 | 42 | 46 | 49 | 52 | 53 | 54 | 102 | 118 | 119 | 177 |
| 1 | 71 | $\infty$ | 7 | 21 | 63 | 22 | 81 | 18 | 19 | 131 | 149 | 142 | 202 |
| 2 | 74 | 7 | $\infty$ | 24 | 66 | 25 | 84 | 15 | 16 | 134 | 152 | 145 | 205 |
| 3 | 64 | 11 | 14 | $\infty$ | 56 | 21 | 74 | 25 | 26 | 124 | 142 | 135 | 195 |
| 4 | 45 | 30 | 33 | 33 | $\infty$ | 40 | 55 | 44 | 45 | 105 | 123 | 116 | 176 |
| 5 | 67 | 8 | 11 | 17 | 59 | $\infty$ | 77 | 22 | 23 | 127 | 145 | 138 | 198 |
| 6 | 39 | 36 | 39 | 39 | 43 | 46 | $\infty$ | 50 | 51 | 99 | 117 | 116 | 174 |
| 7 | 78 | 11 | 8 | 28 | 70 | 29 | 88 | $\infty$ | 12 | 138 | 156 | 149 | 209 |
| 8 | 81 | 14 | 11 | 31 | 73 | 32 | 91 | 14 | $\infty$ | 141 | 159 | 152 | 212 |
| 9 | 39 | 36 | 39 | 39 | 43 | 46 | 49 | 50 | 51 | $\infty$ | 117 | 116 | 174 |
| 10 | 38 | 37 | 40 | 40 | 44 | 47 | 50 | 51 | 52 | 100 | $\infty$ | 117 | 175 |
| 11 | 42 | 33 | 36 | 36 | 40 | 43 | 52 | 47 | 48 | 102 | 120 | $\infty$ | 173 |
| 12 | 41 | 34 | 37 | 37 | 41 | 44 | 51 | 48 | 49 | 101 | 119 | 114 | $\infty$ |

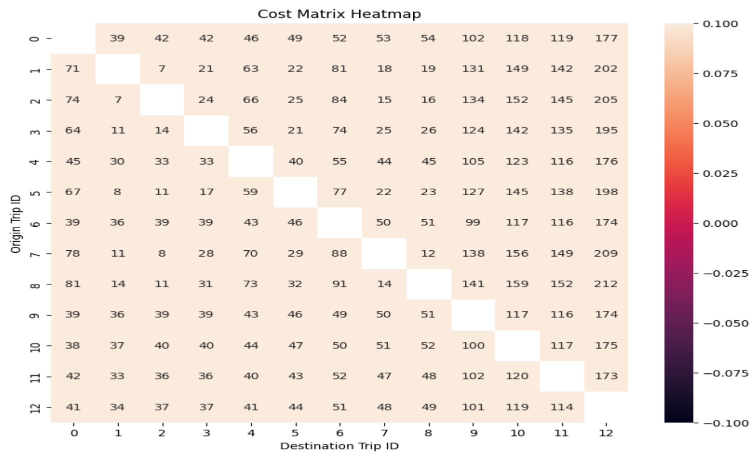


Figure 14: Histogram for Peak Traffic

Observing Fig 14, it's evident that the costs vary significantly across different origin and destination pairs, with lighter shades indicating lower transition costs and darker shades representing higher costs. Notably, diagonal cells, which represent transitions from a trip to itself, are missing or marked to denote prohibited or undefined transitions. The variation in cost across the matrix highlights routes that are potentially more efficient or costly, enabling targeted optimizations for routing strategies. This visualization effectively underscores the disparities in travel costs across various routes, which is essential for optimizing traffic flow and managing transportation logistics efficiently.

The implementation of the Ant Colony Optimization (ACO) algorithm on the dataset resulted in the identification of an optimal path with respect to the defined cost function. The best path found and the corresponding total travel cost are detailed below.

## Best Path Discovered my ACO for Peak Traffic

The best path discovered through the ACO is represented by a sequence of transitions between nodes (or trips). The sequence of moves and the final cost of this path are as follows:

Path: $(0 \to 2 \to 1 \to 2 \to 1 \to 2 \to 1 \to 2 \to 1 \to 2 \to 1 \to 2 \to 1 \to 0)$

### Total Cost

The total cost associated with the best path is given by:

Total Cost: 190.0

The best path found, which intricately loops between nodes 0, 1, and 2, reveals a cyclic pattern, highlighting a potentially repetitive yet cost-effective route within the network. With a remarkably low total cost of 190.0, this result underscores the algorithm's capability to uncover optimal paths that may not be immediately apparent through traditional analysis.

## ACO Optimization Results for Off-Peak Data

| Step | Transition |
|---|---|
| 1 | 0 to 20 |
| 2 | 20 to 48 |
| 3 | 48 to 64 |
| 4 | 64 to 19 |
| 5 | 19 to 5 |
| ..... | |
| ..... | |
| 61 | 31 to 52 |
| 62 | 52 to 26 |
| 63 | 26 to 33 |
| 64 | 33 to 60 |
| 65 | 60 to 32 |
| 66 | 32 to 24 |
| 67 | 24 to 0 |

For the peak dataset, the best path found forms a short, repetitive loop involving just three nodes (0, 1, 2) with a remarkably low total cost of 190.0. This indicates a tightly constrained routing scenario possibly due to heavy traffic conditions or limited route options during peak times, leading to frequent transitions between a small set of nodes.

In contrast, the off-peak dataset results in a much more complex and extended path that encompasses a significantly broader network of 67 transitions across diverse nodes, culminating in a higher total cost of 6337.0. The expanded route diversity and increased path length suggest more available options and potentially less congestion, allowing for more extensive navigation through the network.

The table below shows the progression of pheromone levels at each intersection over five epochs, demonstrating the dynamic adjustments made by the Ant Colony Optimization algorithm:

Table 6: Pheromone Levels Across Epochs after Passing Peak Traffic Info Through the Proposed Algorithm

| Intersection | Epoch 1 | Epoch 2 | Epoch 3 | Epoch 4 | Epoch 5 |
|---|---|---|---|---|---|
| 0 | [6.14, 4.90, 6.42] | [8.43, 6.98, 8.61] | [9.58, 8.45, 10.35] | [10.78, 9.69, 11.10] | [11.11, 10.60, 12.23] |
| 1 | [6.28, 5.55, 5.23] | [8.41, 7.62, 7.43] | [9.47, 9.30, 8.97] | [10.35, 10.92, 9.51] | [11.03, 12.01, 10.02] |
| 2 | [5.70, 5.70, 5.55] | [7.83, 8.17, 7.26] | [9.25, 9.19, 9.05] | [10.27, 9.50, 10.75] | [10.88, 10.46, 11.49] |
| 3 | [4.36, 5.39, 6.55] | [6.39, 6.91, 9.10] | [6.99, 7.85, 11.36] | [7.68, 9.26, 12.27] | [8.42, 9.64, 13.33] |
| 4 | [6.14, 4.73, 5.39] | [7.54, 6.21, 8.53] | [10.09, 7.22, 8.97] | [11.16, 7.74, 10.25] | [11.96, 8.14, 11.19] |

From Table 6, particularly focusing on the progression of pheromone levels across five epochs, reveals significant insights into the algorithm's performance and adaptation strategies. At the outset in epoch 1, the pheromone distribution starts relatively balanced but shows variations, for instance, Intersection 0 displays values like [6.14, 4.90, 6.42], suggesting an initial disparity in pheromone concentration across different paths.

As the epochs progress, a clear trend of increasing pheromone levels can be observed, indicative of the algorithm reinforcing paths that are deemed more effective or probable. By epoch 2, every intersection shows increased pheromone values, with Intersection 0 notably jumping to [8.43, 6.98, 8.61]. This trend continues robustly into epochs 3, 4, and 5, where Intersection 0 reaches a peak of [11.11, 10.60, 12.23] by the final epoch.

This increasing trend suggests that the ACO is effectively learning and adapting, concentrating pheromones on paths that yield better results, hence likely improving the routing decisions over time. The significant increase at Intersection 3 by epoch 5, reaching levels as high as [13.33], highlights paths at this intersection becoming increasingly preferred, possibly due to their strategic importance or lower associated costs in the modeled network environment.

These observations underscore the ACO's dynamic capability to optimize based on real-time feedback and adjustments, a critical feature for adaptive systems such as dynamic routing and traffic management where conditions can change rapidly. This data not only supports the efficacy of ACO in finding optimized paths but also provides a detailed view of how algorithmic adjustments are implemented over successive iterations, a valuable insight for both theoretical exploration and practical application in complex networks.

# 5 Conclusion

This project delves into the innovative application of heuristic techniques, specifically focusing on enhancing traffic signals through the development of a Q-Learning Ant Colony Optimization algorithm. Recently, advanced Ant Colony Optimization (ACO) algorithms for continuous-domain optimization have gained popularity. However, they frequently face challenges in adapting to environmental changes, primarily relying on pheromone trails to direct their evolutionary process.

This issue was evident throughout the project. All the analyses required substantial computational resources, and despite efforts to process the fuel emission data, computational complexities led to errors, making it unclear whether the issues stemmed from the code or the computational limits of the system used. By leveraging the diversity within the ant colony, the Q-Learning Ant Colony Optimization algorithm enhances the selection of optimal strategies across different evolutionary phases, thereby maximizing rewards and bolstering its capacity for global searching and rapid convergence.

The results indicate that the Q-Learning Algorithm, although traditionally employed for scheduling tasks, surpasses conventional ACO methods in performance. Attempts to illustrate this through a convergence graph were unsuccessful, as the graph displayed a flat line, suggesting no variation over time. Nonetheless, this research not only highlights the efficacy of the Q-Learning technique in tackling complex constraint optimization challenges but also lays a robust groundwork for future scholarly inquiry. There are promising prospects for further refining this method, commonly used for scheduling, to improve its efficiency and robustness across a wider array of challenges. These heuristic techniques are applicable not only in sectors like logistics, finance, and engineering but also in traffic management, where effective constraint optimization is crucial.

# Code accessibility

For comprehensive access to the complete codebase, including all analyses, please refer to the GitHub repository. Additionally, I have included my final report in the same repository for archival purposes.

`https://github.com/jerrinjxavier/Research_Project_B`

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