A Fully Decentralised Method for Traffic Optimisation using Reverse Pheromone Signalling

Alleviating Network Congestion through Peer-to-Peer Interactions

By

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Abstract

Urban traffic congestion poses significant challenges to transportation efficiency and sustainability. While centralised intelligent transportation systems and decentralised intelligent transportation systems connected to internet infrastructure have been proposed, they face limitations in scalability, resilience, and privacy. This dissertation presents a novel decentralised traffic routing approach using principles of swarm intelligence to enable cooperative congestion avoidance between connected vehicles. Combine with the 'inverted pheromone' model which is introduced wherein vehicles mark congested routes to steer others towards alternate pathways, we proposed a fully distributed 'reverse pheromone' mechanism is proposed to eliminate reliance on infrastructure, localising peer-to-peer communication and coordination between equipped vehicles. The model is evaluated through Monte Carlo simulations on a Manhattan-style grid network. By adjusting junction rules and pheromone parameters, the impact on network congestion is analysed using the travel delay time, gridlock frequency and the time spent from the start of the network to gridlock metrics. Results demonstrate substantially reduced congestion and travel delays by controlling the rule while vehicles are passing the junction and integrating pheromone technology into at least 5% of vehicles versus none Moreover, limiting communication distance further improves coordination. This research advances decentralised swarm intelligence techniques and provides a robust framework for self-organised traffic systems. While simplified assumptions warrant further testing, the model shows promise for gradual integration in real-world settings to significantly improve network fluidity.

Dedication and acknowledgements

I would like to express my deepest gratitude to my supervisor, Professor Seth Bullock, for his continuous support, guidance, and mentorship throughout the course of this research. His expertise and insightful feedback have been invaluable in shaping this dissertation. Without his guidance, this work would not have reached its current form.

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Last but not least, I thank everyone including my family who has directly or indirectly contributed to this dissertation. Your support has been integral to the realisation of this work.

Author's declaration

I declare that the work in this dissertation was carried out in accordance with the requirements of the University's Regulations and Code of Practice for Research Degree Programmes and that it has not been submitted for any other academic award. Except where indicated by specific reference in the text, the work is the candidate's own work. Work done in collaboration with, or with the assistance of, others, is indicated as such. Any views expressed in the dissertation are those of the author.

SIGNED: .... DATE: 01.09.2023

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Chapter 1

Introduction

The rapid growth of the human population in the modern world has amplified the demand for transportation, especially in urban areas, resulting in an increase in the flow of traffic and traffic congestion. Such congestion not only serves as an inconvenience for the masses, but more concerning implications that many cars caught in traffic jams stay in running mode for extended periods, resulting in augmented exhaust emissions. These emissions, comprising several greenhouse gases, have been identified as significant contributors to global air pollution, which has detrimental health impacts on humans due to the intensification of global warming [1].

1.1 Motivation

In this context, the emergence of Intelligent Transportation Systems (ITSs), including autonomous driving, is considered an appropriate choice to provide a reliable transport network [2]. Autonomous driving technologies offer a beacon of hope for tackling the problem of traffic congestion, which are important concepts for human beings to achieve sustainable development. At present, most autonomous driving can achieve Level 3 (The driver must take over at any time if the vehicle system fails or can not handle) or Level 4 (the vehicle system can handle it without the driver) [3]. Much literature has proven that autonomous driving technology can alleviate traffic congestion to a certain extent and improve the overall traffic system in different ways [4][5]. Moreover, the electric vehicles used in autonomous driving can also be combined with renewable energy, which is in line with the current trend of environmental protection and green energy [6]. Therefore, it is important and necessary to assist in the improvement of the overall system of autonomous driving.

With the advent of cutting-edge technologies in the domain of intelligent transportation systems as well as autonomous driving, researchers have significantly advanced the development of traffic routing systems [7][8]. Despite these advances, challenges persist. A prevailing trend within the existing body of research is the reliance on centralised approaches for performing vehicular routing within complex traffic networks [9][10]. While these methods have demonstrated utility, inherent limitations in terms of scalability, potential single-point failure and privacy present substantial obstacles [9][10]. In an effort to circumvent these challenges, some studies propose the utilisation of the Ant Colony Optimisation (ACO) algorithm—one of the renowned algorithms of swarm intelligence—as a mechanism to foster decentralised and self-organised transportation systems [11][12]. Yet, even with this approach, issues persist. In the absence of sufficient inter-vehicle cooperation, a common problem emerges where multiple vehicles opt for identical travel paths, thereby precipitating rapid congestion. To address this specific concern, recent proposals have introduced an inventive pheromone model known as the 'inverted pheromone model' [13]. This model utilises an ACO-based traffic routing method and records the negative feedback from congested road segments into roadside units (RSUs) [13], which are fixed infrastructure components deployed along roadways as part of Intelligent Transportation Systems, and then exchanges information between vehicles and RSUs. It was also proven as a solution to the congestion problem.

The above approach achieves some level of decentralisation. However, despite the advantages, the design's reliance on RSUs again exposes the model to the previously mentioned drawbacks of centralised management: cost of infrastructure, scalability, single point of failure, and privacy issues.

1.2 Objective

Therefore, inspired by the advantages of decentralised traffic control methods, the inverted pheromone model and the limitations of previous research, in this dissertation, we proposed a completely decentralised cooperative traffic routing method with an improved inverted pheromone system for collaborating connected vehicles in traffic networks. The main contributions will be summarised as follows.

- We introduce an enhancement to the existing inverted pheromone model, termed the reverse pheromone model, which innovatively shares the reverse pheromones using peer-to-peer communication directly between each vehicle's routing mechanism. The RSU is omitted. By deploying this pheromone-based traffic routing method, the system aims to minimise travel time through the selective avoidance of congested routes, without the cost of building infrastructure.

- We proposed a new approach to pheromone information sharing to alleviate concerns about the complete decentralisation of the traffic control system, including congestion detection methods and data persistence.

- Our research delves into the dynamics of cooperative negotiation between vehicles at road junctions as a means to further augment traffic efficiency. Through a strategically orchestrated collaboration process, vehicles near the junctions are enabled to pass the junctions efficiently. This coordinated distribution effectively mitigates the propensity for traffic congestion within shared pathways, thus contributing to the overall optimisation of traffic flow within the networked environment.

In the following chapters, we delve into swarm intelligence and traffic control research which has informed and shaped my research. Subsequent to this, I lay out the detailed methodology employed in this study, ensuring a comprehensive understanding of the approach taken. The results chapter follows, where I juxtapose the traffic efficiency under various junction rules and the application of the reverse pheromone system. The discussion then elucidates the significance of both the methodology and the findings, diving deeper into the broader implications and insights derived. Wrapping up the dissertation, the conclusion chapter encapsulates the entirety of the research, highlighting key contributions and pinpointing any limitations. This chapter also provides a glimpse into potential future endeavours and underscores the practical implications of the work presented.

Chapter 2

Related Work

Exploring intelligent transportation systems and swarm intelligence techniques for traffic coordination is an active realm of research. Scholars strive to develop innovative solutions to solve transportation challenges as urbanisation expands. This chapter reviews seminal works that have informed the theoretical foundations and technological developments for this study's proposed model. We delved into key areas including ant colony optimisation, inverted pheromone model, digital twins, decentralised intelligent transportation systems, agent-based modelling, and Monte Carlo simulation of grid-based networks. By summarising the advances and limitations of prevailing techniques, we highlighted the motivation for the present work.

2.1 Ant Colony Optimisation

The origin of the algorithm in this dissertation for a pheromone-like system is inspired by ground-dwelling social insects, primarily ants and termites, utilising chemicals to mark their surroundings and convey crucial information to their peers, such as directions to food sources or the safest routes back to their nests [14]. An illustrative example is when an ant discovers a potential pathway to a valued destination like sugary food. The ant then marks the route with an alluring pheromone. Under optimal conditions, other ants react to this pheromone and amplify it, allowing the entire colony to discern the most efficient option from numerous alternatives, such as pinpointing the shortest route. This mechanism of positive feedback has been renowned for providing insights into high-performing algorithmic variants [15], generic algorithmic frameworks for the ant colony optimisation(ACO) algorithms and NP-complete problems, leading to the development of the ACO heuristics in operational research [16][17]. Commonly used formulas in ACO were listed in the following, based on [18][14]:

- Transition Probability:
  The probability p_{ij} of an ant moving from node i to node j is often expressed as:

  $$p_{ij} = \frac{\tau_{ij}^{\alpha} \cdot \eta_{ij}^{\beta}}{\sum_{k \in N_i} \tau_{ik}^{\alpha} \cdot \eta_{ik}^{\beta}} \tag{2.1}$$

  Where:

  - τ_{ij} is the pheromone level on the path from i and j.
  - η_{ij} is the desirability of the move, often represented by some heuristic information.
  - α and β are the parameters that respectively control the relative importance of the pheromone trail and the heuristic information.
  - N_i is the set of feasible next nodes from i

- Pheromone Update:
  After all ants have completed their movements, the pheromone level will be updated. The pheromone evaporation and deposition can be represented as:

  $$\tau_{ij} = (1 - \rho) \cdot \tau_{ij} + \Delta\tau_{ij} \tag{2.2}$$

  Where:

  - ρ is the decay rate, usually between 0 and 1.
  - $\Delta\tau_{ij}$ is the amount of pheromone deposited, often calculated as $frac1L$, where L is the length (or cost) of the path taken by the ant.

- Pheromone Deposition by Individual Ants:
  The amount of pheromone $\Delta\tau_{ij}$ diffused by a single ant k can be expressed as:

  $$\Delta\tau_{ij}^{k} = \frac{1}{L_k} \tag{2.3}$$

  Where L_k is the length (or cost) of the path taken by ant k

While ACO is a potential method for vehicle routing problems, some limitations persist. A key issue is that ACO algorithms often converge prematurely, getting trapped in "best in local" rather than finding global solutions [15]. Additionally, basic ACO algorithms perform poorly in dynamic environments where changes occur over time [19]. The algorithm should be adjusted to maintain the solution quality when network conditions frequently change [20]. Furthermore, ACO techniques can face challenges in scaling to large, complex vehicle routing instances with thousands of customers [21]. Excessive computational time may be required for convergence [22]. Therefore, hybridising with other methods is often necessary for adapting real-world routing complexities [23]. Although ACO is a useful swarm intelligence approach, these limitations for vehicle routing problems must be addressed through algorithmic enhancements and careful parameter tuning.

2.2 Inverted Pheromone-Based Model

In addition, the current ACO routing methodology often suggests the same optimal course for multiple vehicles, leading to congestion and diminished overall traffic performance. There is a related proposal suggesting an "inverted pheromone-based" system, wherein the pheromone acts as a repellent rather than an attractant, to potentially alleviate traffic congestion [13]. Basically, if an (artificial) ant's route towards its objective is obstructed, say by overcrowding and resulting queues, it emits a 'frustration' signal that deters others, motivating them to seek alternate routes. Such a method has proven effective in simulations [13].

2.3 Digital Twin

Nonetheless, a practical challenge persists: Vehicles cannot literally mark roads or detect upcoming conditions. Therefore, it is generally theorised that these dynamics occur within a virtual representation of the real world, known as a Digital Twin (DT) [24][25]. Here, avatars representing vehicles can place and perceive a 'virtual' pheromone. While Digital Twins offer a kind of practical centralised model of operation, there are key concerns associated with its implementation. Firstly, it requires hosting and operation, potentially leading to significant infrastructure and operational costs. To ensure its functionality, all vehicles must be consistently connected to the central Digital Twin, enabling real-time reading and writing of virtual pheromone information. This centralised system also presents a vulnerability as a single point of failure, susceptible to both technical faults and cyberattacks [26][27]. We thus began to look for methods to decentralise transportation systems.

2.4 Decentralised Intelligent Transportation Systems

Compared to the traditional Intelligent Transportation Systems (ITS) where a central server or hub gathers local data and makes decisions for a wide area [28] that might be plagued by problems of scalability, latency, and single points of failure, Decentralised Intelligent Transportation Systems (DITS) is quite a different approach to managing and controlling transportation infrastructures. DITS distribute decision-making responsibilities across multiple nodes within the system (like vehicles in a city) to achieve coordinated outcomes [29].

As depicted in Figure 2.1 (referenced from [13], the advantages of Vehicle-to-Everything (V2X) communications, including vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I), become evident when connected vehicles promptly communicate real-time traffic information to either other vehicles or Roadside Units (RSUs) [13]. Combined with the 'Inverted Pheromone-based' model, vehicles can interact with each other by utilising the digital pheromones stored by RSU [30][31][12][13]. Then when appropriate algorithms for connected vehicles are added, the enhancement of the utility of transportation and the reduction of traffic congestion become significant. Although the DITS returns the decision-making power of the vehicle to the decision-making itself, much information such as the pheromone concentration still needs to be integrated through the Internet. The above-mentioned concerns of the centralised system still cannot be properly resolved.

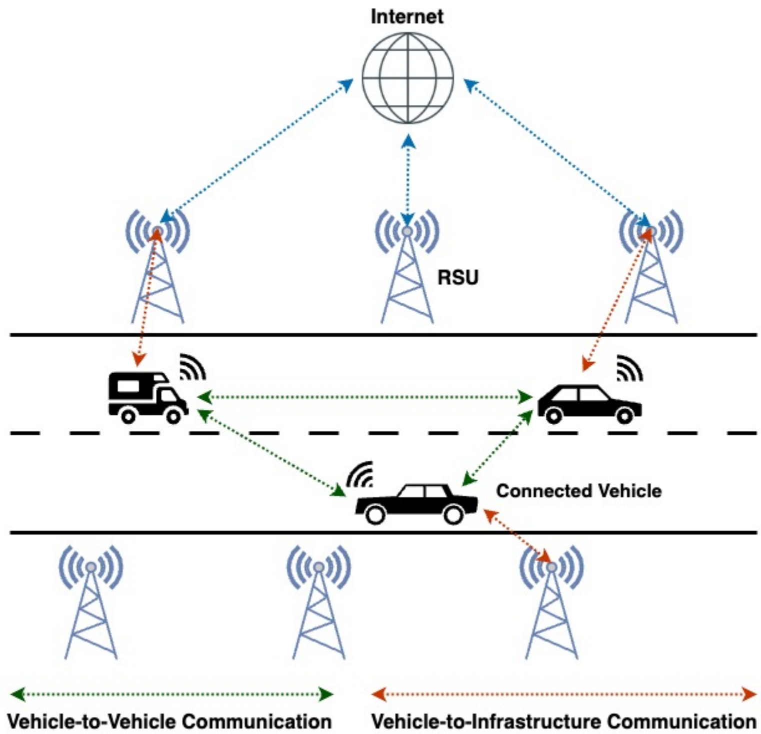


Figure 2.1: Decentralised Intelligent Transportation Systems

Therefore, as illustrated in Figure 2.2, we abstained from connecting to the Internet and modified the information required for vehicular decision-making. Originally, the method involved depositing pheromone concentrations at fixed roadside locations; we have adapted this to a system where pheromone levels are carried by individual vehicles, thus achieving a completely distributed traffic system. This decentralised approach also aligns more with the swarm intelligence paradigm and carries numerous benefits, including robustness against various disruptions, being more resource-efficient, eliminating the need for dedicated infrastructure, reducing the strain on communication networks and making the system boast scalability.

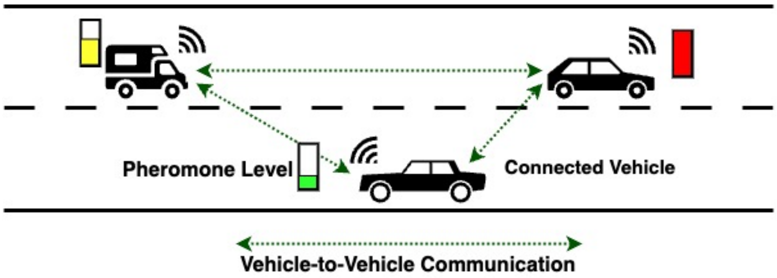


Figure 2.2: Pheromone-based V2V communication

2.5 Agent-Based Model

Agent-based modelling (ABM) is an important simulation approach that could have applications in evaluating decentralised intelligent transportation systems. In ABMs, individual entities called agents interact and make decisions based on defined rules, generating complex emergent system behaviours. As Lu et al. discuss, 'agent-based modelling has been applied in transportation systems for applications like evaluating traffic flow, assessing transportation infrastructure designs, and testing vehicle coordination algorithms' [29]. The ability to model each vehicle as an independent agent aligning with the decentralised paradigm makes this a useful technique. Agent-based modelling can capture phenomena like congestion arising from the interactions of autonomous decision-making vehicles in a way that is difficult to reproduce with traditional analytical methods. My research could benefit from applying ABM to simulate decentralised vehicle routing decisions and interactions, providing a more robust test environment before real-world implementation.

While ABM shows promise for evaluating decentralised traffic systems, it has some inherent limitations that warrant consideration. Firstly, developing realistic behavioural models for individual vehicles as agents can be challenging, with simplifying assumptions potentially reducing accuracy [32]. Factors like driver imperfections, non-compliance to rules, and heterogeneous capabilities across a vehicle fleet are difficult to capture [33]. Secondly, ABMs face computational constraints in scaling to model massive transportation networks with hundreds of thousands of agents. Significant computing resources are required to simulate large systems [34]. Thirdly, accurately modelling complex real-world environments like intricate road networks and diverse landscapes brings difficulties [35]. Finally, ABMs can be non-deterministic, producing variable outcomes across simulations even with unchanged parameters [36]. These limitations of ABM must be addressed through rigorous calibration and sensitivity analysis to produce reliable insights.

2.6 Monte Carlo Simulation of a "Manhattan-style" Road Networks

Monte Carlo simulation has proven a valuable technique for modelling and analysing traffic patterns on grid-based road networks reminiscent of New York City's archetypal Manhattan layout, which is a street layout characterised by perpendicular intersecting horizontal and vertical roads [37] and also utilised in various cities worldwide. Pioneering work by Newell applied Monte Carlo simulation to study traffic congestion propagation through a probabilistic queueing model of Manhattan's traffic [38]. Since then, Monte Carlo methods have been extensively utilised to simulate vehicular movement and interactions within Manhattan-style grid networks [39][40]. Its key advantages are the ability to easily generate stochastic urban mobility models and the computational efficiency for modelling large grids [41]. Researchers have leveraged the Monte Carlo simulation of Manhattan-like networks to evaluate traffic flow under various demand patterns [37], assess self-driving vehicle coordination algorithms [42], and test urban planning interventions [43]. The simplicity, efficiency and flexibility of modelling urban road topologies as Manhattan grids make Monte Carlo simulation a mature and widespread approach for initial theoretical testing of solutions prior to real-world implementation [37][42]. However, care must be taken to validate results on more complex networks due to its shortcomings.

Although Monte Carlo simulation on Manhattan-style grids offers a useful initial modelling approach, the method has some inherent limitations. Firstly, real urban road networks involve much greater complexity than the abstraction of a perfect grid [35]. Factors like variable lane numbers, irregular junctions and rules are difficult to capture [44]. Secondly, basic Manhattan networks lack realism in driver behaviours, vehicle performance, and control systems [45]. As we had mentioned, both simulated network and agent-based modelling require more sophisticated algorithms for accuracy [33]. Thirdly, the randomness involved means results can suffer from high variance and convergence issues [46]. Extensive repetitions may be needed to achieve statistically robust outputs [47]. Fourthly, basic Manhattan models overlook critical real-world aspects like varied demands, accidents, vehicle breakdowns, and infrastructure failures [48]. Whilst a simplified starting point, these limitations mean Monte Carlo Manhattan models should be cautiously applied. Thorough validation of real traffic data is crucial before relying on the techniques. Overall, Monte Carlo simulation on idealised Manhattan grids provides a foundational methodology to rapidly prototype and refine solutions at scale before deployment in intricate real-world environments, which is the reason why this study used it, but care is essential in transitioning solutions to a real-world environment.

Chapter 3

Methodology

3.1 Overview

3.1.1 Main Idea

The methodology devised in this study is motivated by the benefits of the decentralised traffic control systems, with a particular focus on the innovative utilisation of an 'inverted pheromone model'. This approach aims to overcome the intrinsic limitations associated with traditional centralised operation systems.

We introduce a novel, fully decentralised cooperative traffic routing method that employs an enhanced inverted pheromone system, henceforth termed the 'reverse pheromone system'. This system is designed to coordinate connected vehicles around and within the junctions in traffic networks, anchored in the principles of swarm intelligence [49]. The method is predicated on the concept of inverted pheromones, amalgamated with the notion of decentralisation [49].

The model presupposes the integration of onboard computing devices in some proportion of the vehicles and refers to these vehicles as being 'equipped with pheromone technology' throughout the dissertation. Vehicles equipped with this technology engage in collaborative communication via local, peer-to-peer (P2P) interactions, thereby obviating the need for a centralised control hub. This approach accentuates distributed, autonomous control and adaptability.

We validated our methods through a Monte Carlo simulation of a 'Manhattan-style' road network, establishing rules for vehicle movement, junction decisions, and pheromone diffusion. Within specific time units, simulation performances were assessed by adjusting parameters and analysing the resulting effect on the congestion experienced by all vehicles on the road network.

3.1.2 Results and Evaluation

In the subsequent results and evaluation section, we will address the following inquiries:

1. Assessing the significant differences in travel delay caused by congestion when varying proportions of vehicles are equipped with pheromone technology.
2. Analysing the impact of rule modifications governing vehicle behaviour at junctions on congestion.
3. Comparing the outcomes between different peer-to-peer communication distance limits to ascertain the effect of communication distance on congestion.

3.2 Simulation Environment

3.2.1 Grid Network Design (Figure 3.1)

- **Layout**: A grid network patterned after a 'Manhattan-style' layout, comprising 6x6 blocks.
- **Block Dimensions**: Each block measures 15x15 cells, with interspaces serving as roads.
- **Road Width**: Roads are 2 cells wide, with one cell allocated for each direction.
- **Overall Dimensions**: The complete grid network spans a 100x100 cell matrix.

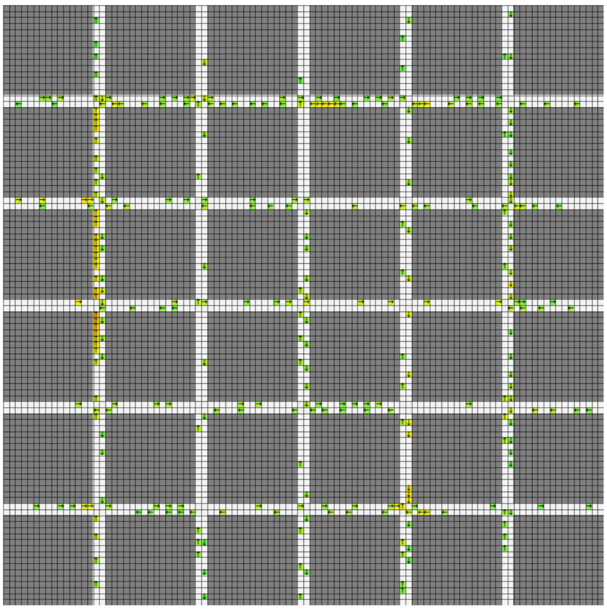


Figure 3.1: The grid network in overall dimension: 36 distinct blocks, 10 roadways (5 'streets' and 5 'avenues'), 25 junctions (each encompassing 4 cells) and 20 entrance/exit gates

3.2.2 Vehicle Information

In this simulation, each vehicle has its own memory, which mainly includes the following variables:

- **ID**: represented by a non-negative integer, created in the order of entry into the system.
- **Location**: The current cell that the vehicle is at, represented by coordinates combined by 2 non-negative integers(x and y).
- **Exit**: The destination cell for the vehicle, represented coordinates combined by 2 non-negative integers(x and y).
- **Direction**: the directions the vehicle will travel represented by 2 characters(N for North, S for South, E for East, W for West).
- **Delay**: The vehicle is delayed by a certain number of time units, represented by a non-negative integer. In other words, the actual total time taken by the vehicle to reach the exit equals the assumed fastest arrival time plus the delay, starting with 0.
- **Pheromone level(PL)**: The numerical "quantity" of pheromone that is 'carried' by the vehicle, represented by a non-negative float and starting with 0.
- **Delta**: The numerical "quantity" of pheromone that will be defused, represented by a negative float calculated by the pheromone level.

3.3 Algorithm

The algorithm can be separated into three phases in total, Figure 3.2 is the flowchart:

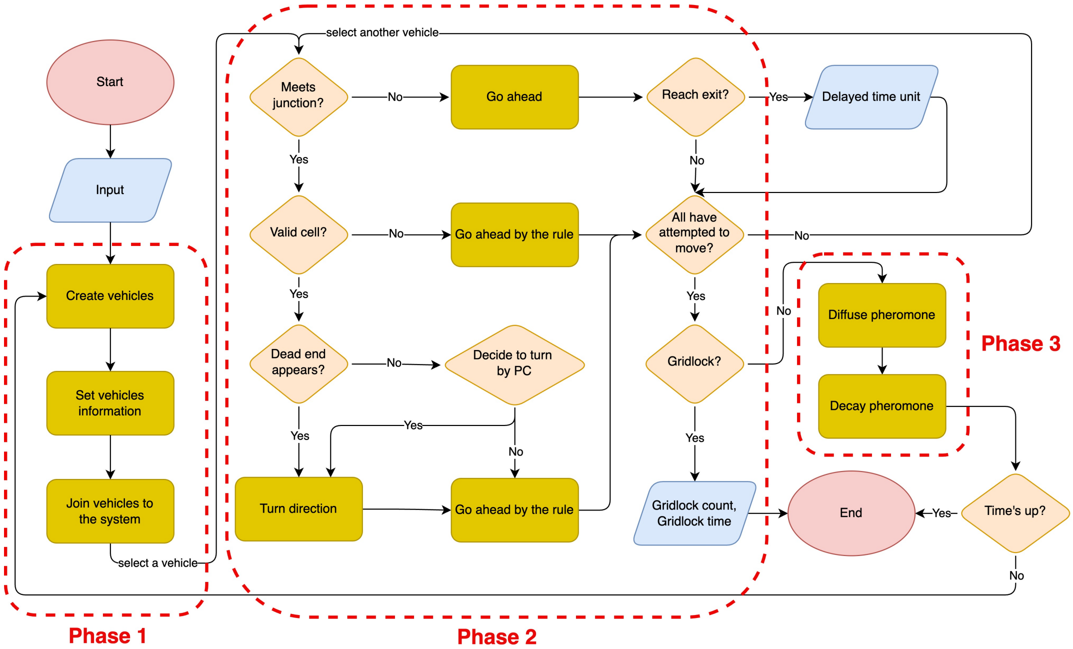


Figure 3.2: Algorithm Flowchart

3.3.1 Introducing New Terms

1. **Time Unit**: Given that the simulation remains in the theoretical stage, real-time units are not defined. Instead, the term 'time unit' is used to express temporal measurements. For instance, a delay may be described as 'This car is delayed by 18 time units'.

2. **Space Unit**: To streamline the experiment, space is represented discretely(cells), with vehicles occupying individual cells and transitioning from one cell to the next in their travel direction.

3.3.2 Phase 0: Input Parameters

Before the simulation, we initialised input variables, including how many times of simulation is, how long the time is, the speed of vehicles, the ratio of diffusion and the decay rate. Besides the parameters mentioned above being defined empirically, we also initiated the control variables. All variables will be defined in detail later.

3.3.3 Phase 1: Initialisation of Vehicles and Configuration of Information

1. **Adding Vehicles / Entrance Decision**

   - **Monte Carlo Simulation**: Vehicles are added using a Monte Carlo simulation, necessitating the determination of the probability of vehicles entering through each of the 20 designated 'entry gates'.
   - **Density-Based Probability**: The probability for each entrance is governed by *density* (The average number of cars entering the system per time unit.), representing the average number of vehicles entering the system per time unit. Consequently, in each time unit, a vehicle will be introduced at each entry gate based on this probability.

$$P_{density} = \frac{density}{exit\, gates}$$

2. **Route / Exit Decision**

   - **Exit Selection**: Although there are 20 entrances, vehicles target one of the 14 exits, ensuring that entrance and exit gates are never aligned on the same axis. This configuration mandates at least one 90° turn in every vehicle's journey.
   - **Path Constraints**: Only the shortest paths between entrance and exit gates are considered valid. The vehicles are restricted to travelling in up to 2 directions in a single journey. This constraint ensures that no detours are taken, and the travel direction can be determined based on the entrance and exit.

3. **Proportion of Using Pheromone Technology**

   - **Adjustable Proportion**: Recognising that not all vehicles are equipped with pheromone technology, the proportion of vehicles utilising this system can be adjusted. Observations are made regarding the impact of the number of vehicles with this technology on the overall performance.

3.3.4 Phase 2: Vehicle Movement

We structured this phase into distinct stages with various rules and plans to assess interactions with junctions, other vehicles, and the road's grid system. The vehicles are shuffled into a random order in each time unit, and this order will be used for the entire phase 2 in this time unit. That is, the order in which each vehicle attempts to move is randomised at each time unit.

For every vehicle and at every time unit, the final result of its movement can be categorised into one of two states: "move" or "stop". If the is "stop", increase both the amount of pheromone and delay time unit by 1.

Below is an elaborate description of each stage:

- **Stage 1: Checking for a Junction**
  This initial stage involves evaluating whether a vehicle is encountering a junction. 'Encounter a junction' means the vehicle is in the cell in front of a junction or in a junction. If the answer is True, then go to stage 2. Otherwise, try to move forward directly.

- **Stage 2: Vehicle Passage through the Junction**
  3 rules are established to govern the movement of a vehicle when it crosses the junction. Rule 1 serves as the default, with subsequent rules building on its principles, including a special adaptation for roundabout scenarios. The decision of which rule to follow has been initialised in phase 0.

  - **Rule 1: Strict Clearance Principle**
    When a vehicle is on a cell immediately before a junction or inside a junction, it can only move forward if the junction cells ahead of it and the exit cell beyond them are all clear.

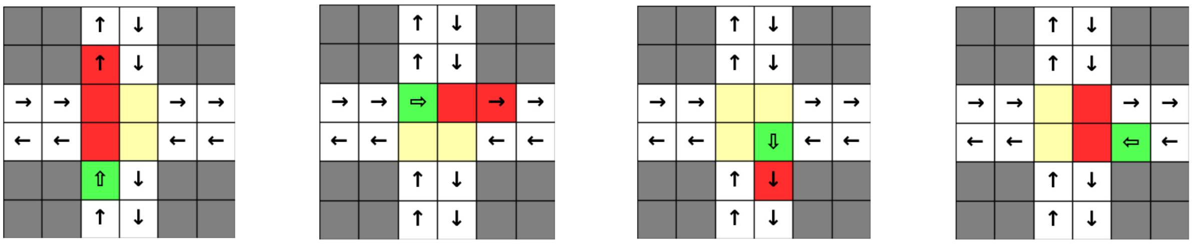
  - **Rule 2: Pre-Junction Clearance Principle**
    When a vehicle is on a cell immediately before a junction, it can only move forward if the junction cells ahead of it and the exit cell beyond them are all clear. When it is inside a junction it can move forward if the cell ahead is empty.

  - **Rule 3: Clockwise Precedence Principle**
    When a vehicle is on a cell immediately before a junction, it should check for vehicles coming from the right side. If there is no car coming from the right side, then try to go ahead. This rule is similar to the concept of a clockwise roundabout.

Figure 3.3a, 3.3b, 3.3c and 3.3d illustrate the junction rules. The arrows in the figure represent the direction of traffic flow and the vehicle's current direction, and the meanings of the colours are shown in Table 3.1:

Table 3.1: The meaning of the cell colour

Cell colour	Grey	White	Green	Yellow	Red
Meaning	Blocks	Roads	Vehicle location	Junction cell	Checked cell



(a) Rule 1 (b) Rule 1 (c) Rule 1 and 2 (d) Rule 3

Figure 3.3: Junction rule examples

- **Stage 3: Decision Making in Junctions**
  Congestion avoidance is a decentralised process. The rules of navigation within the junctions adhere to the shortest path rule:
  - **Valid Cell**: Vehicles must be in a valid junction cell for turning.
  - **Dead end**: If the journey's destination exit cell is on the same horizontal or vertical axis as the vehicle, there is only one valid option for the vehicle to prevent unnecessary detours, continue directly towards the journey destination exit cell.
  - **Pheromone Technology**: If the vehicle is in a valid junction cell and it is not on the same axis as the exit, then it has the option to proceed forward or make a turn. j and k are the directions in which the pheromone-level signals are received, and they were calculated in the previous time unit$(t-1)$, broadcasted by the nearest car in each direction. See Figure 3.4a
    The probability of deciding the direction(P_j and P_k) will be influenced by the pheromone-level signals($PL_{t-1,j}$ and $PL_{t-1,k}$), where w_j and w_k are the reciprocals of the strength of the pheromone-level signal. However, since the relationship between pheromone level and traffic flow is nonlinear, a nonlinear amplification parameter (α) is needed to measure the impact of flow on traffic.

$$w_j = \frac{1}{(1+PC_{t-1,j})^{\alpha}} \qquad w_k = \frac{1}{(1+PC_{t-1,k})^{\alpha}} \tag{3.1}$$

$$P_j = \frac{w_j}{(w_j+w_k)} \qquad P_k = 1 - P_j \tag{3.2}$$

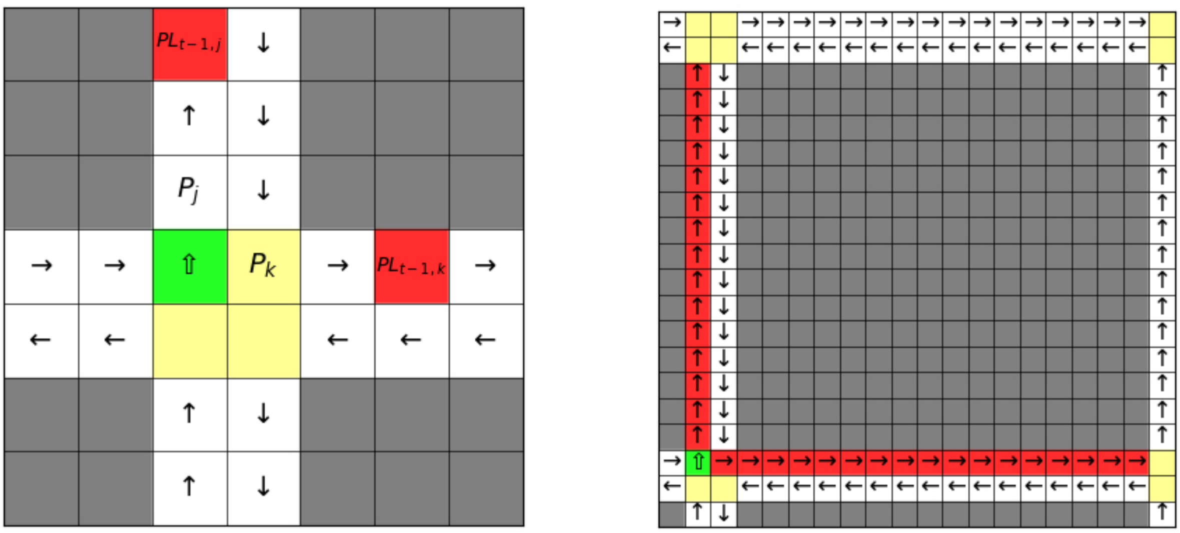
We established three plans for comparison. Without equipping vehicles with the pheromone technology (set α to 0) means that the P_j and P_k are both 0.5 and leading to the vehicle's choice is entirely random (Plan 1). When using the pheromone technology, we determined α to 10 empirically.

However, since our algorithm's purpose is to enable the vehicle to assess the current situation. Delays caused by long-distance communication between agents, as well as changes in road conditions at distant locations, can result in premature or delayed decisions that affect the simulation's performance.

Therefore, we separated the factor of using pheromone technology into two plans(Plan 2 and Plan 3). In Plan 2, the vehicle could detect the pheromone-level signals regardless of distance. In Plan 3, we limited the communication and perception distance for each vehicle. If the vehicle cannot receive a pheromone-level signal within the length of a block, we assume that the received signal is 0.

The three plans when making decisions are outlined as follows:

* **Plan 1**: Random direction decision-making, will be called 'without the pheromone technology' in the rest of this study.
* **Plan 2**: Unlimited communication distance in perceiving pheromone signals.
* **Plan 3**: Limited communication distance in perceiving pheromone signals. See Figure 3.4b



(a) The vehicle(green cell) receives the signals $PL_{t-1,j}$ and $PL_{t-1,k}$ from the other two vehicles(red cell) from two directions(j and k), and makes the decision (P_j and P_k).

(b) In Plan 3, the vehicle(green cell) receives the signals only before meeting the next junctions(red cells). If no vehicles within one block set the received pheromone level to 0.

Figure 3.4: Junction decision illustrations

- **Stage 4**: Data Collection
  - **Vehicles that reach the destination**
    When the vehicle arrives at the designated exit, we will record the time units that the vehicle is delayed and remove it from the grid.
  - **Gridlock**
    A gridlock means that at a certain point in time, all vehicles are stuck, and no vehicles can enter the system. When the system reaches a gridlock, stop the simulation and record the time unit on which gridlock was detected.

3.3.5 Phase 3: Pheromone Diffusion Mechanism

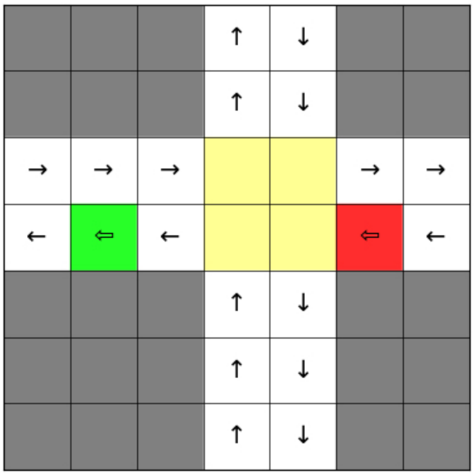
For the pheromone diffusion process, it is imperative to negate the potential for unwanted persistent memory effects and to rectify the challenges of information updates stemming from decentralised control. Consequently, we engineered a novel pheromone diffusion mechanism capable of decaying the pheromone at an adjustable rate. This design emphasises the primacy of the most recent information and facilitates pheromone sharing among vehicles, ensuring continuous communication.

Therefore, in this phase, if the vehicles release their reverse pheromone-level signals(δ) by a rate($diffusion$). This pheromone then diffuses through space and decays by a rate($decay$) over time. Contrary to diffusing between neighbouring spaces, the signal instead spreads its pheromone towards its closest 'upstream' neighbours. A modifiable amount of this pheromone is 'transferred' between nearby vehicles based on predefined simple rules. Specifically, the pheromone diffuses upstream from each vehicle's location in every direction of its movement. Importantly, to eliminate the possibility of unwanted persistent memory effects, the signal's strength decays at an adjustable rate. In this way, we eliminated the possibility of unwanted persistent memory effects and compensated for the problem of information updates caused by decentralised control.

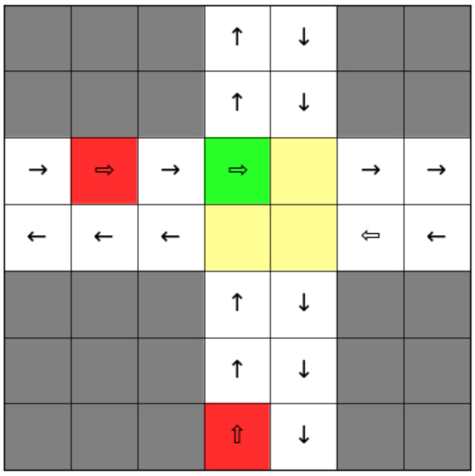
Before Phase 3 in each time unit, each vehicle will retain its individual pheromone level($PL_{t-1,i}$) from the previous time unit. Then $PL_{t-1,i}$ will diffuse a portion of this pheromone (δ) to its upstream neighbours. Notably, if a vehicle is situated within a junction cell, it will split δ and distribute it in 2 directions(Figure 3.5). Similarly, each vehicle will also acquire a certain amount of pheromone($PL_{t-1,j}$) from its downstream neighbour. After the processes of diffusion and reception, the pheromone quantity will decay by a certain ratio *decay* over time. Ultimately, the updated pheromone level($PL_{t,i}$) is established.

$$\delta = -(PC_{t-1,i} * diffusion) \tag{3.3}$$

$$PC_{t,i} = ((PC_{t-1,i} + \delta) + PC_{t-1,j}) * decay \tag{3.4}$$



(a) If the vehicle(green cell) is outside the junction, it diffuses its pheromone(δ) to the vehicle(red cell) only in one direction.



(b) If the vehicle(green cell) is inside the junction, it divides and diffuses its pheromone($\delta/2$) to the vehicles(red cells) in two directions.

Figure 3.5: Pheromone diffusion illustration

3.4 Inputs and Outputs

- **Input Parameters**

  In this study, we define the execution of the algorithm once as 1 time unit, and each simulation is performed for 20,000 time units. For each experiment, we uniformly set the number of simulations to 1,000 times. The vehicle speed is 1 cell per time unit, while the ratio of diffusion($diffusion$) and the decay rate($decay$) are 0.5 and 0.9, respectively.

  The parameters mentioned above are constant variables, which we defined empirically. The following parameters are the control variables, including 3 different junction rules, 3 different pheromone technology plans, 4 different proportions of vehicles equipped with pheromone technology (1, 0.5, 0.05, 0), and the 16 density values of adding vehicles to the system (range from 2.2 to 3.8, with increments of 0.1).

- **Outputs**

  The simulation will yield the following outputs:

  1. **Average delay time**: The average delay of the vehicles that successfully exit the system.
  2. **Gridlock frequency**: The frequency with which the system reaches a gridlock.
  3. **Gridlock time**: The average time taken for the system to reach a gridlock. If the system doesn't reach a gridlock within the limit time, the output will be the same as the limit time.

With the methodology clearly defined, we now turn to the results that these experimental procedures have yielded. As will be evident in the next chapter, the methods employed not only validate the research hypothesis but also offer valuable insights into the approach to alleviating network congestion.

Chapter 4

Results

This chapter presents the simulation results and discussions based on the methodology introduced in Chapter 3. The primary objective is to understand the implications of various factors on network congestion. The data obtained from the simulations is systematically organised and subjected to both comparative and statistical analyses. The study aims to address the following research questions:

1. Does the alteration of junction rules significantly influence network congestion?
2. Can vehicles equipped with pheromone technology substantially alleviate network congestion?
3. Does limiting the peer-to-peer communication distance result in a more pronounced improvement in network congestion than when no such limitations are imposed?
4. Is the improvement in network congestion sustainable when the percentage of vehicles with pheromone technology is reduced?

In evaluating network congestion, we employed the following metrics:

1. Average delay time: This represents the average latency experienced by vehicles leaving the network successfully.
2. Gridlock frequency: Defined as the frequency with which the network enters a state of complete congestion.
3. Average time to gridlock: Denotes the average duration required for the network to reach a gridlock state.

Based on the simulation outcomes, a reduction in average delay time, a decrease in gridlock frequency, and an elongation of average time to gridlock collectively suggest enhanced fluidity in the simulated network traffic.

4.1 Junction Rules & Traffic Congestion

In this section, we evaluated the impact of different junction rules on traffic congestion, excluding vehicles with pheromone technology.

Figure 4.1 shows that at all densities, Rule 1 (strict clearance principle) consistently underperforms compared to Rule 2 (pre-junction clearance principle) and Rule 3 (clockwise precedence principle). In addition, Rule 2 exhibits longer delay times than Rule 3 at all densities.

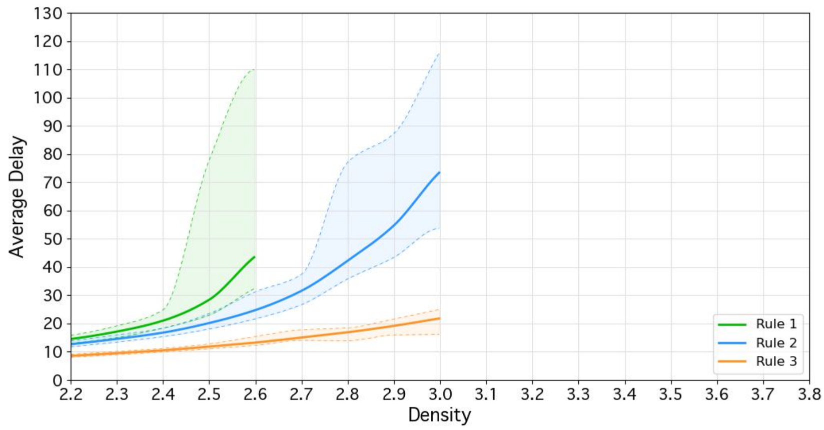


Figure 4.1: The average delay time for vehicles exiting the network, under various junction rules without the use of pheromone technology, was measured prior to the network reaching a state of gridlock. The solid line is the average value of 1000 simulations, and the two dotted lines above and below the solid line are respectively the highest and lowest values of the simulations.

Table 4.1 indicates that Rule 1 starts to congest at the density of 2.5 and reaches 100% gridlock frequency by density 2.7. Rule 2 begins congestion at density 2.9 and 100% gridlock frequency by density 3.1. Meanwhile, Rule 3 starts congestion at density 2.6 and 100% gridlock frequency by density 3.1. The congestion values are detailed in Figure 4.2. Overall, Rule 2 exhibits better performance.

Table 4.1: The gridlock frequency under different junction rules without the use of pheromone technology.

	Rule 1	Rule 2	Rule 3
began to congest	2.5	2.9	2.6
100% gridlock frequency	2.7	3.1	3.1

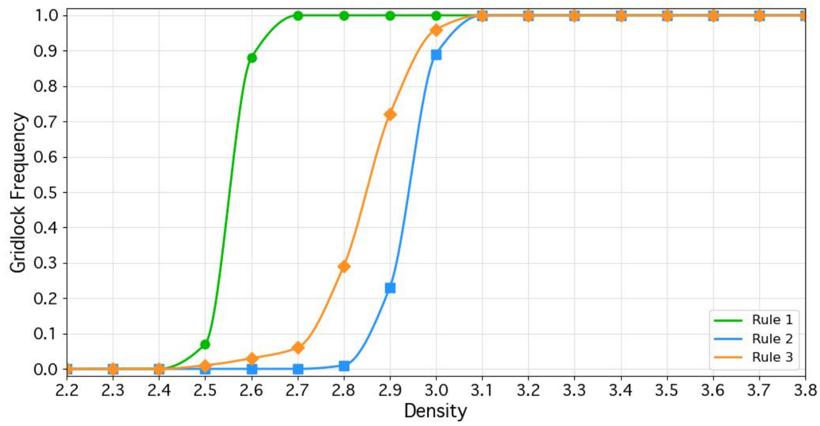


Figure 4.2: The gridlock frequency under different junction rules without the use of pheromone technology. Each data point contains 1000 times simulation.

Figure 4.3 shows that at the density of 2.9, Rule 1 takes fewer than 2,000 time units, on average, from start to reach gridlock. In contrast, Rule 3 necessitates approximately 12,000 time units to reach gridlock on average. Surprisingly, Rule 2 requires even more than 18,000 time units for the same outcome. This trend is consistent across other densities examined. Therefore, when the objective is to prolong the average time to reach gridlock, Rule 2 performs the best.

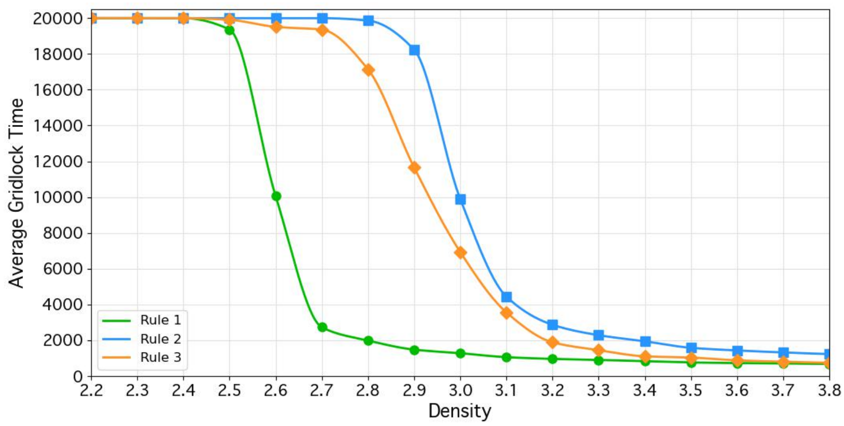


Figure 4.3: The average time from start to reach gridlock under different junction rules without the use of pheromone technology. Each data point contains 1000 times simulation.

From the data presented, Rule 1 consistently underperforms compared to Rule 2 and Rule 3. While Rule 2 exhibits longer delay times than Rule 3 at low densities, it outperforms Rule 3 at higher densities in preventing network congestion. Thus, Rule 3 is preferable at low densities, whereas Rule 2 is more effective for high-density traffic.

In conclusion, junction rule modifications significantly influence congestion states of the network, with their efficacy varying based on traffic density. Given Rule 2's better performance in alleviating congestion, it will be the primary focus in subsequent sections. Detailed results for Rules 1 and 3 can be found in the appendix.

4.2 Pheromone & Traffic Congestion

This section evaluates the network congestion improvement when vehicles are equipped with pheromone technology versus without it, referencing junction Rule 2. Detailed Results for rules 1 and 3 can be found in the appendix.

Figure 4.4 shows that at all densities, the result of the average delay time with vehicles equipped with the pheromone technology consistently outperforms compared to the result without the pheromone technology.

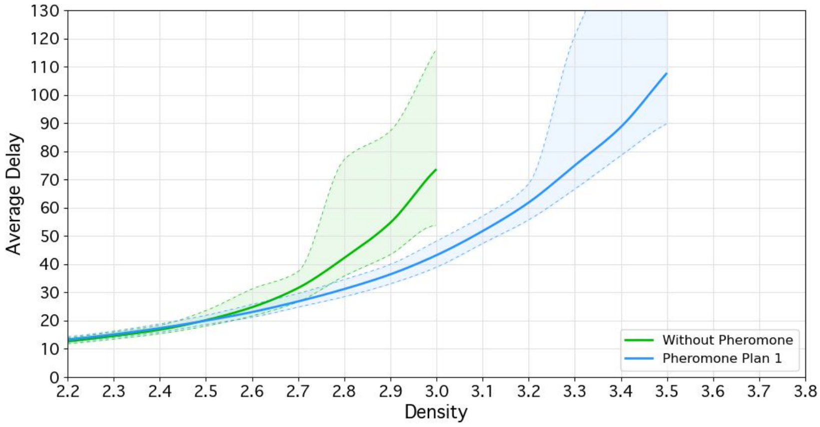


Figure 4.4: The average delay time for vehicles exiting the network with and without the use of pheromone technology, was measured prior to the network reaching a state of gridlock. The solid line is the average value of 1000 simulations, and the two dotted lines above and below the solid line are respectively the highest and lowest values of the simulations.

Table 4.2 indicates that without the pheromone technology, the network starts to congest at the density of 2.9, and reaches 100% gridlock frequency by density 3.3. With the pheromone technology, the congestion begins at density 3.3 and 100% gridlock frequency at density 3.6. The congestion values are detailed in Figure 4.5. Overall, the result with pheromone technology exhibits better performance.

Table 4.2: Gridlock frequency with and without the use of pheromone technology.

	Without pheromone	With pheromone Plan 1
began to congest	2.9	3.3
100% gridlock frequency	3.3	3.6

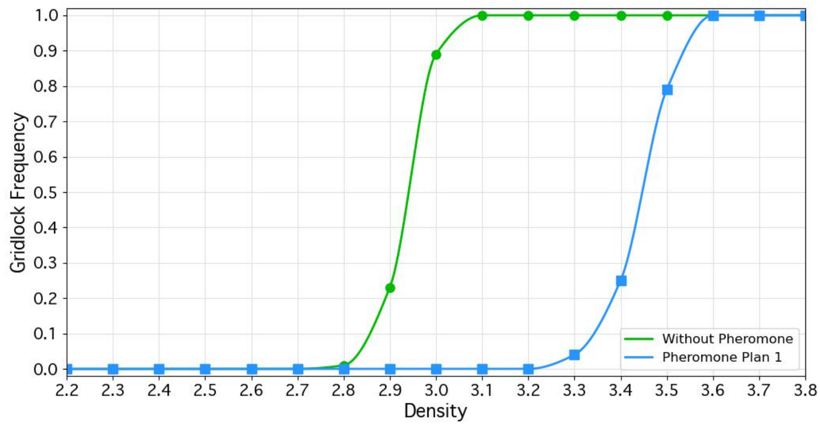


Figure 4.5: The gridlock frequency with and without the use of pheromone technology. Each data point contains 1000 times simulation.

In Figure 4.6, it is evident that the usage of pheromone technology results in an increased average time to reach a gridlock, as compared to scenarios devoid of this technology. This difference is particularly observable when the traffic density exceeds 3.0, as the system does not enter gridlock conditions at lower densities. Consequently, it can be concluded that the network's performance in terms of average time to reach gridlock is enhanced through the utilisation of the pheromone technology.

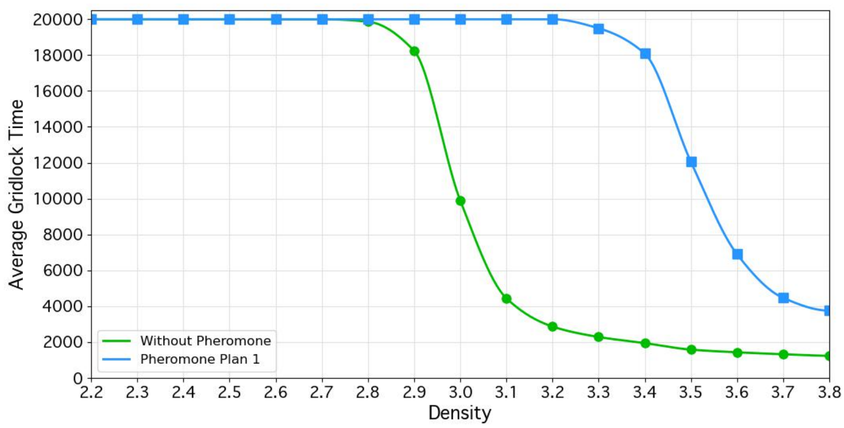


Figure 4.6: The average time from start to reach gridlock with and without the use of pheromone technology. Each data point contains 1000 times simulation.

Based on the presented data, it is evident that the effectiveness of the pheromone technology consistently surpasses those without this technology in terms of performance. Consequently, it can be conclusively stated that the integration of pheromone technology into vehicular systems substantially alleviates network congestion.

4.3 Impact of Communication Distance on Congestion

This section examines the effects of limiting peer-to-peer communication (Plan 2) versus no limitations (Plan 1) on network congestion, focusing on junction Rule 2. Results for Rules 1 and 3 are in the appendix.

Figure 4.7suggests little difference in delay times between the two plans, indicating that limiting communication might not greatly benefit delay times.

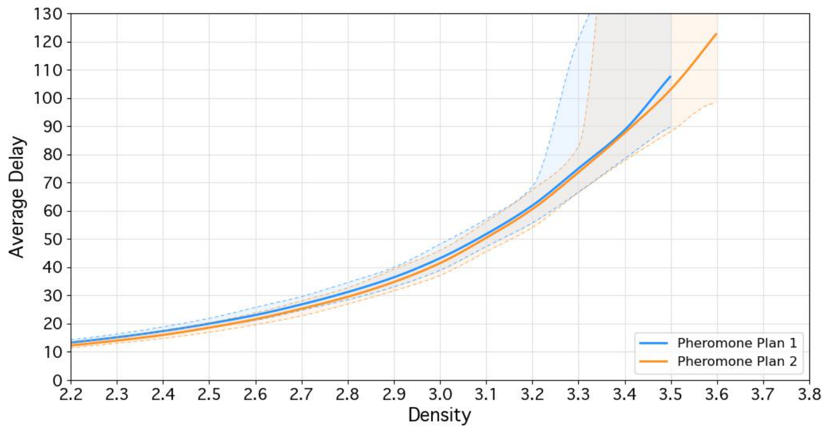


Figure 4.7: The average delay time for vehicles exiting the network when different pheromone technology is used, was measured prior to the network reaching a state of gridlock. The solid line is the average value of 1000 simulations, and the two dotted lines above and below the solid line are respectively the highest and lowest values of the simulations.

However, Figures 4.8 and 4.9 indicate enhanced congestion control. Both the density of beginning to congest and 100% gridlock frequency are postponed, as illustrated in Table 4.3 and Figures 4.8.

Table 4.3: The gridlock frequency based on the pheromone technology used.

	Pheromone plan 1	Pheromone plan 2
began to congest	3.3	3.4
100% gridlock frequency	3.6	3.8

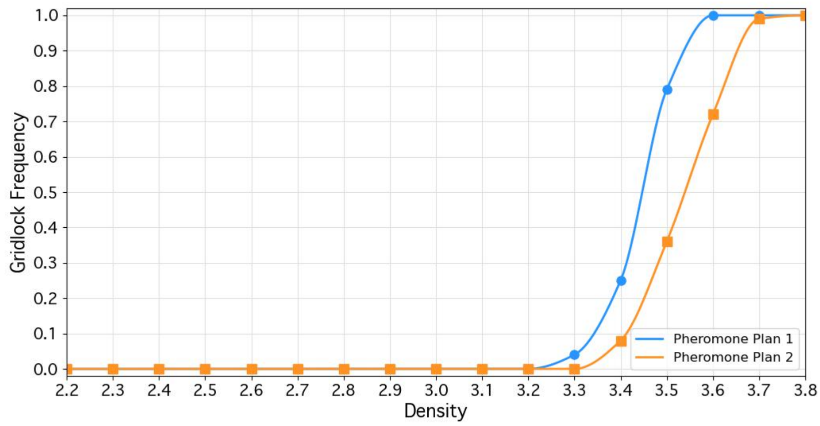


Figure 4.8: The gridlock frequency when different pheromone technology is used. Each data point contains 1000 times simulation.

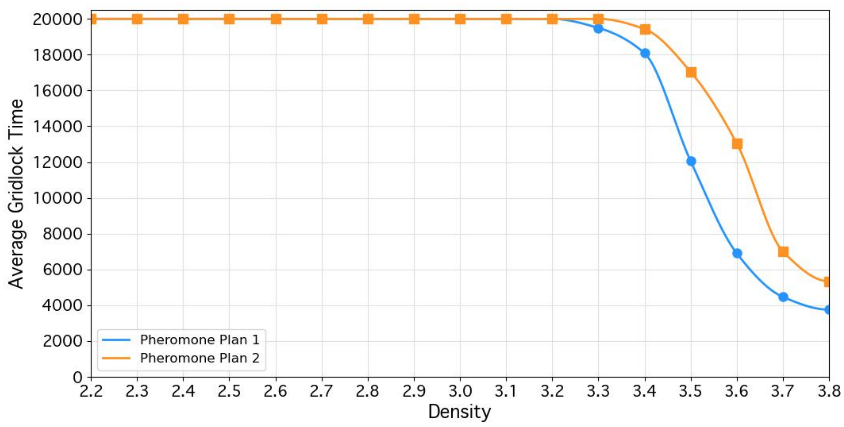


Figure 4.9: The average time from start to reach a gridlock when different pheromone technology is used. Each data point contains 1000 times simulation.

For a deeper statistical analysis to verify the question of this section, we performed a paired t-test:

- Null hypothesis: Limiting peer-to-peer communication doesn't affect the average time for networks from start to reach gridlocks.
- Alternative hypothesis: It does have an impact.

Data was gathered before and after limiting communication in simulations with densities from 3.3 to 3.8, using 500 random samples per density, where values with equal density were paired. The results:

- t-statistic-value: -12.16306
- Degrees of Freedom: 2999
- p-value: $p < 0.00001$
- Confidence Interval (CI): $[2393, 3313]$
- Mean Difference: 2853

With a p-value of < 0.00001, below the 0.05 alpha level, we reject the null hypothesis, indicating statistical significance. The mean difference of 2853 time units to a notable latency in the average time to reach a gridlock from start, suggests that limiting vehicle communication distance significantly improves network congestion. The 95% confidence interval [2393, 3313] reinforces this difference between the two plans. Thus, limiting communication distance in vehicles appears beneficial.

4.4 Impact of Reduced Pheromone Tech on Congestion

This section examines the impact on network congestion as the percentage of vehicles with pheromone technology decreases.

Figure 4.10 illustrates that as the proportion of vehicles equipped with pheromone technology decreases, the average delay time correspondingly declines. Moreover, this differential in delay time becomes more pronounced as the overall density of the network increases.

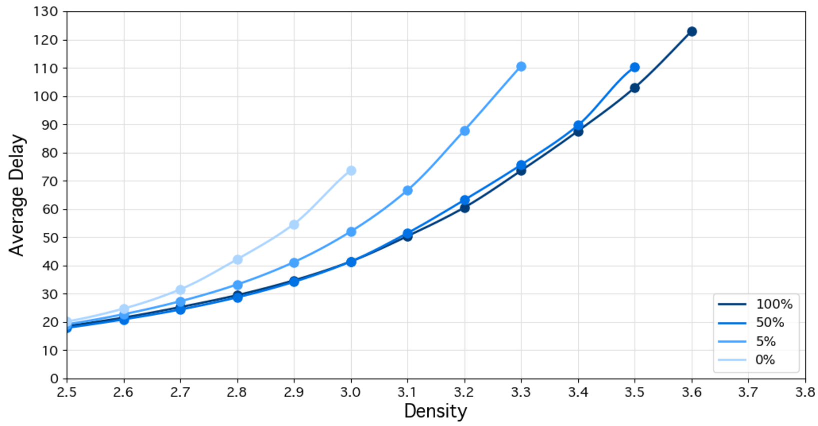


Figure 4.10: The Average delay time for vehicles exiting the network, under various proportions of pheromone-equipped vehicles, was measured prior to the network reaching a state of gridlock. Each data point contains 1000 times simulation.

Table 4.4 derived from density 3.0 results, provides a deeper analysis. By comparing delay times at different pheromone proportions to a no-pheromone scenario, we measured the improvement levels. As seen in Table 4.4, a 50% reduction in pheromone-equipped vehicles still offers nearly the same delay benefits. Even at 5% equipped, we retain two-thirds of the improvement.

Table 4.4: The average delay time for vehicles exiting the network under various proportions of pheromone-equipped vehicles at density 3.0

	100%	50%	5%	0%
Delay Time	41	42	52	74
Delay Improvement	1	0.97	0.67	0
Pheromone Reduction	1	0.5	0.05	0

Figure 4.11 illustrates that the lower the proportion, the lower the density that begins to congest and the density that 100% gridlock frequency, which means that network congestion can be prevented less. Table 4.5 allows for a more intuitive comparison.

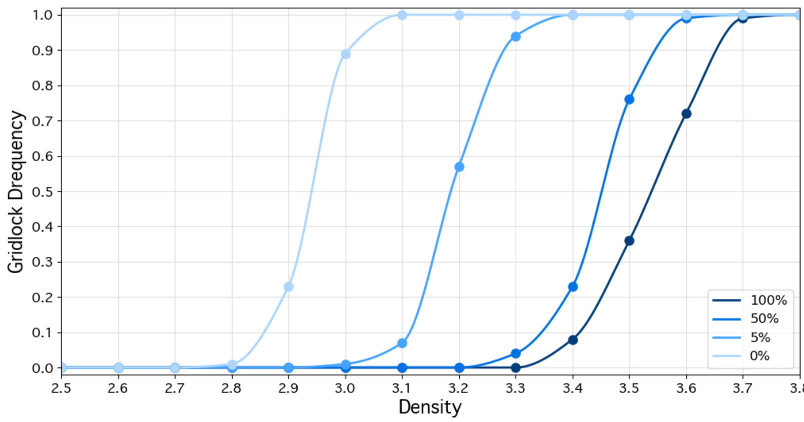


Figure 4.11: The Gridlock frequency under various proportions of pheromone-equipped vehicles. Each data point contains 1000 times simulation.

Table 4.5: The gridlock frequency under various proportions of pheromone-equipped vehicles.

	100%	50%	5%	0%
began to congest	3.4	3.3	3.1	2.9
100% gridlock frequency	3.8	3.7	3.4	3.1

Figure 4.12 shows that the lower the proportion, the shorter the average time it takes for the network to reach gridlock.

The presented data reveals a negative correlation between congestion alleviation and the proportion of vehicles with pheromone technology, though not linearly. That is, certain effects can be achieved even if not every vehicle is equipped with pheromone technology.

In summary, our method exhibits significant advantages in terms of both reducing the delay time and alleviating network congestion as corroborated by multiple standard tests. Another important lesson in this chapter is that we can get almost all of the benefits from the pheromone technology (90% of the maximum benefit) with only a 50% uptake. Even with a 5% uptake, we can get most of the benefits (50% of the maximum benefit). However, it is pertinent to note that these tests were largely conducted in a simulated environment, introducing a degree of limitation to the findings. These preliminary results pose further questions: Can these advantages be sustained under varying and uncertain real-world conditions? To comprehensively

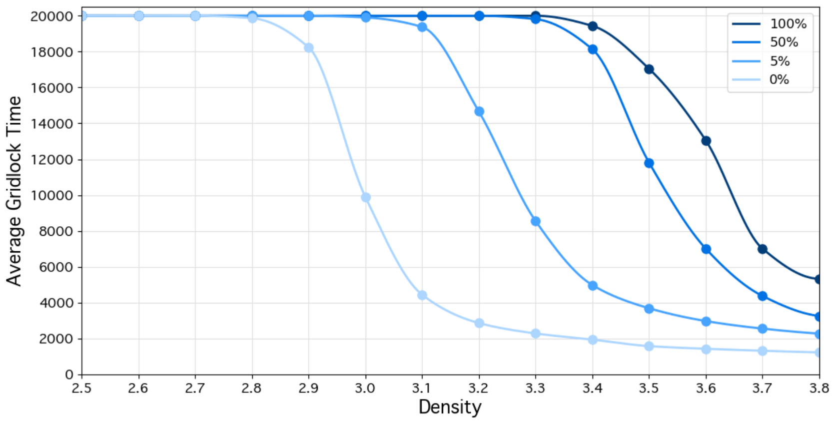


Figure 4.12: The average time from start to reach gridlock under various proportions of pheromone-equipped vehicles. Each data point contains 1000 times simulation.

address these questions and provide a more rigorous evaluation, we will delve into a detailed discussion and analysis of our findings in the subsequent chapter.

Chapter 5

Discussion

The rapid growth of the human population in the modern world has amplified the demand for transportation, especially in urban areas, leading to increased traffic congestion. This not only inconveniences the masses but also contributes to global air pollution due to the prolonged running of cars in traffic jams. Addressing this, our study introduced a decentralised traffic routing method using the reverse pheromone model, which coordinates vehicles at junctions, substantially improves network fluidity and reduces congestion-related emissions. Besides, this model thus aligns well with the motivation of leveraging swarm intelligence and multi-agent systems to develop solutions that promote transportation sustainability. In this chapter, we will delve deeper into the evaluation of results, compare with prior work, discuss implications, and highlight limitations.

5.1 Results Evaluation

In the context of the modern world's transportation challenges:

- Different junction rules have varying impacts on network congestion. The 'Pre-Junction Clearance' rule was found to be most effective in high-density traffic scenarios, reminiscent of urban congestion. In contrast, the 'Clockwise Precedent' rule was more suitable for low-density traffic. The reason why a 'Clockwise Precedent' rule underperformed at higher density is that the junction traffic rules will affect the efficiency of road utilisation at the junction, and the junction design similar to the roundabout requires a larger capacity than the general junction. When the increase in traffic flow leads to the insufficiency of the capacity of the roundabout, such a junction rule will make more vehicles wait in front of the junction, resulting in congestion.

- Integrating pheromone technology into each vehicle, a step towards leveraging modern technological advancements, significantly reduced congestion.

- Limiting the communication distance between vehicles equipped with pheromone technology further optimised congestion relief. Statistical analysis validated this finding. The reason why we explored this option is we later found in the previous ACO algorithms for travelling problems, that there was a strategy known as 'local search' or 'neighbourhood search' [50]. In this kind of strategy, each agent communicates only with its "neighbours," implying that their scope of collaboration is limited. This approach is usually used for large-scale optimisation problems and distributed systems.

- Though the benefits of network congestion alleviation declined when the proportion of vehicles with pheromone technology was reduced to 50% and 5%, the performance still improved significantly compared to scenarios without pheromone technology, suggesting scalability in real-world applications.

5.2 Comparison with Prior Work

Our research improved upon previous ACO-based traffic routing studies by introducing a fully decentralised pheromone model, eliminating the need for RSUs. The decentralised system addressed modern concerns of scalability, single-point failure, and privacy. This study ventured beyond traditional models by exploring additional factors like junction rules and communication distance.

The introduced peer-to-peer communication rules compensate for the lack of central coordination, this method addresses several problems—for example:

1. **Scalability**: A decentralised system can greatly expand the scale of the network without having to think about infrastructure issues.

2. **Single-point failure**: A decentralised system does not have a severe impact on overall performance due to the failure of one point or even a part of the system.

3. **Privacy concerns**: The information will be stored on their respective vehicles to avoid leakage of privacy.

While previous reverse ACO models demonstrate congestion avoidance, this work explores additional factors like junction rules and communication distance that significantly impact performance. The findings provide new insights beyond prior implementations.

5.3 Implications

In light of the global transportation challenges:

- **Theoretical Implications**
  Our model advances swarm intelligence techniques for decentralised systems by negating

the need for external control hubs. The ‘pheromone diffusion mechanism’ ensures up-to-date congestion data sharing without unwanted memory effects. Moreover, our model theoretically demonstrates the feasibility of self-organised traffic coordination based solely on local interactions between vehicles and pushes the boundaries of swarm intelligence techniques for decentralised systems. It opens avenues for fully decentralised solutions in other domains facing similar challenges, showcasing the potential of self-organised traffic coordination based on local interactions.

- **Practical Implications**

  This research presents a tangible solution to the modern world’s traffic woes, offering a decentralised framework to enhance real-world traffic flows using peer-to-peer communication. As vehicular automation advances, such systems will be crucial for scalable, efficient network coordination.

  The model can be reasonably implemented using current technologies like VANETs [51]. Given the current technological landscape, the model’s implementation seems feasible and beneficial, even with partial vehicle upgrades. This provides practical pathways for gradual integration with existing infrastructure.

5.4 Limitations

While our study offers promising solutions to modern traffic challenges:

While the current simulations validate the proposed model’s effectiveness under ideal conditions, further rigorous testing using diverse real-world scenarios remains imperative. Although the simplified grid-based network employed is useful for initial analysis, the study’s reliance on a simplified grid-based network might not capture the intricacies of complex real-world environments and precludes comprehensive insights into performance within intricate real-world environments.

The model’s assumption of uniform acceptance of coordination rules among vehicles might not account for the unpredictable nature of human-driven vehicles on today’s roads. Further iterations should consider these various factors such as heterogeneous vehicle capabilities, unpredictable human driver behaviours, and complex urban road networks must be addressed. Therefore, advancing the model requires accommodating vehicle and behavioural heterogeneity through extensive simulations using realistic traffic networks. The model should be validated and optimised through more comprehensive testing for applicability in an uncontrolled real-world implementation.

Chapter 6

Conclusion

In light of the pressing challenges of modern urban transportation and the amplified demand leading to increased traffic congestion, this study embarked on an innovative journey. We introduced a decentralised traffic routing method using reverse pheromone models, aiming to address the very heart of these challenges. Motivated by the limitations of both centralised and the current decentralised systems highlighted in our studies, our research culminated in a fully distributed model. Through Monte Carlo simulations on a Manhattan-style grid network, we validated the model's effectiveness, echoing the urban challenges and the need for sustainable solutions.

Our findings were significant: even a mere partial integration of pheromone technology in vehicles led to a substantial reduction in congestion. The results demonstrated that integrating pheromone technology into 50% vehicles still substantially reduced congestion compared to no pheromone scenarios. Moreover, limiting communication distance further augmented this congestion alleviation. This not only theoretically advances the realm of decentralised swarm intelligence techniques but also offers a practical blueprint for modern urban transportation systems.

Reflecting on our discussions, the research's implications are manifold. Theoretically, we've paved the way for future studies in self-organised traffic coordination based solely on local interactions. Practically, we've provided a tangible solution to the modern world's traffic woes, suggesting a decentralised framework that can be integrated with existing infrastructure.

There are several worthwhile directions for advancing this work in the future.

6.1 Future Work

- **Expanding Network Scalability**
  The current simulations utilise a simplified small-scale grid network. Testing the model in larger networks with more complex real-world road topologies is necessary to evaluate its scalability. This can be achieved by modelling urban environments using tools like SUMO [52][53] and importing these realistic maps into the simulation.

- **Enhanced Traffic Realism**
  While a basic vehicle speed was modelled, incorporating heterogeneous speeds, acceleration profiles, and terrain effects can enhance realism. Additionally, fixing vehicle trips between preset origins and destinations will better approximate real-world conditions. This allows assessing model performance for diverse traffic flows.

- **Departure Time Optimisation**
  In the real world, a proportion of vehicles like commuters have fixed routes and departure times. Therefore, some specific locations might have a larger traffic flow at certain times. We could apply reinforcement learning techniques to identify optimal departure times and routes for vehicles based on congestion data can further enhance coordination. This can minimise delays and maximise trip efficiency.

- **Infrastructure Optimisation**
  Simulating road design changes like widening lanes, increasing junction capacity, and integrating dual roundabouts can reveal complementary infrastructural improvements to the routing approach. The combined impact can be quantified through comparisons.

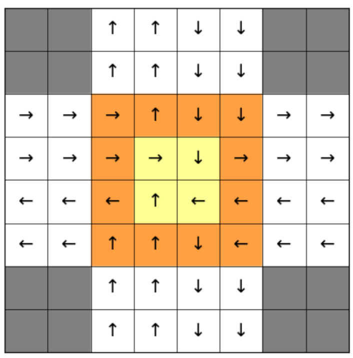
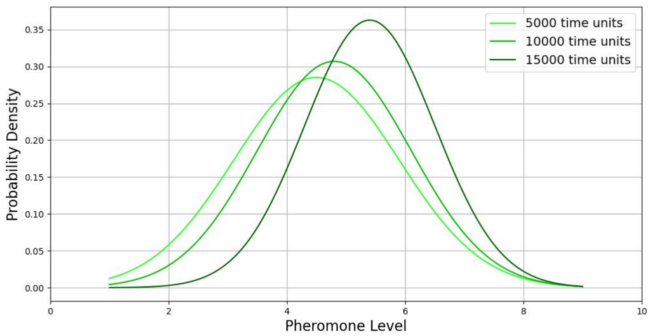
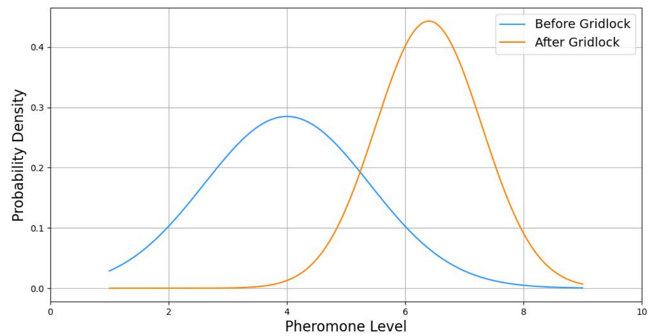


Figure 6.1: A design of widening lanes and dual roundabouts

- **Congestion Prediction by Pheromone Level**
  Preliminary observations indicate a relationship between pheromone level distribution and traffic congestion. In the density plot 6.2a, when the network reaches a gridlock, the pheromone level distribution appears to increase on average and the standard deviation becomes smaller. Although further experiments should be conducted, this is reasonable. The congestion of the network before gridlock will lead to the accumulation of pheromones in the vehicles, which will increase the pheromone level on average, and the use of pheromone technology will make the road usage tend to be average, causing each vehicle holding similar pheromone level and the decrease of the standard deviation. We can formalise this into a predictive model using machine learning approaches, probably more like the density plot 6.2b, that might enable proactive congestion avoidance based on pheromone data.



(a) The density plot where x is the pheromone level, and y is the probability density. We randomly picked one of the simulations following junction rule 2 and the density at 3.6. The density plot seems to be similar to Figure 6.2b.



(b) The density plot where x is the pheromone level, and y is the probability density. The ideal changes in the pheromone-level distribution are when the network starts to congest, the mean of the vehicles' pheromone level will increase and the standard deviation of the vehicles' pheromone level will decrease.

Figure 6.2: Pheromone-Level Distribution

In conclusion, this research explores a decentralised technique to optimise traffic flows, leveraging principles of swarm intelligence. The limitations of prevailing centralised and decentralised models for intelligent transportation systems were prime motivations. By proposing a fully distributed model using local vehicle interactions, this work advances environmentally-conscious solutions. While the journey ahead demands further testing, this study has paved a path towards self-organising transportation systems using distributed techniques. With further development in the future, the model shows promise as a sustainable technique to alleviate ubiquitous traffic congestion challenges. The findings reveal insights for realising intelligent transportation systems that promote efficiency and reduce emissions.

Appendix A

Results of Rule 1 for 4.2 and 4.3

Figure A.1, A.2 and A.3 are the outcomes compared by Default(without pheromone tech), Plan 1(pheromone technology without limited communication distance) and Plan 2(pheromone technology with limited communication distance) when following Junction Rule 1.

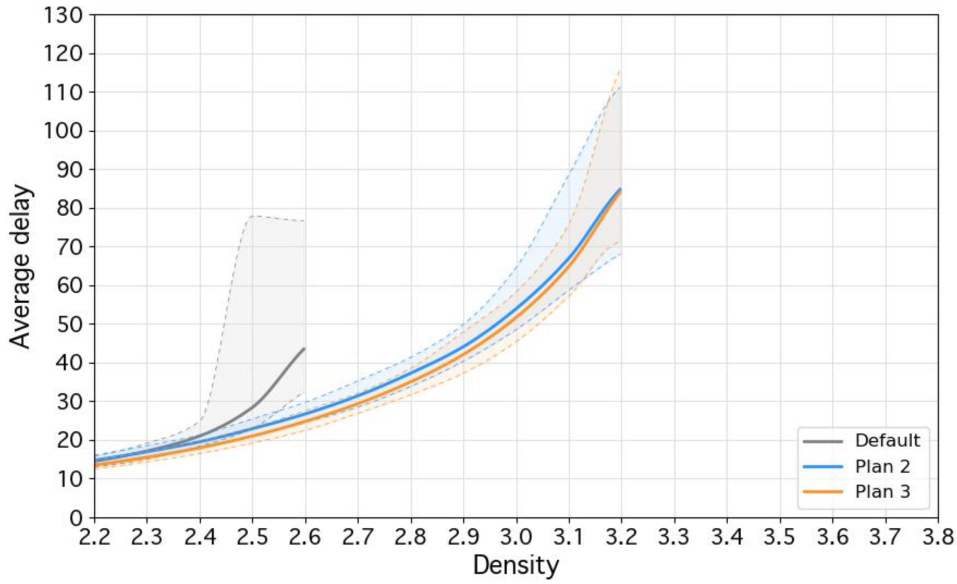


Figure A.1: Average delay time

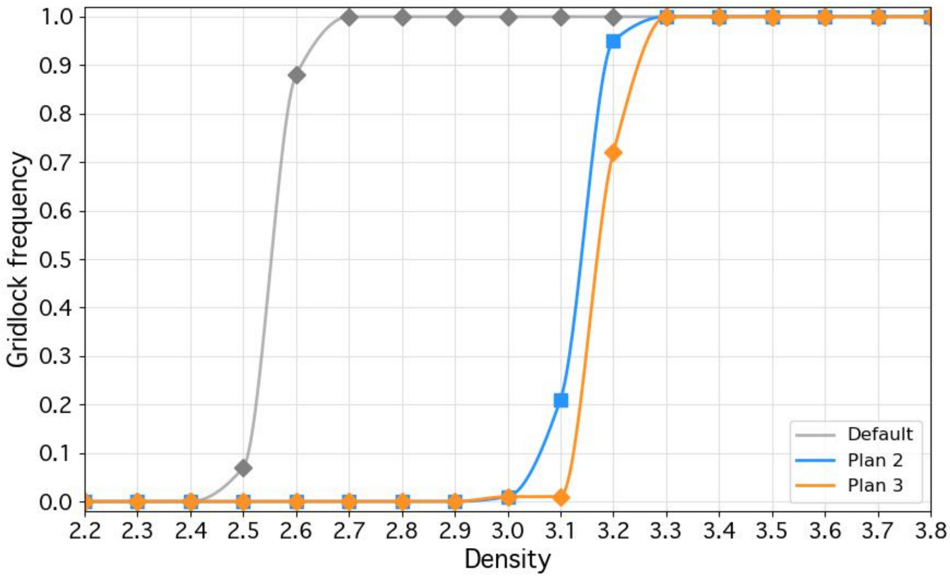


Figure A.2: Gridlock Frequency

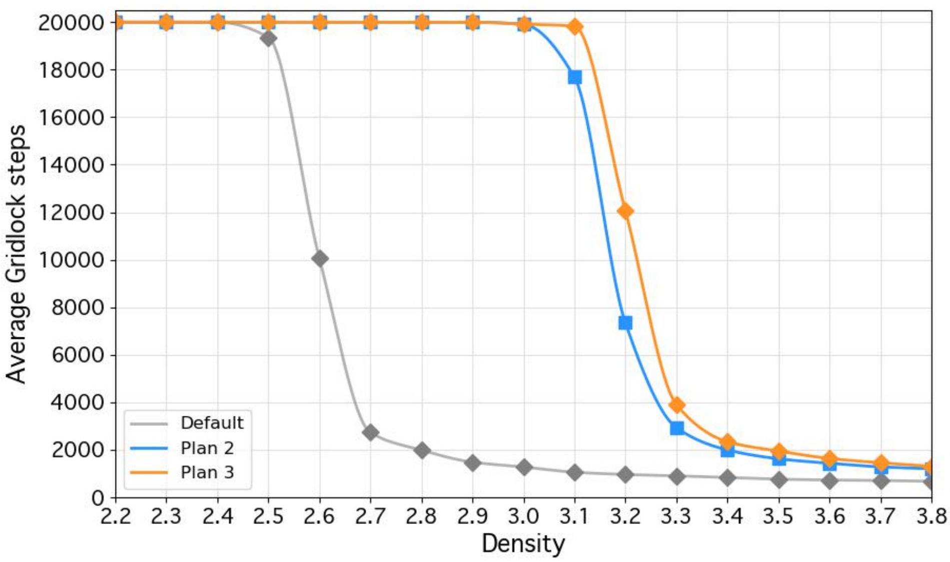


Figure A.3: Average time from the start to gridlock

Appendix B

Results of Rule 3 for 4.2 and 4.3

Figure B.1, B.2 and B.3 are the outcomes compared by Default(without pheromone technology but follows Rule 1), Plan 1(without pheromone technology), Plan 2(pheromone technology without limited communication distance) and Plan 3(pheromone technology with limited communication distance) when following Junction Rule 3.

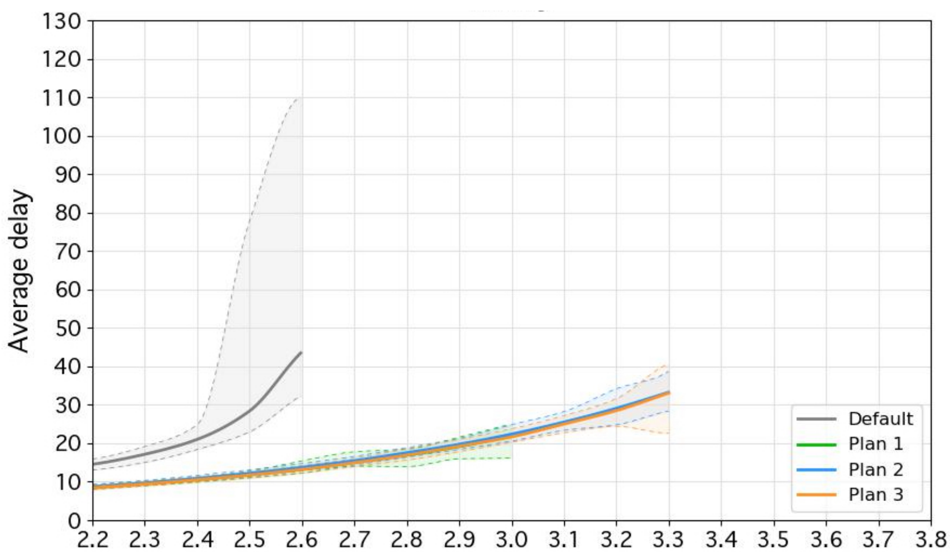


Figure B.1: Average delay time

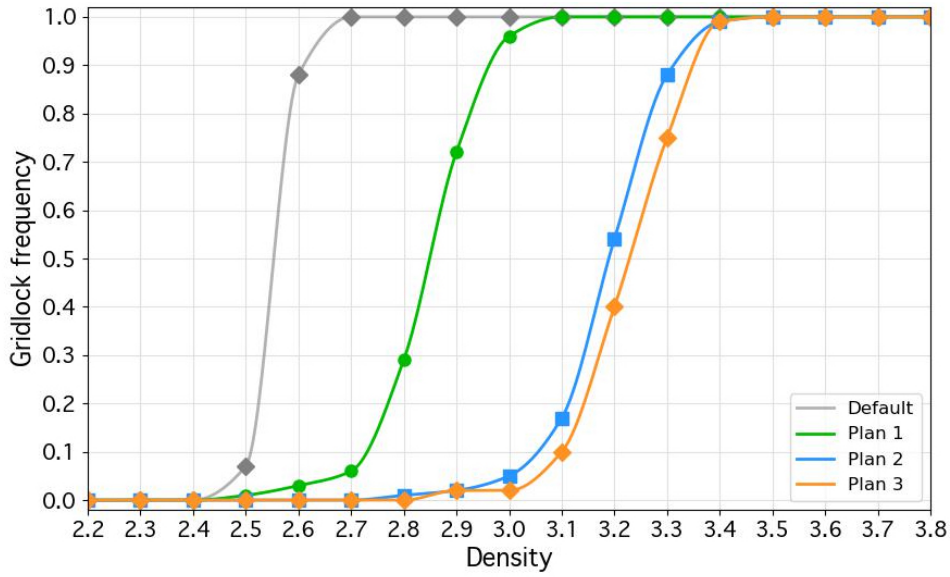


Figure B.2: Gridlock Frequency

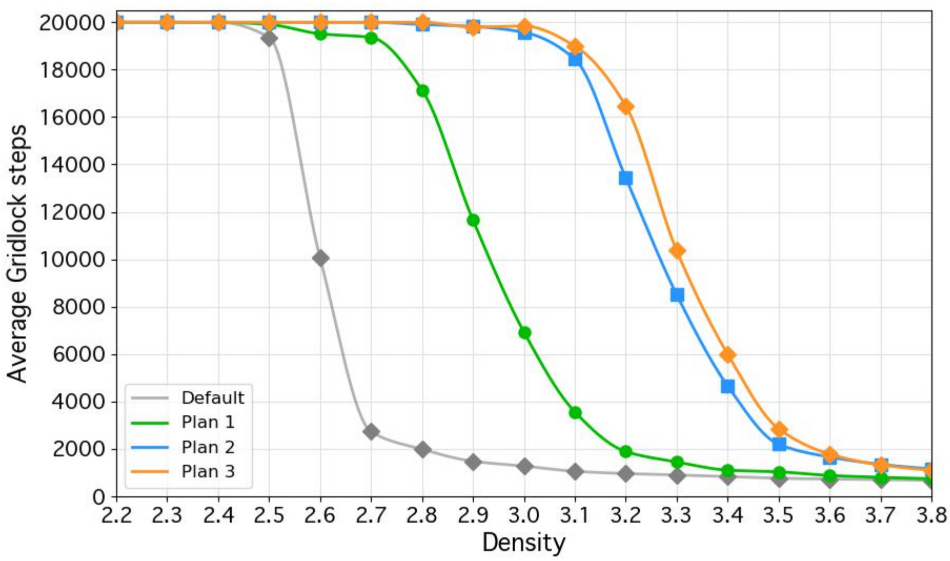


Figure B.3: Average time from the start to gridlock

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