Distributed, Decentralised and Compensational Mechanisms for Platoon Formation

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Abstract

Traffic problems have been on the rise corresponding with the increase in worldwide urbanisation and the number of vehicles per capita. Platoons, which are a formation of vehicles travelling close together, present themselves as a possible solution, as existing research indicates that they can contribute to better road usage, reduce fuel consumption and emissions and decongest bottlenecks faster. There are many aspects to be explored pertaining to the topic of platooning: safety, stability, communication, controllers and operations, all of which are necessary to bring platoons closer to use in everyday traffic. While extensive research has already made substantial strides in all the aforementioned fields, there is so far little work on the logical grouping of vehicles in platoons. Therefore, this work addresses the platoon formation problem, which has not been heavily researched, with existing examples being focused on large, freight vehicles travelling on highways. These cases find themselves on the strategic and tactical level of planning since they benefit from a large time horizon and the grouping can be optimised accordingly. The approaches presented here, however, are on the operational level, grouping and routing vehicles spontaneously and organically thanks to their distributed and decentralised nature. This creates so-called opportunistic platoons which could provide a promising premise for all networks given their flexibility.

To this extent, this thesis presents two novel platoon forming algorithms: a distributed approach derived from classical routing problems, and a supplementary decentralised compensational approach. The latter uses automated negotiation to facilitate vehicles organising themselves in a platoon based on monetary exchanges. Considering that all traffic participants have a set of preferences, limitations and goals, the proposed system must ensure that any solution provided is acceptable and beneficial for the individual vehicles, outweighing any potential effort, cost and sacrifices. This is achieved by offering platooning vehicles some form of incentivisation, either cost reductions or traffic light prioritisation.

To test the proposed algorithms, a traffic simulation was developed using real networks with realistic traffic demand. The traffic participants were transformed into agents and given the necessary functionality to build platoons and operate within them. The applicability and suitability of both approaches were investigated along with several other aspects pertaining to platoon operations such as size, traffic state, network positioning and incentivisation methods.

The results indicate that the mechanisms proposed allow for spontaneous platoons to be created. Moreover, with the distributed optimisation-based approach and using cost-reducing incentives, participating vehicles benefited regardless of the platoon size, traffic state and positioning, with utility improvements ranging from 20% to over 50% compared to the studied baseline. For time-based incentives the results were mixed, with the utility of some vehicles improving, some seeing no change and for others, deteriorating. Therefore, the usage of such incentives would not be recommended due to their lack of Pareto-efficiency. The compensational and completely decentralised approach shows some benefits, but the resulting improvement was overall negligible.

The presented mechanisms are a novel approach to platoon formation and provide meaningful insight into the mechanics and applicability of platoons. This sets the stage for future expansions into planning, designing and implementing more effective infrastructures and traffic systems.

Kurzfassung

Verkehrsprobleme nehmen mit der weltweiten Urbanisierung und der Zunahme der Anzahl der Fahrzeuge pro Kopf zu. Platoons, eine Formation von eng hintereinander fahrenden Fahrzeugen, stellen sich als mögliche Lösung dar, da bestehende Forschungen darauf hinweisen, dass sie zu einer besseren Straßenauslastung beitragen, den Kraftstoffverbrauch und die Emissionen reduzieren und Engpässe schneller entlasten können. Rund um das Thema Platooning gibt es viele Aspekte zu erforschen: Sicherheit, Stabilität, Kommunikation, Steuerung und Betrieb, die allesamt notwendig sind, um den Einsatz von Platooning im Alltagsverkehr näher zu bringen. Während in allen genannten Bereichen bereits umfangreiche Forschungen durchgeführt wurden, gibt es bisher nur wenige Arbeiten, die sich mit der logischen Gruppierung von Fahrzeugen in Platoons beschäftigen. Daher befasst sich diese Arbeit mit dem noch wenig erforschten Problem der Platoonbildung, wobei sich die vorhandenen Beispiele mit auf Autobahnen fahrenden Lastkraftwagen beschäftigen. Diese Fälle befinden sich auf der strategischen und taktischen Ebene der Planung, da sie von einem großen Zeithorizont profitieren und die Gruppierung entsprechend optimiert werden kann. Die hier vorgestellten Ansätze befinden sich hingegen auf der operativen Ebene, indem Fahrzeuge aufgrund der verteilten und dezentralen Natur dieser Ansätze spontan und organisch gruppiert und gesteuert werden. Dadurch entstehen sogenannte opportunistische Platoons, die aufgrund ihrer Flexibilität eine vielversprechende Voraussetzung für alle Netzwerkarte bieten könnten.

Insofern werden in dieser Arbeit zwei neuartige Algorithmen zur Bildung von Platoons vorgestellt: ein verteilter Ansatz, der von klassischen Routing-Problemen abgeleitet wurde, und ein ergänzender dezentraler kompensatorischer Ansatz. Letzteres nutzt automatisierte Verhandlungen, um es den Fahrzeugen zu erleichtern, sich auf der Basis eines monetären Austausches in einem Platoon zu organisieren. In Anbetracht der Tatsache, dass alle Verkehrsteilnehmer über eine Reihe von Präferenzen, Einschränkungen und Zielen verfügen, muss das vorgeschlagene System sicherstellen, dass jede angebotene Lösung für die einzelnen Fahrzeuge akzeptabel und vorteilhaft ist und den möglichen Aufwand, die Kosten und die Opfer überwiegt. Dies wird erreicht, indem den Platooning-Fahrzeugen eine Form von Anreiz geboten wird, im Sinne von entweder Kostensenkung oder Ampelpriorisierung.

Um die vorgeschlagenen Algorithmen zu testen, wurde eine Verkehrssimulation unter Verwendung realer Netzwerke mit realistischer Verkehrsnachfrage entwickelt. Die Verkehrsteilnehmer wurden in Agenten umgewandelt und mit der notwendigen Funktionalität ausgestattet, um Platoons zu bilden und innerhalb dieser zu operieren. Die Anwendbarkeit und Eignung beider Ansätze wurde zusammen mit verschiedenen anderen Aspekten untersucht, die den Betrieb von Platoons betreffen, wie Größe, Verkehrszustand, Netzwerkpositionierung und Anreizmethoden.

Die Ergebnisse zeigen, dass die vorgeschlagenen Mechanismen die Bildung von spontanen Platoons ermöglichen. Darüber hinaus profitierten die teilnehmenden Fahrzeuge mit dem auf verteilter Optimierung basierenden Ansatz und unter Verwendung kostensenkender Anreize unabhängig von der Platoon-Größe, dem Verkehrszustand und der Positionierung, mit Nutzenverbesserungen von 20% bis über 50% im Vergleich zur untersuchten Baseline. Bei zeitbasierten Anreizen waren die Ergebnisse uneinheitlich, wobei sich der Nutzen einiger Fahrzeuge verbesserte, bei einigen keine Veränderung eintrat und bei anderen eine Verschlechterung zu verzeichnen war. Daher wird die Verwendung solcher Anreize aufgrund ihrer mangelnden Pareto-Effizienz nicht empfohlen. Der kompensatorische und vollständig dezentralisierte Ansatz weißt einige Vorteile auf, aber die daraus resultierende Verbesserung war insgesamt vernachlässigbar.

Die vorgestellten Mechanismen stellen einen neuartigen Ansatz zur Bildung von Platoons dar und geben einen aussagekräftigen Einblick in die Mechanik und Anwendbarkeit von Platoons. Dies schafft die Voraussetzungen für zukünftige Erweiterungen in der Planung, Konzeption und Implementierung effektiverer Infrastrukturen und Verkehrssysteme.

List of Symbols

Symbol	Definitions
G=(V, E)	graph
$v \in V$	vertices
$e \in E$	edges, $e \equiv (i,j)$
T	Traffic
ΔN	total number of vehicles
Q	traffic flow
P	traffic density
barV	mean speed
TL	traffic lights
t_B	standard time to clear the signalised approach
q_S	signalised approach saturation value
q_i	volume of stream
t_U	total traffic light cycle time
t_{RG}	minimum required green time
t_{ATG}	available green time
t_{Gi}	available green time for stream
Vehs	all vehicles considered in a Platoon Formation Problem
R	route
c_e	cost of an edge
d_e	traffic density of edge e
nvp	number of vehicles in a platoon
ψ	subsidisation coefficient
U_v	vehicle utility
ρ,σ	vehicle preference coefficients
l_e	length of edge e
t_e	time it takes to traverse edge e
s	speed
y(e)	binary variable, 1 if $e \in R_{\forall v \in Vehs}$, 0 otherwise
$x_v(e)$	binary variable, 1 if $e \in R_v$, 0 otherwise
K_v^*	maximum cost preference
Λ_v	maximum length preference
Ω_v	maximum time preference
i	initiating bidding agent
a	accepting bidding agent
RV	reservation value
AV	aspiration value
X(0)	first offer
X(n)	opponent bid in round n
n	round number
$\alpha(n)$	time and agent strategy effect coefficient
D	maximum number of rounds, deadline
β	bidding agent type coefficient
Y(s)	ego-bid
comp	compensation

Contents

1 Introduction

Grouping vehicles in some sort of formation has been an area of study for many years, spanning from military purposes to logistic transports and currently even individual automobiles (Madeleine et al., 2012). Researchers theorised since the 1960s that if vehicles would travel closely together, in a line formation, fuel consumption, as well as the safety of the passengers, flexibility and workload of the drivers could be improved.

Many conditions are necessary to ensure that such a formation achieves all the stated goals: reliable and constant communication, secure controllers, an appropriate balance of privacy and sharing, standards and protocols as well as a sizeable soft- and hardware architecture need to be put in place.

The stages of driving in a formation from a temporal point of view can be decomposed into formation, operation and disbandment. Each of theses stages have their own intricate and numerous issues that need to be addressed, including formation logic, necessary manoeuvres, and communication threshold. Hence, a solution can only be deemed appropriate under the condition that it is both beneficial for the parties involved and reliable in its execution.

Besides large transports that are planned and coordinated on a long-term basis, other vehicles can benefit from travelling in formations, which from now on will be referred to as platoons. Platoons take up less road space (Amoozadeh et al., 2015), are quicker in their manoeuvring, and contribute less to traffic congestions than the equivalent number of vehicles travelling independently (Lioris et al., 2017).

Due to the previously mentioned advantages, one area that could considerably benefit from platoons is urban networks. However, not much research has been carried out in this type of environment. Instead, the focus has been on implementing platooning in highway scenarios for heavy-duty vehicles (Bhoopalam et al., 2018). It is clear why highways have been the preferred environment for the study for platoons; in addition to the original two advantages (take up less space, contribute less to congestion), vehicles travelling on them can also benefit from the reduced wind-drag effect that positively impacts fuel consumption and by extension costs and emissions (Tsugawa et al., 2011). Not only this, but highways offer appropriate infrastructure for the manoeuvres necessary to form, operate and disband platoons (merging, right-hand and exit lanes), too. In contrast, urban networks offer less space, are denser and manoeuvring can be more difficult. Despite the added complexities of urban landscapes, the common features of high-density traffic, varying infrastructure and multiple bottleneck points do lend themselves to platooning but require a higher degree of flexibility.

The analysis of the platoon formation problem started from urban networks, where appropriate scenarios and requirements were first considered. Because traffic in urban spaces is particularly volatile, planned and centralised solutions would not be feasible. Therefore, any solution presented must find itself at the operational level of planning, with spontaneous and immediate coordination. The investigation of these barriers and challenges lead to the selection of decentralised and compensational mechanisms, as they address manageability and scale on the one hand, and on the other, they widen the scope of situations where platooning would be beneficial.

To this extent, the distributed approach to platoon formation would ensure that so-called opportunistic platoons (Bhoopalam et al., 2018) can be created irrespective of network type, being a good fit for both sparser networks with steady flows and denser ones with ever-changing traffic alike. Assuming that vehicles could be joined together to increase flow in the network, would create a win-win scenario for the drivers, owners, traffic management and ecological authorities.

Deconstructing the topic further, completely decentralised platooning, where vehicles would convene in a platoon on their own accord, presents a new foray in this research topic. Seeing as platoons benefit all traffic actors alike, vehicles could leverage said benefit to organise new platoons directly in exchange for monetary rewards. This compensational platooning seeks to continue and expand the rate at which traffic collaboration occurs.

If we were to analyse traffic from a modelling granularity perspective, two divergent forces occur at the same time. On the microscopic level, there are the individual vehicles which act selfishly in an attempt to maximise their utility and on the macroscopic, there is the traffic management authority whose goal is to improve the general societal welfare. Co-operative traffic measures attempt to design, operate and optimise the traffic system such that user goals and system goals are achieved to an acceptable amount. Therefore, these measures which include platooning can be placed at the mesoscopic level in that, on the one hand, platoons are composed out of traffic participants, which are given a way to specify their preferences and accept outcomes that are favourable for them; but on the other, it is considered as one entity by traffic management, which can set parameters and define rules to maximise the system goals.

While an appropriate solution can be found, the impact on the network must be accurately measured and the respective resulting benefits used as incentives to increase the penetration rate, thus leading to a self-sustaining cycle of network decongestion with single and even two-fold returns for cooperative traffic participants (Lioris et al., 2017).

Platoons do not necessarily have to mean a strict formation of large and heavy vehicles collaborating to save fuel (Tsugawa et al., 2011); imagine also neighbours returning from their commute, and forming a platoon on the last stretch of their route to avoid traffic jams in their residential area, or shoppers using the metropolitan network to reach the commercial areas placed at the city outskirts, or delivery companies that send out smaller vehicles, combining spontaneously on the road to make deliveries to businesses or residential areas.

1.1 Case Example: Platoon Formation

To visually represent how platoons would form, please see Figure 1.1. Vehicles in two different platoons approach the same intersection, but they follow different headings, denoted by the arrows floating above them (top-left). The vehicles communicate their destination, preferences and limitations to a distributed agent placed in the environment, denoted by the connectivity-enabled traffic light (top-left). This agent runs the proposed algorithms and identifies two new platoons (top-right). The new formation and routes are communicated back to the vehicles, which then perform the necessary protocols and manoeuvres to create the new platoons (bottom-left). The travel then continues normally until all vehicles either arrive at their destination, disband from the formation to follow their route, or (like in this presented case) new vehicles join the platoon (bottom-right). To put into perspective the potential benefits of platoons in this case, previous research indicates (Lioris et al., 2017) that the presented formations can facilitate increased throughput at intersections.

1.2 Motivation

Drawing inspiration from underlying principles of routing problems, this work aspires to provide additional insight and expand on the existing state of research by contributing distributed, decentralised and compensational approaches to platooning. Considering the application scenarios of these approaches, they must fulfil certain important characteristics, such as scalability, flexibility, swiftness and soundness.

Distributed and decentralised platoon coordination must be highly flexible and adaptable as it must execute fast enough to be a good fit both for volatile urban traffic, as well as high-speed travel on freeways. Such an approach to platooning does not benefit from a large planning horizon which allows for a more complex and centralised solver considering

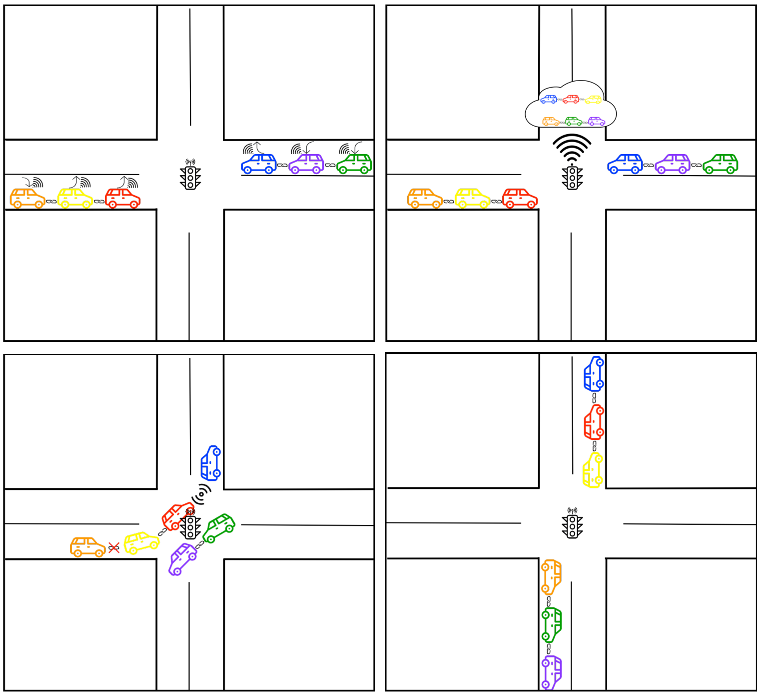

Figure 1.1: Vehicle interaction and group formation

more factors (fuel consumption, travel time, detour optimisation). Nevertheless, the method employed cannot be reductive, in the sense of decreasing the number of variables for the purpose of lower complexity. Instead, it needs to allow for a high degree of variation not only between traffic participants, their limitations, preferences and capabilities, but also for the network's size and density.

Having a base approach that is distributed, one can also further improve on the solution provided with a decentralised and compensational coalition formation mechanism. Once a collaboration has been put in place (in this case by the distributed solution), the members can continue their partnership outside of the scope given by direct contracting through payments.

To ensure the satisfaction of all traffic actors: the drivers, traffic management, public transportation, emergency services and company representatives (taxis, logistics and food deliverers), any platooning that takes place must serve the purpose of freeing up traffic congestions, minimising time on-road and/or costs, thus improving individual and overall utility.

The issue of platooning was always a multi-faceted one with numerous fields of study, therefore the subject of logical grouping and routing with not only one, but two different approaches, at two different levels of distribution is a sizable effort requiring in-depth study and experimentation.

1.3 Knowledge Gaps

As this work considers several research fields, certain gaps are observed in each of them, which can be very overlapped to define the exact scope of this study.

Within traditional routing problems, most of them focus on one economic entity with a singular goal, making that the objective function (Laporte & Osman, 1995) of an optimisation problem. To the best of our knowledge, there is no research investigating routing for groups of heterogeneous vehicles that accounts for different goals, preferences, and limitations.

While in the field of multi-agent systems the collaboration aspect has been one of the main focuses since its inception, the field of traffic management has relied more on fixed methodologies. Different authors, e.g., Raiffa (1982), Chakraborty et al. (2018), have shown that cooperation can outperform uncoordinated or strictly egotistic approaches. By creating opportunities for individual traffic participants to coordinate, collaboration can be fostered and achieved, so that the effects of selfish routing (Roughgarden & Tardos, 2002) be somewhat managed. Still, the amount of research on using coordination or collaboration to solve the problem of congestion is still sadly limited.

In the field of platooning, most current research and small scale implementations focus on freeway transports (due to the fuel-saving property of reduced wind drag), communication technologies, safety, and manoeuvring (Bhoopalam et al., 2018). More urban research regarding platooning deals with traffic engineering (Haas & Friedrich, 2017), network design (Scherr et al., 2018), and platoon control (Khalifa et al., 2018) and design (Ali et al., 2015).

Platoon coordination, also referred to as platoon matching, have not been thoroughly addressed in general, but specifically not for a non-centralised approach.

Only a few papers tackle the issue of platoon matching and coordination, but it is in the context of large freight transports (Larson et al., 2016), (Sokolov et al., 2017), which can be planned and operate on larger time and space horizons as they are executed centrally. In such a scenario, the vehicles and governing entities benefit as platooning guarantees the use of fewer resources, be they fuel, manpower, or road occupancy. For a distributed scenario, the same benefits do not apply, therefore an applicable platooning approach needs other clear benefits to compete with selfish routing, in order for the traffic authorities, commercial representatives and vehicles to participate. This benefit can be quantified either as time-savings (since platoons decongest intersections faster) or cost-reductions (if a road tolling system is applied).

1.4 Research Questions and Methodology

To gain perspective over the existing state of the art, the problems encountered, the limitations of implemented approaches and consideration of significant factors, a literature review was undertaken in the beginning. On that note, it was concluded that platooning as an overarching cooperative concept needed to be addressed by examining important determinants both from a routing and individual preference point of view. In that context, platooning was tackled through the lens of distributed/decentralised/compensational methods in synthetic as well as realistic environments.

The research questions addressed concern themselves with four major aspects: the benefit of the individual vehicles and determinants that can influence it, the external factors that affect individual benefit, the efficacy and applicability of the compensational approach and lastly, the computational performance of the proposed solutions.

In transitioning from the research questions to testing and quantifying their merit, certain methodological assumptions were put in place at the skeletal level of the evaluating framework and environment. At that, it is assumed that there are sufficient vehicles in traffic that have the necessary functionalities to platoon, namely they are communication-able and have a state of the art controller that allows for latitudinal as well as longitudinal motion control. It is also assumed that vehicles are receiving some form of preferential treatment for platooning, and are willing to platoon if the benefits outweigh any costs, effort or sacrifices. The vehicles will act in a perfectly rational fashion, according to their own set of preferences and limitations. Once a platoon has been formed, the vehicles are bound to that formation and route until their split point. Technical errors are considered to be non-existent, so a failure in the communication or of the controller will not lead to platoon disbandment. It is also assumed that traffic management will provide platoons not only with benefits but also the infrastructure necessary to allow for platoon formation.

To accurately judge the performance and benefits of the algorithms presented in this thesis, a baseline of overlapping routes was chosen as a straightforward way of establishing platoons. In line with this baseline, the vehicles travel on their ideal route and when common-ground is found with others, they will coordinate to form a platoon. While not ideal in practice since the effort, manoeuvres and space required to form platoons can be high for short-lived cooperations, this overlapping approach is a solid and realistic practice to compare one's performance against.

The first algorithm put to test was an adaptation of the classical shortest route problem which accounted for multiple vehicles with discrepant limitations and preferences. This was deployed in a distributed setup to ensure optimal grouping and routing irrespective of network structure and traffic. On the other hand, the second approach was only made available to individual vehicles and thus performed on a strictly decentralised basis. This was used to investigate the suitability of a compensational approach to platooning, where continued cooperation is fostered through the exchange of monetary incentives.

A simulation tool was therefore developed specifically for these approaches, and numerous experiments were performed where all influencing factors were varied to assess and prove the applicability and soundness of the methods employed.

1.5 Main Contributions

In this thesis, two novel platoon forming and routing algorithms are presented, that work in a distributed and decentralised way to quickly and "profitably" form a platoon. From an operational standpoint, and as further elaborated on in Chapter 3, travelling in groups can garner significant advantages, both in commercial and private routing setups. However, taking into account the voluminous data, the inherent variety in contributing factors, the discrepant environmental structures and the underpinned time constraints, it becomes clear that such a multifaceted problem necessitates a comparably sophisticated approach. The proposed algorithms are an early attempt at consolidating existing findings and developing them further to allow for a unified, holistic framework. More specifically, the algorithms are quick, respect each vehicle's preferences and limitations, and execute with maximum traffic decongestion in mind. In this context, preferences and limitations are derived from the driver's/owner's host of self-serving interests and are embedded in the algorithm to ensure the satisfaction of the vehicle agents to guarantee that the solution provided is very likely to be accepted.

As part of this thesis' research questions, two different premises are investigated through the lens of design-appropriateness and operating effectiveness to examine within the margin of reasonable assurance their capacity to incentivise platooning. The two scenarios touched on herein are giving platoons priority in traffic (thus reducing travel time) or lowering travel tolls. A feasibility analysis was undertaken to quantify the net outcome after the implementation of each incentivisation method against the absence of the conditional factor to establish the existence of a factual positive impact. On a secondary level, the numerical results of both hypotheses were juxtaposed to highlight their comparative performance and put it into perspective.

On an analogous note, this thesis also sets out to explore the potential benefits or impediments other factors may confer upon this model, based on compatibility, feasibility, probability and materiality criteria. These determinants span the broad spectrum of routing norms and principles and encapsulate elements such as traffic state, size of formations and positioning of origins and destinations for the involved vehicles.

The proposed approach executes in two stages; the first being a distributed optimisation approach and the second being a fully decentralised compensational one. While the first stage will always execute, as it is sure to find some grouping and route based on the current state of traffic, the second is optional and left to the vehicles' discretion. This two-staged approach is chosen to ensure that the computational effort required to form a platoon is not solely reliant on a single cooperating vehicle, thereby allowing the decentralised approach to have an adequate support framework.

In that vein, particular attention is paid to the previously unexplored compensational platoon formation as a platform for generating cooperative connections in an efficient, sustainable and direct way. As part of its implementation assessment, negotiation served as the primary driving force for bringing together agents with diverse interests and tolerances. To deliver useful results, this compensational approach is investigated both from an applicability and efficacy standpoint, as it is an endeavour in its infancy in the field of platooning and no prior data was available for performance evaluation or benchmarking.

1.6 Structure

The thesis is structured into nine chapters providing what the author hopes to be a thorough and comprehensive reflection of the endeavour of the past four years.

Chapter 2 introduces the basic theoretical concepts and definitions underlying this thesis, encompassing routing problems, traffic flow and management, platooning as a whole, group formation, multi-agent systems and negotiation.

Chapter 3 presents research works of note. These build the research puzzle that this thesis seeks to add a missing piece to.

In Chapter 4, the research methodology is explained. This includes the discussion of design alternatives and the justification of design decisions, as well as the choice of the framework used for evaluating this work.

Chapter 5 formally describes the problem of logically forming platoons, and the model used to solve it, where the constituent elements and their respective relationships are presented.

Chapter 6 extends the model from Chapter 5 by the specification of two mechanisms for platoon formation. First the decentralised algorithm is presented as a a mixed-integer optimisation problem that accounts for the destination, preferences and limitations of the vehicles. The decentralised and compensational algorithm is based on automated negotiation, with vehicles exchanging payments for continued collaboration. This chapter hosts the core contribution of this work.

The next chapter (7) presents the implementation of the aforementioned model (Chapter 5) and proposed algorithms (Chapter 6). This makes up the software architecture of the simulation tool.

Subsequently, Chapter 8 presents the experimental process, from hypotheses to the data pipeline and actual results. Closing off this chapter, the previously specified research questions are discussed and answered based on observations from the experiments.

Chapter 9 provides a conclusion to this work, addressing its contributions and discussing its limitations. Moreover, possible research avenues emanating from this work are presented.

2 Background

This chapter encompasses the theoretical foundation of the proposed solutions to the platoon formation problem by addressing relevant concepts as applied within this body of work. At that, this chapter touches on routing, traffic, platooning in general, group-building, multi-agent systems and negotiation as key elements for cultivating effective cooperation between selfish individual vehicles and for generating positive effects on everyday life. Firstly, the baseline notion of routing is described with respect to its mathematical definition, and potential variants with its evolution over time and with different requirements. Moving forward, traffic is expressed mathematically too, as it pertains to its measurable defining attributes. Next, the previous framework is further refined to account for traffic controls, by showcasing applicable methods and practical implementations thereof. Within this operational context, platooning is introduced as a potential solution to several problems that traffic engineers, planners and participants face. Building off on that, grouping functionalities are discussed with regards to their applicability to the researched topic. Multi-agent systems follow as a means of representing the high degree of variance that can be found in traffic with several classical coordination mechanisms being laid out to reflect the increased level of complexity that the platooning problem garners. Negotiation and all its building blocks are described next, which due to its flexible and highly decentralised nature is deemed the most appropriate mechanism for the subject of study.

2.1 Routing Problems

While this work focuses on how to group vehicles in a platoon, at a simpler and convoluted level it does boil down to routing. The optimal formation is one in which all vehicles are satisfied not necessarily with the group, but rather with the route that the group takes. Therefore, already existing problems were studied to allow for the correct formulation of the platooning routing problem.

Routing has been a field that has been studied since ancient times when communication and information dissemination was a slow and complicated process. The phrase "Veni-Vidi-Vici" became so famous due to the sacrifice that it entailed. Through the evolution of transportation, the roads became broader, the travel times shorter and the means quicker. This makes us closer, and more connected with each other in many ways and through many different roads. However, the underlying problem of routing has not changed much over the centuries, with the question "How to get from point A to B with as little sacrifice as possible?" still taking new meanings to this day. On one hand, it makes the problem of routing very concrete and stable, but on the other, it also means it is persistent and will change and evolve with the times and thus never be completely solved.

One of the more wide-spread ways of formulating and solving the routing problem is through linear programming/optimisation. The main components of a linear program are the objective function, the problem and variable constraints, so the general form is:

$$\begin{aligned} \text{maximize} \quad & c_1x_1 + \cdots + c_nx_n \\ \text{subject to} \quad & \begin{aligned} a_{11}x_1 + \cdots + a_{1n}x_n &\leq b_1 \\ &\vdots \\ a_{m1}x_1 + \cdots + a_{mn}x_n &\leq b_m \end{aligned} \\ \text{and} \quad & x_1, \ldots, x_n \geq 0 \end{aligned} \tag{2.1}$$

Through optimisation, a possible outcome space is defined based on the number of variables. Considering the constraints defined, that space is reduced to a geometric shape called a polytope which represents the *feasible* solutions. Should any constraints contradict each other, the problem is considered unfeasible. However, if such a feasible outcome space exists, there are many feasible solutions placed at the points of the polytope and one optimal solution should exist at the lowest or highest point in the polytope (depending on the objective function used).

For routing, the objective function can be made to maximise the profit or the utility or to minimise the resources used. The problem constraints can be themselves tied to travel times, length of the final route, or maximal cost permitted, whereas variable constraints ensure that the route flows through the network, or that some locations are guaranteed to be in the route or excluded therefrom.

One of the first routing problems, which then evolved in all the variants that we know today, is the Travelling Salesman Problem (**TSP**) (Miller et al., 1960). It seeks the shortest route that a door-to-door salesperson can take, ensuring that they reach all the proposed targets and return to their origin point. This problem got generalised into one of the largest families of routing problems, namely Vehicle Routing Problems (**VRP**) (Toth & Vigo, 2002). First defined in the late '50s (Dantzig & Ramser, 1959), the broader definition of such problem is "Given a set of transportation requests and a fleet of vehicles, determine a set of vehicle routes to perform all (or some) transportation requests with the given vehicle fleet at minimum cost" (Irnich et al., 2014). This also evolved and diversified over time taking many shapes, objective functions and constraints. The problem, even in its simplest form, is NP-hard and while modern-day solvers can find solutions in milliseconds, new heuristics are still developed to this day to simplify and ease the computational load for each of the variants (presented in Subchapter 3.1).

The classical Shortest Path Problem problem definition is:

$$\min \sum_{(i,j) \in E} x(i,j) \cdot c(i,j)$$

$$x(i,j) \geq 0, \forall \text{edge } (i,j) \tag{2.2}$$

$$\sum_{j} x(i,j) - \sum_{j} x(j,i) = \begin{cases} 1 \iff i = O \\ -1 \iff i = dest \\ 0 \text{ otherwise} \end{cases} \quad \forall v \in \text{ Vehs}, \forall (i,j) \in E$$

Many factors come into play when choosing a route; quantifiable ones like length and time, cardinal ones like complexity or familiarity, and even highly subjective ones like the scenery and the need for safety. But when formulating a routing problem, we are forced to employ a strictly rational decision-making process dependent on quantifiable measures.

2.2 Traffic Flow Modelling

Traffic influences not only how we move, but maybe most importantly which way we move. In a way, traffic is not like other measures of the world, such as temperatures. When a meteorologist predicts a sunny day, the masses put on sunscreen and sunglasses but the temperature is not affected. However, if traffic is predicted, it tends to nullify the prediction due to the drivers choosing alternative routes and congesting those instead of their original ones. So the complexity of choosing a route based on traffic takes the process of routing (already NP-hard) and adds on top the complexity of predicting and anticipating traffic changes.

Traffic can be represented differently depending on what problems need to be studied. At a lower level of granularity for both space and time (macroscopically), traffic is represented through flows, merging and splitting to and from one another. With a higher level of granularity (microscopic), traffic turns into moving particles that act independently from one another. However, for both cases as well as hybrid measures (mesoscopic), the modelling is based on traffic demand. These are deterministic, strict, given measurements of traffic participation which are used to model flows. With their "Traffic Flow Dynamics", Treiber & Kesting (2013) provide mathematical models to explain, study and simulate the different aspects of vehicular traffic. Based on university lectures, this book presents the measures of traffic, their representations, flow modelling aspects and different models (macroscopic, car-following, cellular automata, etc), and practical applications of the theory. The definitions and examples presented in this work are used to model the implementation of a traffic simulation, described in more detail in Chapter 5.3.

There are multiple ways of measuring traffic, the most detailed of which is the cross-sectional method. This is achieved by building stationary induction loops into the infrastructure, which the vehicles drive over and which provide the following measurements: the time the vehicle starts driving over the loop t_α^0 and the time the vehicle finishes passing over the loop t_α^1.

From here secondary measurements can be extrapolated, such as the length of individual vehicles (if a median speed is assumed), the speed of the vehicles (if a median vehicle length is assumed), time headway, time gap, distance headway and distance gap between two vehicles. Let l,α, v, t, d, and s be the length, vehicle, speed, time, distance headway and distance gap respectively.

Length: $l_\alpha = \bar{v}(t_\alpha^0 - t_\alpha^1)$

Speed: $v_\alpha = \bar{l} \div (t_\alpha^0 - t_\alpha^1)$

Time Headway: $\delta t_\alpha = t_\alpha^0 - t_{\alpha-1}^0$

Time Gap: $T_\alpha = t_\alpha^0 - t_{\alpha-1}^1 = \delta t_\alpha - \frac{v_{\alpha-1}}{l_{\alpha-1}}$

Distance Headway: $d_\alpha = v_{\alpha-1} \cdot \delta t_\alpha$

Distance Gap: $s_\alpha = d_\alpha - l_{\alpha-1}$

While all these measurements can be used to finely and microscopically simulate the vehicles, for a meso- to macroscopic simulation, a larger and more general dataset is required. This is achieved by aggregating and generalising the previous measurements, which are presented at length in Section 5.3, as they are used in the model and implementation.

2.3 Traffic Management

In the context of this work, traffic management acts both as a regulator as well as an instigator for platoon formation, since the incentivisation methods presented and used in this work are to be implemented by the traffic management authority.

Ensuring continuous flow as well as safety in traffic is done by rules, regulations and control systems which are implemented by traffic engineering and management. They can act on three different elements: roads, intersections and systems, to modify and improve traffic quality in the transport supply.

The first measure that comes to mind is infrastructure improvement, which includes maintenance as well as new expansions. However, this does not usually have the desired result, but rather the opposite, through a phenomenon called Induced Travel Demand (Cervero, 2002). This combined with an ever-increasing rate in urbanisation (Ritchie & Roser, 2018) means that there needs to be a shift towards traffic systems as a way of ensuring satisfactory levels of service. Designated lanes for specific flows (right, right-and forward, forward and left), traffic rules (right-hand priority), signs (yield, priority, minimum and maximum speeds), lights (static or dynamic, two or three-phase, urban and ramp metering) are some of the things we are accustomed to encountering, that ensure traffic participants act consistently and are also treated equally.

However, some level of preferential treatment is given to certain traffic participants, with special infrastructure designed for public transport (special lanes) or emergency services (ambulance, firetrucks and police) being able to disregard traffic rules (crossing on red, creating emergency corridors). Average road users, however, receive penalties. Toll lanes have existed since the '50s and are still used throughout the world. Although they were originally used as a means of paying for infrastructure development and maintenance, traffic engineers soon realised they could also be used to "puppeteer" traffic. Tolls could be implemented on highly congested roads (de Palma & Lindsey, 2011) or in areas with high pollution (Ulmer et al., 2014). But costs imposed on vehicles can also be used as an incentive, as reductions in tolls could be applied to specific vehicles or traffic participants to further dictate how traffic flows develop.

A more traditional way of controlling traffic is through signals, specifically traffic lights. Traffic engineers have used this method to decongest and improve flow through the network since the popularisation and introduction of private vehicles in the '20s. To appropriately design the control with traffic lights, the following elements need to be calculated: cycle time (the duration of all light phases), intergreen times (duration when opposing flow lights are both red), phase logic (coordination of different flows lights so that there are no conflicts) and green-time distribution (allowing the higher flow to have a longer green-phase). Exact definitions and calculations are presented in Section 5.4.

Calculating the appropriate times of a traffic light cycle is the first step of ensuring appropriate network throughput at busy intersections. However, based on these measurements and design decisions, more measures can be taken to ensure systemic and constant decongestion.

These methods can be classified based on their placement on a road:

– Single point: local capacity utilisation, pedestrian control, public transport stops etc.

– Line: creating green-waves, traffic jam management etc.

– Network: utilising the capacity of the network, incident management, traffic strategy etc.

Another classification is based on the levels of decision, namely long- (strategical), mid- (tactical), and short-term (operational):

– Strategical: adjusting the goals of traffic management and the traffic itself to the existing network.

– Tactical: designing and adjusting parts of the control to fit several traffic flow scenarios and situations.

– Operational: adjusting the controls to short-term traffic changes.

Depending on the input factor, several control methods can be enacted like selecting appropriate signal schedules, which is both traffic and time dependent. The adjustment and development of these plans, however, is solely dependent on the traffic conditions.

Lastly, the final type of control classification is rule- vs model-based controls, the latter focusing on using and optimising certain parameters to achieve better flow. Rule-based controls are, on the contrary, executed step-wise with a variable degree of standardisation and free-programmable solutions. Defining rule-based controls (Busch, 2018) follows the steps presented in Figure 2.1. By going through the presented steps, certain plans are formulated based on different traffic situations. An example of the selection process of such plans is shown in Figure 2.2 depending on different volumes of traffic.

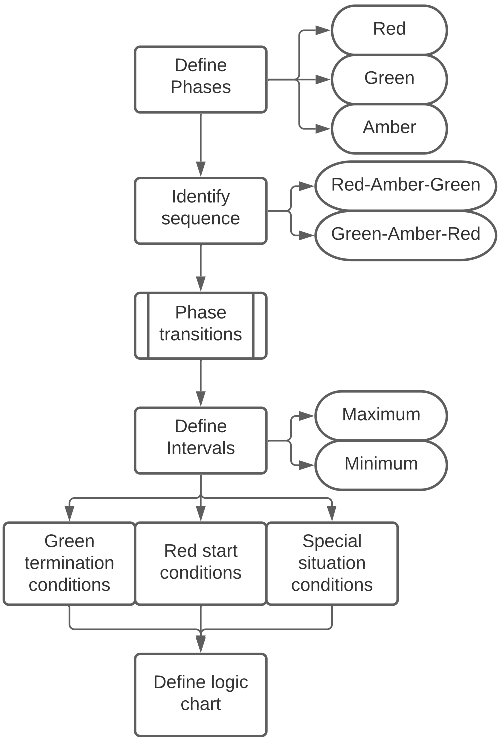

Figure 2.1: The process of defining rule-based traffic controls

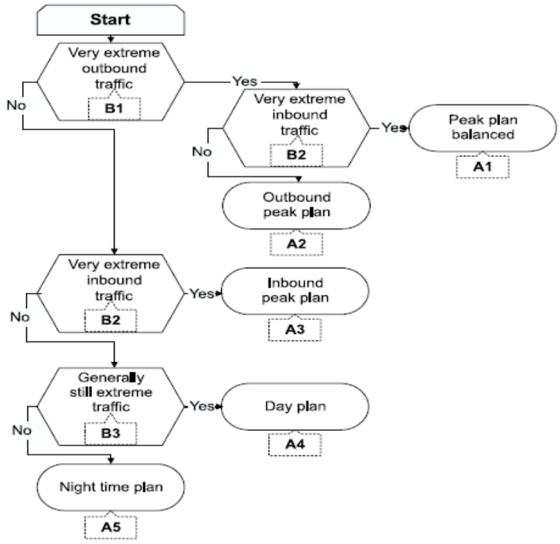

Figure 2.2: An example of plan selection

2.4 Platooning

Since platooning is the cornerstone of this work, it is important to lay the foundation, understand how it started and what heights it has now achieved. The first mention of platooning was in 1955 with Schuhl study of traffic on highways, defining platoons as ”consecutive vehicles separated by a gap less than some given value” (Schuhl, 1955). This idea was further concretised by Lewis (1958) which determined the cause of such vehicular formations, namely a signalised intersection. However, the platoons from the '50s were just loosely connected so the grouping seemed more by chance and not a coordinated effort. The concept of platooning evolved to mean any number of vehicles operating in some sort of formation, be it for agricultural reasons or military (Madeleine et al., 2012).

Nowadays, however, the area of platooning that is garnering the most attention and has the most research behind it is the column-driving of vehicles with small inter-vehicular distances. The vehicles all perform the same manoeuvres at (mostly) the same time, acting more like a train made up of cars rather than independent vehicles. Platooning seems to have many advantages over regular driving with the main two being the reduction in fuel consumption (Larson et al., 2014) and improving road-occupancy (Amoozadeh et al., 2015).

With automation slowly taking over many aspects of human life, we can see how platooning is not only achievable but can also be continuously improved.

There are many areas of studying when it comes to platooning due to its complexity; vehicular communication is needed to ensure swift and secure decision making, sensing that provides an extra layer of control and safety, controllers that can ensure smooth navigation both longitudinally and latitudinally, standards and protocols that are put in place to specify features and requirements of platooning vehicles, and platooning logic that governs over operations.

Due to the main benefits of platoons, the majority of research has been focused on highway traffic of large trucks. Given their size and weight, they tend to consume large amounts of fuel, fighting not only the force of inertia but also the "wind-drag" that comes with travelling at high speeds. By reducing the gap between trucks, at least the latter force could be reduced for the "follower" vehicles, improving fuel usage by up to 12% (Larson et al., 2014). Another advantage when talking about truck platooning is coordination, as these transports are planned with a large time window in mind, rendering the formation of such platoons and their operation an easy feat with considerable returns on investment.

However more recent research has shown that platoons could improve urban traffic as well, not only due to their improved road usage but also coordinated actions, meaning that bottlenecks could be more easily decongested (Lioris et al., 2017). With this new breath of life into platoons, all the necessary fields mentioned above had to improve, shorten, tighten and stabilise their approaches to account for quick-changing urban traffic.

One problem that (to the best of our knowledge) was not tackled extensively in existing research was the logical operations of a platoon. In itself, a platoon has to first be formed by its comprising vehicles, operate for a certain length of time or distance and then disband with the vehicles taking over individual control. Research on how to form, operate and disband platoons has been done manyfold, with necessary protocols and controls ensuring all the safe transitions of vehicles to and from a platooning state. The logical aspect, however, was never specified, all works assuming that the grouping and routing of the vehicles exists, leaving a research gap for this work to fill.

Given its complexity, multiple stakeholders can be defined in the platooning problem. Starting from the lowest level and moving upwards we have the vehicles (drivers) themselves, emergency services, public transportation companies, logistics companies and lastly ecological and traffic authorities, each one with their own goal. The vehicle (driver) wants to reach their destination as quickly as possible, the emergency services want a clear path to their destination, the logistic companies want to keep their costs as low as possible, public transportation needs to be able to plan their trips very precisely, the ecological authorities to keep emissions and noise pollution low and lastly, the traffic authorities wish to avoid and manage the formation of traffic congestion.

While tackling the problems from all points of view is difficult, two stakeholders stand out as potential "umbrella" ones for the rest: the vehicle and the authorities. As one of the benefits of platooning refers to improving network occupation and throughput, we can only expect the traffic management authorities to want to facilitate and support platoon formation and operation. In doing so, they can not only free up traffic but be able to control and regulate it through the use of incentives. Considering potential incentives, the vehicles would also do their best to participate in platooning, thus making the situation a win-win.

2.5 Group Creation

Building off the previous chapter, a platoon is nothing more than a cooperative group of vehicles driving together as one. Cooperation has been the main way to generate better results for the group as well as for the individuals comprising it. Humans have been doing it since their beginning and building small societies of hunters and gatherers has had as much of an influence on human progress as the agricultural, industrial and technological revolutions have had. However, group building has had as much of an exclusionary effect as it has contributed to establishing togetherness. Members outside the group were treated with hostility due to their threat to the group's resources (Choi & Piazza, 2016). And this has remained constant even in today's world of abundance, having evolved past threat and taken the form of competition. In traffic, this manifests by being the one who makes it through the intersection just before the light turns red, or leaving the first when it turns green to ensure you have your pick of the lane you choose to follow. But even here some cooperation is needed, whether wittingly or not, when merging in lanes in a congested scenario. Even in cases of extreme competition, cooperation has proven to lead to better results for all members involved.

Similar to traffic, grouping vehicles can also be addressed at the different decision levels. At the strategic level, long-term cooperations can be established through contracts and scheduling like grouping regular large freight transports to minimise air drag and improve fuel usage (Larsson et al., 2015). At the tactical level, a group can be formed based on daily schedules like platoons containing public transport vehicles, or scheduled logistic deliveries. Lastly at the operational level, a group of vehicles would form spontaneously and opportunistically without a prior or future desire for cooperation.

Creating a group of moving vehicles takes not only a lot of coordination at an operational level but also on a strategic level which is in direct dependence on the route. As we have seen in the Platooning subchapter, groups of vehicles are easily identifiable as they travel in the same direction roughly at the same speed. So naturally, grouping based on the route seems to be an obvious and easy answer to platooning. However, due to privacy concerns the vehicles might not choose to disclose their origin and destination, as well as their route with others. Therefore, we require a centralised unit to match, inform and group the vehicles into groups. A downfall of this approach is that with one centralised unit taking on a plethora of requests, however simple, it is still computationally inefficient. Hence the case is made for a distributed approach where instead of taking up all requests in a network, one instance only handles a handful.

Even with a distributed entity that can group vehicles according to their route, an optimal system solution is not reached. This approach just takes the trips by vehicles that would have already existed and compacts them slightly thus improving circulation only marginally. Therefore, a new approach that optimises the grouping of vehicles and their trips is needed, which is still computationally solvable and fast.

Therefore we go back to the Vehicle Routing Problem which is conceptualised for a fleet of vehicles such that the best distribution of the requests is achieved. However, with platoons, we are looking for the optimal grouping of multiple best distributions. A logical approach would be to maximise the route that multiple vehicles can travel together, but that does not necessarily achieve the goals desired, as the vehicles might be on the road for longer than originally planned. We can use restrictions set by the vehicles/drivers themselves to avoid this from happening. However, that still does not guarantee that vehicles are not travelling more than needed, but that they are as much as they deem maximal. The approach of the VRP of minimising the route is sound but needs to be applied for all vehicles together.

Distributed systems are not the only solution to the platoon formation problem, with decentralised group building also being a strong contender, with the framework for such a system being described in (Görmer-Redding, 2018). Vehicles can be allowed and equipped with mechanisms to come to a consensus on their own. With a small workaround set in place for the privacy aspect, vehicles can use voting (S. Dennisen, 2021), auctioning (Rewald & Stursberg, 2016) or negotiation (Sebe et al., 2021) as a fair way to organise themselves in platoons.

2.6 Intelligent Agents and Multi-agent Systems

To correctly implement distributed and decentralised platooning the vehicles have to be logically individually represented. While analytical approaches can provide us with robust solutions, they are also rather inflexible. Given the setting in which this study takes place, a more flexible methodology is required to account for sudden changes, varying degrees of freedom and spontaneous shifts in variables. A way of modelling different entities with a high degree of variance in between one another and volatile interactions is using multi-agent systems. In this subchapter, a short overview of the applicable information about agents and their systems is provided, based on the book by Michael Wooldridge "(An Introduction to) MultiAgent Systems" (2009).

While defining an agent proves to be a difficult task even for experts in this topic, a consensus was struck with the description that "An agent is a computer system that is situated in some environment, that is capable of flexible autonomous action to meet its design objectives" (Jennings et al., 1998, p. 8). This definition arches into the field of *autonomy*, which is defined in the same context as "the system should be able to act without the direct intervention of humans (or other agents), and that it should have control over its actions and internal state" (Jennings et al., 1998, p. 8) as well as *situatedness* which "means the agent receives sensory input from its environment and that it can perform actions which change the environment in some way." (Jennings et al., 1998, p. 8)

With the addition of *flexibility*, the concept moves away from simple goal-oriented autonomous systems to intelligent agents, and here further definitions are needed. An agent is flexible and by extension "intelligent" when it presents *reactivity* (sensing the environment and reacting quickly to satisfy their objective), *proactivity* (taking initiative to achieve their objective, not just react to changes in the environment) and *sociability* (interacting with other agents and people to achieve their objectives).

Another definition of agent which is less scientific and more reader-friendly is "a computer system that is capable of *independent* action on behalf of its user or owner. In other words, an agent can figure out for itself what it needs to do to satisfy its design objectives, rather than having to be told explicitly what to do at any given moment" (Wooldridge, 2009, p. 5). Therefore, by giving an intelligent agent a goal and ideally some characteristics, it can be assumed (taking for granted the agent was correctly designed) that they will selfishly attempt to fulfil it to the best of their design.

Many things can be qualified as agents: living things such as our cells, insects, animals, ourselves or man-made things like traffic lights, computers in a blockchain and the satellite network orbiting the Earth. Every single one of these examples has functions and goals that serve a purpose. However, just as all agents have a goal, they also are not acting alone. Cells interact with each other to transfer vital elements, insects create colonies, animals have packs and humans societies. Traffic lights will coordinate, computers will share and satellites will relay information from one to another. So no agent is left to achieve their goal on their own, but they exist in a world of many and will interact, coordinate and cooperate to do so.

Wooldridge states that a multi-agent system "consists of a number of agents which *interact* with one another, typically by exchanging messages" (Wooldridge, 2009, p. 3). The world in which the agents are supposed to operate takes form and their interaction is defined as clear communication. The cells "communicate" through their membrane, insects through dances and pheromones, animals through sounds and humans through emojis. With technological objects, communication is much simpler, as electro-magnetic impulses are the universal language. The world influences agents and in turn, the agents shape the world, hence to design a multi-agent system, both things must be designed with the other in mind.

At a glance, one can see similarities with other types of frameworks used in computer science but some distinctions make multi-agent systems a better fit for some applications. With distributed/concurrent systems, the coordination and synchronisation of agents happen at run-time and are not hard-wired into the design. Moreover, agents will act independently and even selfishly to achieve their goals with a disregard for the greater good of the system. When referencing the field of Artificial Intelligence, multi-agent systems tend to be either a patch, or the whole forest depending on whom you ask, but distinctions arise mainly in their use. One could design an intelligent agent using AI, but agents can be just a "simple" machine made up of basic programmes and while multi-agent systems rely heavily on the social perspective, AI focuses on the "components of intelligence (learn, plan, understand images)" (Wooldridge, 2009, p. 9). Game Theory also studies the optimality of solutions from an individual point of view, but very theoretically, with no clear solution. If one is presented, it is generally computationally expensive. Moreover, at least in the study of human societies, the game-theoretical concept of rational agent falls flat and proves to be inadequate due to humanity's implicit lack of perfect rationality.

Explaining the decision process of agents as well as judging how well they are achieving their goals, both for their motivation and from their owners perspective, must be a quantifiable measure since we are dealing ultimately with representations made of bits of code. Assume that in the world where agents interact, each action results in a state of said world. Also, assume that agents must perform a set of actions and even interactions that lead to a finite set of these outcomes, and that agents will have strict preferences over these outcomes. They are hard-wired into the agent by their designer and are supposed to help the agent in taking the best decisions to optimise their outcome. The utility function of each agent is meant to transform those preferences, which can be cardinal, ordinal or a combination thereof, into a real number, meaning that they can be ordered. "Utility functions are just a way of representing an agent's preferences." (Wooldridge, 2009, p. 108) and it is generally used as a formalisation of the decision-making rationality of the agent.

Unlike humans, agents are considered to be perfectly rational, only taking the actions and performing the tasks that maximise their utility. However, as agents are meant to interact with one another, they can establish cooperation, switching from purely self-interested to benevolent. Sharing information can turn into sharing tasks and resources as long as doing so guarantees an improved outcome. This is governed by the mechanisms agents use to interact, encompassed in the computational mechanism design research field, which influences the way agents make their decisions and can and should fulfil certain properties. The canonical mechanisms are auction, voting, argumentation and negotiation.

Auctions are generalised as the exchange of one good between one auctioneer and a pool of potential buyers called bidders. The former wants to maximise their profit and designs the auction protocol accordingly, while the latter seeks to minimise the price paid while adhering to the set rules. Auctions can be classified as simple where there are a single auctioneer and multiple bidders; reverse, where multiple auctioneers are offering to a single bidder; and double where there are multiple auctioneers and bidders. Some of the canonical auction types are English (amount offered starts low, grows with every bid, with the highest one winning and all agents know what the bids are), Dutch (amount offered starts high and descends, the first agent to make a bid wins), First-price sealed (all agents make one secret bid, the highest one wins), and Vickrey (all agent make one secret bid, the highest one wins but pays the amount of the second-largest bid). Each of these types has a winning strategy and suits a different degree of risk-aversion of the agents but issues like lying, collusion and counter speculation can occur.

Voting is a widespread method of reaching a consensus considering individual preferences. When discussing voting the following elements need to be considered: candidates, voters, voter preferences and the voting rule. The candidates are the set of potential outcomes and they can vary in number from two to many. The voters represent the pool of interested parties that need to reach a consensus, each with their own set of preferences, which directly translates into a specific ordering of candidates. The voting rule specifies how the outcome will be decided, as well as how the votes are handled (multiple rounds, weighted votes). The most known voting rules are Plurality (voters choose only one candidate and the one with the most votes wins), Score (voters rank all candidates and the one with the highest score wins), Approval (voters approve only the candidates that fit their preferences and the one with the highest approval rate wins), Condorcet (voters rank only candidates they approve of and the winner is the one that has the most pairwise wins) and Borda (voters rank all candidates which are then given points inverse to their ranking and the one with the most points wins) (Brams & Fishburn, 2002).

Argumentation is a method used by humans to justify their position in an interaction and it can be done in different modes, appealing to different facets of human nature. However, with agents only one mode can be applied, namely logical argumentation. This can be easily translated into arguments that are for or against a proposition, and they attack, reinforce and defeat other arguments until one or more conclusions are reached. Since argumentation is more of an abstract method, it is used in conjunction with others, such as negotiation, with the first example being the PERSUADER agent of Sycara (1990) meant to aid with salary negotiations.

While the above-described mechanisms can and in some cases have been implemented to create groups of vehicles (Rewald & Stursberg, 2016), (S. Dennisen, 2021), negotiation appeared to be the road less travelled and with the paradigm of monetary exchanges thrown in the mix, also seemed the most appropriate to explore.

2.7 Negotiation

In the context of this work, negotiation acts as a strictly decentralised way of forming, continuing or maintaining the platoon. The vehicles negotiate on routes and payments to foster continuous cooperation. The topic of automated negotiations is studied to that purpose, with new contributions not only based on scope, but also within improved bidding strategies.

Negotiation is a technique that allows for its participants to reach agreements in settings of mutual interests. A negotiation must have participants and their strategies, a subject, a specific space from which offers can be made and a protocol that dictates how the offers can be exchanged and when the negotiation comes to a close (whether by agreement or not). (Wooldridge, 2009, p. 315)

Negotiations can be categorised by many attributes; here are presented only a few of relevance:

- Domains: task vs worth
- Number of issues: single vs multiple
- Number of participants: two vs many agents

In task domains, the agents negotiate on the best distribution of tasks such that their utility is maximised. In worth oriented domains, agents negotiate on what the state they wish to achieve would be as well as how to achieve it. A multi-issue negotiation takes place over different values of many attributes which are interconnected, whereas a single issue just deals with one such attribute. Negotiations with two agents, called bilateral, are pretty straightforward. One-to-many negotiations can be modelled as concurrent bilateral, and many-to-many, besides increasing the complexity evermore, can be modelled as concurrent one-to-many.

But coming back to the components of a negotiation, certain terms and explanations need to be put forth. (based on Sebe et al. (2021))

Agents engaged in a negotiation take on a role, based on their initial action; sending or receiving an offer, *initiator* or *acceptor*. However, depending on the negotiation type they may also have both (one-to-many or many-to-many). An initiator agent is the one which puts forth an offer to the pool of acceptor agents. So any agent that is not proposing an offer is considered an acceptor. When speaking about negotiation, terms like opponent may also be used. In this case, we consider the agent from whose point of view the problem is analysed, the *ego-agent* and any other agent with whom they are engaged in negotiation, an *opponent*.

An agent's *strategy* depends on their preferences and the rules of the negotiation. When just considering preferences, agents can be highly selfish and rigid, resisting any counter-offers their opponent puts forth (also called Boulware). On the other side of the spectrum, we have flexible and giving agents, who do everything in their power to reach an agreement (called Conceders). Other types of strategies can be Linear (always conceding in equal jumps), Random (no pattern can be identified in the jumps in concession), Copycat (conceding as much as the opponent did in the previous round) and any number of intelligent agents which adapt their strategy to their opponents.

The *offer* is the subject of negotiation, what the agents are trying to agree upon. An offer can consist of a singular element or a combination thereof. If dealing with a multitude of elements, they are in direct connection and the offer can be changed by adjusting them according to the wants and needs of the agents.

To create adjustments on an offer we need to define the agent's *offer space*. This refers to the minimum and maximum value they are willing to accept for any element making up an offer. In more technical terms we are referring to the *aspiration value (AV)* and *reservation value (RV)*, which represent the endpoints of the offer-space and depending on the role of the agent, can be reversed. To reach an agreement, the offer must be within the intersection of both agents' offer spaces. Such an offer is considered *viable*.

The *protocol* represents the rules of negotiation; how the offers have to be formulated, how the agents interact, when a negotiation has reached its end and when an agreement is valid. The formulation of offers depends mainly on what type of negotiation it is (multi or single issue), but the protocol can also instate rules, such as for repeating offers (whether they are allowed or not). The agent interaction is defined by the protocol as to how the offers are exchanged; agents can send offers much like in an English auction, they can go one at a time, in multiple or single rounds. A negotiation has, in theory, two valid endings, agreement or disagreement. However, agents may choose to leave before the end of negotiations, or it might be a never-ending process, or the line of communication can fail, all situations for which the protocol must have handlers. A *deadline* can be used as a catch-all, where a negotiation ends when a set time has passed or a set number of offers have been exchanged. Lastly, in the case of agreement, the protocol must specify which offer made in the offer-space intersection will be the final one. Whether it is the first one, or can the agents continue negotiation until the deadline.

To generalise, please consider the buyer-seller example. The agents are the buyer, which is the initiator, and the seller is the acceptor. They are negotiating over a singular good, the value of which is represented by its price. An offer is then a singular value, representing the price that the buyer would like to pay to receive the good, and respectively the price for which the seller is willing to part with the good. The buyer's offer space is delimited by the aspiration value as the minimum and the reservation value as the maximum. For the seller, however, the minimum endpoint of its offer-space is the reservation value (the least amount it is willing to accept for the good), and the maximum is the aspiration value. Because an agreement is the desirable outcome, we can consider both agents to have a *linear* strategy, raising and respectively lowering the price offered in constant increments. And since in a traditional bargaining the offers exchanged are done one by one, the protocol used is the Alternating Offers by Rubinstein (1982) which allows the agents to exchange offers consecutively until the first viable offer is made or the deadline is reached.

3 State of the Art

This chapter presents and discusses the body of scientific results underlying or related to the principal areas of study at whose intersection this work finds itself. Each section presents such an area, starting from the general, and narrowing down the scope, such that the research gaps are made apparent, and the precise placement of this work is identified in the greater fields of research.

First, the field of routing problems provides insight into the development of mathematical formulations pertaining to various routing relevant determinants such as time, flow, cost etc. over time. Second, traffic dynamics are dissected to allow for a comprehensible analysis of the problems hindering effective cooperation, the consequences these underlying issues precipitate and plausible solutions to bridge the gap between the current and desired state. Third, multi-agent systems are introduced as a means of showcasing heterogeneity and embedding it into viable modelling paradigms. In conjunction with the established framework, relevant agreement mechanisms can be utilised at the service of fostering mutually acceptable solutions that cater to the individual parties' needs and preferences. The final and most important research field presented in this chapter is platooning in which the different aspects of how vehicles come to drive together are highlighted. Last, the research gaps are identified, and the investigated research questions are formulated as a segue into the research methodology and model.

A conceptual view of this work in the context of the aforementioned research fields is presented in the Venn diagram in Figure 3.1. The field of routing problems relates to the platoon formation since the objective is to find not only the optimal grouping of vehicles, but the optimal route on which this grouping can travel. Platoons can be used as a flexible way of managing traffic, since current research indicates that they offer several benefits over normal decoupled driving. The system of traffic is made up of multiple entities, acting and re-acting to the environment and each other in a way that fittingly displays the functional properties of multi-agent systems. On that note, platoons serve as the cornerstone of this research topic thereby highlighting the need to address, if not resolve, palpable existing gaps in modern research such as the traits underpinning their logical formation. As this work finds itself at the intersection of these four major topics, it is featured in the centre, represented by the document icon.

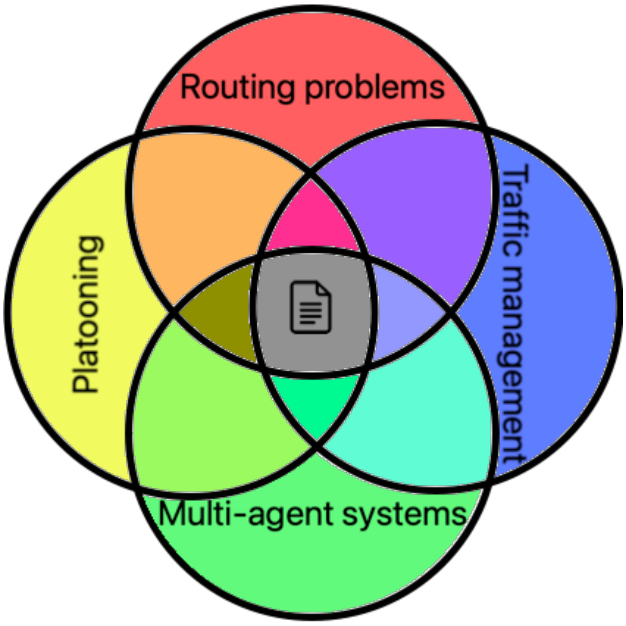

Figure 3.1: Thesis placement with respect to the research fields

3.1 Routing Problems

With the introduction of the Truck dispatching problem by Dantzig & Ramser (1959), vehicle routing problems have taken many forms, growing as new technologies and requirements developed.

The immediate successor would be the Traveling Salesman Problem by Miller et al. (1960) which seeks to find a route with the same origin and destination while covering a collection of intermediary points.

Perhaps the most known routing problem is the Vehicle Routing Problem, discussed at length in Toth & Vigo (2002) and Gendreau et al. (2008). The problem is formulated as an integer program that identifies the best routes that a group of vehicles can take to fulfil deliveries to several customers.

The time-dependent routing problem is discussed by Malandraki & Daskin (1992). Considering traffic, they discuss formulations and heuristics of the problem while addressing both hard and flexible time limits (in the form of delivery windows). They discuss the time-dependent travelling salesman as well as the time-dependent vehicle routing problems, which are adaptations of the classical travelling salesman and vehicle routing problems respectively. What makes these problems unique is the volatility of travel times, namely waiting at intermediate nodes and traffic density.

The arc routing problem by Wøhlk (2008) is mostly used in public transport, and optimises a route that requires certain arcs while minimising the ”dead mileage” (distance travelled without serving any customer). This instance is different from most routing problems as it does not necessarily create a route.

The minimum cost flow problem by Klein (1967) looks for the most cost-effective distribution of resources if the arcs have a set capacity or costs. This problem is one of the core-routing problems along with the travelling salesman and can be solved using the Simplex approach.

Some of the more developed versions of the vehicle routing problem are instances with time windows and pick up and delivery problems with time windows. In Kalina & Vokřínek (2012) the authors present solvers for these problems which run in parallel and are based on a multi-agent negotiation.

Krajewska et al. (2008) define a Pick and Delivery with Time Windows Problem and prove that collaboration between competing logistic service providers can yield benefits overall and individually. These are then shared using the Shapley value, which is the optimal distribution of the gained utility among the members of the cooperation.

Another higher-level problem is the Dynamic Taxi Sharing with Time Windows Problem conceptualised by Santos & Xavier (2013), which is applicable in the field of ride-sharing.

When considering the problem of platooning, a problem definition must be formulated, covering multiple vehicles that travel together, which find the optimal route, while also maintaining individual and group-cost down. This requires a formulation with individual and group variables which none of the existent problems offer thus far.

3.2 Traffic Management and Coordination/Collaboration

As seen with the routing problems defined above, routing is dependent on the conditions of the network, be it physical measures such as length, legal restrictions such as maximum speed, conditional measures like time windows or situational ones like traffic. With the latter, certain states are desired; maintaining and optimising flow, and when that fails, a quick and effective decongestion of those bottlenecks.

In an organised network, certain roads can appear as more valuable or popular, whether by design or chance. In their work Levinson & Yerra (2006) use a toll-based investment system along with traffic demand to identify the fundamental parameters that influence the vehicle's routes. By increasing or decreasing the allowed speed on streets per their use, the network goes through multiple iterations until an equilibrium is reached. This approach can be used in network design problems as it is simple and provides realistic results.

A major issue of traffic, but most specifically urban traffic, is pollution due to emissions. The use of lower gears combined with constant stop-and-go, as well as a very high density of vehicles, has led to measures being taken (to only allow newer vehicles or closing off the centre to traffic completely, for example) to preserve air quality in larger cities. With the development and growth of accessibility of electric vehicles, a decrease in harmful emissions is expected. To this extent, Van Duin et al. (2013) have shown that by using electric vehicles for logistic operations in Amsterdam, both the noise nuisance and the CO_2 emissions were reduced.

The influence that autonomous vehicles will have on transportation is discussed by Friedrich (2016). The network characteristic that most impacts its efficacy is the capacity, which for an urban network is restricted by signalised intersections and the time that vehicles require to pass through it. With human drivers, there is a movement delay between consecutive vehicles of an average of 0.6 seconds, whereas autonomous vehicles are expected to have at most a 0.3-second delay. This leads to an increase of at least 40% in vehicles crossing an intersection, with even higher values reachable through an increase in crossing speed. It is this factor along with the reduction of inter-vehicular distances that make the case for autonomous vehicles improving capacity and with it, traffic flow.

While traffic management studies and enforces ways to decongest and smooth out traffic, their contribution is mostly observable in urban environments with urban planning, infrastructure development, control and so on. One of the most studied ways of improving network throughput is synchronising and planning traffic light phases to create what is commonly known as a "Green Wave".

Brockfeld et al. (2001) analyse different traffic light strategies to maximise flow in an urban network. At first, they study a simple synchronised system and conclude that cycle length is the determining factor for capacity in the network, with the next ones being the distances between lights, traffic density and travel speed. Hence they enrich the previous model with an offset that accounts for the aforementioned three factors and creates the aforementioned "green wave" allowing for free-flow travel. The connection between flow and cycle length remains and the authors propose a fully randomised plan which proves to be surprisingly effective in low-density traffic.

Similarly, Wiering et al. (2004) use reinforcement learning to study and develop different adaptive strategies for traffic light control. Vehicles use a voting mechanism to determine the light cycle duration and through estimations, choose the route that minimises their travel time. Experiments run both on a simplified Manhattan grid network and a realistic urban network, prove that using reinforcement and co-learning allows the vehicles to avoid overcrowded intersections, thus ensuring flow in the network.

With Held et al. (2018), a model is proposed that adjusts the vehicle's speed to the incoming light allowing for a minimal to optimal fuel consumption. The authors measured a 26%

reduction in consumption, therefore we can add contraction of emissions as a benefit of synchronising traffic lights.

Calle-Laguna et al. (2019) present a new model of calculating cycle-lengths based on fuel consumption, emissions and vehicle delay. The new model is data-driven and uses logarithmic functions to determine the optimal cycle length. Unlike the previously used Webster model, which only focused on vehicle delay and which overestimated the necessary length, the proposed approach takes all three factors into account and delivers easily calculable methods.

A study on traffic participant volume was performed for Budapest in Juhász et al. (2016) with an emphasis on the suitability of the fundamental traffic diagram for urban and more specifically congested traffic. The authors concluded that while flow-capacity-speed curves can be applied to an urban environment, they can and will deviate slightly from the norm. As far as congestion goes, the speed is not necessarily affected by the saturation of the streets, rendering travel times to be fairly homogeneous.

3.2.1 Traffic Management: Beyond the Classical Approaches

Besides instituting traffic control strictly with synchronising lights, some researchers also considered singular vehicles and vehicle formations as ways of shaping and reconstructing traffic.

The idea behind having particular lanes reserved for a special type of traffic has been used for some time, but now we are seeing a shift from high-occupancy vehicles (carpooling and bus lanes) to high-occupancy toll lanes where a fee can be paid to use the aforementioned lanes (Burris & Xu, 2006). This strategy could be employed by logistics services providers to ensure that deliveries reach their customers on time, or by emergency services, but a derivative could also be implemented for platoons more akin to the carpooling lanes.

In (Xie et al., 2011) a multi-agent approach with look-ahead capabilities is presented as a solution to the dynamic and adaptive traffic signal control problem. Each intersection is adapted with a decision agent that can either change or prolong the current light phase, while also sharing their knowledge with the other agents in the immediate network. The traffic is organised into three categories (”anticipated queue, platoon and minor cluster”) with the control favouring the constant movement and passage of the first two groups by either extending the green phase to allow for an incoming platoon to pass or prolonging a red phase to accommodate for a platoon stuck at an up-stream light.

In (He et al., 2012) the authors propose introducing probe vehicles into the traffic, that would send information about the level of congestion or the number of vehicles on the road back to central planning, thus allowing real-time adjustments to be made. These probes are considered to be the "lead" of a group of normal vehicles and the headways between them are used to identify and cluster said vehicles into platoons. They formulate a mixed-integer linear program to address the traffic signal control problem and assess its performance based on the delay (queueing or signal) that vehicles experience. The authors address common issues like platoon splitting over multiple light cycles and network capacity and demonstrate that their approach performs better than other state-of-the-art coordinators.

3.2.2 Vehicle Collaboration and Coordination in Traffic

A comprehensive description of the collaboration between vehicles comes from Cleophas et al. (2019). The first classification of collaboration can be described on the time scale; cooperation can be arranged on a long (strategic), middle (tactical) or short (operational) term. When planning strategic cooperation, we are addressing infrastructure, network design, vehicle design issues. In this collaboration stage, actors are concerned with creating value in the long-term as well as deciding which partnerships to join. In the tactical phase, the rules and contracts are applied, updated and maintained. The issues addressed in this phase are the planning schedules, deployment of new lines or any novel stochastic approaches. On the operational level, actors are focused on managing profit, planning with dynamic information such as request routing and assigning.

Although focused on logistic operations, an overview of traffic collaboration is given in (Gansterer & Hartl, 2018). The authors studied papers that used operations research formulations as well as whether the problem considered time-windows or not, pickup and delivery or not, considering whether the vehicle uses its full capacity or not, the solution methodologies used (exact, matheuristics, metaheuristics, other) and methods to divide the profits. Unlike most other surveys, the authors pay close attention to a centralised approach to the problem and classify the literature into "Collaboration Gain Assessment" and "Methodological Contributions". They do note that most research has been in the gain assessment category and that the main issue with attempting to solve these problems in a centralised manner is the very high complexity and size of the problem. For the decentralised approach, they differentiate between Partner Selection, Request Selection and Request Exchange problems with two classes of solutions; auction-based and other.

In (Audy et al., 2012) the basics of a collaboration framework for logistic transport are laid out. The authors focus on the planning level with joint or collaborative approaches which requires a higher level of information exchange and a stronger level of business interactions. The steps needed to manage such a collaboration are defining the responsibilities, selecting the leader and addressing the benefits (evaluation, planning and sharing) and lastly creating an appropriate coordination mechanism. As an example, five generic such mechanisms are presented, each with their best application domain:

– maximisation of savings with financial flow benefit-sharing (producer and seller sharing transportation costs)

– maximisation of savings with economic principles benefit-sharing (producer and seller sharing the costs and profits based on set rules)

– maximisation of savings with constrained benefit-sharing (producer and seller switching tasks so that the resulting plans cost less than operating individually)

– concomitant maximisation of savings and benefit-sharing (producer and seller split costs and profits proportionally)

– partial maximisation of savings with multiple coalition opportunities (producer and seller define their own collaboration rules based on a semi-optimised plan)

Traffic collaboration does not apply strictly to large companies using trucks but can be used for smaller shipments where demand is unknown or volatile. Yilmaz & Savasaneril (2012) define this problem using Markov decision chains and with a game-theoretical approach to address the issue of sharing benefits in a way that allows the collaborations to continue and develop.

A study that regards autonomous vehicles specifically is done by Aschermann et al. (2017). The authors investigate methods of vehicle collaboration in the case of 2+1 roadways, more specifically, what are the factors that influence precedence and driver satisfaction and the potential methods to employ that account for fairness as well as the aforementioned driver satisfaction.

3.3 Multi-Agent Systems and Agreement Mechanisms

Coalition and group actions are analysed from a theoretical standpoint in Pynadath & Tambe (2002) work. They define the Communicative Multiagent Team Decision Problem as a tuple of states, actions, dynamic problems, agent observations, information structures, beliefs and rewards, with an extension that allows for communication. This allows for teamwork to be studied for general and specific domain applications.

Using multi-agent systems is a reliable way of simulating and testing traffic measures. One very important study is the one done by Roughgarden & Tardos (2002) where the impact of selfish routing of agents is measured on the system, wherein they describe it as a non-cooperative way to achieve Nash equilibrium.

Collaborative driving modelled through multi-agent systems is presented in Hallé & Chaib-draa (2005). The authors propose structuring the driving model on three layers (guidance, management and traffic control) to operate centralised (leader coordinates the follower vehicles) and decentralised (participant vehicles operate relatively autonomously) platoons. The guidance layer is at the bottom and operates the vehicle controls and the sensing, the management layer coordinates intra- and inter-platoon actions as well as planning. The traffic control layer finds itself at the top and is independent from the vehicle itself having to do with traffic rules, regulations, state and information. The authors investigated two implementations each of centralised and decentralised platoons, and while the centralised had the advantage of being low in communication requirements, the teamwork decentralised scenario proved to be flexible enough as well as able to handle uncertain situations better, thus making it the frontrunner for further research.

3.3.1 Agent Rationality: Relevant Factors and Utility Functions

Because the subjects of this study are platoon coordination mechanisms, their effect on the individual vehicles needs to be measured. Therefore a utility-based model is applied with individual and overall betterment as the objective. To determine the components of the utility function, the following research work was investigated.

3.3.1.1 Cost

Coming back to the main resource for agents, Wooldridge (2009) does mention that a utility function cannot just be simply calculated based on the costs, although in the general sense it could be simplified as such. A hundred euros might not bring that much utility to a millionaire, but it would be a massive improvement in utility for a school child. On the opposite end of the spectrum, the same holds, a debt in the thousands would not shift that much in (dis)utility with a donation of a hundred euros, but for a debt of the same value, it is a considerable improvement.

In the context of traffic, a study addressing pricing for the convenience of faster passage was the one carried by Burris & Xu (2006), where they implemented tolls on specific lanes of the highways around the major city of Houston, Texas. The authors had an in-depth look at what level of tolling can be applied considering the economic standard of the drivers and concluded that a considerable number of the road users would use the toll-lanes outside of peak hours, which would have a positive effect on traffic decongestion as well as generate revenue for future developments.

3.3.1.2 Time

In (Benyahia & Potvin, 1998), the utility of a detour to pick up a new delivery is calculated based on the delay the actual detour accrues, the average lateness of future pick-ups and drop-offs as well as the pickup and delivery time of the extra order.

When looking at platooning benefits in the sense of time-saving when travelling, either by allowing driving on a separate lane or giving precedence to platoons at red lights, one still has to be able to transform that time to either utility or even better, quantifiable monetary value. A clear definition of this process is given by (Brownstone & Small, 2005, p. 280) as "the marginal rate of substitution of travel time for money in a traveller's indirect utility function".

If this ratio is communicated to the traffic management entity, a better trade-off can be arranged, where the platooning vehicles are allowed for even faster passage and the load on the network is eased for the traffic planners. In short, the break-even line, across all actors, can be more easily identified and adjusted.

3.3.1.3 Distance

In (Kleiner et al., 2011) the valuation of a route is based on the length of the route, considering detours and price per kilometre. Since the subject studied is ride-sharing, the goal of the approach proposed by the authors is to minimise Vehicle Kilometers Travelled (VKT) while also ensuring a high rate of matches between passengers and drivers.

In (Zachariadis et al., 2010) the authors present a novel methodology of solving a classical routing problem, namely the Vehicle Routing Problem with Simultaneous Pick-ups and Deliveries (VRPSPD). In this work a route's utility is calculated based on its length, the number of times it was previously taken and its cost.

3.3.2 Agreement Mechanisms

Kraus (2001) describes in detail techniques for agreement mechanisms in multi-agent systems, based on their application scenario and modelling technique, while also evaluating them based on five criteria of performance: negotiation time (finite and quick), efficiency (Pareto solutions are desired), simplicity (lower computation time), stability (agents benefit from sticking to their strategies), and lastly implementing monetary transfer as a way to resolve conflicts. The author presents negotiation models used in distributed artificial intelligence (distributed planning for distributed problem solving and task, state and worth oriented domains for multi-agent systems), social sciences (formal bargaining and negotiation guides) and strategic negotiation (alternating offers protocol). She also presents auctions as a way of resolving contracts and the different types are showcased and analysed (one-to-many: English, first price sealed, second price sealed, dutch; many-to-many: double), and introduces the concept of market-oriented programming to address the distributed resource allocation problems. Lastly, coalition formation is discussed, presenting different approaches to resolving the NP-complete problem of finding/creating the best coalition that maximises overall as well as personal utility.

Cooperation has been proven to improve not only system-wide utility but also individual utilities of participating agents, even in the case where they are in direct competition. Especially for individuals, private information leads to uncertainty, which in turn can cause a lesser degree of cooperation than expected and required. Kraus et al. (2003) showcase a negotiation protocol specifically designed for this case, with accompanying heuristics. The protocol is an auction-based model, where an agent can propose or accept an offer, which is valid for one single negotiation round. The process is overseen and managed by a neutral, non-disclosing third-party agent, which has more complete and accurate knowledge of the system than the negotiating agents. The two heuristic approaches are as follows: The Marginal Heuristic: to rank, sum the costs of all agents participating and subtract the value of the coalition (normalised by dividing through the maximum value of the coalition), which is best for a complete information scenario; and the Expert Heuristic: reduction of competition, capitalising on expertise. An agent is an expert when there is a low number of other agents able to perform a specific subtask, and they prefer tasks where they have little competition. This heuristic is best applied for cases where we have incomplete information.

Overall there have been many studies (Chakraborty et al., 2018), (Vo et al., 2016), (Gal & Pfeffer, 2007), (Guttman & Maes, 1998), (Raiffa, 1982) proving time and time again that cooperation, in comparison to independent action, leads to better results, both globally and individually and for both cooperative and competitive agents.

3.3.2.1 Voting

Stepping away from the strictly theoretical studies, Parhami (1994) presents voting algorithms specifically designed to be used in computational systems.

IPCon (Sanderson & Pitt, 2012) is an improvement of the Paxos consensus specifically made with decentralised, open and resource-limited systems (like vehicular networks) in mind, addressing issues like situational changes, anarchic behaviour or breakdown. The authors describe, implement and prove its correctness.

When considering traffic, vote-based agreeing mechanisms need to be highly scalable, flexible and considerably quick. S. L. Dennisen & Müller (2015) identify the needed architecture and describe the degree of fulfilment, as well as address the appropriate design decisions needed to implement voting as a coordination mechanism in traffic.

In the context of platoons, voting was investigated as a coordination mechanism by Teixeira et al. (2018). They compared the suitability of four voting rules in single-candidate elections: plurality, approval, Borda, and Copeland, and evaluated them based on platoon utility and the time it took to reach a consensus. The performance of all voting rules was good and relatively similar for both metrics, legitimising voting as a suitable coordination mechanism for driving as long as the voting population is small. With platoons with over nine members, the consensus is reached in over two seconds, thus making it unfeasible for traffic applications.

3.3.2.2 Auctions

Auctioning is used as a method of load allocation for logistic transports in (Robu et al., 2011). The authors designed, modelled and implemented a multi-agent auctioning system to be used by an actual logistics company in Nijmegen, the Netherlands. The platform is used to create and assess different bidding strategies and can accommodate automated bidding agents and human bidders alike.

Rewald & Stursberg (2016) propose the use of auctions to determine driving strategies in 100% autonomous traffic and differentiate their work from other auction-based approaches by not only taking the global goals and constrictions into account but the vehicle's preferences and restrictions as well. The subject of the auction is the order in which the vehicles will travel in case of contention and the payment is the increased cost a vehicle will accrue if they allow for the other to take precedence. In the interest of fairness, the vehicle with the higher cost "wins" the auction and travels before the other. Their cost function is dependent on the lane the vehicle is occupying, the distance to the preceding vehicle, the speed, the acceleration on the curved part of the road, the time and distance it takes to execute the overtaking manoeuvre. To discourage over-gauging of their costs each round, the authors propose combining a previously lost auction with the current one, due to the likelihood of facing the same opponent regularly, thus fostering continuous cooperation during the drive.

3.3.2.3 Negotiation

Since automated negotiation can be easily manipulated by controlling the interaction protocol, Sandholm (2000) presents technologies that would combat this practice and ensure computational efficiency. First, the contracts that result should be combinatorial, to not allow for marginal cost manipulation (since the agent's utility increases over time). To account for changes over time, levelled commitment should be implemented. Instead of trying to find the best coalition to join, the agent could consider the whole crowd as a potential coalition, and then through a slice-and-dice approach, identify the best sub-coalition. The computational cost should be sacrificed to improve the quality of the coalition, forcing self-interested and potentially insincere agents to search parallelly, thus ensuring enough effort is provided in finding a "fair" solution. And lastly, splitting the exchange and manipulating the order of execution of the parts, exchanges can occur directly, without the use of an intermediary.

A more general analysis of automated negotiation is provided by Jennings et al. (2001). The authors define the core elements of automated negotiation and discuss the main analytical approaches to it, concluding with the need for a centralised resource containing multiple negotiation techniques, each applicable to a specific scenario.

Bartolini et al. (2004) attempt the standardisation of automated negotiation, where they define declarative rules that would describe a multitude of negotiation mechanisms, supported by an example and followed by a software framework that implements all the previously mentioned rules. The rules they describe fall into several categories: admission (states which agent can participate), proposal validity (offer needs to fit a template), protocol reinforcement (when to post, what can a new offer be considering previous offers and if and when proposal can expire), updating (how parameters change with certain events, who can view a proposal, whether and how participants are given information about proposals), agreement (which proposals are compatible and what agreements can form) and lastly lifecycle rules (when to stop proposal posting). The authors define a protocol as having three stages: admission (propose message sent to host, responds with "accept" or "reject"), proposing (propose message sent, continues until termination, proposals are checked, if not rejected information is updated, notifications sent, can be withdrawn if allowed) and agreeing (host finds compatible proposals, matches and informs the parties). The software framework consists of a host, which is an agent with subsidiary ones, each responsible for the enforcement of one category of rules (gatekeeper, validator, enforcer, updater, maker) all interacting through a blackboard. The other negotiating agents communicate directly with the host.

Faratin et al. (1998) propose a formal model to be used in automated negotiation defining the terminology, conditions, tactics and strategies. The different tactics that can be used in negotiation are resource-, behaviour- and time-dependant. Assuming a time-dependant negotiation, agents can fall in the following categories: Boulware, where the agent does not concede until the end of the negotiation; Linear, where the concessions made are constant and equal; and Conceder, where the agent "gives up" rather quickly. With a resource-based system, the offers primarily depend on the resource, but also on the time the agents are willing to spend negotiating and the cost of the communication. Lastly, for behaviour-dependant tactics, an agent's offer is dependant on the opponent's in a tit-for-tat manner.

Following the previous paper, Fatima et al. (2001) determine the best strategies that can be applied in negotiations with incomplete information considering the effect of time on the exchange. The authors define six different types of environments with regards to the agent's utility over time, and with different levels of accuracy for estimating the opponent's reservation values, form the optimal strategy. The theoretical outcomes of negotiations when both agents used their respective best strategies are also presented and the two main conclusions are that the agent with a longer deadline will benefit more when this agents' utility increases with time, an agreement will be reached by the earliest deadline, but when the opposite holds, the negotiation will end sooner rather than later.

Also in the same vein, Hou (2004) proposes and demonstrates several heuristics for each of the three negotiating tactics using linear regression to learn about the opponent.

Applicable use of negotiation in the context of traffic collaboration is a method for creating incentive contracting. This phenomenon happens where one agent persuades another competing or non-benevolent agent to cooperate and carry out a non-common task through monetary incentives. This means that an agent can maximise their utility, achieving certain goals more easily than they would if acting on their own. A specific study in the field of multi-agent systems is done by Kraus (1996) where she provides different techniques to create incentive contracts considering a multitude of scenarios. These can be certain vs uncertain situations; full vs partial or symmetric vs asymmetric information; and bilateral exchanges vs ones with multiple agents. The specific scenario studied in this thesis would fall under certain, partial but symmetric information and a mixture of bilateral and multiple agent exchanges.

Vo et al. (2016) prove that splitting the winnings from a coalition results in a higher degree of successful negotiations in the case of incomplete or private information. The mechanism they propose relies on giving cooperative agents a higher "cut" from the surplus resulted, and it applies best in multilateral negotiations since there is no need to consider any potential opponents. With this incentive, the negotiations tend to end both in an agreement, as well as sooner, since higher concessions mean that the intersection of offer spaces is reached more quickly, thus also reducing the risk of breakdown.

3.3.2.4 Opponent Modelling

To ensure that negotiations end favourably for all parties involved, it is recommended to develop an opponent model within the bidding system of an agent. This ensures not only that negotiation is kept short and simple, but also increases the likelihood of a win-win conclusion (Baarslag et al., 2016b). To create a successful model the agent must learn the acceptance strategy, the deadline, the preference profile or the bidding strategy of the opponent. Not all aspects are necessary, but a combination thereof would provide more desirable results.

A more in-depth study on opponent modelling is the one by Baarslag et al. (2016a). The arguments brought in favour of automated negotiation with an opponent model are higher chances of favourable agreements for all parties, reducing time and computational effort used in negotiation and averting being manipulated. The methods most commonly used to learn about the opponent are Bayesian learning, used for all previously mentioned opponent attributes; non-linear regression, for the bidding or acceptance strategy and deadline; Kernel density estimation, for the acceptance strategy and preference profile; and artificial neural networks for the acceptance and bidding strategies.

In time-sensitive domains, agents concede at different rates until they reach their reservation value, and negotiation is successful when an offer is made that lies in both agents' offer spaces. However, conceding immediately to an offer that the opponent is likely to accept or holding on in hopes that the opponent will concede is never the best strategy. One solution to this problem is presented in (Baarslag et al., 2015), where an adapted simultaneous search algorithm is used to create the succession of bids that yield the best utility, considering how likely they are to be accepted. The authors prove that this approach performs better than other state-of-the-art bidding strategies and leads to a high rate of win-win outcomes.

Artificial Intelligence is emerging as an application to automated negotiation. One example is the work of Bakker et al. (2019). The authors propose a combination of reinforcement learning with the BOA framework (bidding module, opponent modelling and acceptance strategy) to create and adapt a negotiation strategy that leads to beneficial results applicable for multiple domains, opponents and negotiation settings.

3.4 Platooning

While there are many sides to platooning (safety, stability, communication, control) the focus here will be on platoon coordination, manoeuvres and routing. However, a brief overview is given on the topics outside the area of interest.

A platoon ontology is presented in (Maiti et al., 2017) which defines three main elementsm, namely *platoon, vehicle* and *operation* and their properties. While *platoon* and *vehicle* are simple and only feature characteristics, *operations* can be broken into sub-atomic functions (primitive and derived) and sub-subcategories. *Atomic functions* are defined as simple actions that "can represent any platoon operation by changing their order of occurrence" (Maiti et al., 2017, p. 7). They are: verify the condition, lead selection, execution, perform selection, information sharing, information update, commitment, inform lead. The *primi-*

tive operations refer to active manoeuvres, namely merging (front, back and creating) and splitting (front, back and destroy), and consist of the aforementioned atomic functions. *Derived* operations, however, are composed out of primitive and atomic functions, or recursive calls to a primitive operation. The authors define middle merge, change of leader, give way, group middle merge, middle split as derived.

B. Li (2017)provides a guideline to modelling platoons. He addresses vital characteristics, namely size, intra- and inter-platoon headways, and speed from a statistical point of view.

While platoons tend to refer to a classical column formation, Madeleine et al. (2012) address other formations: line echelon and wedge for less transportation-focused applications, like agriculture or military operations. The authors consider the platoon to be led by a human-driven vehicle and base the model of the alternative formations on the classical column approach. The automated follower vehicles have a virtual image of the leader that is projected in front of them, with a lateral longitudinal translation, depending on the desired formation. This allows the platoon to perform as a logically classical column, while physically not being one. Simulation experiments with these alternative formations provided satisfying results concerning trajectory, stability and security.

An overview of existing literature on truck platooning is presented in (Bhoopalam et al., 2018) where the authors present platoon characteristics, some of which being applicable in urban scenarios as well. Firstly, the time-horizon of the platoon planning: scheduled, real-time or opportunistic. Then the goal of the platoon: saving fuel or creating an as large as possible convoy. While the first aspect is also applicable in an urban space (maybe without the opportunistic case, since waiting in traffic would impede it further, as well as needing changes in the infrastructure), the second does not since fuel reductions are not theorised at such low speeds and considerations that the size of the platoon has to be confined. The authors also present restrictions that large freight transport platoons might face and ways of sharing the profits generated through platooning (discussed in an upcoming subchapter).

To be able to reap the benefits of platooning, Van Arem et al. (2006) concluded that a penetration rate of at least 60% is needed in a high traffic scenario, or even higher in lower traffic. Given that this study was conducted with a highway system in mind, it is safe to assume that these values would be the bare minimum if urban environments are considered.

3.4.1 Communication in Platoons

Platooning and all its stages (formation, operation and dissolution) require communication and while this is not the focus of this work, it is important to present and understand certain features which are presented in the following subsection.

The first mention of intelligent transportation is made in (Qu et al., 2010) where the authors survey potential technologies that would be able to implement such a system.

Suitable protocols were investigated in (Willke et al., 2009). Based on their findings, urban platooning would require a protocol with small latency, high reliability, potentially with receiving confirmations, a low scaling requirement, a small range, and high group persistence.

Requirements and applications for vehicular communication were discussed in (Karagiannis et al., 2011) and for platooning, the authors specify the minimum frequency to be 2 Hz and the minimum latency to be 100 ms.

Pallis et al. (2009) study the effect of time on an ad-hoc vehicular network, examining localised, community and network-wide metrics. They conclude that it is not the connectivity degree of a node that is the most important factor in maintaining connectivity, but rather betweenness (fraction of the shortest paths between any pair of nodes that pass through a node) and lobby index (the largest integer k such that the number of one-hop neighbours with a degree at least k equals k), however, as a whole, a Vehicular Ad-hoc network (VANET) cannot be considered robust.

Lastly, in (Jia et al., 2015) the authors discuss at length architectures, standards, protocols, constraints and preliminaries while also addressing traffic on a networking modelling level. Issues like management, stability, cooperation, inter- and intra-platoon communication in the current platooning systems are also addressed, followed by an in-depth analysis of the current simulation platforms.

Practical experiments were presented in (Gao et al., 2016) where the authors used "Dedicated Short Range Communication" with a platoon of two trucks in multiple networks and road types. The authors argue the need for two antennas, one on each side of the truck, to allow for continuous communication in curves where the signals might be blocked by infrastructure or the truck's own trailer. They found their approach to be highly effective, with continuous communication being achieved even at 78 metres distance, but they do note that for better performance, the use of antennas should be alternated to avoid interference.

Gerrits et al. (2019) introduce the concept of "Multi-brand platoons", namely trucks from different manufacturers, to study the need and effect of Cooperative Adaptive Cruise Control (CACC) standards in a critical application.

3.4.2 Platoon Safety and Stability

Ensuring that platoons are safe is the first hurdle in the journey of introducing them into everyday traffic and reaping their benefits, hence a few works of note about how this could be achieved are presented here.

One of the most important aspects of platooning is maintaining a safe inter-vehicular distance. To this extent, Swaroop & Hedrick (1999) discuss the different spacing strategies (grouped in constant, variable and hybrid) and their string stability.

- Control with information of reference vehicle information only: best platooning performance but unsafe, best lateral control strategy.
- Autonomous control: based on board sensors, unstable, sinusoidal speed.
- Semi-autonomous: weak string stability.
- Control with information of lead and preceding vehicles: string stability.
- Semi-autonomous control with vehicle ID knowledge: propagation errors and noise.
- Control with information of only r immediately preceding vehicles: only weak string stability.
- Mini-platoon: string stability guaranteed.
- Mini-platoon with leader info: leader info is supposedly slower.

A major consideration when discussing platoons must be given to the safety of such formations, mainly measured in the form of string stability. This describes the level of force attenuation to be expected downstream if a sudden movement (either acceleration or most likely deceleration) is produced upstream. Ploeg et al. (2013, 2017); Ploeg & de Haan (2019) have addressed this issue at length and a summary of their works will be presented here. Just as other researchers have argued, singular direction (longitudinal) movement is not comprehensive enough to accurately define platooning. Ploeg describes the latitudinal movement as manoeuvres that are critical when it comes to the formation and dissolution stages of platooning. Therefore, a new definition of string stability specifically thought out for platoons is introduced in (Ploeg et al., 2013). The authors presented that a time headway of 0.7 seconds would be enough for the platoon to achieve L_2 stability and with reduced communication latency, this headway could be reduced further.

Then the practical approach to platooning, in the form of the 2016 Grand Cooperative Driving Challenge, was discussed in (Ploeg et al., 2017). The authors employed a layered control architecture, dividing the systems into three layers for long (strategic), mid (tactical) and short-term (operational) actions and decisions. The operational layer handles the controls for manoeuvres, the tactical handles the coordination between vehicles for speed adjustments or manoeuvres and the strategical layer takes on decisions like routing or fuel-optimisation. The two scenarios investigated were highway lane reduction, where two platoons would be compelled to join into one due to a lane blockage, and an intersection scenario, where competing vehicles would form a logical platoon to coordinate a smooth crossing. With the challenge being a competition, the developing teams were judged, but the overall achievement of the event was furthering the development of cooperative driving.

Coming back to safety, a more recent paper (Ploeg & de Haan, 2019) discusses safety issues that might arise with platooning either from "safety of the intended functionality" threats or functional safety failures. The authors note that the current standardisation does not fully cover all issues related to automated driving, since they just address partial automation. However, possible countermeasures are listed for each major threat or failure, and these can be categorised as "graceful degradation and fail-safety". To implement these countermeasures, the authors propose again a layered controlled architecture combined with an agent-based system, which is responsible for each manoeuvre.

To add even more security in case of communication breakdown and rapid deceleration upstream, Ligthart et al. (2018) propose the use of an automated "Collision Avoidance" controller. This takes over when the normal controller fails to ensure a safe driving condition and brakes gradually until safety is again achieved. The controller is tested by measuring the minimal safety inter-vehicular distance and performs well even in emergency full-brake situations.

3.4.3 Platoon Controllers

Platoon controllers are algorithms embedded in the vehicles that ensure the correct operation of platoons and this subchapter presents a small but relevant set.

In (van Willigen et al., 2013) an artificial intelligence algorithm meant to optimise travelling in platoons is presented. While the authors only focused on two aspects, namely speed and passenger comfort (measured by the number of lane changes), their algorithm created controllers that outperform other state-of-the-art controllers such as the Intelligent Driver Model (Treiber et al., 2000).

In (Alam et al., 2015) a controller for large transport trucks is presented that takes into account the engine's response times and the dynamic coupling between vehicles while also being relatively computationally simple. In contrast to other controllers presented before, this approach can be applied to any length of a platoon, meaning other trucks could join a platoon without any significant problem, making it highly scalable. The performance was not only analysed mathematically but was also tested on a three-truck platoon where multiple factors (breaking reaction, acceleration, inter-vehicular distance, speed matching, etc.) were observed to ensure the good performance of the controller.

Another controller for platoons is presented in (Kianfar et al., 2015) which fulfils safety, performance, accelerating, actuating, speed and string stability constraints by combining a model predictive controller with a linear one. The authors performed a real-life test for the proposed controller and noted positive results in speed matching (from acceleration to deceleration and complete stops) as well as string stability.

Although thought out for freeway applications, Amoozadeh et al. (2015) present a communication protocol for managing a CACC-enabled platoon. They define three needed manoeuvres; merge, split and lane-change, that are coordinated with a series of message exchanges between each vehicle and its direct leader. The authors model the necessary interactions as finite state machines and test the effectiveness of their protocol on flow stability in state-of-the-art simulation software.

Qian et al. (2016) propose a hierarchical model predictive controller for autonomous driving in formation. First, a virtual centre point is calculated for the formation, which through latitudinal and longitudinal projections is used to control all the participating vehicles. Then the trajectory is defined considering obstacles on the road (mobile or static, on or off-road). A lower level Model Predictive Control (MPC) is also used at the vehicular level to model the actual forward movement.

Santini et al. (2018) present a longitudinal controller based on the distributed consensus of the vehicles' speed and absolute positions, which ensures stability even with changes in the platoon formation and manoeuvres. The presented model accounts for delays in communications and the simulation tests presented cover the most likely platoon manoeuvres: joining and splitting from the end as well as joining and splitting from the middle.

In (Shet & Schewe, 2019), a new State-of-the-Art CACC is presented and compared to other longitudinal controllers like the Adaptive Cruise Control (ACC) and CACC presented above. The difference between this controller and the classic CACC is the "feed-forward feedback gap control enhanced with the speed control mode and emergency braking as well as fallback ACC". The new controller is then evaluated based on safety, communication reliability and passenger comfort. While on the safety side the proposed controller matches the other State-of-the-Art ones, it fully outperforms them in the area of comfort for the four manoeuvres studied: acceleration, oscillation, brake and catch up.

Another controller developed for highway and large freight use is presented in (Abraham et al., 2020). The newly proposed controller features the following characteristics: followers track the speed and are responsible for maintaining the gap to their respective leader; each vehicle computes its controls based on information about its leader and the head of the platoon; speed and position are continuously communicated by all vehicles engaged in a platoon; followers always have available the speed and position of both its respective leader and the head.

Schindler et al. (2018) study urban platooning at length and propose the use of state machines as controllers for each of the platooning logic elements. The platooning state machine represents the stages of a vehicle respective to platooning; not able to join, willing to join or create, currently in a platoon and leaving a platoon. The second state machine is the forming one; this is active when a vehicle is currently in a platoon and is used to describe the stages of forming the platoon (waiting for trajectory, currently forming, normal platooning). The messaging state machine is next and is based on extended legacy cooperative awareness messages (ECAM) and platooning cooperative extended messages (PCAM). Lastly, the distance state machine measures the gap to the preceding vehicle and categorises it as normal distance, gap distance, close distance. The authors describe the platooning process as vehicles joining together at an intersection, where the last vehicle to join the platoon transmits the information to a potential joining vehicle. Each vehicle is responsible for its own decision to split from the platoon, as the leader is not responsible for the safety of the members. Due to the volatility of urban traffic, in the case when the platoon is "interrupted" by a non-platooning vehicle, the resulting gap may be increased to allow it to merge, and only when it registers as directly in front, will the platoon split in two, with the possibility of other vehicles joining in.

Khalifa et al. (2018) developed a controller to address the longitudinal control of vehicles in platoons with urban driving in mind. Instead of relying strictly on information from the leader or the preceding vehicle, the driving goals are defined based on the path coordinates and information the sensors can pick up. Beyond this controller, they also address platooning in the case of a communication breakdown, through a consensus mechanism that ensures stability and safety.

A controller for platooning in an urban scenario is presented in (Khalifa et al., 2020a). Due to the type of roads (significantly more curved and short), the network complexity (highly connected) and driving behaviours (aggressive vs careful drivers) controllers designed with highways in mind cannot be used. The authors combine sensors with communication, to gather information about the state of the vehicles in a platoon in a way that respects string and asymptotic stability. The novelty of this approach lies with the introduction of an observer who is responsible for estimating the distance to the leader without using communication and that accounts for the time delay of the sensors.

Another controller for urban environments is presented by the same previous authors (Khalifa et al., 2020b). With this work, they propose a longitudinal controller with less communication overhead and more of a sensory-based information loop. It is based on a "hybrid Information Flow Topology (IFT)" where a platoon leader relays information to all followers, and they, in turn, execute the more finely granular manoeuvres based on light detection and ranging (LIDAR) measurements of their respective predecessor. On top of this, consensus-based methods are used to account for delays in communication and sensing.

More recent controllers include a non-linear ACC by Karafyllis et al. (2020) and one using macroscopic information to ensure string stability by Mirabilio et al. (2020).

Adjacent to all the presented controllers, Wijnbergen & Besselink (2020) develop and prove the existence of specific conditions that decentralise controllers must exhibit to maintain safety and stability in the platoon. Consider a leader-follower structure, where the responsibility for inter-vehicular spacing falls solely on the follower vehicle, and then with the help of geometric control theory, the respective conditions are calculated based on the desired spacing policy.

3.4.4 Platoon Operations

Under platoon operations, all works on actual platooning activity are presented. They may fall under manoeuvring, network design, logical operations, ecological impact, resource distribution and matching to name a few.

M. A. Khan & Boloni (2005) discuss the logical aspects of platoon formation with the aid of a convoy driving device, which will not only assist in deciding whether to join a platoon or not but also in the merging and splitting actions. The authors prefer a decentralised formation, where all concerning vehicles would agree on the coalition, to a centralised approach (leader decides and followers must comply) due to the highly dynamic setting with multiple vehicles moving constantly at various speeds. The decisions done by the vehicle about the convoy/platoon, are done depending on the utility that they entail; this is discussed further in the next study (M. Khan et al., 2008). The authors also tested their claims through simulated realistic traffic conditions and concluded the idea to be feasible.

M. Khan et al. (2008) discusses the effects on utility both from a singular (vehicle) and collective (platoon) point of view. Upon either operation (joining, staying or leaving), individual vehicles will make the selfish choice of going for the best option, namely the one which provides the best utility. But on the whole, each vehicle has a distinct influence over the group utility: it can either adapt to the current state of the platoon and maintain stability without any major utility changes, come to a common arrangement with all the other participating vehicles, or try to influence the group by forcing change (for example as a leader, speeding up or down, and the rest of the vehicles following suit).

Considering that fully autonomous vehicles are not only a far future but that it will take even longer for traffic to solely consist of them, Guo et al. (2012) present a manoeuvre for platoons operating in mixed traffic. In the event of a human-driven vehicle cutting through a platoon of autonomous vehicles, it usually has to split into two, thus losing efficacy. The authors propose an anticipatory manoeuvre that allows for the safe passage of the intruding vehicle while also maintaining the platoon formation(but not the columnar shape) and then reassembly.

A platoon coordination mechanism is proposed by Dao et al. (2013). They formulate the problem as a linear integer problem to minimise costs which are dependent on the number of vehicles in the platoon and the distance between the entry point and destination of all vehicles participating. The authors consider the following preliminaries: once the platoon is set it must stay intact until the vehicles' respective destinations; there is a maximum number of vehicles allowed in a platoon; the destinations of all vehicles in a platoon must belong to a specific interval; they are sorted by their destinations (closest destination goes last, the leader goes furthest); and if no feasible platoon is found the vehicle is designated as the leader of a new one.

A more recent approach to spontaneous platoon formation comes from Ma et al. (2020). The authors present a novel map-matching algorithm combined with a spatial clustering information approach to identify trucks that are travelling close enough to create a platoon. The authors only consider speed adjustments as a method of platoon formation, thus keeping the manoeuvring to a minimum. The novelty of this approach is that it tackles the issue of platooning not only on highways but also on smaller roads (trunk-roads) that run close, if not parallel to highways, leading to potential difficulties in the map-matching phase of computation due to GPS errors.

Platoon manoeuvring is tackled from a cooperative point of view in (Lam & Katupitiya, 2013), where inter-platoon interactions are modelled. The authors propose event-chains to mitigate any obstacles and inconsistencies that may occur in manoeuvre execution, as they are dynamic and concurrent. In the presence of a road hazard, a platoon overtaking manoeuvre can be adapted in several ways depending on the platoon's speed or size.

Urban platooning and control are discussed by Ali et al. (2015). They argue that to correctly implement platooning in a more complex network with more curved roads, the longitudinal and lateral controls must be independent of one another. They use a decoupled kinematic lateral with a dynamic longitudinal model and study the effects on the string stability of the platoon, while also reducing inter-vehicle distances to better fit the urban network.

Platoons are modelled as a hybrid automaton in (Banjanovic-Mehmedovic et al., 2018). The authors define several modules to account for the different platoon roles and functions: leader, cooperative, behaviour scenario modules and a controller for each of the following vehicles. This system is then coupled with a NARX neural network to develop prediction models, specifically for vehicle interaction and cooperation when executing manoeuvres.

Marinică & Boel (2012) consider the whole of urban traffic to be completely made up of informal platoons due to the traffic lights regulating the flow and forming groups of vehicles indirectly. They propose a new queueing model to aid with traffic control and decongestion. To do so they measure traffic throughout the network of Dendermonde, Belgium, monitoring different types of streets and intersections (signalised, non-signalised and roundabouts) and found out that the number of "platoons" does not vary based on changes in traffic density (such as different times of the day or different days) but rather the number of vehicles in the platoon does. They present a new queueing model in the form of an automaton and derive it into an event-based simulation with the following events: "platoon-entering intersection; platoon-entering link; platoon-leaving intersection; platoon-leaving link; all switching times of traffic lights; platoon-generated-by source; all transitions in automata for all queues".

Platoon behaviour in roundabouts is discussed in (Haas & Friedrich, 2017). The authors found that the penetration rate of platoons is more important in such a scenario than the total number of vehicles considered.

As demonstrated in (Lioris et al., 2017), intersections and other similar bottleneck-prone setups, could highly benefit from platooning. The increase in the capacity of the road, due to the decrease in inter-vehicle distances, allows for a larger number of vehicles to pass through an intersection without affecting the duration of the light cycle. The authors study their assumptions under three different queueing models; one not-so-realistic which does not account for traffic lights, another based on memoryless queueing that works for isolated intersections, and the last one using fluid queueing which mirrors the results of the second model. For the two latter models, they conclude that by using platooning there can be an increase in the demand by a specific factor, which also increases the queueing length by the same factor, leaving the delay however unchanged. If the light-cycle is altered, this affects both delay and queueing length, as all three are linear. While the argumentation and experiments are conducted considering a penetration rate of CACC of 100%, the benefit is considerable with a two- and even three-fold increase in throughput.

Intersection crossing strategies for platoons are discussed in (Bisht & Shet, 2020). The authors propose and compare their new approach of proximity-based control (the closest platoon to the intersection has the priority) to the established density-based (the denser/larger platoon gets priority crossing) or space-based controls (platoons get restructured to maximise the number of vehicles crossing). An analysis of the waiting time and distance travelled across all controls proved that the newly proposed approach outperforms the others and provides better network throughput.

Practical experiments already exist using platooning; Energy-ITS (Tsugawa et al., 2011), which focused on large freight transport platooning in freeway scenarios, GCDC (Kianfar et al., 2012) which analysed platooning both in an urban (formation) and a freeway (operation) environment, and SARTRE (Robinson et al., 2010), which started with focusing on freeways scenarios with the potential of extending to an urban environment as well; all showing promising outlooks for platooning.

Platoons used for logistic deliveries in an urban environment are addressed in (Haas & Friedrich, 2018) from a traffic management point of view. The authors look into the number of vehicles and platoons in a city's network for a single day and present an interaction model for platoons in a roundabout scenario. Three aspects of platooning are studied, namely the number of non-platooning vehicles, the size and number of platoons and it is concluded that the number of platoons has the highest impact on the traffic. This ends up being a double-edged sword since, with an increase in the number of platoons, an increase in the intersection crossing time is also noticed.

With (Scherr et al., 2018), the authors consider the network design needed to accommodate both human-led and completely autonomous platoons given that some edges may be unavailable to the latter group. They formulate the "service network design for autonomous vehicles in platoons (SNDAVP)" based on the fixed charge capacitated multicommodity network design (CMND) with service selector decision variables and constraints to account for the three necessary platooning manoeuvres (merging, operating, splitting).

Complementary work is presented by Scherr et al. (2019) where they address the mixed fleet size and composition for a service network design problem. Considering that autonomous delivery vehicles can split, merge and operate as platoons, the authors investigate the necessary fleet composition and size to fulfil deliveries in a two-tiered predetermined network, where autonomous vehicle access is restricted for some corridors.

Rounding off the previous two papers is (Scherr et al., 2020) by the same authors, where they take the problem even further, addressing the scheduling issue of coordinating mixed platoons. To that extent, the authors extend the dynamic discretisation discovery scheme to the "service network design problem with mixed autonomous fleets (SNDMAF)" and develop algorithms that with the help of heuristics can achieve optimal results in comparatively shorter times.

Platooning was always envisioned as a way of simplifying the driver's life by allowing the vehicles to control themselves, but an equal advantage arose from an ecological standpoint, namely minimising fuel consumption through reduced wind drag. The perfect contender for this scenario was large freight transportation, which is not only essential but also a major cause of emissions and pollution. Therefore Larsson et al. (2015) developed the "platooning problem", an NP-hard routing problem with fuel-saving as the objective. They present two formulations of this problem, one with deadlines for arrival and one without, as well as a couple of accompanying heuristics.

Platoon matching in an urban scenario is discussed in (Farokhi & Johansson, 2013). The authors consider some vehicles to have platooning capabilities, which would benefit from travelling together. Their utility depends on the congestion tax applied on the roads, the average speed of each of the streets in a route and any penalties occurring from travelling late. They model the problem as an atomic congestion game with an achievable Nash Equilibrium, whose contributing factors (fuel-savings, different departure times, the penetration rate of platooning capable vehicles) are also analysed.

Platoon matching is discussed from a game-theoretical standpoint in (Johansson et al., 2018). The authors study the problem of creating a platoon with multiple competing trucks departing from the same origin, travelling to different destinations, with different preferred departure windows. Forming a platoon leads to higher utility and a too-large deviation from a vehicle's preference leads to a utility reduction. They formulate the problem as a non-cooperative game and prove that it has the potential to reach a Nash equilibrium. A further conclusion is that even when the vehicles are directly competing, cooperation leads to better results.

Gerrits et al. (2019) introduce "opportunistic" truck platooning, where they argue that spontaneous platoon formation as the vehicles are travelling would be more advantageous since the vehicles are not "wasting" any resources (like time or gas waiting for the opportunity of a platoon to arrive). They describe three scenarios of platoon formation: none found, one vehicle or platoon, and propose two matching algorithms: "first-viable match" and "best match". The authors concluded that both algorithms positively affect the cost of the trucks, not by fuel reduction (as was and is previously theorised) but by eliminating the need for multiple drivers and thus reducing salary costs.

A spontaneous platoon formation framework for large freight transports is presented in (Hoef et al., 2019). The authors developed a coordination system that provides participating trucks with a platooning plan consisting of the route, time profile and platoon coordination to maximise the fuel savings across all vehicles. This system gathers information from many sources like the vehicles themselves, their operators, road-side units, traffic and weather forecasts etc. The novelty of this approach does not rely on re-routing the vehicles, but rather adjusting the departure times and speed profiles to accommodate cooperation, while also continuously refreshing since disturbances can occur due to traffic.

The concept of sharing profits when platooning is discussed in (Johansson & Mårtensson, 2019). When large freight vehicles platoon, they experience a reduction in air drag and therefore also in fuel consumption. This directly translates into cost-saving which, to further incentivise platoon travel, the vehicles split among themselves. The authors investigate three competing and one cooperative game-theoretic approaches and conclude that for competing vehicles an even distribution of profit leads to the best individual utility. However, their formulation assumes the optimisation of departure time based on the perceived profits and is, therefore, a centralised approach which the authors themselves note as being unrealistic.

Gerrits (2019) presents a multi-agent system simulation as a way to study the factors that come into play when platoon matching trucks on highway systems. Considering previous platooning literature, he assumes that cost reductions would ensue from platooning through reduced fuel consumption and reduction of salaries of the drivers of the follower vehicles. The author addresses the issue both from an offline/centralised and an online/decentralised point of view but focuses on a more centralised approach, where the trucks search and form a platoon while they are stationed in a specific plaza. The two algorithms used are First Viable Match (which is also applicable for real-time matching) and Best Match, and unlike other works proposes a system of splitting the winnings equally among all platooning vehicles to positive results.

Resource exchange as payment for platooning was also proposed in (Liu et al., 2019) where the authors claimed that for platoons of electric vehicles, the leader would charge the following vehicles to offset their battery expenditure from taking detours, thus allowing for a specific energy-efficient grouping.

The effects of truck platooning are studied in (Bridgelall et al., 2020) from an ecological point of view. Previous work and literature imply that platooning with larger vehicles on a highway system with higher speeds and longer distances can significantly reduce fuel consumption due to reduced wind drag on the following vehicles. In this study, however, the authors argue that the fuel savings were not as substantial as previously theorised and stated. They argue that the electrification of trucks would have a much greater impact, where if one electric truck would be introduced, it results in a "13-fold reduction of national petroleum consumption relative to platooning".

Given that platoons are only possible with vehicles that have a certain degree of automation, and since such vehicles do not yet exist in such a high number to make them a common occurrence, it is safe to assume that for a considerable amount of time traffic will consist of mixed vehicles (non-autonomous and some autonomous). To that extent, Chang et al. (2020) argue that nonetheless, platooning can have a positive effect on traffic even with a low penetration rate. The authors analyse mixed traffic using the Intelligent Driver Model to model non-automated vehicles and the CACC model for the autonomous vehicles and study the conditions for equilibrium. The addition of autonomous vehicles and platoons improve the stability of the system if the critical speed is maintained under a certain *unspecified* value, but a certain maximum length for platoons must be maintained.

On the other hand, K. Li et al. (2020) argue that platoons might not be the best distribution of autonomous vehicles in mixed traffic. They investigate the capability of traffic smoothing of three types of vehicle formations (distributed, random and platoon) at a 20% penetration rate, with ACC control on a ring road. They concluded that a distributed formation and platoons perform the best, but when strong string stability is desired, the distributed approach prevails.

The performance of autonomous platoons in mixed traffic is investigated in (Yao et al., 2020). The authors investigate two approaches to platoon organisation, considering that only some vehicles may be fit to lead, with special consideration for reliable communication. The study shows that the more selective leader approach performs better in reducing interactions with non-autonomous vehicles and communication reliability.

3.4.5 Negotiation and Platoons

While negotiation has been used in the context of platooning, with a few works being discussed in this section, it is to be noted that negotiation was not employed as a way to further or create a new platoon on a logical level, but rather as a mechanism to resolve conflicts.

Although not specifically for platoons, in (Kneissl et al., 2018) a negotiation algorithm is presented that allows automated vehicles to cross an intersection safely. Both vehicles communicate their information to a "central intersection management unit" that handles a time-based negotiation between them, thus ensuring not only privacy but also a lighter computational load. The authors intended to follow up with a study on platoon intersection crossing which they do in their following work (Kneissl et al., 2019), using a convex Jacobi update function.

Lind & Ekmark (2016) propose a system that uses negotiation for merging operations within the platoon. They do state that the use of negotiation can be extended to any platooning control system, not just merging.

Bengtsson et al. (2015) also use negotiation to merge two platoons. This is done by comparing estimated arrival times, giving way and creating gaps to accommodate a higher priority vehicle.

A practical approach to platoon ordering is proposed in (Lesher et al., 2018), which looks into how vehicles are organised in a platoon based on driver quality. The vehicles negotiate with each other, but the ones being operated by the better drivers have precedence and can choose their desired position in the platoon.

Lam & Katupitiya (2013) use negotiation to optimise intersection throughput of vehicle platoons contending for who goes first. Each vehicle bids on their passing time and an overall winner is decided, however, platoons may break up in the process. Similarly Medina et al. (2015) transforms vehicles approaching an intersection into virtual platoons to mitigate which has the right of way.

The closest thing to the issue addressed in this work is (Rasmussen et al., 2017) concept paper. The authors address platoon formation of trucks in a highway system, which would be possible in hubs, docks and rest-stops and not spontaneously and dynamically. They propose "lane blending", which would order the trucks in lanes/columns in the platoon formation before the platoons departure. Besides a base path-matching algorithm, the trucks would negotiate on the route that the platoon would take (more specifically the end-point of their common route).

3.4.6 Platooning vs. Ride-sharing

Due to its similarity to the application of platooning considered in this work, in this sub-chapter certain works of interest are presented in the field of ride-sharing.

Kamar & Horvitz (2009) recognise that cooperation and altruism are hard to implement in a dynamic setting like ride-sharing and therefore separate the model into three components; one for representing the agent's preferences, one for the optimiser that will create the ride-sharing plans, and one for payment that provides the agents with incentives. They have found that by using the Vickrey-Clarke-Groves algorithm, the drivers get paid substantially more than what is given by the passengers. To maintain the sustainability of the ride-sharing system, the surplus needs to be divided back to the passengers.

Zhao et al. (2014) prove the previously used Vickrey-Clarke-Groves mechanism, although incentive-compatible, individually rational and efficient (at cost minimisation), runs a very high deficit.

A way of ensuring that matches between drivers and passengers are made is to implement an auctioning system (Kleiner et al., 2011); instead of relying on fixed assignments made to minimise the distance travelled, the agents' preferences are the driving force of matches. The passengers are bidding to increase their ranking, and thus their visibility to drivers, whereas drivers can select passengers according to their preferences. The system proposed performs close to optimality, having a trade-off between the length of all drives and the success rate of matching.

Goel et al. (2016) tackle the subject of ride-sharing from a privacy perspective which applies perfectly to this case study since vehicles, much like private passengers, would not like to disclose their final destination. They use imprecision in the sense of not disclosing the location of the passenger and only negotiating on a pick-up location after a match is made. The authors present three privacy-focused strategies; namely negotiating on one of the endpoints first, negotiating on both at the same time or the best match being selected by an algorithm for negotiation. The strategy that performs the best is the second one, which allows for matches to be done in fewer rounds than the other two.

3.5 Research Gap and Research Questions

In this section, we summarise the discussion of the state of the art, and locate the research gaps in the major fields of routing, traffic, multi-agent systems and platooning, and more importantly, a considerable one at their intersection.

The current routing problems, although they consider multiple vehicles, are assumed to be a fleet owned by one entity, so the optimisation is made with the owner's optimality in mind. While the vehicles may be heterogeneous in size, power, driver behaviour, etc., while they belong to one economic entity, their goal is aligned and taken from that entity. Routing for heterogeneous vehicles as far as limitations, utility and preferences go is not featured and the problems evolve in different directions, accounting for different aspects of driving like time windows, optimising fuel usage, etc.

Insofar as traffic management is concerned, the more alternative methods employed for decongestion focus too much on a very specific type of traffic participant (logistic transports and carpoolers) and the cooperation aspect is not addressed or used enough to make any sort of impact. As general studies have shown (Chakraborty et al. (2018); Raiffa (1982)), cooperation always leads to better results and the field of traffic should be no exception. Therefore, studying new ways of fostering cooperation in a traffic setting warrants more attention than it is currently given.

Platoons have been an intense field of study, especially since the idea of automating driving tasks materialises more and more with every passing year. Research in communication, safety, stability, controllers has allowed actual platooning experiments to take place, with overall positive results. However, most works addressing this topic take as a given that the platoon already exists, focusing on the travelling aspect. Very few pieces of research investigate how a platoon would come to form, and even here, most address the actual manoeuvres, safety gaps, communication protocols needed to physically create the platoon. While there are a small number of research works that consider the logical aspect of vehicle group formation, with how and why the vehicles would come to travel together, the methods employed differ from the decentralised and compensational one proposed here.

Lastly, while agents and their systems have a very rich history, solidifying them as a research methodology for other fields, research gaps still exist, but they mostly arise from use-cases rather than pure theory.

Based on the overview of the current state of research presented, the following research themes and questions arise:

I Platooning benefits for individual vehicles through different incentives

  i How much do individual vehicles benefit from platoon participation in contrast to normal driving?

  ii What characteristics of the incentivisation methods will affect the benefits positively or negatively?

II Factors influencing platoon operations

  i What influence does the platoon size have on the individual vehicles' benefits?

  ii What influence does traffic volume/density have on the individual vehicles' benefits?

  iii What influence do the origin or destination of vehicles have on the individual vehicles' benefits?

III Benefits of compensational platooning

  i How much do individual vehicles benefit from the proposed compensational mechanism?

  ii How applicable is compensational platooning?

IV Computational efficiency of the proposed approaches

  i How much time does it take to apply the optimisation-based mechanism?

  ii How much time does it take to apply the negotiation-based mechanism?

Based on the research works presented in Section 3.3.1, three major factors were identified that contribute to a vehicle's rationality when deciding on a route, so any incentivisation methods will target one of these factors. While cuts in cost or time can be easily implemented through traffic management, the distance is strictly dependent on the road network and cannot be reduced. Therefore, to investigate Theme I and its adjacent research questions, vehicles travelling in platoons will be offered preferential treatment either based on cost or on time and the subtleties of how that affects vehicle behaviour will be studied.

To answer Questions II.i to II.iii similar experiments will be considered where only the focus of the question will fluctuate while any of the other variables need to remain constant.

Questions belonging to theme III deal with the compensational approach to platoon formation and an automated negotiation approach will be developed and employed to test its suitability.

For topic IV what needs to be shown is that any mechanism employed in the grouping of vehicles in platoons can be executed rapidly so that it does not stall ongoing traffic. Therefore the computational time of any proposed mechanism should be at most a small fraction of a standard traffic light cycle so that it allows for communication as well as manoeuvres to be performed.

The design of the model as well as its implementation seeks to be as close to reality to correctly test and adjust factors in a way that would allow for these questions to be answered.

4 Research methodology

This chapter acts as a primer, describing the parameters with which the proposed approaches will work. First several assumptions are presented that simplify and make the scope of the methodology more concrete. Then the research procedure is explained, justifying several design decisions based on State of the Art literature. With the need to test the proposed approaches, the suitability of existing traffic simulators is investigated with respect to platooning formation mechanisms.

4.1 Assumptions

Density as the main traffic measure It is assumed existing traffic is represented by traffic density. This allows for the modelling of the usual impediments that traffic creates without having to model a (relatively high) number of vehicles moving in the environment. By taking this approach, the result output will not be cluttered by information about all vehicles in the simulation but rather have them restricted to the vehicles and platoons that are explicitly studied.

Self-interested but open to cooperation It is assumed that the vehicles are self-interested yet still eager to engage in cooperative behaviour within the margins of their own set of preferences and limitations. They function independently while also attempting to form or join a platoon. The vehicles will only join a platoon if it improves their results and will not act benevolently.

Existing communication and coordination It is assumed that perfectly viable communication and coordination exists within the vehicles in the platoon and with the distributed agent. The ability to communicate is needed, as shown in (Taleb et al., 2007) and (Khalifa et al., 2018), not only to execute safe travels in a platoon but also to communicate with the distributed agents placed in the environment. Sensitive information such as destination, preferences, route and offers are not communicated directly between the vehicles, but rather through one of the aforementioned distributed agents.

Platooning operations To create a platoon, at least two vehicles are necessary, but there is also an upper margin to the platoon size (determined based on the network type, but for the sake of generalisability will be five vehicles). To platoon, the vehicles must be at the same point in both space and time. Since we are also considering congested urban traffic, waiting for an advantageous platoon is not allowed. The platoons will form based on the presented algorithms, namely we assume each vehicle to accept the solution provided by the algorithm, with the caveat of it being more advantageous than the originally given solution. This is ensured through different fail-safes implemented in the distributed agent. The travel speed of the platoon will be uniform and will respect the traffic laws, all vehicles' capabilities and the constrained flow speed given by current traffic.

Platooning incentivisation Due to their proven ability to increase road use and a potential doubling of intersection throughput, it is assumed that platoons will be receiving preferential treatment from the traffic management authority. This can be implemented in many ways like allowing for the use of dedicated lanes or electrifying roads to allow for charging while driving (which are potentially far future developments), but more realistically and immediately applicable would be congestion pricing subsidisation and traffic light precedence.

Incentivisation methods The first incentivisation method is based on congestion pricing and means that the vehicles would be required to pay less when travelling in a platoon rather than alone. The second is based on prioritising platoons in intersection crossing, by allowing them to form in a dedicated area right before the conflict zone of an intersection, as well as benefiting from a reduced red-light waiting phase. The first case sets congestion pricing on the streets of the network, directly proportional to how busy the traffic is. If a vehicle forms and travels in a platoon, the tolls are partially subsidised directly proportional to the platoon size. The second scenario allows for the faster passage of platoons through an intersection, using the system proposed in (Barthauer & Friedrich, 2019) and giving platoons a precedence rank based on their size. In both scenarios, the size of a platoon is limited to approximately the length of a jointed bus, but while a larger platoon is more profitable in the second scenario, for the first, this is not always the case.

Measured penalty In both scenarios, the measurement of the penalty, either by tolls or the time spent in traffic, will be represented by the traffic density. In both cases, this is an appropriate measure since it translates into the occupancy level of the road. The busier a road is, the more time it will take to traverse it. Therefore, the need and desire to direct incoming traffic away from it will grow, which can be achieved through the implementation of tolls.

4.2 Design Decisions

Agent-based discrete-event simulation According to a study done by Law et al. (2000), an agent-based discrete-event simulation applies best to the studied model since the state of vehicles changes a finite number of times.

Mesoscopic simulation In (Sanderson et al., 2012) the authors propose a three-tiered information dissemination system on a micro (individual vehicles), meso (groups of vehicles) and macro (full system) level. The microscopic level relies on an "intelligent anticipatory vehicular architecture" (Sanderson & Pitt, 2011) where vehicles, as agents, execute the action of driving based on specific goals, with an assessment of the current situation and the actions of their neighbours. On the mesoscopic level, since we are dealing with groups of vehicles rather than individual agents, a method is needed to reach an agreement when confronted with possible interaction (platoons or crossing a non-signalised intersection). The macroscopic level deals with system-wide issues and the authors address this as a "Common Pool Resources" problem (Ostrom, 1990), where the allocation of said resources is done through a binding contract. Given the problem that is addressed in this work, we are situated on a mesoscopic level and will build the verification tool thusly.

Distributed coordination In (Larson et al., 2014), the authors present a framework that allows for coordinating platoons of large freight trucks in a distributed way. The authors use a controller that, based on the vehicles' best route, computes the pairings with the best fuel-saving potential and, through the use of speed-matching, pairs nearby vehicles together.

Forming and disbanding as platoon operations Larson et al. (2016) presented a platoon coordination scheme to allow for better fuel usage. They use the platooning problem defined by Larsson et al. (2015) and extend it to platoon coordination as well. This includes platooning operations of forming and disbandment for optimal fuel usage across all considered trucks.

Grouping based on destinations An early attempt at tackling the platoon formation on a logical level was done by Hall & Chin (2005) where they sorted and grouped trucks at highway entrance ramps so that the distance travelled in a platoon is maximised. They investigated four different strategies and analysed them according to platoon size, queueing mechanisms and throughput; "random, destination group, dynamic grouping, dynamic grouping and platoon splitting". Overall the destination grouping strategy performed the best, which when considering the preliminaries of the model (platoon must form before the highway, no spontaneous platoon formation and splitting from a platoon is permanent) is expected and provides some insight into what a better grouping for platoons would look like in general.

Third party request handling Given the aforementioned work and the privacy concerns of Goel et al. (2016), the introduction of a distributed agent in the network to handle routing and grouping requests is made clear. The agent, most likely placed in Road-Side Units (RSU) or traffic lights, is equipped with communication capabilities as well as information regarding its extended network to accurately and efficiently route the vehicles on the best path. With the introduction of negotiation, the distributed agent can ensure the correctness and fairness of negotiations, as well as ensuring they do not take too long, disrupting the traffic.

Manoeuvres definition Urban driving manoeuvres are classified and studied in (Hartjen et al., 2019). The authors discuss previously used definitions but note that they do not include "state preserving manoeuvres", thus leading to the creation of three separate categories. First is the "Vehicle State Manoeuvres" which include active actions on the movement of the vehicle: acceleration, braking, maintaining speed or reversing the direction of travel. The second category is the "Infrastructure Manoeuvres", which refer to interactions the vehicle has with the infrastructure: lane changes, lane keeping, crossing or approaching an intersection, crossing or approaching a crosswalk and turning. Lastly, there are the "Object Manoeuvres", which encompass interactions of the vehicle with other objects which could be movable (like other vehicles, cyclists or pedestrians) or immobile (like an unexpected obstacle in the road); these manoeuvres are: overtaking, falling behind, approaching and following. Therefore the manoeuvres considered in this work will be: accelarating, braking, approaching intersection, leaving intersection, joining platoon and splitting from it.

Traffic light cycle of 60-90 seconds Traffic control is easily implemented through traffic lights with cycle lengths of 60 to 90 seconds (Bonneson et al., 2011) to "permit frequent gaps and consistent crossing opportunities, creating a more permeable network" (NACTO., 2013). This cycle length also performs well with regards to fuel consumption and toxic emissions of carbon dioxide, hydrocarbon, carbon monoxide, and oxides of nitrogen (Calle-Laguna et al., 2019).

Pre-sorting and pre-signalling specific traffic participants In (Barthauer & Friedrich, 2019), a pre-sorting and -signalling approach is proposed as a way of network decongestion. Vehicles that can drive autonomously are given priority when crossing an intersection due to their ability to communicate and coordinate with each other. This is achieved by allowing a portion of the street preceding a signalised intersection to be solely available to autonomous vehicles and allowing them to pass before the change of the traffic light to green. The main factors to consider in such an approach are the number of total lanes, how many of them will be used by the autonomous vehicles, how long the reserved space is, the length of the light cycles, the penetration rate of autonomous vehicles and "the saturation headways".

Opponent models for fairer negotiations To ensure that negotiations have a higher chance of ending in an agreement as well as ensuring an adequate level of fairness, all vehicle agents will be equipped with a negotiation and bidding module operating based on the Greedy Concession Algorithm (Baarslag et al., 2015). This algorithm creates an optimal sequence of bids that have a high likelihood of being accepted by the opponent, while also ensuring that the ego-agent's utility is maximised.

4.3 Choice of Traffic Simulator

Considering the problem at hand, a simulator is needed to test the hypothesis and the feasibility of the algorithms proposed. In this subchapter, an overview of the more common traffic (and platooning) simulators is given and their suitability for the problem at hand is investigated. Their characteistics are summarised in Table 4.1

Table 4.1: Traffic simulators and their characteristics

Simulator	Multiagent	Communication	Platooning	Cooperation
VISSIM	-	-	-	-
MATSIM	+	-	-	-
SUMO	0	-	-	-
TraCI	0	+	-	-
TraNS	0	+	-	-
Veins	0	+	-	-
PLEXE	0	+	+	-
VENTOS	0	+	+	-

VISSIM (Fellendorf & Vortisch, 2010) is a commercial microscopic, multi-modal and behaviour-based traffic simulator developed in C++. It can model both highway and urban networks, as it is intended for the optimisation of traffic flows and can model everything from pedestrians to large trucks and public transport. The simulator is based on four blocks, with the first three: infrastructure (road network, parking, railways and signposts); traffic (vehicles, volumes and routing); and control (traffic lights, rules) being the backbone, and the last block providing the reporting.

MATSIM (W Axhausen et al., 2016) is an open-source, microscopic agent- and activity-based traffic simulator developed in Java by Kai Nagel, Kay Axhausen and Andreas Horni. It can handle large networks, with queueing-based models for traffic representation. These flows are generated based on agent activity chains. Each agent attempts to optimise its utility by varying route, time, mode and destination.

SUMO (Krajzewicz et al., 2002, 2006) is an open-source, multi-modal microscopic traffic simulator developed by the German Aerospace Centre in C. In comparison to other simulators, SUMO does not model just vehicular traffic, but any type of moveable object, down to the pedestrian. This simulator is highly customisable through a series of XML files, from the network to the flow, the traffic rules, traffic lights and simulation specifications. In theory, each user can develop their functionalities into their installation of SUMO, as it is highly robust, but this also makes it rather inflexible.

TraCI (Wegener et al., 2008) is an open-source combination of the traffic simulator SUMO and the network simulator ns-2 (Fall et al., 2005) that enables realistic studies on how VANETS would influence traffic. The two simulators run concurrently and communicate directly through a TCP connection. Given that changes in the network simulator influence the actions of vehicles in the traffic simulator in real-time, they are assigned a client and a server role respectively. Simulation runs show that TraCI can outperform the classic decoupled method of simulation and can be used for high-density scenarios such as accidents.

TraNS (Piorkowski et al., 2008) is also an open-source combination of SUMO and ns-2 that uses TraCI to provide more in-depth looks at the results of the two individual simulators. What is different in TraNS is that the mode can be switched, so either the network simulator can be fed traces produced by the traffic simulator or the other way around, much like TraCI.

An implementation of platooning for the SUMO simulator was made by Fernandes & Nunes (2010). The authors developed a new car-following model based on the Intelligent Driver Model (Treiber et al., 2000), meant to represent CACC, and with an added communication layer, provided by TraCI, investigated the platoon's performance. Coordination within the platoon is initiated by the leader, which informs the followers about the upcoming manoeuvre, awaits confirmation from all participants and then executes. Therefore the communication scheme chosen was continuously updated with token cycles. The simulation results presented indicate a stable and safe operation, however, they neither account for sudden braking (to test string stability) nor are they replicable.

Veins (Sommer et al., 2010) is implemented the same vein as TraCI as it combines a traffic simulator with a communications one, SUMO and OMNeT++ (Varga, 2001) respectively. An added feature is the emission measurement, which was previously only available in commercial simulators such as VISSIM. Veins differentiates itself from the TRaCI approach by having bi-directional communication between the simulators, OMNeT giving SUMO commands, and after executing them, the movement traces are sent back from SUMO to OMNeT. This guarantees that not only are all the decisions current and applicable but also that the execution of both is done synchronously.

PLEXE (Segata et al., 2014) is an open-source extension to Veins, that allows for the implementation of platooning controls and manoeuvres. The authors use the implemented cruise control car-following presented in SUMO and with adjustments to the TRaCI platform, high-level CACC can be achieved. For platooning manoeuvres a framework is also set in place, allowing users to develop their controllers and scenarios.

VENTOS (Amoozadeh et al., 2019) is also based on the combination of SUMO and OMNet++ through TraCI, building upon the Veins State-of-the-Art IEEE 802.11p wireless communication. The new features of VENTOS include new car-following models like the classic CACC, extensions to TraCI, different traffic control signalling and new modules to help with the generation of traffic demand.

The simulation tool developed and presented in (Gechter et al., 2012) goes in-depth on three levels of autonomous driving: physics, sensing and functional, which render vehicles and traffic in a realistic, 3D, real-time way. The authors performed a platoon comparison between an actual platooning experiment and a simulation with the same factors as the experiment (vehicle types, environment, etc) to validate their model. The evaluation factors were inter-vehicular distance and lateral deviation which were the same or extremely similar when comparing the real and simulated cases. While this tool can be used to test out car following and platooning models, the large emphasis on sensing makes it more attractive for testing different sensors and their placement.

The necessary factors that would make a simulator suitable to test the approaches proposed are communication, platooning and cooperation capabilities of the vehicles and a multi-agent approach to the modelling of traffic participants. It is clear that no available system provides a flexible enough representation of vehicles in traffic, and that none, even though having platooning capabilities, are equipped with mechanisms in which the vehicles can cooperate and coordinate themselves. Therefore a new simulator is needed (which is described both in theory and in practice in Chapters 5 and 7) that has more of a focus on traffic collaboration.

5 Model of Platoon Formation and Cooperation

This chapter starts by defining the Platoon Formation Problem. Based on the formal definition, the elements, their respective relationships, functionalities and how they come together are presented, to create a model that enables the logical formation and cooperation of platoons. This consists of the description of the environment, the traffic modelling, the actors participating in the form of agents, and the relationships and interactions the components thereof have. In this chapter, the domain of platooning is transformed into a conceptual one, creating a framework with strict definitions and rules, where the proposed solutions to the platooning formation problem can be investigated.

5.1 The Platoon Formation Problem

A platoon is formed out of multiple vehicles *Vehs* that drive together within the premises of a network G (defined in Section 5.2) . The operation of the vehicles is influenced by a set of jobs meant to represent traffic T (defined in Section 5.3) . Movement within the network can be regulated and thereby coordinated via traffic lights TL (defined in Section 5.4). The vehicles (defined in Section 5.5) have their own destination, set of preferences and limitations which dictate the route on which they travel. Therefore, the Platoon Forming Problem is defined as tuple $<G,\ T,\ TL,\ Vehs>$ (or $<G,T,\ Vehs>$ if no traffic control is desired/required). The expected outcome comprises routes for all vehicles $\mathrm{R_v} \forall \mathrm{v} \in \mathrm{Vehs}$ that share some common path.

5.2 Environment

When modelling traffic, one must consider the properties of the network, movement type and the participants. On highway traffic, the length of distance travelled is longer, the speeds are higher, the movement tends to be constant with very little dramatic changes, and the participants are diverse (from motorcycles, personal vehicles and small to large trucks). Therefore the network can be a very sparse graph with a few nodes and long edges.

Traffic in an urban network is very different. The network is denser with many interconnected streets, the length of which can vary greatly, but interrupted by intersections which themselves can be extremely different. Movement is slower but features a lot of "stop-and-go" bottlenecks, specifically at intersections. As far as participants are concerned, there is even more diversity, especially on the "smaller" scale with pedestrians, cyclists, scooters, motorcycles, personal vehicles, vans, public transport vehicles and emergency services.

Since the approach is on the mesoscopic level, the network is modelled as a dense graph where the intersections or interchanges are represented by nodes and the streets by edges. In addition to this, edges are broken down into a series of cells, called blocks, to ensure a fine enough granularity for the movement of vehicles.

Nodes, $v \in V$ Represent the intersections as they connect two or more streets/edges. They are defined by their name and their position in space. Much like geographical or X-Y coordinates, the node's position is defined by two real numbers named (for generalisability's sake) latitude and longitude. The node's name acts as its unique identifier, which is also used to denote the vehicle's origin and destination.

Edges, $e \in E$ (i,j) Represent (very generally) streets consisting of one or more lanes. Their functionality can also be extended to account for individual lanes, however with an aggregated traffic model such as the one used here, edges were restricted to represent streets. They are defined by a unique name, their start and end nodes and their weight. As we are dealing with a directional graph, one edge represents a one-way street; if a street is bidirectional, two edges need to be defined. The name reflects the direction the edge has between its start and end node. To correctly represent an edge's length, one needs an additional function that calculates the length based on the coordinates of the edge's nodes.

Graph, $G = (V,E)$ An unmodifiable directed sparse multigraph based on the nodes and edge elements defined above. The routing is done based on the weight of the edges following the Dijkstra shortest path algorithm.

5.3 Traffic Demand

As was shown in previous chapters, traffic is how vehicles can move in the network. To accurately account for this force, the network itself must be adapted, without any changes to its physical structure. Therefore weights are given to the edges, representing traffic demand, allowing for realistic routing.

The simulation proposed is at a midway point between microscopic and macroscopic, therefore aggregated measures are used to model background traffic. Based on (Treiber & Kesting, 2013), the following measures are calculated and used.

Number of vehicles, how many vehicles pass over the selected section:

$$\Delta \mathrm{N} \tag{5.1}$$

Traffic Flow, the number of vehicles that pass over the section during a time interval:

$$\mathrm{Q}(\mathrm{x,t}) = \frac{\Delta \mathrm{N}}{\Delta \mathrm{t}} \tag{5.2}$$

Traffic Density, the number of vehicles that occupy one part of the section:

$$\mathrm{P}(\mathrm{x,t}) = \frac{\Delta \mathrm{N}}{\text{section length}} \tag{5.3}$$

Knowing these two aggregated measurements, number of vehicles per time unit and number of vehicles per length unit, the **Mean Speed** can be calculated as:

$$\bar{\mathrm{V}}(\mathrm{x,t}) = \frac{\mathrm{Q}(\mathrm{x,t})}{\rho(\mathrm{x,t})} \tag{5.4}$$

Therefore it can be concluded that the main measures of traffic are in themselves distance and time, in a strict balance where the trade-off is subject to individual preferences, biases and heuristics.

5.4 Traffic Coordination

5.4.1 Traffic Lights

Traffic lights are introduced in the model as a means of controlling traffic. Much like real-life, they are situated on the edges and cycle between red and green light states. They must be manageable, to allow for various degrees of synchronisation.

In this work, changes to the infrastructure are not considered, so all traffic control methods presented will be in the scope of intersection and systems control, namely traffic light systems.

When designing a traffic light coordination system, the following steps need to be taken:

- Analysing existing traffic: measuring volumes, flows and identifying conflicts.

- Defining phases: determining conflicting, partial or compatible streams. Existing systems are two-phase, two-phase with left, four-phase, three-phase at T-intersection.
- Calculating intergreen times: the crossing plus the clearing minus the entry times.
- Determining the saturation volumes: which at normal conditions are 2000 cars per hour.
- Determining the relevant volumes: dependent on the three possible streams, forward, right and left.
- Calculating cycle time: usually between 60 and 90 seconds.
- Calculating the required green time.
- Calculating the available green time and allocation.
- Determining Capacity and Saturation Levels.

These are the steps that will be applied (if appropriate) in determining the traffic light characteristics in the model. Given that the approach is a bit simplified, intergreen times and three-phase light systems will be ignored. All the formulas presented in Busch (2018) have been adjusted to reflect these changes.

Time required in a standard green phase of a traffic light for a single car to exit the signal approach:

$$\mathrm{t_B} = 1.8 \text{ seconds/car} \tag{5.5}$$

Saturation value, how many vehicles can exit the signal approach in one hour of green phase:

$$\mathrm{q_S} = 3600/\mathrm{t_B} = 3600/1.8 = 2000 \text{ cars/hour} \tag{5.6}$$

Relevant volume of single stream, how many vehicles are incoming from a single direction:

$$\mathrm{q_i} \tag{5.7}$$

Total cycle time, how long the complete cycle lasts:

$$\mathrm{t_U} \geq \frac{5}{1 - \mathrm{Q(x,t)/q_S}} \tag{5.8}$$

Minimum required green time, how long the go-phase of a traffic light has to be:

$$\mathrm{t_{RG}} = (\mathrm{q_i} \cdot \mathrm{t_U}/3600) \cdot \frac{3600}{\mathrm{q_S}} = \mathrm{q_i} \cdot \mathrm{t_U}/3600 \cdot \mathrm{t_B} \tag{5.9}$$

Available total green time, the total time available for the go-phase of a traffic light:

$$\mathrm{t_{ATG}} = \mathrm{t_U} \tag{5.10}$$

Available green time for a single stream, how much of the go-phase of a traffic light is allocated for a specific direction:

$$\mathrm{t_{Gi}} = \frac{\mathrm{t_{RG}}}{\sum_\mathrm{i} \mathrm{t_{RGi}}} \cdot \mathrm{t_{ATG}} \tag{5.11}$$

5.4.2 Adaptive Traffic Lights

The mechanism to be used in this model is traffic light coordination, which enables the formation of so-called green waves. This refers to the phenomenon that happens when vehicles leaving an intersection at the turn of the green light are ensured to continue passing through following lights (due to them already being switched to green) if speed is maintained constant. This is mostly used on large continuous roads, or straight roads experiencing large volumes of traffic, to ensure that flow is maintained.

To successfully implement a green-wave, the network must meet specific requirements (Busch (2018)). First the distance between coordinated intersections has to be less than 750 meters, as anything larger would lead to irregularities in the vehicle's speed. Second, green waves are only beneficial on highly travelled roads, where the degree of saturation is above 85%, anything less would not be worth the effort of coordination. The vehicles must build up their speed progressively, but to ensure that they maintain the wave, they must travel at between 85 to 100% of the maximum allowed speed. As far as the infrastructure is concerned, at least two lanes must be present, with an extra one made available for left turns. There should be no available parking on the side of the road and also no non-signalised pedestrian crossings.

5.5 Traffic Participants as Agents and Traffic as a Multi-Agent System

Traffic participants come in many shapes and sizes, with different places of operation, actions and even characteristics of the same action. The sole thing they have in common is that they have one or more goals. Therefore, each participant must be accurately represented in fine enough detail to capture all characteristics that influence their actions in achieving said goal. In that, traffic becomes a system in which multiple actors (agents) act and interact in their quest to optimally achieve their goals.

To represent the traffic participants they will be referred to collectively as agents. What all agents have in common is their unique identifier: their name. From here, agents can be at first split into two categories, static and dynamic. In the first group, there are clients, logistic service providers (LSP) and traffic management. While they can have a physical location in the environment (like the LSPs and clients) or not (traffic management), they all influence the simulation.

In the second group, there are all the agents that can navigate the environment: humans, bicycles and vehicles. While pedestrians do not play a major role in this area of study, their influence should be modelled in the form of intersection management with traffic light phases. When considering platooning, the focus is more on personal and delivery vehicles of all sizes.

In a meso- and microscopic level simulation dynamic agents need individual modelling. Each agent has to have an origin and destination with further optional intermediary points if needed. Their properties also need to be modelled: size, acceleration/deceleration capabilities, limitations, preferences, minimum speed, capacity and even consumption levels (if things emissions and fuel-reduction policies are studied).

5.5.1 Dynamic Agents

To enable movement, a dynamic agent has to keep track of its current location and position. In addition to their names, dynamic agents are also defined by their origin, destination and optionally their mid-way nodes.

5.5.2 Modelling Movement

Much like real-life, movement in a simulation is dependent on distance and time. Simulation time is discrete, and is modelled as a timer that gets incremented similar to seconds on a real clock. Distance is calculated based on the coordinate system chosen, whether it is actual geographical coordinates or a simpler X-Y-axes system.

To increase the flexibility and applicability of the model, two movement modes are defined; microscopic and macroscopic movement. The macroscopic movement implies travel at a constant speed on every edge, namely no accelerations or breaking. This speed is the mean speed calculated above based on the traffic flow and density.

The microscopic movement depends on the agent's physical capabilities of acceleration and deceleration as well as the maximum speed achievable on the edge depending on flow and density.

Both types of movement are used depending on the type of platooning incentivisation studied: macroscopic movement for the reduction in congestion pricing and microscopic for traffic light prioritisation.

5.5.3 Time and Space Transformation

Since the simulation is taking place in a virtual space and running on virtual time, an intermediary layer is needed to translate this into real measurements like meters and seconds or, inversely, real measurements into simulation ones. This ensures the simulation performs as close to reality as possible and, no matter the computational capabilities of the machine running the simulation, the results are consistent.

5.5.4 Agent and Movement Events

Due to the choices of how movement is modelled, more coarse-granular milestones have to be defined to simplify the evaluation. Therefore the following events are defined.

Creation The simulation creates an instance of an agent.

Departure A dynamic agent departs from any node along their route.

Arrival A dynamic agent arrives at any node along their route.

Forming The dynamic agent has joined a platoon.

Splitting The dynamic agent is disbanding from the platoon, either because it has reached the end of the common route, or because it arrived at its destination.

Completion The dynamic agent has reached its destination node (arrival would happen first, followed by a completion event).

In addition to these, when negotiation is implemented the following types are also added to the event list.

Joining The agent entered a negotiation protocol.

Sending The agent is transmitting an offer to its opponent.

Receiving The agent has received an offer from its opponent.

Accepting The agent has accepted the offer. This brings the negotiation to an end.

Rejecting The agent has rejected the offer. This brings the negotiation to an end.

Leaving The agent is leaving the negotiation protocol.

Therefore the agent logic can be represented by finite state machines, first for movement in Figure 5.1 and for negotiation in Figure 5.2.

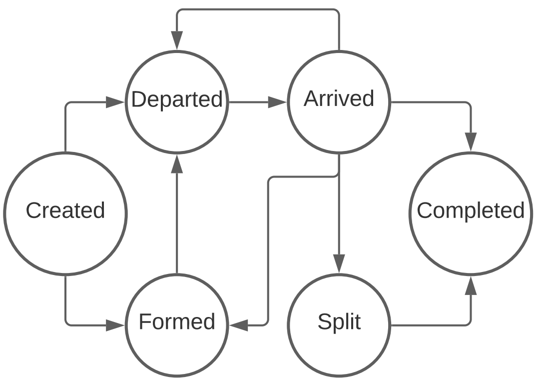

Figure 5.1: Agent logic for movement

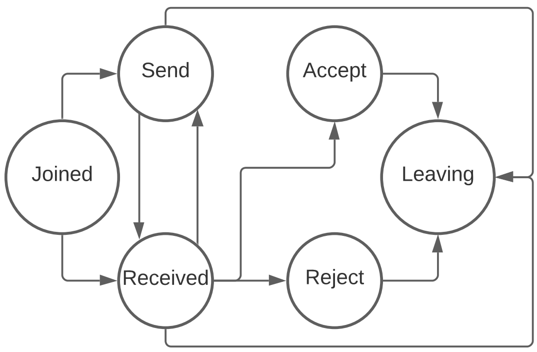

Figure 5.2: Agent logic for negotiation

When logging these events, the following information needs to be recorded.

- The subject of the event, the dynamic agent that has acted. WHO
- The event type, one of the twelve described above. WHAT
- The location where the event took place, the intersection/node name. WHERE
- The time-step when the event took place. WHEN
- Additionally if the event-type is a platoon formation, the partner agents. WITH

5.5.5 Dynamic Agent Functionality

5.5.5.1 Routes

A route is defined as a set of edges, in a strict sequence. Each agent begins the simulation with a given route, which can be modified when it participates in a platoon.

$$\mathrm{R} = ((\mathrm{Origin},\mathrm{v_i}),(\mathrm{v_i},\mathrm{v_i}+1),...(\mathrm{v_{i+n}},\mathrm{Destination}))$$

5.5.5.2 Pricing Function

This is only applicable if the congestion pricing approach is studied. Travelling alone would incur the full price of the route, whereas for platoons a reduction is given as incentives. As stated in (Sebe et al., 2021), the pricing increases linearly with the number of vehicles in the platoon, but this is then shared equally among them, resulting in a lower individual cost.

$$\mathrm{c_{ev}} = \frac{\mathrm{d_e}}{\mathrm{nvp}} + \frac{\mathrm{d_e}}{\psi} \tag{5.12}$$

5.5.5.3 Utility Function

To objectively quantify the profitability of a trip, a simple additive function is used. While there is a multitude of systems to measure a vehicle's impact from very diverse points of view, like environmental (emissions), economic (fuel-consumption) or human (driver happiness), a very simple approach was used, since considering all the factors would substantially increase the complexity of the problem, compromising the ability to solve it. As discussed in the Traffic section of this chapter, a simplified model was used, based on the two simple building blocks of travel (distance and time) and the outside influence that affects travel the most: traffic density. However, depending on the type of incentivisation used (cost or time), different utility functions have to be defined.

For congestion pricing, a route's length and price are used, since the latter also takes time into account, both factors being influenced by traffic density.

$$\mathrm{U_v} = -\sum_{\mathrm{e}\in\mathrm{R}} \rho \cdot \mathrm{l_e} + \sigma \cdot \mathrm{p_e} \tag{5.13}$$

For platoon precedence, the route's length and time are used, as the latter includes the effects of traffic density since it directly influences the speed at which vehicles can drive.

$$U_v = -\sum_{e \in R} \rho \cdot l_e + \sigma \cdot t_e \tag{5.14}$$

The coefficients ρ and σ allow for each dynamic agent to specify the importance or weight of each of the factors to accurately reflect their preference.

5.5.5.4 Agent Preferences

To allow for individual control on their route and behaviour, vehicles are given some preferences. The first category is physical properties that describe the way the agent can move; namely the maximum acceleration and deceleration. They are used to control the movement and the braking of the agent if microscopic movement is selected. The second category of preferences is referred to as restrictive, as they can limit the route and the potential partners that an agent can take and have. They are maximum route length, travel time and lastly cost. At the intersection of the first and second categories lie the minimum and maximum speed, as they control the movement and can also be potentially restrictive.

As the agent travels through the environment, the maximum length, time and cost have to be updated to correctly reflect the remaining "travel budget". This update is performed upon the agent's arrival at the end node of each edge in its route.

5.6 Visualisation of the Model and its Relationships

A visual representation of the elements discussed thus far and their relationships can be seen in Figure 5.3. This presents the model at the conceptual level, where the real aspects of traffic have been transformed into fixed notions that can be simulated. Although simplified, it should give the reader a better understanding of the modularity and limited dependence of the elements. The green elements represent the environment, with the pink being the necessary background information. Purely functional elements are represented with purple and agents are in orange.

5.7 Adjustable Factors

Based on the research questions developed, several control mechanisms are implemented in the model, which can be adjusted and changed to enable the search for answers. Different ways to assess the applicability, benefits and influencing factors of platooning will be:

- prioritisation at traffic lights vs reduction in congestion pricing.

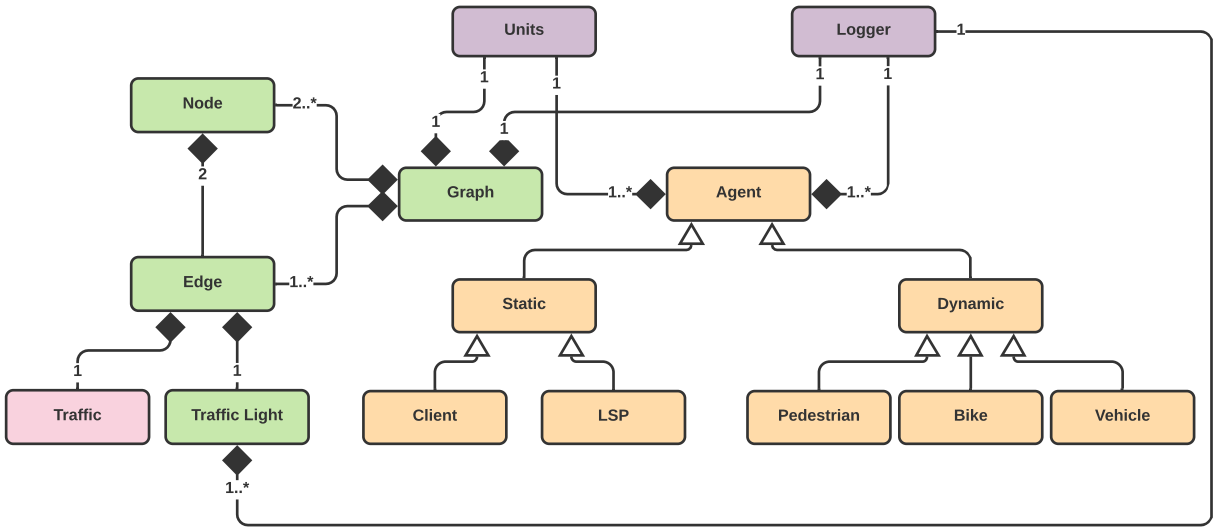

Figure 5.3: Simple UML diagram of the conceptual model.

- regular vs rush-hour vs night traffic.
- central vs peripheral origin point.
- central vs peripheral destinations.
- platoon size (two to five vehicles).
- different subsidy increase coefficient ψ.
- different synthetic network structures.
- uncoordinated vs coordinated traffic lights.

6 Platoon Formation Algorithms

This chapter presents the main contribution of this work, namely two platoon formation algorithms, each different in their method and distribution. The first approach is presented in the form of a Mixed Integer Problem which establishes a common route for the vehicles which is minimal in cost, while respecting the vehicles' preferences. This is meant to be running distributively throughout the network, ideally at each intersection and is to be operated and controlled by the traffic authority. The second approach is more organic, being operated by the vehicles themselves in a completely decentralised fashion. The vehicles would use the functionalities, protocols and strategies presented to automatically negotiate on alternative routes, offering money in exchange for cooperation.

6.1 Optimisation-based Algorithm: Platoon Forming and Routing Algorithm

Considering the literature review, the first mechanism will be based on aspects and restrictions of any heterogeneous group building problem. When taken into account the different characteristics of the environment, traffic and its participants, the level of heterogeneity increases exponentially, rendering our problem highly difficult to solve. The drivers want to minimise distance and time spent in traffic while the vehicles themselves are bound by their tank/battery capacity or speed.

Such a problem with multiple factors and restrictions can be tackled using a mixed-integer linear programming. The preferences and restrictions can be modelled as linear constraints to affect the time and length of the final route. Using such a method can provide multiple "best" solutions that can be further processed into an optimal grouping and routing for all vehicles involved.

The objective of the problem is to find a route that vehicles can travel together while also respecting their restrictions. This can be created by modifying the Shortest Path Problem (described in Chapter 2.1 and 3.1), to accommodate multiple vehicles.

To account for the fact that we are dealing with multiple vehicles that we are trying to route together, some alterations need to be made to the original. While the goal of keeping the costs as low as possible is staying the same, it has to be switched from an individual vehicle to multiple; this is achieved through a new variable y which accounts for all vehicles considered. To ensure that routes are also calculated for each vehicle, the x variable/s is still used. As before, both variables are binary, greater than 0, and to ensure correct representation in the value function, y is always greater or equal to x. This means that the cost of every edge which is a part of any vehicle's route is added to the total cost which we are trying to minimise. The last equation, which is the flow constraint, remains the same but has to be applied to all vehicles. Therefore the minimal platoon formation problem is:

$$
\begin{gathered}
\min \sum_{(i,j)\in E} y(i,j) \cdot d(i,j) \\
x_v(i,j), y(i,j) \geq 0, \forall \text{edge } (i,j) \\
x_v(i,j) \leq y(i,j) \forall \text{edge } (i,j) \text{ and } v \\
\sum_j x_v(i,j) - \sum_j x_v(j,i) = \begin{cases} 1 \iff i = O \\ -1 \iff i = dest_v \\ 0 \text{ otherwise} \end{cases} \quad \forall v \in \text{ Vehs}, \forall (i,j) \in E
\end{gathered}
\tag{6.1}
$$

While the goal function of minimising costs guarantees that the resulting routes are short, some level of detouring is to be expected. To account for such cases, more constraints can be added to the formulation.

Length A very direct approach to limit detours is to set a constraint on the length of the route. Having the previously discussed preferences, we can set the constraint that the length of all edges cannot exceed said preference.

$$
\sum_{x(e)_v=1} l_e \leq \Lambda_v \forall v \in \text{Vehs} \tag{6.2}
$$

Time In the context of traffic, one might argue that travel time is considerably more important in the utility of agents than travel distance. Again, based on the given preferences, we can introduce the following constraint:

$$\sum_{x(e)_v=1} \frac{l_e}{s_e} \leq \Omega_v \forall v \in Vehs \tag{6.3}$$

The complete formulation of the platoon formation problem comprises Equations 6.1, 6.2, 6.3 and the pricing function 5.12, which then becomes:

$$\min \sum_{(i,j)\in E} y(i,j) \cdot d_{(i,j)}$$

$$y(i,j), x(i,j) \in \{0,1\}, \forall \text{ edge } (i,j)$$

$$x(i,j)_v \leq y(i,j) \forall \text{edge } (i,j), \forall \text{ vehicle } v$$

$$\sum_j x(i,j)_v - \sum_j x(j,i)_v = \begin{cases} 1 \iff i = O \\ -1 \iff i = dest_v \\ 0 \text{ otherwise} \end{cases} \quad \forall v, \forall (i,j) \in E$$

$$c_{ev} = \frac{d_e}{nvp} + \frac{d_e}{\psi} \; \forall \; v$$

$$c_{ev} \geq 0 \; \forall \; v, \forall \; e$$

$$\sum_{(i,j):x(i,j)_v=1} c_{(i,j)v} \leq K_v^*, \; \forall \; v$$

$$\sum_{(i,j):x(i,j)_v=1} l(i,j) \leq \Lambda_v \; \forall \; v$$

$$\sum_{(i,j):x(i,j)_v=1} \frac{l(i,j)}{s} \leq \Omega_v \; \forall \; v$$

6.2 Negotiation-based Algorithm: Compensational Platooning through Automated Negotiation

Having a deterministic solution in place is the first step. However, it has certain problems. Because the solution designed is conceptualised at the system level, purely decentralised adjustments can be made that improve the individual utility even further. Locally the vehicles can propose alternatives to the distributed solution that could prove to be more profitable.

To put this effect into perspective, Figure 6.1 is presented. The two vehicles would travel alone to their respective destinations if only the decentralised mechanism is used. But if they collaborate they could reach a mutually beneficial solution that has them platoon for one extra edge (O-B).

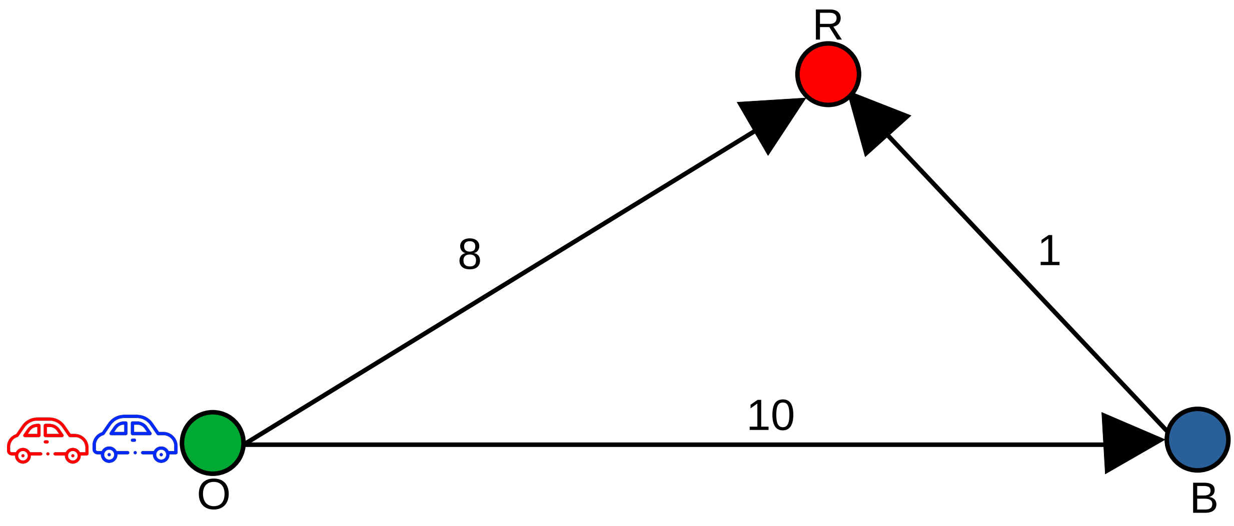

Figure 6.1: Suboptimality example of decentralised approach

Therefore, to foster even more cooperation between vehicles, automated negotiation is used to expand on the solution found by the optimiser in a decentralised manner. At the end of the common route given by the first mechanism, vehicles can propose further travel to their co-platooners in exchange for monetary compensation. This value has to be low enough to generate some profit for the agent initiating the negotiation, but also high enough for the other agents to accept the detour. This negotiation-based decentralised system will be referred to as *compensational platooning* henceforth.

6.2.1 Basic Concepts

6.2.1.1 Negotiating Agents

Vehicle agents are transformed into bidding agents with two distinct roles: initiator and acceptor. The initiating agent is the vehicle that proposes a new route to its fellow co-platooners, and they, in turn, become accepting agents.

6.2.1.2 Offer Structure

Offers are the medium that the agents use to exchange bids. The main components of an offer are the route that is up for negotiation and the buyout amount. With every round, an agent receives an offer, evaluates the buyout, and if unsatisfactory, rejects the offer, or updates the buyout and sends it as a counteroffer. Viable buyouts are the ones that are acceptable for both negotiating agents and are found at the intersection of the agents' acceptable offer spaces.

6.2.1.3 Agents' Offer Spaces

An agent's offer space refers to the interval from which they can make or accept payments. The limits of this interval are the aspiration and reservation values respectively. As negotiations take place, and the aspiration value changes, so does the payment interval. Therefore we define the offer space as $[X(0)_{\mathrm{i}},RV_{\mathrm{i}}]$ for an initiating agent and $[RV_{\mathrm{a}},X(0)_{\mathrm{a}}]$ for an accepting opponent, where X(0) represents the opponent's respective first offers.

A visual example is presented in Figure 6.2 where we have two agents engaged in negotiation. The blue agent is the initiator (or buyer) and the red is the acceptor (or seller). The acceptance value (AV) for the blue agent would be on the lower end of the spectrum, as a lower cost ensures him the best utility. The opposite holds for the red agent as they would benefit most from a higher price. In this example, there is an intersection in the agents' offer spaces (between the AV and the RV) and any bid selected from that interval would be acceptable to both agents. This is denoted by the green bid called "End". However, any bids made outside of this area of intersection is not acceptable to both parties, and will be rejected (here pictured as the red and blue Bid 1,2,3 respectively).

6.2.1.4 Negotiation Protocols

Negotiation protocols are the communication buffer between two negotiating agents, dictating the rules of the interaction. Multiple protocols can be used in negotiation but for the scope of this work we focus on two specific ones: "Take it or leave it" and "Alternating

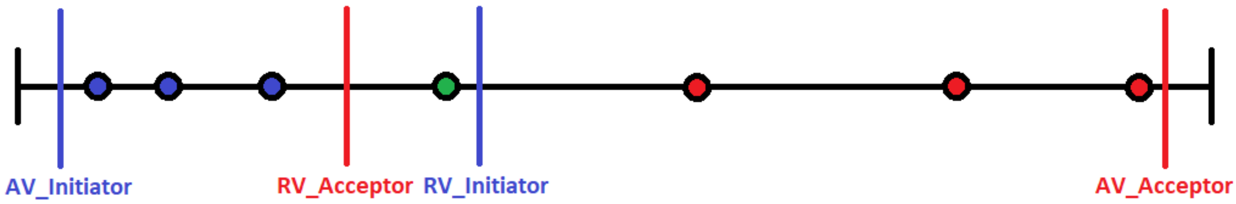

Figure 6.2: Offer spaces example

offers". By using two different protocols, one can test the profitability of using negotiation in the context of platooning, whether it is a simple and quick approach or a longer and more complex one.

In the Take it or Leave it Protocol, a single offer is sent out by the initiating agent, which can only be directly accepted or rejected.

The Alternating offers protocol allows for the agents to exchange offers in multiple rounds, one at a time.

6.2.1.5 Deadlines as Failsafes

To ensure that the negotiations do not go on for too long, a deadline is put in place that ensures the negotiation ends whether the agents have agreed or not. Each offer exchanged counts as a round and the negotiation has to end when the deadline is reached. This deadline is set according to how congested the traffic around the node is.

6.2.1.6 Acceptance Rule

No matter the role of the agent, they will only accept an offer or a counter-offer if the utility for the negotiated route is better than their original route. Namely, the condition 6.4 is required to hold.

$$\mathrm{U_v} < \mathrm{U'_v}, \forall \mathrm{v} \in \{\mathrm{a,i}\} \tag{6.4}$$

6.2.2 Compensational Platooning

The initiating vehicle selects a subset of edges from its route, calculates the compensation based on the reservation value and sends out the offer to possible accepting agents.

To correctly assess the offer, the accepting vehicle needs a complete route from the current point (where the platoon split) to its destination. Since this information is sensitive and an agent does not have any routing capability, this task is taken by the distributed agent. It adds to the route offered by the initiating vehicle so that it finishes at the accepting vehicle's destination. Having the new route, the accepting vehicle knows the length, total cost and the compensation offered, but not how much it is expected to pay. Having this information could lead to the accepting vehicle calculating the initiating vehicle's optimal route, and by extension, its reservation value. To remediate the situation, the distributed agent sets the initial compensation offered to also cover the platoon savings.

The route evaluation process starts with making sure that it does not step over the length and time limitations. This is done by calculating the utility, which either returns a value, meaning the route is viable or zero if it is not. Afterwards, the reservation value is calculated to determine which compensation would be acceptable for the new route. Should the compensation offered by the initiating vehicle be below this value, the accepting agent can send a counteroffer which starts the bargaining process of negotiations.

"Modelling the behaviour of an agent in a negotiation is also dependent on the coefficients ρ and σ of the utility function. It can be safely assumed the vehicles will not act in a benevolent manner, purposefully choosing a less-than-favourable option for the sake of being cooperative. All of the vehicle agents presented in this paper are selfish and competing; some might be greedy, attempting to get the best monetary value (if σ is the largest coefficient) while some will reject substantially longer alternative routes (if ρ dominates)." (Sebe et al., 2021, p. 325)

6.2.3 Negotiation Strategy

To ensure that most negotiations end favourably for both parties involved, the bids need to be within the acceptable range of the respective opponent. Agents will use whatever knowledge they can extrapolate to create bids that maximise their utility while also having a high likelihood of being accepted by their opponent. One of the values that can be observed and estimated is the reservation value. This allows agents to not only create acceptable bids, but also predict future bids. Agents can keep track of the bids made and create probability distributions for their opponents' reservation value.

Making a bid that is very likely to be accepted does not necessarily translate into a bid that is high in utility, so the Greedy Concession Algorithm (Baarslag et al., 2015) is used to determine the acceptable bid with the highest utility at every round.

According to Fatima et al. (2001), bids follow a so-called "concession curve" which depends on both time and strategy.

$$X(n) = \begin{cases} RV + (1 - \alpha(n)) \cdot (X(0) - RV) \text{ initiator} \\ X(0) + \alpha(n) \cdot (RV - X(0)) \text{ acceptor} \end{cases} \tag{6.5}$$

The α coefficient presented above encompasses the effect of time and agent strategy on the offers made; based on (Hou, 2004), it can follow either a polynomial or exponential curve.

$$\alpha(n) = X(0) + (1 - X(0)) \cdot \frac{n}{D}^{\frac{1}{\beta}} \tag{6.6}$$

$$\alpha(n) = e^{(1-\frac{n}{D})^{\beta} \cdot \ln(X(0))} \tag{6.7}$$

The β coefficient represents the agent type, namely how fast they approach their reservation value as the deadline approaches. The opponent can be a Conceder, with a β value considerably larger than one, a Boulware agent, with β considerably smaller than one or linear, with a static β value of one. Figure 6.3, taken from (Hou, 2004) presents different such concession curves. With β values of 50 and 10, the agent is a Conceder-type, going quickly to their reservation value, whereas with β values of 0.1 and 0.025 the agent is a Boulware-type, not caving in at all until the deadline is reached.

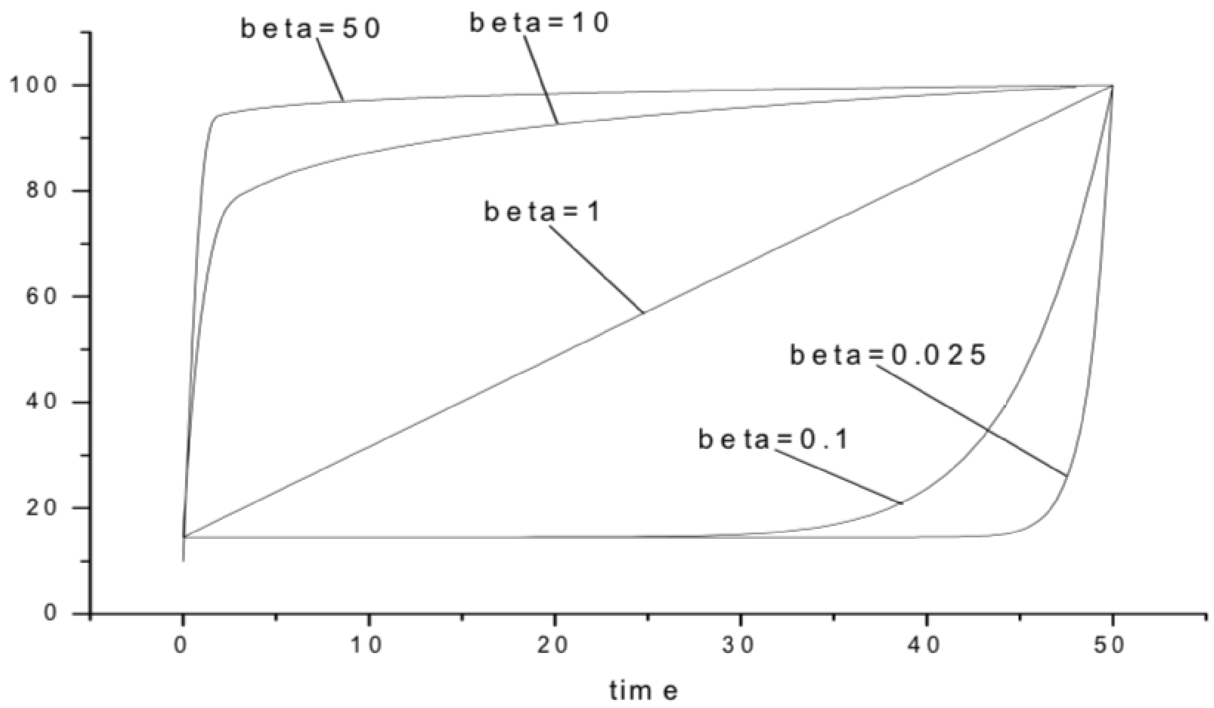

Figure 6.3: Concession curves for different initiator tactics (Hou, 2004, p. 3)

Studying the strategy of the opponent can lead the agent to calculate the exact reservation value. However, the method used in this work is to transform the reservation value probability distribution into an acceptance probability of bids. This allows agents to start with no prior knowledge and update and refine their beliefs with every round, skewing the reservation value distribution.

Sebe et al. state that "knowing the distribution of the reservation value, as well as the agent bidding strategy, we can extrapolate the acceptance probability of a bid at a certain point in time. As mentioned before, bids follow a concession curve as time progresses based on the agent's strategy, which ends in the deadline with their reservation value. By having a distribution of the potential reservation value, we can create multiple such curves, with a higher density at the peak of the distribution (depicted in Figure 6.4 by the black lines). From here, the acceptance probability of any of our bids depends on the values on these curves for the specific time-step considered. For an initiator opponent, our bid has a higher acceptance probability if it is higher than the projected values, while an acceptor opponent is more likely to accept it if it is lower" (Sebe et al., 2021, p. 326).

Hence, the probability of a bid Y(s) being accepted is:

$$P(Y(s))^{\text{accepted}} = \begin{cases} P(X(s) \leq Y(s)) \text{ acceptor} \\ P(X(s) \geq Y(s)) \text{ initiator} \end{cases} \tag{6.8}$$

where X(s) is defined in Equation 6.5.

6.2.4 Negotiation Component

Each agent is fitted with a negotiation module that takes over the inner workings of negotiating away from being directly implemented in the agent. While the protocol handles the communication and adapting the offers to each role, the negotiation module handles the offer assessment and formulation based on roles and protocol types.

Although the vehicle agent is in charge of directly receiving, sending and logging the offers, all the other functionalities are moved to this negotiation module. When a vehicle joins a negotiation party, a new module is created. Upon receiving an offer, the module calculates the new route utility, compares it with the original utility and based on these results and the type of negotiation protocol, directs the vehicle towards accepting, rejecting or further negotiation on the offer.

Sending an offer is also protocol dependent, since the two types implemented are "Take it or Leave it" and "Alternating Offers". In the case of the Take it or Leave it, the offer must maximise both the utility of the offering agent as well as the probability of acceptance for

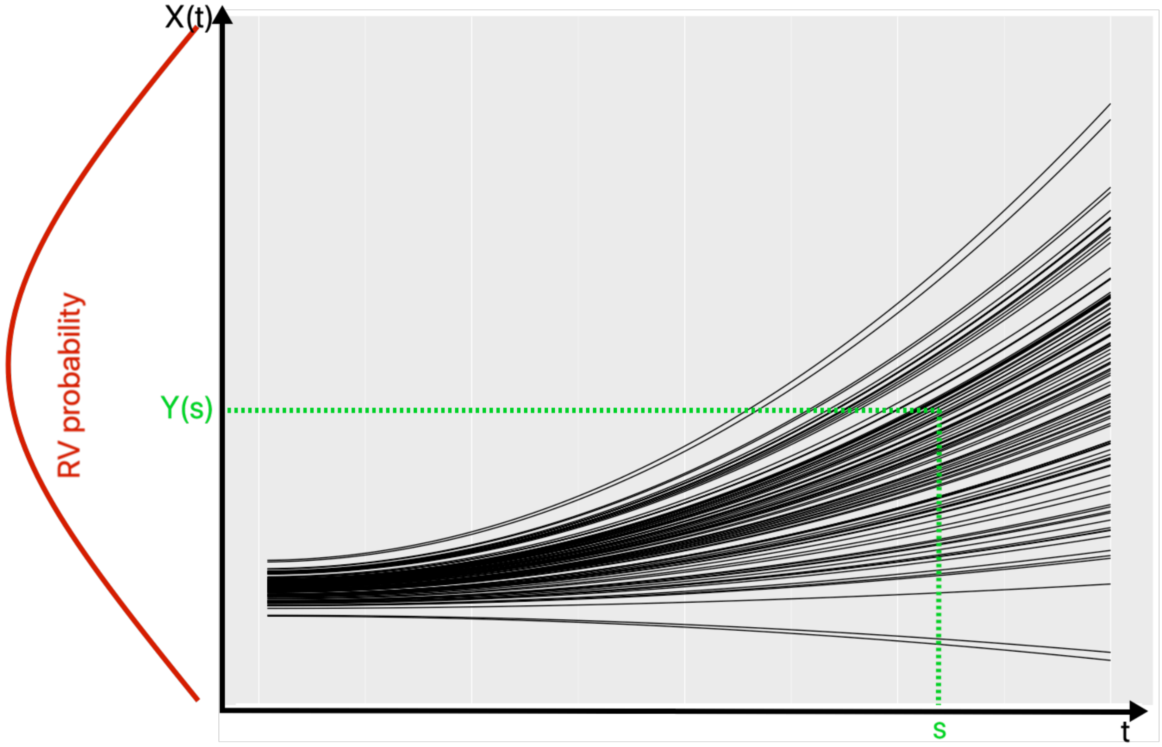

Figure 6.4: Determining the best bid

the accepting agent. In the Alternating Offers case, the first offer will always look to just maximise the utility. The offer is given a buyout based on the route and sent back to the vehicle to be forwarded to the protocol.

In the case of bargaining, the module differentiates based on the agent role (be it initiator or acceptor). In the case of an initiating agent, the aspiration value is increased based on the best bid provided by the bidding module, while keeping it above the reservation value. For an accepting agent, the opposite holds, with the aspiration value and by extension the counter-offer reduced based on the deadline of the protocol and the bidding module.

6.2.5 Bidding Component

The bidding module is created to increase the likelihood of negotiations ending in an agreement as well as avoiding exploitation. Choosing the best bid depends on approximations of what the opponent's reservation value is, as well as how far along in the negotiation the respective bid is made. A logical agent would concede slowly at first and increase as the negotiation draws to a close. Based on the opponent's history of offers, a probability distribution is created and, using the Greedy Concession Algorithm (Baarslag et al., 2015), the bid with both the highest likelihood of being accepted and the maximum utility is chosen.

The bidding module is activated inside the negotiation one when agents start bargaining based on the alternating offers protocol. This object is responsible for:

– keeping track of the opponent's bids
– estimating, learning and adjusting the hypothetical strategy of the opponent
– creating the probability distribution of the opponent's reservation value
– choosing the best bid according to current beliefs

6.2.6 Negotiation Agent and System Structure

The negotiation data model class diagram is presented in Figure 6.5 where only the functionalities relevant to the negotiation are shown. The agent itself must have utility, preferences and transformation unit attributes along with references to the negotiation status (currently negotiating or not), events and the protocol used. Functions include joining and leaving a protocol, sending, receiving and bargaining on offers. One important attribute is the negotiation component described above, which features relevant information about the ego-agent. This information includes the negotiation role (acceptor or initiator), the protocol used, the original route cost for comparison, initial as well as current offers, the reservation and aspiration value, estimated reservation value peak and all the agent specifications (utility, preference and transformation unit). The functionalities of the negotiation component are offer-related with sending, receiving and bargaining, as well as choosing the best bid at the current moment, for which the bidding component is used. This component keeps track of the opponent information, like role, strategy, first bid and all the previous offers, as well as protocol-specific information such as the deadline and the current negotiation round. Its functionalities are described in the section above, but the main one is to select the optimal bid at the current moment.

As far as the negotiation system is concerned, a simplified visualisation is given in Figure 6.6. Offers are tied to all the elements, whereas the protocol, the negotiation and bidding component are connected directly in a one-to-one fashion.

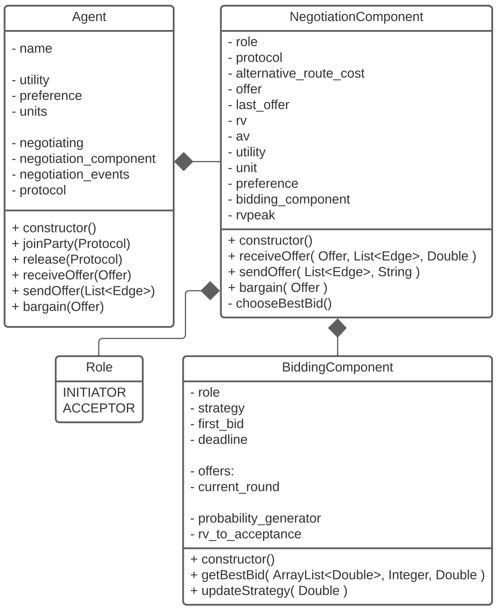

Figure 6.5: The negotiation data model class diagram

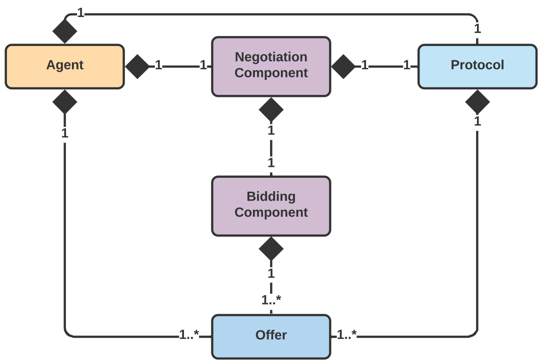

Figure 6.6: The negotiation system architecture

7 Implementation

This chapter explains how the elements of the model and the mechanisms are implemented in the practical simulation. While most of the functionality was described in the model, this chapter serves as a more technical description of the processes and frameworks that were developed or used. For the simulation, Java is used as the sole programming language, with the Maven build tool as the support for loading of necessary frameworks and libraries, ensuring code conformity, documentation and testing.

7.1 Environment and Background Traffic

7.1.1 Environment as a Multigraph

The environment is modelled as a sparse multigraph made up of the previously defined nodes and edges. The graph is built using the Jung framework that facilitates the modelling, routing, visualisation and analysis of the network. The graph is defined as an unmodifiable directed sparse multigraph, with routing done using the Dijkstra shortest path algorithm based on the edge's weight. To protect access to the graph, its nodes and edges, accessor functions are defined to retrieve a specific node or edge identified by their name. The provided routing algorithm finds the shortest path between two nodes and returns a set of edges. To expand on this, other functions were defined allowing the user to specify one or multiple intermediate nodes.

The data used to create the environments is (Stabler et al., 2018). The collection contains the nodes, edges, zones and trips between zones. The nodes and edges were transformed into a collection of JSON objects that make up the graph part of the input file.

Alternatively, for synthetic networks, a JSON file was composed based on the network structure to be studied (grid, spiderweb, etc).

7.1.2 Traffic Lights

To offer a more microscopic dimension to the simulation, as well as to measure the impact that platooning has on the travel time of the vehicles, traffic lights were introduced into the environment in the form of gate-keeping agents situated (much like real-life) on the edges.

A traffic light cycles between red and green light states. With each time-step, a counter is updated and depending on the duration of each light state the switch between them is made. To correctly synchronise all the lights in a network, another field is specified, called *when*,which specifies the time-step the light begins to function. This is done to ensure that opposing lights are also on opposite light cycles and that green waves can be implemented.

For the actual experiments studying the effect of time on platooning, the traffic lights were given the minimum cycle duration of 60 seconds, with 45/15 split between the red and green phases as well as the offset for green waves being calculated based on the length of the edges.

7.1.3 Generating Traffic Demand

To correctly model traffic, we used data provided by Stabler et al. (2018). Having the zones and the trips between them, the traffic demand for one day was generated. For each trip, random origin and destination nodes were pulled from their corresponding zones. Then routes were generated using the Dijkstra algorithm and aggregated for the complete instance. The number associated with an edge represents the number of vehicles that have used it in the course of a day. From here, the definitions in Section 5.3 were used to calculate the flow, density and mean speed and generate three traffic demand plans; one average, one rush-hour and one night-time.

7.2 Entities as Agents

In the analogous section of chapter 5.5, we defined agents as any entity in the simulation. While a basic implementation was done for all agent types (there can also be static ones like customer and company), the main focus was the dynamic and more specifically the agent vehicle.

7.2.1 Dynamic Agents: Requirements and Functionalities

All dynamic agents must be able to move, both micro- as well as macroscopically, therefore three separate functions are defined, one for each type of movement and one additional to enforce braking (used strictly in the microscopic movement case). Additionally, a dynamic agent must provide access to its origin, destination, location, position and preferences both for routing as well as logging purposes. To the same extent, any departure, arrival and completion must also be registered as an event and logged.

Each dynamic agent has an attribute of location and position. The former indicates which edge or node the agent currently occupies, and serves as a more general and formal indication of the agent's whereabouts. The latter, however, keeps track of how much of the current edge has been transversed at that specific point in time. It gets updated based on the type of movement used and is a more precise way of determining where the agents are.

At departure, the vehicle will register the edge to be travelled as its location and last travelled edge. Upon arrival, the location is updated to the end node of the said edge, and the position is reduced to zero to allow for a new departure. The agent's travel budgets (time, length and cost) are reduced to reflect the distance travelled. Completion is triggered after arrival and just ensures that an extra event is created and logged.

7.2.2 Movement: Macroscopic and Microscopic Implementation

Macroscopic movement is based on the mean flow speed given by the traffic density defined in the previous section. The vehicle assumes the mean speed or its potential maximum speed, based on which is lower, and changes its position on the edge, based on the unit object's transformation of said speed.

In microscopic movement, the vehicle's speed changes either by accelerating or braking. However, we also have regard for the mean flow speed as it also restricts potential movement. The acceleration or deceleration, depending on the case, is transformed into speed, which will adjust the vehicle's current speed and again, the resulting speed is transformed into distance travelled by the unit object's transformation. When calling the simple break function, the same process as above takes place, only strictly with deceleration.

7.2.3 Transformation Unit: from Model to Simulation

This object fulfils multiple requirements that are all tied to space and time. The main functionality, however, is to ensure that the movement is executed correctly, based on the vehicles properties; it features functions that translate acceleration and deceleration into speed, and analogously speed into distance travelled for one time-step.

A unit is defined by two terms, block and time-step specified at the start of the simulation. This facilitates the user to expand or contract the network and simulation time as desired and study the influence of different factors without any changes done to the network itself.

7.2.4 Vehicles: the Main Actors

In addition to dynamic agents, vehicles will enforce all necessary actions for platooning and negotiation.

When a vehicle joins a platoon, the event is created and logged, the indicator for platooning is made active and the companion vehicles are recorded internally. Additionally, to reap the benefits of platooning, the precedence indicator is updated to reflect the size of the platoon. In the case of a split, analogously, the platooning indicator is made inactive and all the companions are removed along with the event creation and logging.

When considering the traffic light precedence, certain functionalities have to be implemented to account for the reduced delay. Therefore we introduce the precedence property, which is based on how many companions the vehicle has and that gets updated whenever one or more vehicles join or leave the platoon. When reaching a traffic light that is in its red state, the vehicle calculates the delay based on the previously mentioned precedence property. Both speed and acceleration are returned to zero to realistically simulate a full stop.

The negotiation aspect is mostly handled by the protocol and negotiation/bidding modules to be described further, but some functionalities rest inside the vehicle agent. First, the vehicle must be able to join or leave a negotiation party. At joining, the negotiation indicator is made active, the negotiation module is created, and the event is created and logged. When leaving the party, the indicator is turned off and the module deleted, thus ensuring that future negotiations are unbiased.

The vehicle will also send, receive and bargain on offers but the main functionalities lie in the negotiation module. At the vehicle level, it's only about creating and logging the respective events.

7.2.5 Utility: Application of Agent Rationality

The agent's utility is represented by an object in itself which has only two attributes that correspond to the coefficients ρ and σ described in the analogous subchapter of the model. The functionality, however, extends further than just calculating a route's utility. It also plays a role in the negotiation process when evaluating the new route or calculating the reservation value to determine a more accurate payment interval.

The utility can be calculated in two ways, depending on the type of evaluation used. The input needed is the route, the speed, the buyout (if applicable), the vehicle's preferences and the simulation transformation unit. This follows the formulas presented in Equation 5.13 and 5.14, but we install a failsafe that guarantees that the route whose utility is being calculated does not overstep the vehicle's length, time and cost limitations.

To calculate the reservation value, the utility for the old route as well as the proposed route, speed and simulation transformation units are needed. The formula for calculating the reservation value is:

$$\mathrm{RV} = (\mathrm{U} - \rho \cdot \sum_{e \in R'} l_e)/\sigma \tag{7.1}$$

7.3 Simulation Input and Output

7.3.1 Simulation Input Structures

As input, two files are used containing all the information for the simulation, one for the graph and agent, and one for the background traffic information. They are decoupled to allow multiple traffic conditions to be simulated without changes to the network. They are given in a JSON format which is defined based on multiple schemas which will be detailed below for each of the elements.

Coordinate is defined as having two elements: "latitude" and "longitude", which can be applied for both coordinate types; "latitude" as the geographical latitude or the X-axis and "longitude" for the geographical longitude or the Y-axis.

Node is defined also with two elements, a name and a coordinate object (defined above).

Edge is defined by a name, an origin node "from", a destination node "to" and a "weight" to be used for routing. The weight can be attributed to any characteristics of the traffic, but for this simulation, it is associated with traffic density.

Vehicle is defined by a name, an origin and destination nodes as well as an optional array of middle nodes, a "preference" and "utility" object.

Preference refers to a vehicle's preferences and limitations; namely a minimum and maximum speed, acceleration, deceleration, as well as maximum time, length, costs.

Utility defines the utility function for vehicles, with the two factors ρ and σ.

7.3.2 Simulation Output Data

At running time, events are displayed on the console along with all operations such as optimisations and negotiations. All actions are also written to an output file detailing them for every time-step. When any type of moveable agent completes their travel to their destination, a closing summary is displayed stating their cost, travel length and duration, as well as what remains of their respective "budget".

For an easier evaluation, another comma-separated value (.csv) file is generated for all moveable agents.

Lastly, a visual representation of the network can be generated, highlighting the routes that were taken, the congestion of the network or the platooning concentration. Due to the visualisation being static, it is generated at the end of the simulation and cannot be generated dynamically to show the agents and platoons along their routes.

Simulation Output Visualisation At the end of a simulated experiment, a visual representation can be generated. All visualisations will contain, as a base element, the environment represented by a directional graph. Based on what is wanted, the following aspects can be represented: single or multiple routes, the traffic density for the whole network and the routes of a platoon (the following examples are presented on a generic 5x5 Manhattan Grid network). Single routes are represented by a single colour on the edges, presented in Figure 7.1. Platoons and traffic are more accurately represented by a heat-map where a high concentration of vehicles maps to a brighter colour and a lower one with a darker colour. The colours used are present in the Inferno palette, presented in Figure 7.2 due to its cognitive ease of understanding by the viewer (Thyng et al., 2016). Different colour palettes can be used, as multiple were implemented – an overview can be found at (Postlethwaite, 2018). Examples of platoon visualisation are presented in Figure 7.3 showing a join within a platoon and Figure 7.4 showing a platoon splitting. If there is no traffic or platooning on an edge, it is left uncoloured.

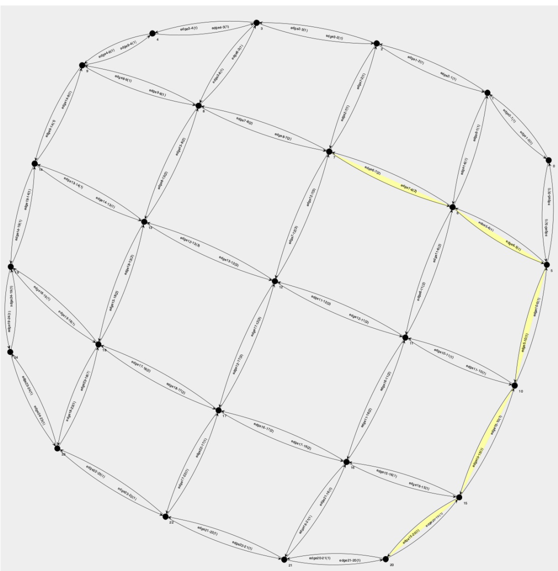

Figure 7.1: A single vehicle route

Figure 7.2: Colour scale

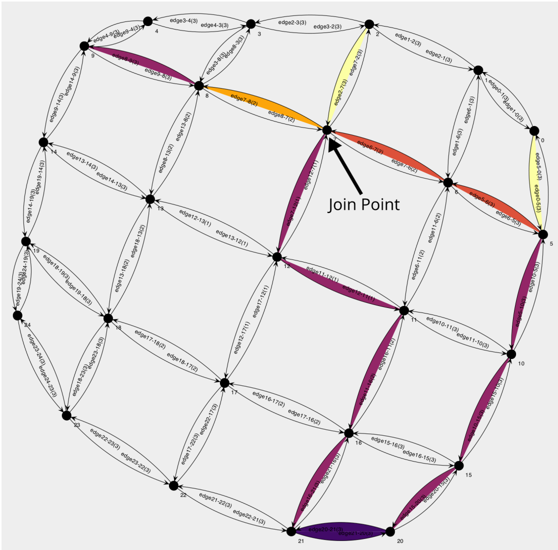

Figure 7.3: A platoon join

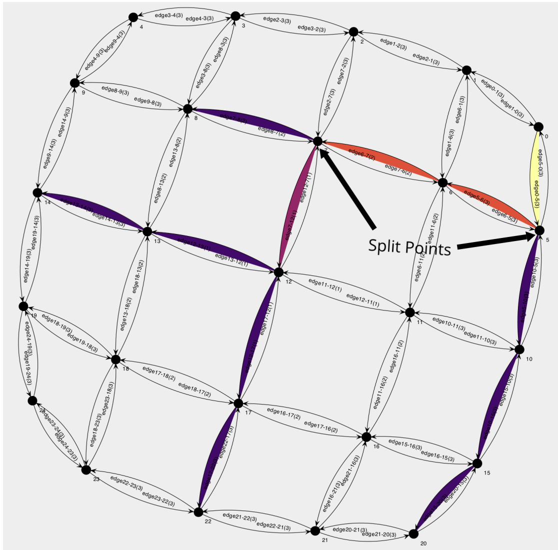

Figure 7.4: A platoon splitting

7.4 Driving and Platooning Mechanisms

7.4.1 Preliminary Sorting and Accounting for Splits

Preliminary Sorting: Before deploying any mechanisms, the vehicles have to be preliminarily sorted and grouped according to characteristics independent of said mechanisms.

1. In the first stage, the location of the vehicles is checked, selecting the ones that are at a node, and not still travelling on an edge. Concurrently, the vehicles are also clustered based on the node they currently occupy. A third check is also performed at this stage, ensuring the current node occupied is not the vehicle's final destination. The clusters with more than one vehicle continue to the second preliminary sorting stage.

2. The second step checks whether the cluster is already an existing platoon. This is achieved by checking whether all the vehicles in the cluster register as the companions of each of the vehicles. If they do, there are no further actions necessary and they can continue on their route. If the cluster is a new platoon or consists of existing platoon/s and individual vehicle/s, this step ensures that they are compatible in their travelling speed preferences, before moving to the next step.

3. The third step consists of splitting the vehicles into two categories; ones that can immediately travel, and those that cannot. This is used to ensure that a platoon is formed only with vehicles that are not currently restricted (most likely by a red light). After this, the mechanisms can be deployed.

4. After the optimisation mechanism runs, the vehicles are again clustered based on the route found by the optimisation algorithm.

5. Next, the vehicles are checked to see if the new route oversteps the maximum costs (time or money) that it can accrue. For some vehicles (named flagged), the route can feature a large detour which would mean that platooning brings no benefits but rather losses. In that case, the algorithm tries subroutes that can be beneficial to the vehicles as well as a platoon. If none are found suitable, the vehicles cannot platoon in the complete formation and the process needs to restart without the aforementioned flagged vehicles.

6. Lastly, the actual formation of the platoon can be triggered.

Edge End: Upon reaching the end of an edge in the route, the platoon needs to go through additional checks and potential adjustments to the vehicle's attributes.

1. First, a function to check whether any vehicle will split from the platoon and if so, the event is generated and the list of companions for each vehicle as well as the precedence are updated.

2. A second function verifies whether any of the vehicles have reached their destinations and in the case that they do, the vehicle in question logs the event, formally splits from the platoon and has its respective companions' lists and precedences updated.

3. The last function is called before the movement procedure is started again, and acts as a failsafe in case there are any vehicles whose platoons disbanded and have not yet registered the split.

7.4.2 Normal Driving and Baseline Mechanism

To provide comparison terms for the proposed approaches, the following two mechanisms are proposed.

The first represents normal driving and is achieved by allowing vehicles to travel independently according to their best route. This is calculated based by the simple Dijkstra algorithm, given to the vehicles which travel along it until they reach their destination.

The second serves as baseline approach to platooning, as is based on overlapping common routes. The same Dijkstra algorithm is used to calculate each vehicle's ideal route, but wherever there is a shared edge or edges, the vehicles are considered to platoon. Once the common route comes to an end, the vehicles split from the formation and the platoon is disbanded. This is a simple and straight-forward approach to building platoons that is Pareto-Efficient and Individual Rational, but in practice might not be feasible due to the short life-span of the coordination and large effort and space required to form and disband platoons. To implement this approach the preliminary sorting algorithm ensures that a platoon is formed but does not stray from the vehicles' individual best route.

7.4.3 Optimisation-based Platooning Formation: from MIP to Code

To implement and solve the linear program described in the analogous subchapter 6.1, the Gurobi solver library was used. It allows the definition of variables, objective functions and restrictions contained in a model and an environment.

The execution of the mechanism is conducted using the following steps:

- The y variable is defined as a Gurobi matrix variable of the size of the graph environment.
- Each of the x variables are also defined similarly and are aggregated into a hashmap corresponding to each vehicle.
- The objective function is defined as Gurobi linear expression and for each of the edges in the graph, the corresponding y variable is added with the edge's corresponding weight. When adding the y variable, all specifications necessary are made: lower and upper bound, objective, type and name.
- In the same loop of going over every edge, a new one is created going over every vehicle where the x variables are also given their specifications.
- The objective linear expression is added to the model and the result set to null.
- The flow constraint is next to be added to the model. For each of the vehicles and then each of the nodes, a new expression is defined to ensure that the sum of in- and outgoing edges is one or minus one if the respective node is the origin or the destination, respectively. Otherwise, the sum should be zero to ensure flow. The Gurobi linear expression is added to the model as a constraint, with the same being done for all following expressions.
- Another constraint is added for the x $\leq$ y property, which loops over every edge and then every vehicle.
- Length constraint follows, which loops over every vehicle adding the length of every edge as a linear expression which is then specified as less or equal to the respective vehicle's length preference.
- The time constraint follows the same logic but is based on the length of the edges divided by the pre-determined speed (the median speed the traffic allows).

– The model is then optimised and the result (the routes) is saved and sorted if valid. The secondary check is performed to ensure that the cost of the new routes does not overstep the maximum cost preferred by each vehicle. This is then called on in the main algorithm as described above.

7.4.4 Negotiation-based Platooning Formation: Framework and Intelligent Agents

7.4.4.1 Offers

There are three types of offers possible: initial, complete and simple and all have a unique id and a buyout.

The initial offer is the first offer to be made and has a simple given id, the initial buyout and the route that is proposed. It is created by the initiating agent and passed to the protocol.

A complete offer is created by the protocol and is strictly used to retain all the information about the offer (a new id, the initiator, the acceptor, the initial route, the alternative route proposed, the buyout, the state and the savings incurred). As the agents negotiate, the buyout is updated and when negotiation ends, the status is updated.

A simple offer is used for the "haggling" or bargaining process, where agents just exchange and propose new values for a buyout.

7.4.4.2 Offer Spaces

The initiating agent's reservation value is calculated as

$$\mathrm{RV_i} = \sum_{\mathrm{e} \in \mathrm{R'_i}} \mathrm{d_e} - \mathrm{p_e} \tag{7.2}$$

The accepting agent's payment limit is done by calculating the offered routes utility.

$$\mathrm{U'_a} = -\rho \cdot \sum_{\mathrm{e} \in \mathrm{R'_a}} (\mathrm{l_e}) - \sigma \cdot [\sum_{\mathrm{e} \in \mathrm{R'_a}} (\mathrm{d_e}) - \mathrm{comp}] \tag{7.3}$$

Should any limitations not be met, the utility value returned is 0. Afterwards, the reservation value can be calculated.

$$\mathrm{RV_a} = (\mathrm{U_a} + \sum_{\mathrm{e} \in \mathrm{R'_a}} \rho \cdot \mathrm{l_e})/\sigma \tag{7.4}$$

7.4.4.3 Protocols

The distributed agent's protocol interface conducts direct communication between the agents and handles the inner workings of the offers so that the agents' only focus is optimising their offers.

The general protocol has an id, which is the name of the node where it was initiated, the deadline and the current round. Additionally, the protocol must be able to receive, send offers, process them, recalculate the routes, equally distribute the savings incurred from platooning, redistribute the adjusted offers, as well as to manage any accepted or rejected offers and, in the case of communication breakdown, the respective aftermath.

In the case of the Take it or Leave it protocol, there is no need for a deadline or a round-counter since only one offer is exchanged and then a response is submitted. Therefore only the receiving offer's functionalities are defined, as well as the receiving of a positive or negative reply.

The protocol opens by adding all the vehicles that are situated at their home id to the crowd of potential negotiating agents. When an agent sends an offer, it is the protocol's responsibility to disseminate it to all the other agents connected. Since the protocol is run on the local agent, which is under the control of traffic management, the protocol can generate a new route for each of the potential accepting agents, containing the new route proposed and ending at their respective destinations.

If the negotiation ends positively with an accepted offer, the protocol:

- updates the status of the offer
- replaces the routes of the accepting agent into the new detoured one
- updates the costs of both agents
- releases the agents from the negotiation
- forms the new platoon

If the negotiation ends with a rejection or if any agents break away, the protocol updates the state of the offer and releases the agents.

For the back-and-forth exchanges (the Alternating Offers protocol), the bargain function is used, which:

- checks if the rounds counter does not go over the deadline
- if yes, no agreement was made so the agents are released and the offer closed
- if no, the rounds counter gets incremented

– depending on which agents sent the bargain offer, the buyout is adjusted and sent to the negotiation partner

For a visual representation of both protocols, please see the sequence diagrams in Figure 7.5 for the Take It or Leave It protocol and Figure 7.6 for the Alternating Offers.

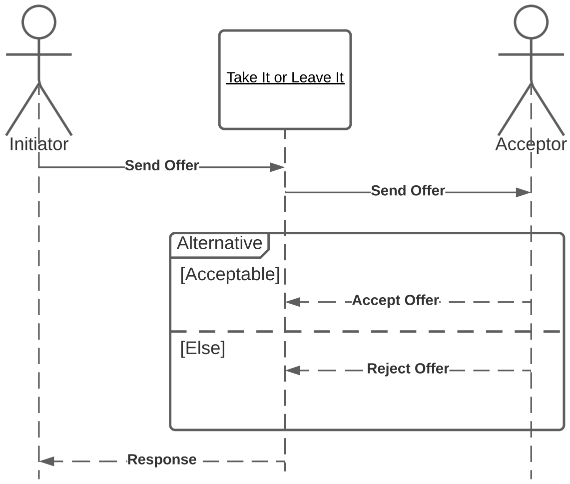

Figure 7.5: The Take it Or Leave It sequence diagram

7.4.4.4 Negotiation Module

The main functions of the negotiation module are sending, receiving and bargaining on offers.

Sending an offer makes the agent take on the *initiator* role. The only thing that must be determined is the buyout it wants to send to the other agents, and that depends on the negotiation protocol. Since with *Take It or Leave It* there is only one chance of influencing the opponent's decision, the agent chooses the value that could maximise both their and their opponent's utility, namely half of the cost reduction gained. With *Alternating Offers* however, there are multiple opportunities to try and skew the negotiation in their favour, so the offer is sent out with a very small portion of the savings.

Receiving an offer triggers the agent to take on the *acceptor* role and to calculate the utility of its route to the route received in the offer. Based on the protocol used, the agent will bargain or conclude the negotiations immediately. With the *Take It or Leave It* protocol, the agent will accept if the new utility is better than the old one or reject otherwise. On the other hand, with the *Alternating Offers* protocol the agent's decisions are also influenced by the preference coefficients, as the bargaining process is only started if they "allow" for any increase in travel length, time or cost. The information received with the offer as well as the utilities are passed on to the bidding module and the bargaining process can begin.

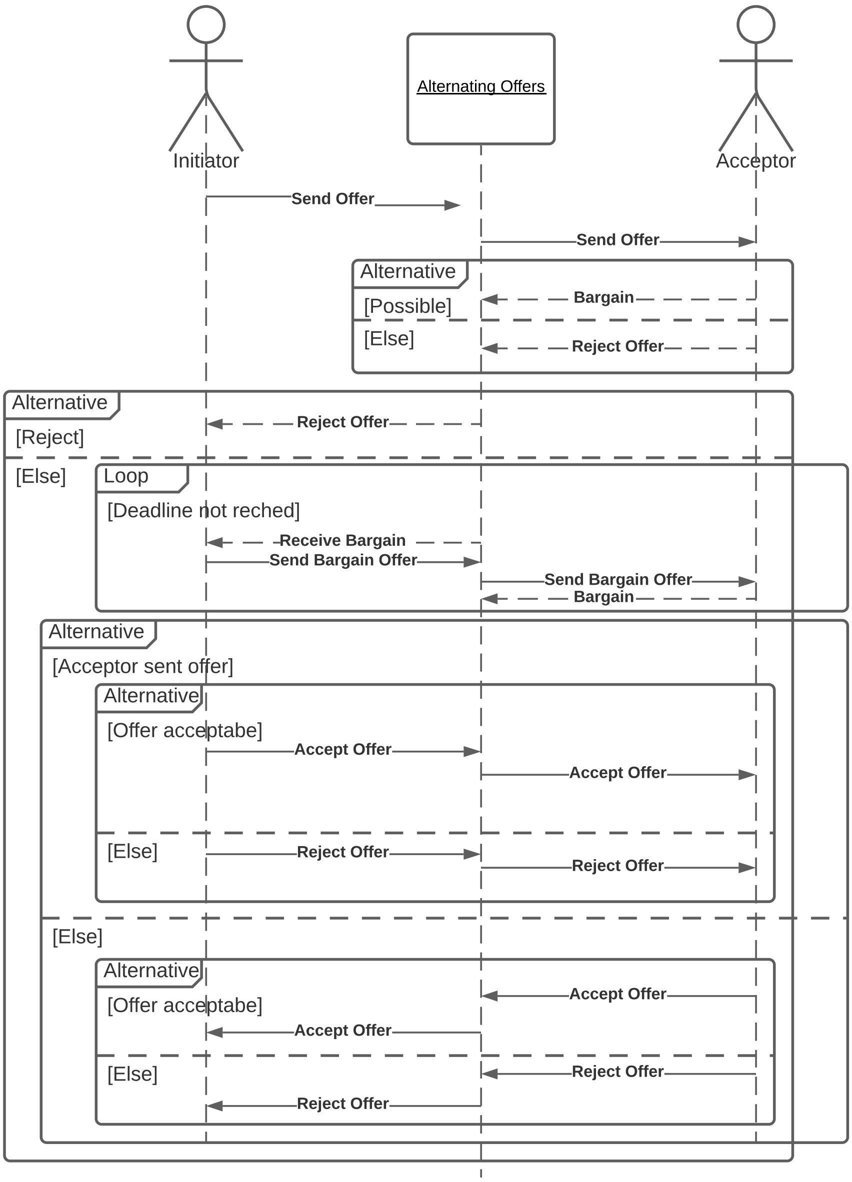

Figure 7.6: The Alternating Offers sequence diagram

Since bargaining can only take place using the *Alternating Offers* protocol, the process depends mainly on the role of the agent. With an acceptor, they are trying to increase the amount that they would receive whereas an initiator would try to keep that value down. As mentioned in the analogous chapter, the way the agents calculate their bid is dependent on the deadline, namely in the beginning of negotiations making only small concessions and towards the end larger ones to secure an *accept* from their opponent. An initiator would bargain until the deadline is reached, or it is approaching and the opponent makes an offer that is below their reservation value. An acceptor would behave similarly, but considering if the offer is under their reservation value. For an acceptor, an extra condition must be fulfilled for an order to be accepted, namely that by taking the new route the maximum cost is not overstepped.

Logical process for the initiator:

```
if ( ( round < deadline )
&& ( ( buyout > RV) || ( round < almost deadline ) ) chooseBid();
else if ( round >= deadline ) && ( buyout > RV ) REJECT;
else ACCEPT
```

The acceptor's logical process:

```
if ( ( round < deadline )
&& ( ( buyout < RV ) || ( round < almost deadline ) ) )chooseBid();
else if ( ( round >= deadline ) && ( buyout < RV ) )
|| ( ( round >= deadline ) && ( newcost >= maxcost ) ) REJECT;
else ACCEPT
```

Throughout the bargaining process, the aspiration value of both agents gets adjusted to the current offer received, to correctly reflect the payment interval possible. Based on this interval, several bids are created, the best one to be chosen by the bidding module. Choosing the best bid comes down to creating a probability distribution of the opponent's reservation value. With every round and every new bargain offer, the estimated reservation value gets adjusted. Having an updated belief as to what the reservation value of the opponent is, the current round, deadline and an array of bids, the one with the highest utility but also the highest likelihood of being accepted can be selected by the bidding module.

7.4.4.5 Bidding Module

The bidding module is in charge of creating a normal distribution of the reservation value, based on the agent's beliefs. Then that distribution is turned into an acceptance probability distribution, based on the opponent's type, strategy and first bid, as well as the negotiation deadline. The Simultaneous Search algorithm (Baarslag et al., 2015) selects the optimal bid at that moment in the negotiation.

The bidding algorithm also keeps track of and updates the strategy of the opponent, described in Equation 6.6 and 6.7 changing the β coefficient to reflect a conceder or a Boulware opponent. To determine the strategy, the bidding module keeps track of all the offers the opponent made, and analyses the "jumps" in payment from one bid to the other, adjusting the strategy coefficient accordingly.

7.4.4.6 Negotiability Degree of a Network

A graph network can be understood as a cumulation of differently shaped and sized polygons, starting with the triangle at the lowest level.

Negotiability A polygon is negotiable if it allows for negotiation to potentially end in an acceptance. For that purpose, one edge is selected, named "original" and the remaining polygon broken into two complementary parts, called "alternative" and "alone", each consisting of at least one edge. The utility is calculated for each of the three elements. All three utilities are calculated with no subsidisation taken into account. For the "alternative" element, another utility value is calculated, this time with double the normal subsidisation, meant to reflect the maximum payment that could be given in the case of a successful negotiation. For negotiability to exist, the following condition must hold:

$$(\mathrm{U}^{\mathrm{plain}}_{\mathrm{common}} + \mathrm{U}_{\mathrm{alone}} > \mathrm{U}_{\mathrm{original}})\&\&(\mathrm{U}^{\mathrm{psi}}_{\mathrm{common}} + \mathrm{U}_{\mathrm{alone}} < \mathrm{U}_{\mathrm{original}}) \tag{7.5}$$

Negotiability Degree In that context, the negotiability of a network can be quantified as the ratio of negotiable polygons over the total number of polygons in the network.

Complete Implementation For the complete implementation of the described simulation tool, please visit https://github.com/sinziana-sebe/PFaRA

8 Evaluation

This chapter presents the outcomes of the experiments. First, some hypotheses are formulated about the presented solutions with respect to the research questions. Second, the experimental setup is presented, starting from the networks, the experimental process and the mechanisms used. The results are differentiated based on the method used: *Dri* for the one completely without any form of coordination or platooning, *Bas* for the baseline approach, *Opt* for the optimisation-based and *Neg* for negotiation mechanisms. The experiment results are framed in the context of the proposed research questions, which are answered in the last section.

8.1 Hypotheses

In an attempt to answer the research questions, the following hypotheses are formulated, relating to each of the overarching topics presented in Chapter 3.5. This seeks to address the questions in a quantifiable context and allow for reliable and concrete experimental setups to be defined.

H1 At least one proposed form of incentivisation will provide a better solution than alone-travel to each vehicle in the platoon, thus having the algorithm provided outperform selfish routing.

H2 The influence of external factors will be negligible to non-existent on the results. Network-related factors like traffic and vehicle locations will not influence the efficacy whereas, the subsidisation factor and resulting platoon composition will.

H3 The benefits gained through compensational platooning are minimal or small enough to be outweighed by the effort, resources and time that are necessary for platoon formation and dissolution.

H4 Considering the proposed methods, the performance will deteriorate with an increased number of vehicles or with longer negotiation time, however, they will still execute fast enough to be implemented and used.

8.2 Adjustable Factors

Based on the similarly-named section in the model 5.7, the concrete measures of varying the experiments are presented here. By varying one factor at a time, the influence of specific factors can be studied.

- priority at the traffic lights will be based on the precedence defined in 7.2.4, and microscopic movement will be used
- reduction in congestion price will be calculated through the increase coefficient ψ which will be given values 2,3,4, and macroscopic movement will be used
- rush-hour traffic will be three times larger than the average
- night traffic will be half the average
- grid will be used as a synthetic network structure
- traffic light coordination will be done according to 5.4

8.3 Experimental Settings

8.3.1 Networks

For all experiments only two networks were used; a smaller synthetic one and a depiction of an actual neighbourhood in Berlin.

8.3.1.1 Real Network: Tiergarten

The realistic network depicting the neighbourhood of Tiergarten in Berlin, Germany features 361 nodes and 765 edges. The background traffic is generated from actual trips recorded for a day, which are presented in (Stabler et al., 2018) and normalised on the streets' lengths. To generate different states of traffic, the resulting traffic volume was divided into 24 to give an average hourly traffic state. For rush-hour, the average traffic was tripled and for night traffic it was halved. While the structure of the network stayed the same, namely the number and position of nodes and edges, the traffic information was changed to fit the three aforementioned traffic states. This network was used to answer the majority of the research questions posed, like compensational mechanism efficacy, computational performance, cost subsidisation and the influence that platoon size, traffic, origin and destinations points have on the platooning outcome.

8.3.1.2 Synthetic Network: Grid

The synthetic network is a 5x5 Manhattan grid with 25 nodes and 80 edges. The background traffic was modelled relatively realistic, with lower density on the outside of the network which progressively got higher towards the centre. This network was used to study aspects that could not be approached on the real network such as using time-based incentives and synchronising traffic lights to create green waves. Due to its small size, traffic lights were implemented on each node and depending on the experiment they were synchronised accordingly.

8.3.2 Driving Mechanisms

To paint an accurate picture, multiple driving mechanisms were designed to present the improvement that platooning provides. The results for any experiment will be presented in conjunction with a baseline of either no platooning or a simple overlapping approach for comparison purposes. Depending on the factor studied, an appropriate network was selected; either the synthetic Manhattan grid or the representation of the Tiergarten neighbourhood of Berlin.

8.3.2.1 No Platooning: Decoupled Driving

In these experiments the vehicles are simply created, their shortest route computed with the Dijkstra's algorithm present in the environment package and then deployed. Since we are not considering any sort of grouping mechanisms, we will consider the grouping effort to be zero. Results of this approach will be denoted by a *Dri* notation as the vehicles are just driving normally.

8.3.2.2 Baseline: Overlapping Routes

Overlapping routes is considered the baseline approach toward platoon building and these results will be denoted by a *Bas*. Platooning does take place, but only on where the individual routes overlap. This is ensured by the pre-sorting step described in Chapter 7.4.1. Therefore we consider the grouping effort to be the execution time of the preliminary sorting. as this is considered a baseline approach to platooning.

8.3.2.3 Optimisation-based platooning mechanism

Experiments will be run using the mechanism presented in 6.1 and be denoted with a *Opt*.

8.3.2.4 Negotiation-based Platooning Mechanism

In these experiments both proposed mechanisms are used, first the vehicles are grouped based on the optimisation algorithm and then at the platoon disbandment point the negotiation is initiated. Should the negotiation mechanism end in a disagreement, the results will be the same as with the optimisation mechanism. The results of these experiments will be denoted with a *Neg*.

8.3.3 Output Data

The results produced by the experiments are presented in two ways; first an overall analysis of the travel-relevant traits (distance, cost and time) followed by a consolidation of them in the form of utility. This is demonstrated for all vehicles in relation with the pertinent determinants via appropriately designed tables.

In the case of performance-based analysis, a respective graph showcasing the computational time is provided for enhanced clarity and visualisation.

8.3.4 Hardware and Software Specifications

The machine used to run the experiments is a 2,3 GHz Dual-Core Intel Core i5 processor and 16 GB RAM Macbook Pro. The same software (IntelliJ IDEA CE) was used to both develop the simulation and perform the testing. To develop the project, Java 8 to 13 was used (the first iteration of it was in September 2017), in combination with Apache Maven build tool to account for dependency management, code-styling, testing, debugging and documentation. After the general model implementation described in sections 5 and 7, several new classes were defined to allow for different experiment types. For each of the four mechanisms (no platooning/normal driving, overlapping/baseline, optimisation and negotiation) two separate instances were set up to account for the two possible movement types (microscopic and macroscopic). In addition to the standard experiments, there were two additional instances created, one for the final reporting (presenting a summary of each vehicle's travel metrics) and one for visualisation (routes, platooning densities, etc.).

8.4 Overview of Experiments

In Table 8.1 an overview of all the performed experiments is given. The displayed table highlights the relevance of all factors discussed in this thesis for the examination of the four Hypotheses and the therein subsumed Research Questions and to offer a comprehensive look at the underlying dynamics and dependencies of platoon formation as translated from conceptualisation, implementation and testing to outcome appraisal.

Table 8.1: Experimental overview

RQ & H	Section	Characteristics
RQI & H1	8.5.1	Grid, Precedence at Traffic Light, 2-5 Vehicles
	8.5.2	Grid, Traffic Light Synchronisation, 2-5 Vehicles
	8.5.3	Grid, Time-based Subsidisation, 2-5 Vehicles
	8.5.4	Tiergarten, $\psi = \{2,3,4\}$, Regular Traffic, 5 Vehicles
RQII & H2	8.6.1	Tiergarten, ψ =3, Regular Traffic, 2-5 Vehicles
	8.6.2	Tiergarten, ψ=3, 5 Vehicles, Different Traffic States
	8.6.3.1	Tiergarten, ψ =3, Regular Traffic, 2-5 Vehicles, Out to In
	8.6.3.2	Tiergarten, ψ =3, Regular Traffic, 2-5 Vehicles, In to Out
RQIII & H3	8.7.1	Tiergarten, ψ =3, Regular Traffic, Negotiation
	8.7.2	Tiergarten, ψ =$\{2,3,4\}$, Different Traffic States, Negotiation
RQIV & H4	8.8.1	Tiergarten, ψ = 3, Regular Traffic, 2-20 Vehicles
	8.8.2	Tiergarten, ψ = 3, Regular Traffic, 5-30 Rounds

8.5 Ways of Incentivisation and Vehicle Benefits

To study the two incentivisation methods, both the Tiergarten and the Grid networks were used. Due to the size of the Tiergarten network, it would be unfeasible to model and run traffic lights on all 361 nodes therefore no experiments using microscopic movement (and by extension the time-based incentives) could be run. Experiments of this network feature only the macroscopic movement and therefore the cost-reduction way of platoon incentivisation. Since the Grid network is user-defined, it was best suited to investigate the effects of time-based incentivisation.

8.5.1 Time: Precedence at Traffic Lights

For this set of experiments, the traffic lights were programmed with a cycle duration of 60 seconds, with 45/15 split between the red and green phases. The traffic lights were lightly synchronised to ensure that opposite lights function on opposite cycles, however, no green-wave synchronisation was implemented. The platoon is given precedence if it encounters a red light, being allowed to proceed before the phase switches to green. The vehicles started from the same origin at the periphery of the network and their destinations vary from central to the periphery (both close to the origin as well as on the opposite side of the network). Distance and time results are presented in Table 8.2.

Table 8.2: Results for Grid, Precedence at Traffic Light, 2-5 Vehicles

Vehicles	$\text{Distance}_{\text{Dri}}$	$\text{Distance}_{\text{Bas}}$	$\text{Distance}_{\text{Opt}}$	Time_{Dri}	Time_{Bas}	Time_{Opt}
pod1	200	200	200	455	455	453
pod2	400	400	400	875	875	885
pod1	200	200	200	455	455	431
pod2	400	400	400	875	875	875
pod3	200	200	200	431	431	431
pod1	200	200	200	455	453	431
pod2	400	400	400	875	875	873
pod3	200	200	200	431	431	431
pod4	600	600	600	1370	1370	1355
pod1	200	200	200	455	453	431
pod2	400	400	400	875	876	872
pod3	200	200	200	431	431	431
pod4	600	600	600	1370	1370	1328
pod5	800	800	800	1775	1775	1775

Due to the distance of the routes remaining constant for all vehicles in all experiment sets, the changes in travel time are clear. In Table 8.3 the results for utility are presented. While for the smallest platoon (of two vehicles) one's minimal improvement comes at the cost of the other (in italics); with the larger platoons utilities either improve or stay constant. However, the improvements are relatively small, with the largest one being 4.75% (in bold).

Table 8.3: Utility results for Grid, Precedence at Traffic Light, 2-5 Vehicles

Vehicles	$\text{Utility}_{\text{Dri}}$	$\text{Utility}_{\text{Bas}}$	$\text{Utility}_{\text{Opt}}$	ΔUtility%
pod1	-404	-404	-402.4	*0.396*
pod2	-780	-780	-788	*-1.025*
pod1	-404	-404	-384.8	**4.752**
pod2	-780	-780	-780	0
pod3	-384.8	-384.8	-384.8	0
pod1	-404	-402.4	-384.8	**4.752**
pod2	-780	-780	-778.4	0.205
pod3	-384.8	-384.8	-384.8	0
pod4	-1216	-1216	-1204	0.986
pod1	-404	-402.4	-384.8	**4.752**
pod2	-780	-780.8	-777.6	0.307
pod3	-384.8	-384.8	-384.8	0
pod4	-1216	-1216	-1182.4	2.763
pod5	-1580	-1580	-1580	0

This method of incentivisation provides vehicles with an overall small improvement in utility. While this does not hold for all vehicles in the platoon, seeing as some utilities remain constant, it rarely provides a negative effect. These facts, in combination with the relative small workload needed to implement such an incentive (a simple communications-enabled mote on the traffic light providing platoons with a premature green signal), make this method a possible way of encouraging platoon formation.

8.5.2 Time: Synchronised Lights

For this set of experiments, the traffic lights were fully synchronised, so opposite lights function on opposite cycles as well as having green-wave synchronisation. The platoon is no longer given precedence at red lights, but the likelihood of encountering a red light is reduced due to the green waves. The vehicles started from the same origin at the periphery of the network and their destinations vary from central to the periphery (both close to the origin as well as on the opposite side of the network). Table 8.4 presents the distance and time results for no platooning, baseline and optimising approaches.

Table 8.4: Results for Grid, Traffic Light Synchronisation, 2-5 Vehicles

Vehicles	$\text{Distance}_{\text{Dri}}$	$\text{Distance}_{\text{Bas}}$	$\text{Distance}_{\text{Opt}}$	Time_{Dri}	Time_{Bas}	Time_{Opt}
pod1	200	200	200	435	435	433
pod2	400	400	400	863	863	875
pod1	200	200	200	435	435	431
pod2	400	400	400	863	863	863
pod3	200	200	200	431	431	431
pod1	200	200	200	435	433	431
pod2	400	400	400	863	863	863
pod3	200	200	200	431	431	431
pod4	600	600	600	1350	1350	1335
pod1	200	200	200	435	433	431
pod2	400	400	400	863	863	863
pod3	200	200	200	431	431	431
pod4	600	600	600	1350	1350	1308
pod5	800	800	800	1775	1775	1795

Much like the previous set of results, the distance travelled remained constant. In Table 8.5 the results for utilities are presented. There are minimal improvements (in bold) and a few constants, however, in some cases, there is also deterioration (in italics).

In contrast to the previous method, traffic light synchronisation has an overall minimally positive to neutral effect on vehicles' utility. A majority of utilities remain unchanged and only a minority benefit or are hindered. The creation of green waves requires a lot of time and effort on the part of traffic managers and would not be a viable endeavour for it to

Table 8.5: Utility results for Grid, Traffic Light Synchronisation, 2-5 Vehicles

Vehicles	$\text{Utility}_{\text{Dri}}$	$\text{Utility}_{\text{Bas}}$	$\text{Utility}_{\text{Opt}}$	ΔUtility%
pod1	-388	-388	-386.4	0.412
pod2	-770.4	-770.4	-780	*-1.246*
pod1	-388	-338	-384.8	0.824
pod2	-770.4	-770.4	-770.4	0
pod3	-384.8	-384.8	-384.8	0
pod1	-388	-386.4	-384.8	0.824
pod2	-770.4	-770.4	-770.4	0
pod3	-384.8	-384.8	-384.8	0
pod4	-1200	-1200	-1188	1
pod1	-388	-386.4	-384.8	0.824
pod2	-770.4	-770.4	-770.4	0
pod3	-384.8	-384.8	-384.8	0
pod4	-1200	-1200	-1166.4	**2.8**
pod5	-1580	-1580	-1596	-1.01

only be applicable for platoons when considering a small penetration rate. Therefore it does not appear that traffic light synchronisation is an appropriate measure to use for platoon incentivisation.

8.5.3 Time: Comparison

Comparing the two time-incentivisation methods, both as far as strictly time, as well as utility improvements are concerned, shows that the rate of improvement is rather small with some deterioration featuring throughout, presented Table 8.6.

However, when we compare green-waves to priority as methods on their own, we can see (Table 8.7) that with green-waves, the vehicles benefit overall. The reduction of travel time is larger with green waves and no platooning than it is with traffic light priority and platooning, which is also reflected in the utility. As expected, green-waves do more than the precedence method, not only for individual vehicles' utility but also for general decongestion. Therefore it is arguable that green waves perform better for overall traffic.

8.5.4 Cost: The Effect of the Subsidisation Coefficient ψ

The effect of cost subsidisation was studied on the Tiergarten network since it consists of real and realistic information, allowing for authentic results. Due to the size of the network, and the subject studied, the macroscopic movement was used, with the vehicles starting from the same origin point and travelling to their destinations, which were scattered throughout

Table 8.6: Time and Utility improvements in percentage for Grid, Time-based Subsidisation, 2-5 Vehicles

Vehicles	ΔTPrecedence	ΔTGreen – waves	ΔUPrecedence	ΔUGreen – waves
pod1	0.43	0.45	0.39	0.41
pod2	-1.14	-1.39	-1.03	-1.25
pod1	5.27	0.91	4.75	0.82
pod2	0	0	0	0
pod3	0	0	0	0
pod1	5.27	0.91	4.75	0.82
pod2	0.22	0	0.21	0
pod3	0	0	0	0
pod4	1.09	1.11	0.99	1
pod1	5.27	0.92	4.75	0.82
pod2	0.34	0	0.31	0
pod3	0	0	0	0
pod4	3.06	3.11	2.76	2.8
pod5	0	-1.12	0	-1.01

Table 8.7: Time and Utility for Grid, Time-based Subsidisation, 2-5 Vehicles

Vehicles	T Prec plat	T Green-waves np	U Precedence	U Green-waves
pod1	453	435	-402.4	-388
pod2	885	863	-788	-770.4
pod1	431	435	-384.8	-388
pod2	875	863	-780	-770.4
pod3	431	431	-384.8	-384.8
pod1	431	435	-384.8	-388
pod2	873	863	-778.4	-770.4
pod3	431	431	-384.4	-384.8
pod4	1355	1350	-1204	-1200
pod1	431	435	-384.8	-388
pod2	872	863	-777.6	-770.4
pod3	431	431	-384.8	-384.8
pod4	1328	1350	-1182.4	-1200
pod5	1775	1775	-1580	-1580

the network. Results for a five-vehicle platoon, with varying cost subsidisation coefficient ψ, are presented in Table 8.8 as far as cost, distance and time are concerned.

Table 8.8: Results for Tiergarten, $\psi = \{2,3,4\}$, Regular Traffic, 5 Vehicles

ψ	Vehicles	Cost_{Bas}	Cost_{Opt}	$\text{Length}_{\text{Bas}}$	$\text{Length}_{\text{Opt}}$	Time_{Bas}	Time_{Opt}
2	blue	19.65	11.65	0.23	0.23	42	42
	red	8.4	4.9	0.19	0.19	33	33
	yellow	253.816	205.316	1.84	1.84	586	586
	purple	133.316	100.316	1.22	1.22	495	495
	green	132.816	84.316	1.09	1.09	486	486
3	blue	19.65	8.983	0.23	0.23	42	42
	red	8.4	3.73	0.19	0.19	33	33
	yellow	253.816	189.15	1.84	1.84	586	586
	purple	133.316	89.316	1.22	1.22	495	495
	green	132.816	68.15	1.09	1.09	486	486
4	blue	19.65	7.65	0.23	0.23	42	42
	red	8.4	3.15	0.19	0.19	33	33
	yellow	253.816	181.06	1.84	1.84	586	586
	purple	133.316	83.816	1.22	1.22	495	495
	green	132.816	60.06	1.09	1.09	486	486

Since only ψ is being varied, it is to be expected that the distance and time do not differ, not only from the benchmarking to the optimisation approach but also for the different coefficients. Therefore the focus is on the cost reduction from the benchmarking (which already features some level of platooning) to the optimiser. The effect can be visualised better in Table 8.9 where the vehicles' utilities are presented.

With the introduction of the optimisation mechanism, vehicles are better organised into platoons and all their utility improved considerably. Naturally, with a larger ψ coefficient there is a larger improvement, but even with the smallest one, the reduction is considerable, with an average over the five vehicles of 32.4%. This is, based on the experiment and information presented thus far, the better way of creating platoons, as the impact on the utility is sizeable.

8.6 Platooning Influencing Factors

8.6.1 The Effect of the Platoon Size

Another factor that will influence how much vehicles can benefit from platooning is the platoon size. Therefore, on the Tiergarten network, the same vehicles were formed into platoons of different sizes, from the minimum viable size of two vehicles to the maximum of

Table 8.9: Utility Results for Tiergarten, ψ = {2,3,4}, Regular Traffic, 5 Vehicles

ψ	Vehicles	$\text{Utility}_{\text{Bas}}$	$\text{Utility}_{\text{Opt}}$	ΔUtility%
2	blue	-15.766	-9.36	40.63
	red	-6.76	-3.95	41.56
	yellow	-203.42	-164.62	19.07
	purple	-106.89	-80.49	24.69
	green	-106.47	-67.67	36.44
3	blue	-15.766	-7.23	54.14
	red	-6.76	-3.02	55.32
	yellow	-203.42	-151.68	25.43
	purple	-106.89	-71.69	32.93
	green	-106.47	-54.73	48.59
4	blue	-15.766	-6.16	60.92
	red	-6.76	-2.55	62.27
	yellow	-203.42	-145.22	28.61
	purple	-106.89	-67.29	37.04
	green	-106.47	-48.27	54.66

five. Results for cost, distance and time for platoons with an average subsidisation coefficient of three are presented in Table 8.10.

Table 8.10: Results for Tiergarten, ψ =3, Regular Traffic, 2-5 Vehicles

Vehicles	Cost_{Bas}	Cost_{Opt}	$\text{Length}_{\text{Bas}}$	$\text{Length}_{\text{Opt}}$	Time_{Bas}	Time_{Opt}
blue	19.5	14.83	0.23	0.23	42	42
red	10.5	5.83	0.19	0.19	33	33
blue	22.83	12.16	0.23	0.23	42	42
red	9.33	4.66	0.19	0.19	33	33
yellow	224.83	214.16	1.84	1.84	586	586
blue	20.75	10.08	0.23	0.23	42	42
red	8.75	4.08	0.19	0.19	33	33
yellow	247.75	203.75	1.84	1.84	586	586
purple	142.75	98.75	1.22	1.22	495	495
blue	19.65	8.98	0.23	0.23	42	42
red	8.4	3.73	0.19	0.19	33	33
yellow	253.81	189.15	1.84	1.84	586	586
purple	133.31	89.316	1.22	1.22	495	495
green	132.81	68.15	1.08	1.08	486	486

Again, the travel distances and times stay constant, both from a mechanism as well as from a platoon-size perspective. The only variable, as expected, is the cost, which for the Benchmarking approach fluctuates as more vehicles are added to the platoon. For the optimiser, however, the costs are steadily decreasing. The effect is more clear when looking at the individual utilities, presented in Table 8.11.

Table 8.11: Utility Results for Tiergarten, ψ =3, Regular Traffic, 2-5 Vehicles

Vehicles	$\text{Utility}_{\text{Bas}}$	$\text{Utility}_{\text{Opt}}$	ΔUtility%
blue	-15.64	-11.91	**23.85**
red	-8.43	-4.7	44.25
blue	-18.31	-9.78	46.59
red	-7.6	-3.77	50.39
yellow	-180.23	-171.7	4.73
blue	-16.64	-8.11	51.26
red	-7.04	-3.3	53.13
yellow	-198.56	-163.36	17.73
purple	-114.44	-79.24	30.76
blue	-15.76	-7.23	54.12
red	-6.75	-3.02	55.26
yellow	-203.42	-151.68	25.43
purple	-106.89	-71.69	32.93
green	-106.47	-54.73	48.6

As expected, due to the way the pricing formula 5.12 is defined, the more vehicles there are in a platoon, the more each vehicle benefits. With the maximum platoon size, the average improvement is 43%, but even with just two vehicles, the enhancement in utility is at a minimum of 23% (in bold). Therefore, with a cost incentivisation method in place, the formation of platoons is always beneficial to the individual participating vehicles, independent of the platoon size.

8.6.2 Influence of Volume and Density of Traffic

Considering that platoons are primarily a method of traffic decongestion, different stages of traffic volume were investigated to determine which one, if any, provides the best platooning application. The Tiergarten network was used and traffic volume generated for an average, rush-hour and night-time state. The results shown in Table 8.12 present cost, distance and time for a five-vehicle platoon operating with an average subsidisation coefficient of three.

Unlike the previous results, we can now see changes at the level of travel distance and time. Given that the traffic density was altered, the vehicles took different routes from origin to destinations, even though these specific locations were not changed. This is to be expected and makes interpreting the results a bit more difficult, therefore, clearer results in the form of utility are shown in Table 8.13.

Overall the improvement in utility from the benchmarking approach to the optimiser one is visible for all vehicles and all states of traffic. The utility enhancement is considerable, with a minimum of 20%(in italic) for the purple vehicle in rush-hour traffic, but going as high as 55% (in bold) for the blue vehicle in the same context. For the other traffic states, the

Table 8.12: Results for Tiergarten, ψ=3, 5 Vehicles, Different Traffic States

Stage of traffic	Vehicles	Cost_{Bas}	Cost_{Opt}	$\text{Length}_{\text{Bas}}$	$\text{Length}_{\text{Opt}}$	Time_{Bas}	Time_{Opt}
Night	blue	25.2	11.2	0.23	0.23	31	31
	red	30.2	13.53	0.5	0.5	62	62
	yellow	153.53	86.20	1.84	2.6	237	328
	purple	108.53	54.86	1.21	1.21	152	152
	green	143.53	85.2	1.086	2.63	143	324
Regular	blue	19.65	8.98	0.23	0.23	42	42
	red	8.4	3.73	0.19	0.19	33	33
	yellow	253.81	189.15	1.84	1.84	586	586
	purple	133.31	89.316	1.22	1.22	495	495
	green	132.81	68.15	1.08	1.08	486	486
Rush-hour	blue	90	40	0.23	0.23	32	32
	red	124.75	56.75	0.5	0.5	63	63
	yellow	839.58	417.42	1.28	1.28	198	198
	purple	628.08	498.58	1.22	1.63	153	228
	green	818.58	407.58	1.3	1.3	188	189

Table 8.13: Utility Results for Tiergarten, ψ=3, 5 Vehicles, Different Traffic States

Stage of traffic	Vehicles	$\text{Utility}_{\text{Bas}}$	$\text{Utility}_{\text{Opt}}$	ΔUtility%
Night	blue	-20.2	-9	55.45
	red	-24.26	-10.93	54.95
	yellow	-123.19	-69.48	43.6
	purple	-87.04	-44.14	49.29
	green	-115.04	-68.68	40.3
Regular	blue	-15.766	-7.23	54.12
	red	-6.76	-3.02	55.33
	yellow	-203.42	-151.68	25.44
	purple	-106.89	-71.69	32.93
	green	-106.47	-54.73	48.6
Rush-hour	blue	-72.05	-32.05	**55.52**
	red	-99.9	-45.5	54.45
	yellow	-671.92	-334.19	50.26
	purple	-502.71	-399.19	*20.59*
	green	-655.13	-326.33	50.19

improvement is still extensive averaging at over 40%. This would mean that platooning is always beneficial to the vehicles platooning, independent of how busy or free the traffic is.

8.6.3 Influence of Origin and Destination Nodes

Another potential influence on the effectiveness of platooning is the location of the vehicle's origin and destinations. This was investigated focusing on the geographical position of these locations, irrespective of the surrounding traffic density. Five different central and peripheral nodes respectively were selected from the realistic network of Tiergarten, to act both as origins as well as destinations, depending on the specific scenario studied.

8.6.3.1 From the Outskirts to the Centre

For this set of experiments, one node from the set of five selected for the periphery was designated as the origin of all vehicles. The five nodes that were placed in the centre of the network were set as the destinations of the five vehicles. Four simulations were run, with a subsidisation coefficient of three and the platoon size varying from five to two vehicles. The results for cost, distance and time are presented in Table 8.14.

Table 8.14: Results for Tiergarten, ψ =3, Regular Traffic, 2-5 Vehicles, Outskirts to Centre

Vehicles	Cost_{Bas}	Cost_{Opt}	$\text{Length}_{\text{Bas}}$	$\text{Length}_{\text{Opt}}$	Time_{Bas}	Time_{Opt}
V1	183.5	102.83	1.54	1.54	196	196
V2	181.5	100.83	1.37	1.37	177	177
V1	166.83	86.16	1.54	1.54	196	196
V2	164.83	84.16	1.37	1.37	177	177
V3	136.33	69.66	0.52	0.52	87	87
V1	158.5	77.83	1.54	1.54	196	196
V2	156.5	75.83	1.37	1.37	177	177
V3	128	61.33	0.52	0.52	87	87
V4	125	58.33	0.48	0.48	76	76
V1	150	69.33	1.54	1.54	196	196
V2	148	67.33	1.37	1.37	177	177
V3	123	56.33	0.52	0.52	87	87
V4	120	53.33	0.48	0.48	76	76
V5	150	69.33	1.56	1.56	198	198

As is expected, the length and duration of the routes stayed constant between the benchmarking and optimisation approach, and a noticeable decrease in cost was observed. The effect of platooning can be seen more clearly when looking at the results for utility, presented in Table 8.15. The improvement in utility ranges from 44% for the two-vehicle platoon, to over 53% for the five-vehicle platoon.

Table 8.15: Utility Results for Tiergarten, ψ =3, Regular Traffic, 2-5 Vehicles, Outskirts to Centre

Vehicles	$\text{Utility}_{\text{Bas}}$	$\text{Utility}_{\text{Opt}}$	ΔUtility%
V1	-147.10	-82.57	43.87
V2	-145.47	-80.94	44.36
V1	-133.77	-69.24	48.24
V2	-132.14	-67.6	48.84
V3	-109.17	-55.83	49.78
V1	-127.10	-62.57	50.7
V2	-125.47	-60.94	51.43
V3	-102.5	-49.17	52.03
V4	-100.09	-46.76	53.28
V1	-120.3	-55.77	54.47
V2	-118.67	-54.14	54.38
V3	-98.5	-45.17	54.14
V4	-96.09	-42.76	55.5
V5	-120.31	-55.77	53.64

8.6.3.2 From the Centre to the Outskirts

Here the opposite process was performed, where the vehicles were given one central node as the origin and five different nodes in the periphery of the network as destinations. The experiments were run similarly, however, again with a ψ subsidisation coefficient of three, and two to five vehicles in the platoon. The results for cost, distance and time are presented in Table 8.16.

Table 8.16: Results for Tiergarten, ψ =3, Regular Traffic, 2-5 Vehicles, Centre to Outskirts

Vehicles	Cost_{Bas}	Cost_{Opt}	$\text{Length}_{\text{Bas}}$	$\text{Length}_{\text{Opt}}$	Time_{Bas}	Time_{Opt}
V31	369	205	1.18	1.18	191	191
V32	370	206	1.32	1.32	206	206
V31	328	164	1.18	1.18	191	191
V32	329.5	164.83	1.32	1.32	206	206
V33	329.5	164.83	1.39	1.39	215	215
V31	307.5	143.5	1.18	1.18	191	191
V32	308.83	144.16	1.32	1.32	206	206
V33	308.83	144.16	1.39	1.39	215	215
V34	308.83	144.16	1.4	1.4	217	217
V31	295.2	131.2	1.18	1.18	191	191
V32	296.45	131.78	1.32	1.32	206	206
V33	296.45	131.78	1.39	1.39	215	215
V34	296.45	131.78	1.4	1.4	217	217
V35	296.45	131.78	1.52	1.52	231	231

Much like the previous experiments, the distance and time travelled remains the same with a noticeable decrease in cost. The true impact can be seen in the results for utility presented in Table 8.17. Again the improvements range from 44% to 55% for the two and five vehicle platoons, respectively.

Table 8.17: Utility Results for Tiergarten, ψ =3, Regular Traffic, 2-5 Vehicles, Centre to Outskirts

Vehicles	$\text{Utility}_{\text{Bas}}$	$\text{Utility}_{\text{Opt}}$	ΔUtility%
V31	-295.43	-164.23	44.41
V32	-296.26	-165.06	44.29
V31	-262.63	-131.43	49.96
V32	-263.86	-132.13	49.92
V33	-263.87	-132.14	49.92
V31	-246.23	-115.03	53.28
V32	-247.33	-115.59	53.26
V33	-247.34	-115.61	53.26
V34	-247.34	-115.61	53.26
V31	-236.39	-105.19	55.5
V32	-237.42	-105.69	55.48
V33	-237.43	-105.7	55.48
V34	-237.44	-105.7	55.48
V35	-237.46	-105.73	55.47

For both experiments (centre to periphery and periphery to centre), the improvement in the vehicles' utility was within the same range, almost to perfection. Therefore, it can be stated that the geographical position of the origin and destination nodes appears to have no impact on the performance of platoons.

8.7 Benefits and Applicability of Compensational Platooning

Compensational platooning is achieved through the negotiation mechanism which runs in conjunction with the optimiser. Therefore, the answers found through the study of the previous experiments would inadvertently apply to this mechanism as well. However, the efficacy and applicability need to be investigated to provide a complete picture of the impact of this work's proposed solutions.

8.7.1 Negotiation Efficacy

The negotiation-based mechanism works independently from most variables of the model (except ψ, to be discussed shortly), therefore an example is presented here for the Tiergarten network. A two-vehicle platoon was selected and the vehicles were given appropriate destinations, based on a "negotiable" shape. Experiments with a ψ coefficient of three were run and the results are presented in Table 8.18.

Table 8.18: Results for Tiergarten with Negotiation, ψ =3, Regular Traffic

Vehicles	Blue	Red
$Cost_{Bas}$	23	26
$Cost_{Opt}$	17.66	20.66
$Cost_{Neg}$	17.48	19.18
$Length_{Bas}$	0.076	0.053
$Length_{Opt}$	0.076	0.053
$Length_{Neg}$	0.076	0.118
$Time_{Bas}$	22	22
$Time_{Opt}$	22	22
$Time_{Neg}$	22	28

Since the negotiation ended with an agreement, the increase in route length and time is noticed for the red vehicle. The costs do decrease for both vehicles but not necessarily by a substantial amount. This minor improvement is visualised better in the utility results presented in Table 8.19.

Table 8.19: Utility results for Tiergarten with Negotiation, ψ =3, Regular Traffic

Vehicles	Blue	Red
U_{Bas}	-18.41	-20.81
U_{Opt}	-14.14	-16.54
U_{Neg}	-14	-15.37
$\Delta U_{Bas \to Opt}\%$	23.19	20.52
$\Delta U_{Opt \to Neg}\%$	0.99	7.07

While the jump from the benchmarking approach to the optimiser one is appropriate to justify its usage, the same cannot be said for the negotiation one. For the Blue vehicle, the improvement is 0.99% and for the Red, it is 7%. Therefore, while negotiation provides some improvement to both vehicles' utility, it may not be substantial enough to justify the time and computation effort required to use it.

8.7.2 Negotiability of a Network based on ψ

Given that the results for the negotiation approach were less than representative, the possibility of negotiation happening often enough to have a more considerable effect on overall results was investigated. The negotiability degree of the Tiergarten network with different traffic states is presented in Table 8.20 with differing ψ coefficients.

Even given the highest coefficient, only two to four per cent of all shapes considered were deemed as "negotiable". This in combination with the low level of impact that negotiation has on the utility, makes this negotiation-based compensational approach not an optimal platoon formation mechanism.

Table 8.20: Degree of negotiability of Tiergarten, ψ ={2,3,4}, Different States of Traffic

Traffic	ψ	Triangles	Polygons
Total		249	594
Regular	2	0 / 0%	0 / 0%
	3	3 / 1.2%	7 / 1.18%
	4	7 / 2.81%	12 / 2.02%
Night	2	0 / 0%	0 / 0%
	3	3 / 1.2%	10 / 1.68%
	4	7 / 2.81%	9 / 1.51%
Rush-hour	2	0 / 0%	0 / 0%
	3	4 / 1.6%	10 / 1.68%
	4	6 / 2.4%	27 / 4.54%

8.8 Computational Performance of Proposed Solutions

The grouping effort of the Benchmarking and Optimisation approaches were compared using the Tiergarten network with macroscopic movement.

For the Optimisation approach only the number of vehicles varied from two to five. However, for generalisability, ten and twenty vehicles were considered to prove that the approach is scalable. The origin node was constant for all vehicles, however, the destinations were unique and varied in their positioning (from close to the origin, to the other side of the network).

For the Negotiation approach the number of vehicles was not varied, since only bi-lateral negotiation is supported. The route negotiated and vehicles involved were constant, whereas the deadline was increased so that the performance can be critically assessed given the time constraints.

8.8.1 Optimiser Performance

Figure 8.1 presents the execution time in milliseconds of the Benchmark (in red) and the Optimisation (in blue) approach for several vehicles.

As it is expected, the optimisation approach performs worse than the benchmarking one, with the computational time growing linearly with the increase in vehicles considered. However, even when performing the mechanism with 20 different vehicles forming a single platoon, an appropriate solution was found in under two seconds. Since this approach runs distributively, ideally at every intersection, it can be safely assumed that a solution can be found in a timely manner. This suggests that implementing the proposed mechanism is feasible and it will execute with enough time to spare for the vehicles to perform the necessary formation manoeuvres.

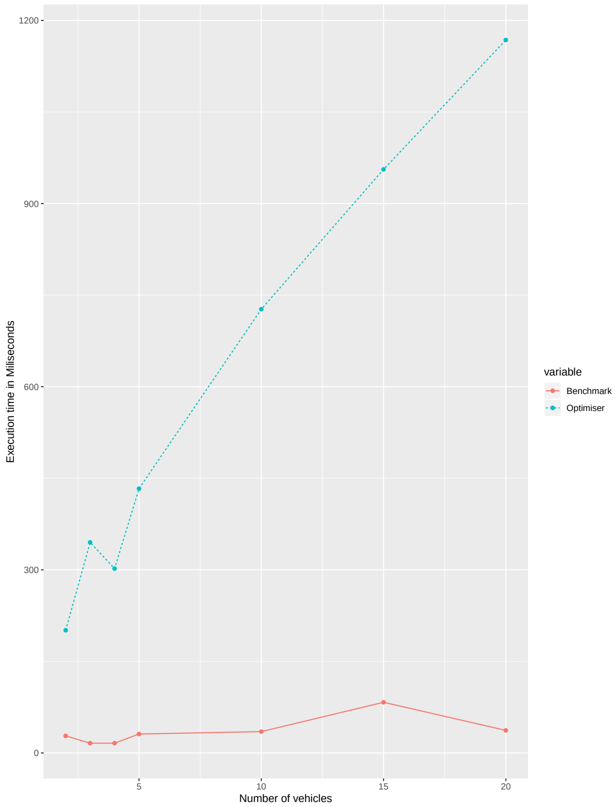

Figure 8.1: Performance analysis of baseline and optimisation algorithms

8.8.2 Negotiation Performance

Figure 8.2 presents the execution time in milliseconds of the Negotiation approach for the same two vehicles (with constant origin and destination points) but with different deadlines on the negotiation exchange. Considering that the vehicles are equipped with an intelligent module to carry out the negotiations, an agreement can be reached within a smaller timeframe. Nevertheless, by increasing the time the vehicles have for negotiation the performance of the algorithm itself can be analysed from an applicability standpoint, ensuring that it is an appropriate tool to be used given the circumstances.

The execution time does rise significantly with a prolonged negotiation time, but even with the longest deadline (30 rounds) it still performs exceptionally quick in under 500 milliseconds. This indicates that the implementation of such a method would be viable as far as performance is concerned and can be feasible in real traffic scenarios.

8.9 Discussion

Based on the results presented so far in this section, we revisit the research questions proposed for this thesis in Section 3.5 and discuss to what extent they could be answered.

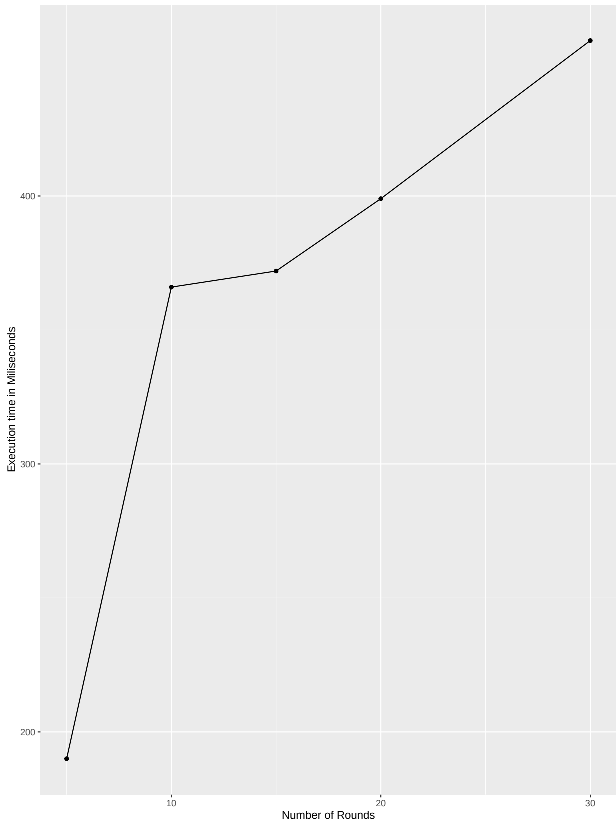

Figure 8.2: Performance analysis of negotiation algorithm

8.9.1 Incentivisation Benefits and Characteristics

Considering the results presented in Section 8.5, certain conclusions can be drawn and Research Questions I.i and I.ii partially answered. Three separate incentivisation methods were investigated, two using time and one cost. First, vehicles travelling in a platoon were given a jump-start when waiting at a red light which proved to not have a huge impact on the vehicle's utility, given the relatively small reduction in travel time. Given the average traffic light cycle duration (60-90 seconds), it would be hard to grant platoons a higher share of the green traffic light and this approach would only be feasible if the vehicles only encountered red lights.

In that vein, the second time incentivisation method, namely switching the traffic lights from an uncoordinated to a coordinated program, thus creating green-waves, was considered as a way of reducing time spent in traffic overall. Again the improvement was minimal to negligible when comparing usual driving with platoon travel. However, when putting the two time-based incentives against each other, synchronised lights yielded better overall results, decreasing the collective travel time.

In the case of the cost-reducing incentivisation mechanism, however, considerable improvements can be noticed. Different coefficients were tested and the improvement was substantia for everyone, averaging at around 25% for the lowest coefficient to 58% for the highest one.

Therefore, time and cost reductions can be used as incentives to encourage vehicles to travel in platoons. However, when analysing the impact the incentives had over the vehicles' utilities, cost reductions appear as the most appropriate method to use.

RQI.i How much do individual vehicles benefit from platoon participation in contrast to normal driving? The benefits are minimal for time-based incentivisation and considerable for cost-based ones.

RQ I.ii What characteristics of the incentivisation methods will affect the benefits positively or negatively? For both time-based methods, a change in the traffic light cycle time would affect the overall result, either positively or negatively depending on the change made (longer cycle time would deteriorate overall results whereas shorter ones would improve them). For the cost-based method, the subsidisation coefficient ψ is linear to the result improvements, but any implementation thereof benefited the vehicles greatly.

H1 Insofar Hypothesis 1 proved to be true, as the cost-based incentive always guarantes improved individual utility.

8.9.2 Platooning Influencing Factors

To study the presented three factors, the simulation was run with the same input data and only the respective factor was varied. The results presented in section 8.6 were overtly positive for all scenarios, meaning that the implementation of platoons in traffic would always have a positive impact irrespective of size, traffic density, origin and destination points.

RQII.i What influence does the platoon size have on the individual vehicles benefits? Based on the results presented in Section 8.6.1, individual vehicles benefit more from platooning when the formation is larger, however even in the case of the smallest possible platoon (two vehicles), platooning provided enough benefits to justify collaboration.

RQII.ii What influence does traffic volume/density have on the individual vehicles benefits? Considering the results in Section 8.6.2, it is concluded that the state of traffic does not influence the formation and operation. Platoons were still able to form and provide benefits to the compounding vehicles irrespective of the volume and density of the background traffic.

RQII.iii What influence do the origin or destination of vehicles have on the individual vehicles' benefits? The results presented in Section 8.6.3 prove that the geographical locations of the origin and destination nodes play no role as platooning is beneficial to all vehicles, no matter their positioning.

H2 Insofar Hypothesis 2 proved to be true, as none of the external influencing factors studied exacted notable effects over the subjects; at the same time, internal factors (subsidisation coefficient and platoon size) did.

8.9.3 Compensational Platooning

To study the benefits and performance of compensational platooning, the negotiation mechanism presented in Section 6.2 was applied, and its benefits for individual vehicles as well as its applicability investigated. The results did not reflect positively on this approach as both aspects studied showed minimal improvement and thus the effort to implement it might not be worth it.

RQIII.i How much would individual vehicles benefit from these compensational mechanisms? The results presented in Section 8.7.1 prove that the benefits from a compensational mechanism are severely limited, rendering an improvement of one to a maximum of seven per cent.

RQIII.ii How applicable is compensational platooning? Considering the results presented in Section 8.7.2, it can be concluded that while a compensational mechanism will lead to more platooning, its applicability is restricted. The structure of the network combined with the incentives offered, is the main driver of whether or not compensational platooning can take place. Therefore when moving from smaller networks to larger ones, the incentives must also reflect that growth.

H3 Insofar Hypothesis 3 proved to be true, as utility improvements with compensational platooning were in the single-digits and therefore easily surpassed by the effort necessary.

8.9.4 Computational Efficiency

Since we are dealing with a fast-paced and volatile environment and both optimisation and back-and-forth negotiations are not known to be the quickest as far as execution goes, the computational time of both proposed algorithms was investigated to ensure their applicability in real-world scenarios.

RQVI.i How much time does it take to apply the optimisation-based mechanism? The results presented in Section 8.8.1 indicate that the proposed algorithm is feasible to use in real-life traffic scenarios. Considering that the shortest average traffic light cycle-time is 60 seconds and that the algorithm's execution time is under one second, it leaves enough time for all the other necessary tasks (communication, positioning manoeuvres, etc.) to be executed.

RQVI.ii How much time does it take to apply the negotiation-based mechanism? Considering the results in 8.8.2, using the proposed negotiation-based compensational platooning algorithm can be viable in real traffic scenarios, as with a reasonable number of rounds (30 or under) it performs in under half a second.

H4 Insofar Hypothesis 4 proved to be true, as with increasing complexity (number of vehicles and longer deadlines) the execution time rose while still remaining brief enough to foster cooperation in a meaningful way.

9 Conclusion

In this chapter, we conclude the contributions and insights gained by this thesis (Section 9.1). We then critically reflect our work and highlight some limitations (Section 9.2). Based on this, we outline promising venues for future research (Section 9.3).

9.1 Summary

This work's contribution is the development of two novel platoon-forming algorithms. The first is an optimisation-based grouping and routing problem that creates instantaneous and opportunistic platoons, as vehicles travel organically through the network. Such an optimisation approach is traditionally ran centrally and is very complex, making it a good fit for longer-term partnerships. The proprietary proposed algorithm executes in under two-seconds for even a large number of vehicles and produces beneficial results for all of them. The second mechanism aids in the formation of compensational platoons, where monetary benefits are exchanged for continued cooperation. This is a new concept all-together and it uses automated negotiation with an opponent model and adaptable negotiation strategy to guarantee a high-rate of agreements that finish quickly and provide both negotiating parties with satisfactory results.

Based on supporting research, the motivation, research gap and design decisions are presented, allowing for the proposed model to be conceptualised. Based on said theoretical model, an implementation and testing software infrastructure is developed and multiple different scenarios are conducted, investigating different aspects and providing answers to the proposed research questions.

Considering the environment of the problem, it is imperative that any methods are fast and scalable enough to accomodate quick changes and a high number of requests. This is proven to be the case with an execution time of under two-seconds for even the most strenuous conditions.

Two incentivisation methods were proposed and investigated, with multiple applications. First, allowing for faster travel with either stop-light precedence or stoplight coordination and second, offering reduced penalisations when vehicles travel together in a platoon.

While implementing the first time-based incentivisation is rather simple and would not require a great effort on the traffic management side, it proved not to be as effective as expected, with the individual and overall benefit being minimal. On the other hand, synchronising stoplights and creating green-waves brought on tangible gains, but the effort needed to implement such a measure is ample and would benefit all traffic participants, thus removing the preferential advantage of platooning.

However, it is clear that a cost-based approach brings about the most benefit for the individual vehicles, with considerable improvements starting from 25% increases in utility. By employing congestion pricing/tolling systems with the aforementioned approach, traffic managers would have a powerful way of controlling and directing traffic with minimal to no effort. Even with the smallest subsidisation factor, it would be worth it for both driver and manager.

Several characteristics of platoons, networks and routes were investigated to assess their influence on the problem with mixed results. No factor had a negative impact, namely they mostly ranged from no influence to beneficial, thus proving that the problems formulation and respective implementation is robust and enforcing it would always be beneficial.

The second proposed algorithm, namely compensation platooning through distributed direct negotiation did not provide as beneficial results as expected. While the model and the proposed solution set in place did allow for more platooning than the distributed optimisation-based algorithm, the benefits were minimal. This applied both to the individual vehicle benefits, as well as to how often it would be possible for compensational platooning to take place. However, this novel approach can be applied to group formation further in the future with different compensational schemes.

9.2 Limitations

Since existing studies focus on the advantages that platoons bring to general traffic (decongestion, better road- and fuel usage), this work focuses solely on the benefit of platooning for individual vehicles. However, the effect of introducing such formations in everyday traffic needs to be quantified from a system point of view. This is regrettably not addressed in this study as existing concrete models to measure the improvement in time or space could not be adapted to the one presented here. Nevertheless, it is important to mention, that based on the Distance results presented in Tables 8.2, 8.4, 8.8, 8.10, 8.12, 8.14, 8.16 and 8.18, the overwhelming majority of vehicles did not travel more in platoons than with individual driving (only four out of 103 vehicles studied overstepped their original optimal route). Therefore, it can be argued that the platoon formation mechanisms presented here do not lead to vehicles spending more time on the road or travelling more kilometres and that the system benefits from any improvements that platoons bring.

The presented model focuses on just three aspects of driving: distance, time and cost. While these are the major factors which traffic participants are trying to minimise, they are not the only ones. Other cardinal and highly subjective factors (safety, stoplights, familiarity etc.) have not been taken into account in the current model. This would mean that the presented model may be perceived as potentially reductive and rigid, but on the other hand, it offers a perfectly rational baseline that can be developed further. On that note, the conscious decision was made to create the underlying infrastructure in such a way that can afford and facilitate additional functionalities, to enrich and diversify the scope of the problem as long as any other factors to be considered can be ported on a fixed scale. Should more cardinally driven permutations be desired, the existing premise could provide a reliable foundation as long as the additional extensions allow for serial ranking to reflect preference hierarchy.

As in the case of many research projects, the proposed and investigated way of compensational platooning proved not to be as beneficial as theorised or hoped. While the current model for how compensation is calculated restricts both the individual benefits and the incidence rate at which platooning can take place, future schemes may be able to overcome this shortcoming and use the proposed method (negotiation with the creation of an opponent model to offer bids that satisfy both parties) with better results. With respect to the established operational status-quo of this framework, it is strongly postulated that further technological developments and data-driven initiatives can instill its core logic with modern and novel approaches that may enhance the framework's capacity to generate viable cooperation and give rise to practicable implementations in real-life scenarios.

On the implementation side, this work relies heavily on static visualisations produced after a simulation has ended, to provide a conclusive overview of the routes taken. At that, it is understood that the lack of a dynamic real-time visualisation reduces the degree of understanding and ease of following. The strict text-based reporting can be rather hard to discern, both during and after the time of running the experiment. While the general outcome is clearly presented in a condensed file, a non-static visualisation tool would highlight this work and its contribution whilst making it more user-friendly for a wider public. In spite of its limitations, the generated visualisations add considerable value to the context communicated, and the cost-benefit relation to developing a dynamic depiction on a real-time basis is heavily skewed toward the former. This can be explained by the current framework's lack of ability to create a visual representation at a fine enough granular level to be able to reflect changes at every simulation time-step, thus even when achieving non-static representations, the representations would change abruptly.

9.3 Opportunities for Future Research

9.3.1 Vehicle-to-Platoon and Platoon-to-Platoon Negotiations

The negotiation framework presented in this work is a simple bilateral approach (one to one), which was tested in a vehicle-to-vehicle scenario. While bilateral negotiations can be generalised to also account for vehicle-to-platoon and even platoon-to-platoon negotiations, one major adjustment needs to be made: the negotiation needs to happen at the agent level. In doing so, both vehicles and platoons can participate on an equal footing with similar parameters.

To apply this transformation at the platoon level, a singular agent needs to be either created or appointed, such that it accurately represents the collective interest of the whole platoon and/or each vehicle to the most effective degree possible. Therefore, the utility function of the agent that negotiates on behalf of the platoon should be derived and then used in negotiation.

Whether created or elected, the representative agent's utility function has to be an aggregate of the participating vehicles' utilities. This creates the need for a social choice function that paints an accurate picture of the collective.

Let the aggregated utility function U_P be defined as:

$$\begin{gathered} U_P = f(U_{v_1}, U_{v_2}, \ldots, U_{v_n}),\ v_i \in \text{Platoon} \\ U_P = -\sum_{e \in R} f(\rho_{v_1}, \rho_{v_2}, \ldots, \rho_{v_n}) \cdot l_e + f(\rho_{v_1}, \rho_{v_2}, \ldots, \rho_{v_n}) \cdot p_e \\ U_{v_i} < U'_{v_i},\ \forall v_i \in \text{Platoon} \end{gathered} \tag{9.1}$$

where

$$U'_{v_i} = -\rho \cdot \sum_{e \in R} l_e - \sigma \cdot [\sum_{e \in R}(p_e) - \frac{\text{profit}}{n}] \tag{9.2}$$

Table 9.1: Platoon Preference Presentation by Negotiation Role

Role	$\rho > \sigma$	$\sigma > \rho$
Initiator	=/+	+/=
Acceptor	-/=	+/=

In Table 9.1, the outcomes of a vehicle-to-platoon or platoon-to-platoon negotiation are presented from the point of view of the/one platoon. If the aggregated platoon utility function prefers a shorter route, then the individual utilities of the compounding vehicles are likely to deteriorate if the platoon is in the accepting role. However, if the platoon is the one initiating the negotiation, the individual vehicle's utility will improve slightly. For a "greedy" platoon the results are rather positive no matter the negotiation role.

Given the insignificant level of improvement that negotiation was proven to bring, and the fact that the resulting profit must be shared evenly with all participating vehicles makes the likelihood of negotiations ending in an agreement with platoons as either the accepting or the initiating agent very low, even if an appropriate social choice function is applied.

However, putting such a function in the context of Arrow's impossibility theorem would lead to the following discussion:

9.3.1.1 Non-dictatorship

Seeing as platoons already have (as they should) a leader, which based on research (Johansson et al., 2018) benefits the least from the coalition and bears the responsibility of making minor executive decisions (changing lanes for example), the argument can be made for the first vehicle's vote to have a higher weight. However, considering how the benefits of platooning are calculated and shared, this ought to be avoided, giving both the leader as well as the following vehicles an equal standing in the aggregated function.

9.3.1.2 Independence of Irrelevant Alternatives

Considering that the preference profiles are rather simple, due to the existence of just two factors, irrelevant alternatives do not come into play. Should the preferences and by extension the utility be expanded on, irrelevant alternatives are bound to appear. However, they can be disregarded due to the existence of a previously calculated optimal route. Said solution can be used as a yardstick to assess any proposed alternatives and thus eliminate the irrelevant alternatives from being taken into consideration.

9.3.1.3 Pareto-efficiency

For conflicting instances (some prefer shorter but expensive routes but the others long and inexpensive) it is difficult, if not impossible, to not leave vehicles rather unsatisfied and misrepresented. A consensus would be hard to achieve and this could mean that in the best case the negotiation does not take place, or in the worst case, that the platoon disbands. However, it would make for an easy to please opponent given the more "middle of the road" preferences.

Other works of note that address the topic of utility aggregation are (Wu et al., 2004a,b) which propose joint utility functions to calculate optimal compound task execution in time-sensitive domains. Keeping fairness in mind, one could use (Aschermann et al., 2017) as a guideline to ensure a higher level of equity in the representation of each vehicle's preference profile in the joint utility function.

9.3.2 Negotiable Networks

Similarly to any other cooperative endeavour, the success of the negotiations between vehicles in a platooning setup is contingent upon the "negotiability" of the underlying infrastructure. At that, negotiability within this operational framework can be understood as the percentage of negotiation-viable subnetworks within the aggregated constellation of all possible subnetworks. Although the respective process was described in Chapter 7.4.4.6 in terms of the proposed model, this current chapter sets out to explore on account of practical paradigms how a negotiable network should be structured to facilitate increased effectiveness of the negotiation process.

One hypothesis on increasing a network's negotiability factor is to transform its density and connectivity through the introduction of more nodes to act as intermediaries. By creating a more dense network with multiple alternative routes, it is possible to allow for more negotiation. On the other hand, by creating these alternative routes, the overall number of negotiable shapes also increases.

To test out this hypothesis, a new network was created in the form of a spiderweb, presented in Figure 9.1. The network is denser in the centre and slowly becomes less connected toward its periphery. Similarly, the simulated background traffic (the edge's weight) follows the same pattern, with a higher density in the centre which decreases going outwards.

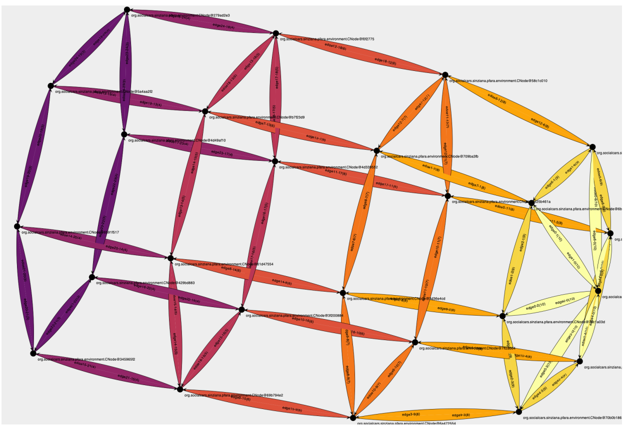

Figure 9.1: Simple spiderweb network

To create a more dense network, nodes will be added in the different "sectors" of the spiderweb to allow for more edges. Since the focus of this study is strictly on negotiability, the new edges will be given an appropriate weight such that even with platooning, the vehicles would not prefer them over the original network. Two different iterations of the network will be presented focusing on the inner-most "circles".

The first iteration meant introducing just one new node per sector and connecting it to the three nodes delimiting its sector, see Figure 9.2. For the second iteration, which features the second circle from the centre, three to four nodes were added and appropriately connected (pictured in Figure 9.3).

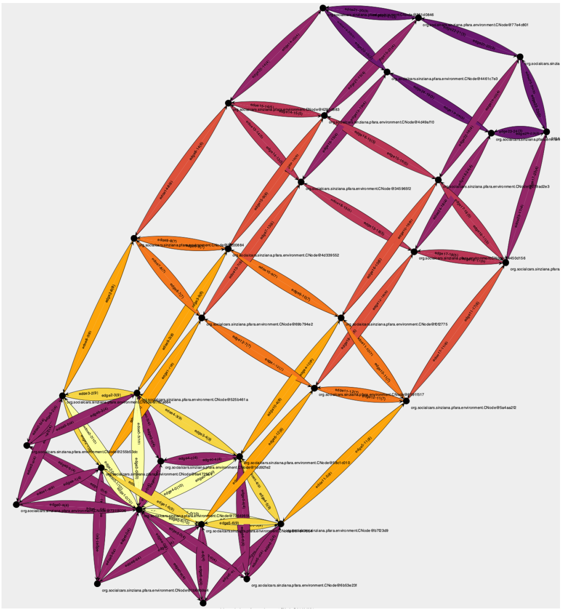

Figure 9.2: Extended spiderweb network

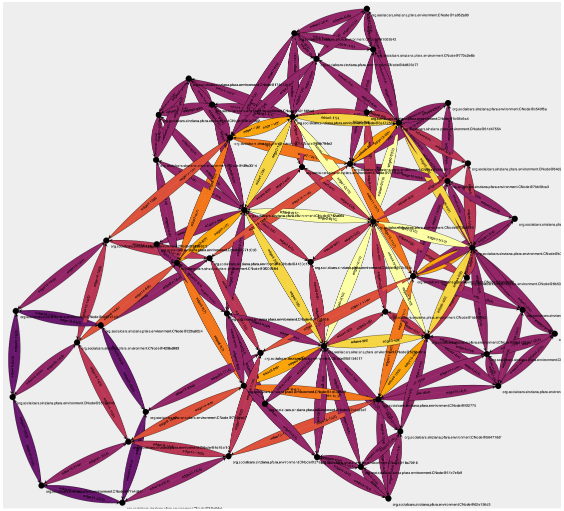

Figure 9.3: Further extended spiderweb network

Experiments were run for the three networks (simple Spiderweb, with one level of extra density and with two levels of extra density) with varying ψ coefficients, with the results being presented in Table 9.2. As theorised, the number of total negotiable shapes was boosted with each increase in density, with the same applying to the negotiable shapes. While the negotiability overall is still rather low, it is an improvement on the level of the original Spiderweb network. The highest rate is 11% which is a considerable result and even the lowest at 2.18% reflects the rate of the real Tiergarten network presented in the previous chapter.

The most interesting finding is, however, related to the subsidisation coefficient ψ. With the first iteration of the network, the highest degree of negotiability is reached with a coefficient of three. Whereas, for the second iteration a four coefficient yields the best result. Therefore, the theory that a denser network would be more negotiable is only true in part. The negotiability of a network is more dependent on the weight of the edges and subsidisation coefficient, but density plays a role as well, even if it is a minor one.

Table 9.2: Degree of negotiability of the Spiderweb network with varying density and ψ coefficients

Network	ψ	Triangles	Polygons
Total		36	96
Regular	2	0 / 0%	0 / 0%
	3	0 / 0%	0 / 0%
	4	0 / 0%	0 / 0%
Total		144	132
1 level density	2	0 / 0%	0 / 0%
	3	16 / 11.11%	8 / 6.06%
	4	4 / 2.7%	4 / 3.03%
Total		492	274
2 level density	2	0 / 0%	0 / 0%
	3	22 / 4.47%	6 / 2.18%
	4	30 / 6.09%	14 / 5.1%

9.3.3 Negotiation for Larger and Sparser Networks

While the negotiation approach was studied (with limited results as far as applicability and benefit are concerned) for smaller and denser (urban) networks, their counterparts, freeways, were not in the scope of this review.

However, a very small and very negotiable network was defined, as pictured in Figure 9.4, to examine transferable properties from smaller to larger scale schemes. To this extent, this network is especially designed so that the vehicles would platoon for three edges (*O-B, B-C, C-E*), split at node *E*, and then continue to their respective destinations alone. With the introduction of negotiation, the blue vehicle makes an offer to the red, which after some bargaining gets accepted, and they platoon for an edge further(*E-DB*). This is the case with the small network, where the edges are one "block" long.

When increasing the size of the network ten times over, meaning that all edges are now ten blocks long, negotiation ends in a rejection, since the amount that the blue vehicle can pay cannot cover the extra-long detour of the red vehicle. To ensure that this is just a matter of cost, the weights of the edges were also increased ten-fold, as pictured in Figure 9.5, and the experiment ran again, this time leading to an acceptance.

When looking at the results for both vehicles presented in Table 9.3, we can see how the distance, cost, as well as the utility grow approximately linearly, as if multiplied by a factor of ten in a proportional manner.

These results indicate that the negotiation approach can be used for larger networks as well, confirming that the "negotiability" of a network is contingent upon the delicate balance of infrastructure and its cost.

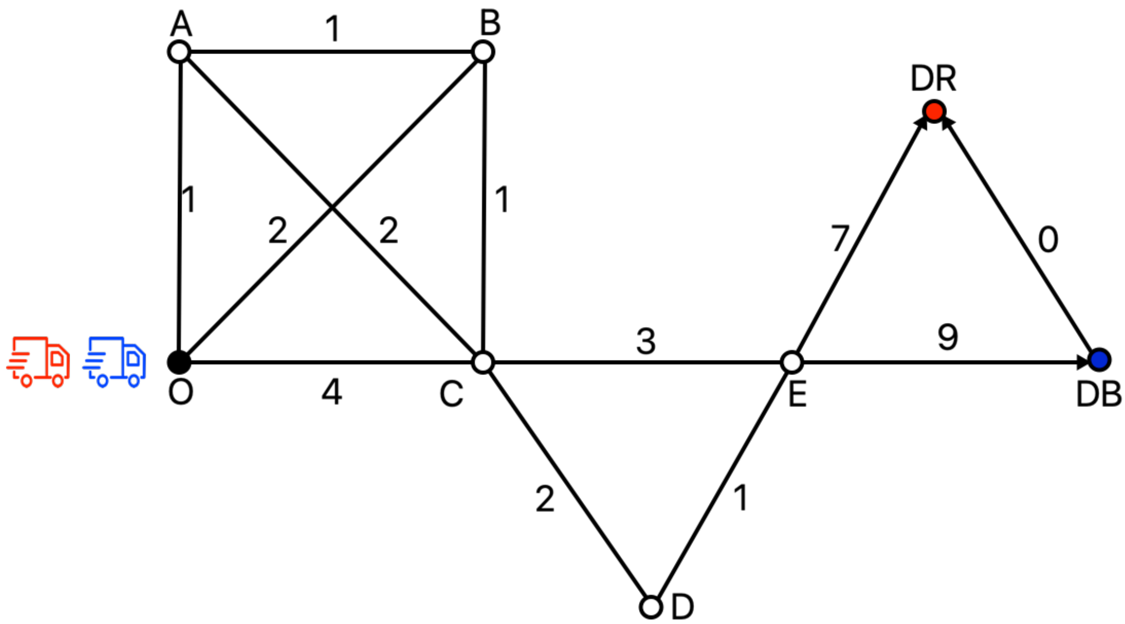

Figure 9.4: Small negotiable network

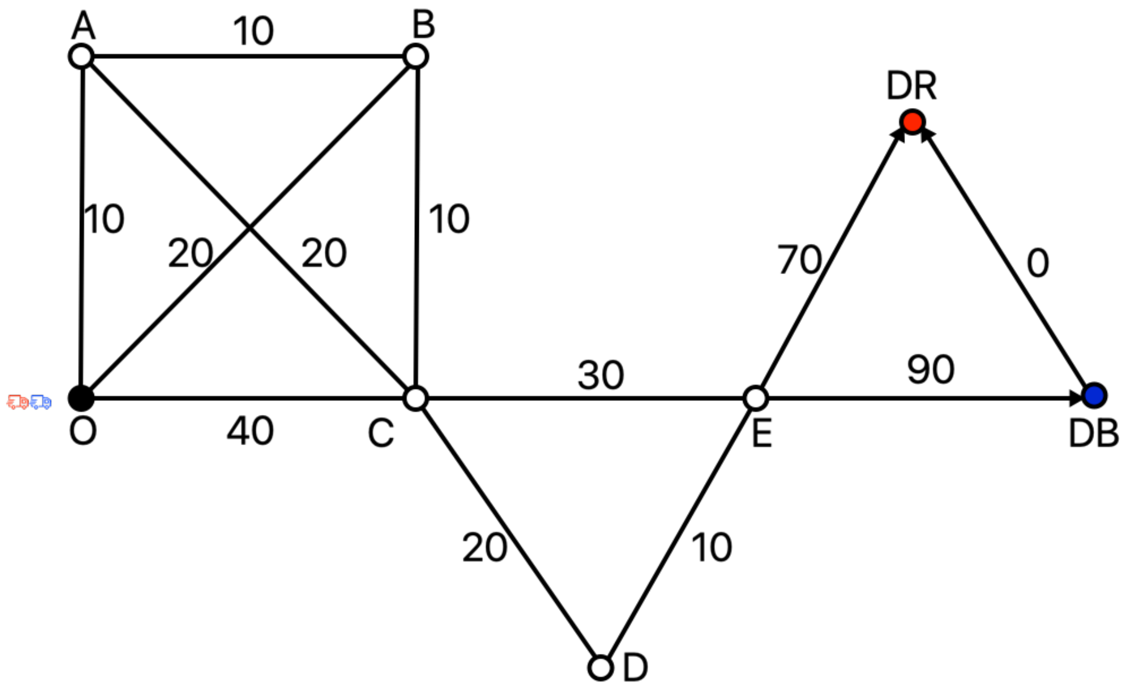

Figure 9.5: Large negotiable network

Table 9.3: Comparison of vehicle measures on investigated networks

Vehicle	*Measure*	*Small Network*	*Large Network*
Blue	Length	4.41	44.14
	Cost	13.97	139.81
	Utility	12.06	120.68
Red	Length	5.41	72.97
	Cost	11.02	110.18
	Utility	9.9	102.74

9.3.4 Other Platooning Incentivisation Methods

On par with the cost and time subsidisation methods presented in this work, one can think of other ways to encourage platooning in a way that makes it more applicable and feasible on a larger scale.

9.3.4.1 Fuelling Reductions

An easy implementation would be awarding vehicles/drivers which have platooned a percentage reduction in the cost of re-fuelling the car, be it typical gasoline/diesel or gas, or electricity (henceforth referred to as power). This requires cooperation between the traffic management authority and the power provider and can be implemented in many ways, by giving a direct discount at the ”pump”, creating a coupon system, etc.

On the side of the vehicle, however, it must be able to keep track of the periods/stretches of travel that were carried out in a platoon. This can be then averaged out over the whole travel period with one ”tank”, and the appropriate subsidisation percentage calculated. While this encourages constant platooning over the whole ownership of a vehicle, it does carry the minute problem of delayed benefits.

9.3.4.2 Services and Perks

While actively still working on the economic side of incentivisation, participating in platoons can be encouraged with selective services and bonuses. Drawing a parallel to the frequent-flyer/bonus miles programs that a majority of airlines implement, drivers can reap some benefits when they platoon often.

Service providers can leverage the platooning platform and its components to harvest user data and optimise their services. In doing so, value can be added to both the service recipient and provider on account of personalised solutions that can elevate the user experience. On that note, the service providers can team up with external third parties to promote offers and premiums tailored to the user's preferences at a discount price or even free, by capitalising on the ever-expanding level of the platooning penetration rate.

9.3.4.3 Gamification

This method of encouraging drivers to platoon will most likely be implemented in the later stages, where the penetration rate of platoons is considerable. This can be achieved by coupling the navigation software used with a ranking system of the platooning score of vehicles and can be applied for the immediate local network (just the platoon, or the whole intersection) or more broadly for a neighbourhood, city, state or even country. While this brings no tangible net increase in utility for the drivers, it appeals to the basic competitive instinct of human nature.

Such a ranking system is already implemented in the crowd-sourced navigation application Waze, where users can gather points through just driving, but also bonuses when reporting an anomaly along their route (potholes, road closures, accidents, police, speed traps, etc.). The ranking is done on a weekly and all-time basis and can be applied for all users or local ones (the respective country), as well as among social-media connections. This hierarchy system can be applied to platooning as it will foster (friendly) competition among friends, family and neighbours.

9.3.5 Non-linear Platooning, from Airborne to Vertical

After addressing the feasibility of platooning in urban spaces, a future step in platooning research would be to use them for other logistic needs.

With the introduction of package delivering drones, an airborne platoon can be formed, and without a fixed infrastructure (no roads), the model can evolve from a 2D to a 3D perspective. Actual columns, rows, diagonals, 3D shapes and swarms are possible and have been implemented already for entertainment purposes as shown in (Records, 2020).

Nautical platoons would be similar to the aerial ones, given the lack of a fixed infrastructure allowing a higher degree of freedom and flexibility. Radar-equipped robots can be deployed to identify and potentially collect debris.

Another application area for autonomous vehicles operating in formation is the detection and detonation of former minefields. Thoroughly and systematically scanning an area with disposable automated vehicles operating in a diagonal (distances accounting for blast radiuses) would provide more security than the random detonators used currently, demonstrated by Hassani (2021).

In the field of logistics, we have seen a shift in how deliveries are taking place. To accommodate for the growth of e-commerce, the distribution network is adapting to a so-called "two-tiered system" (Crainic, 2008; Crainic & Sgalambro, 2014) where the goods are transported first from a large warehouse (called hub) located on the outskirts of a city, to smaller locations (called satellites), and then from the satellite to the customer. The last stretch of travel is called "last-mile delivery" and is considerably costly (Gevaers et al., 2011), making it a perfect candidate for automation. Small autonomous vehicles for deliveries already exist but are quite limited in speed and range. They can only travel at 3 km/h, and have a range of 3km with a 2-hour battery life according to Technologies (2021). Therefore a standard platoon of these robots would not lend itself to busy urban traffic. However, if the typical platoon formation is flipped to an actual vertical column, it would bring a new facet to vehicle formations. A stack of such robots can operate and use another platform-type robot to be carried closer to their destination, from a satellite to a specific neighbourhood or street, thus ensuring a larger range of operation. This approach is potentially the hardest to implement and will have to be carefully planned and organised, as the order of the vehicles is crucial and cannot be adjusted.

These applications of platooning are still outside of our grasp at the moment. But by implementing more complex controllers, we can advance the research to start charting this territory.

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10 Appendix

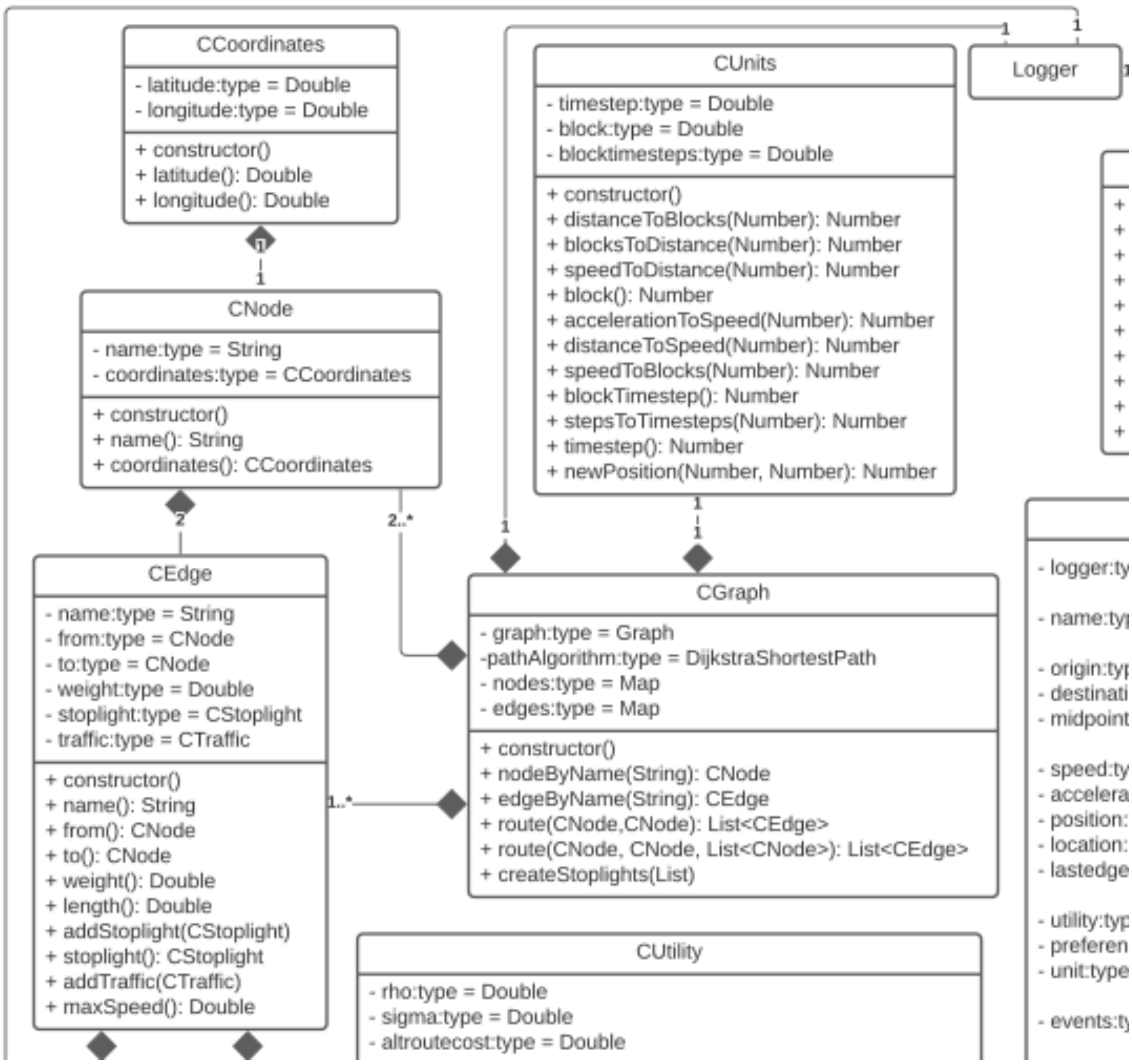
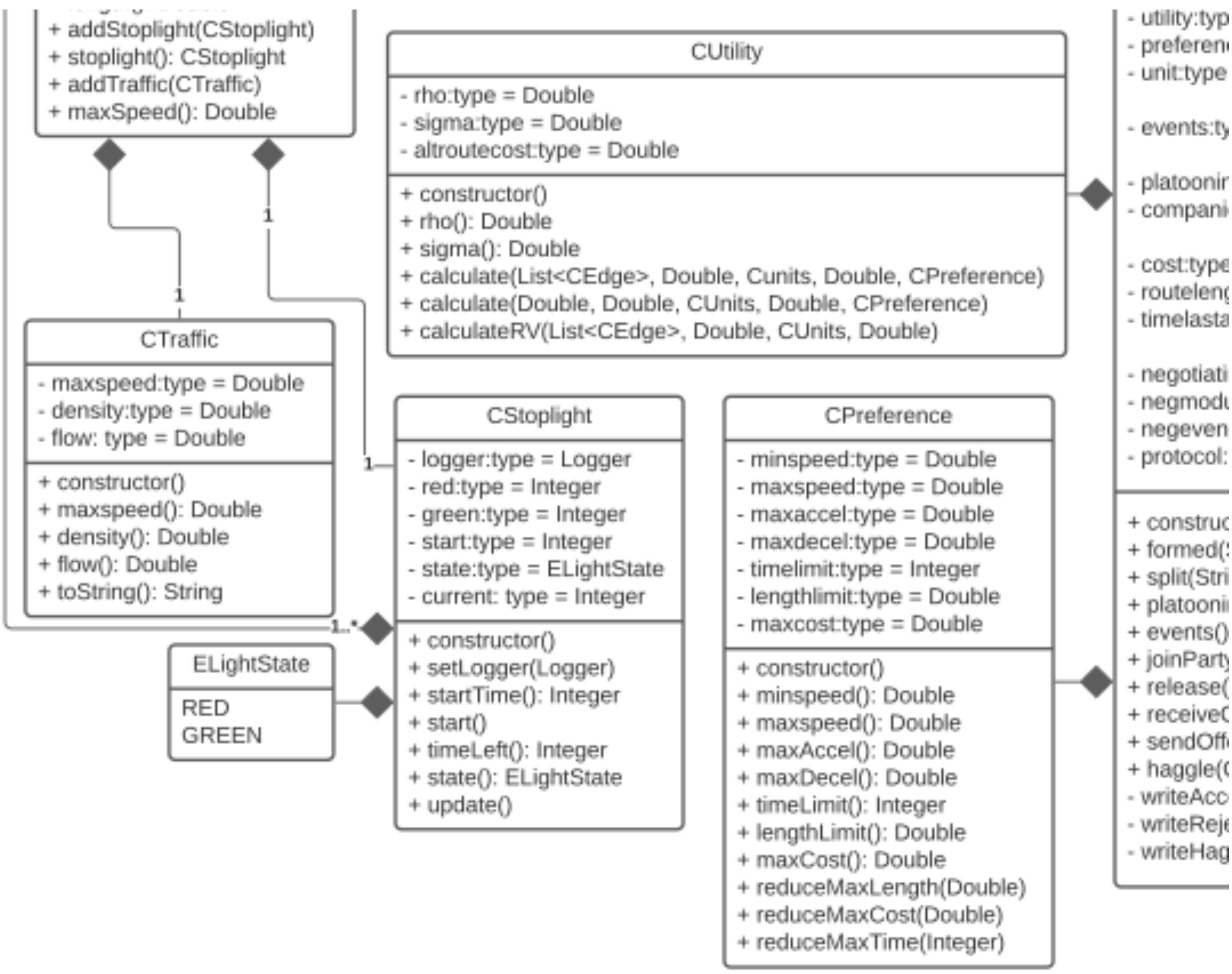


Figure 10.1: Detailed UML Diagram part 1



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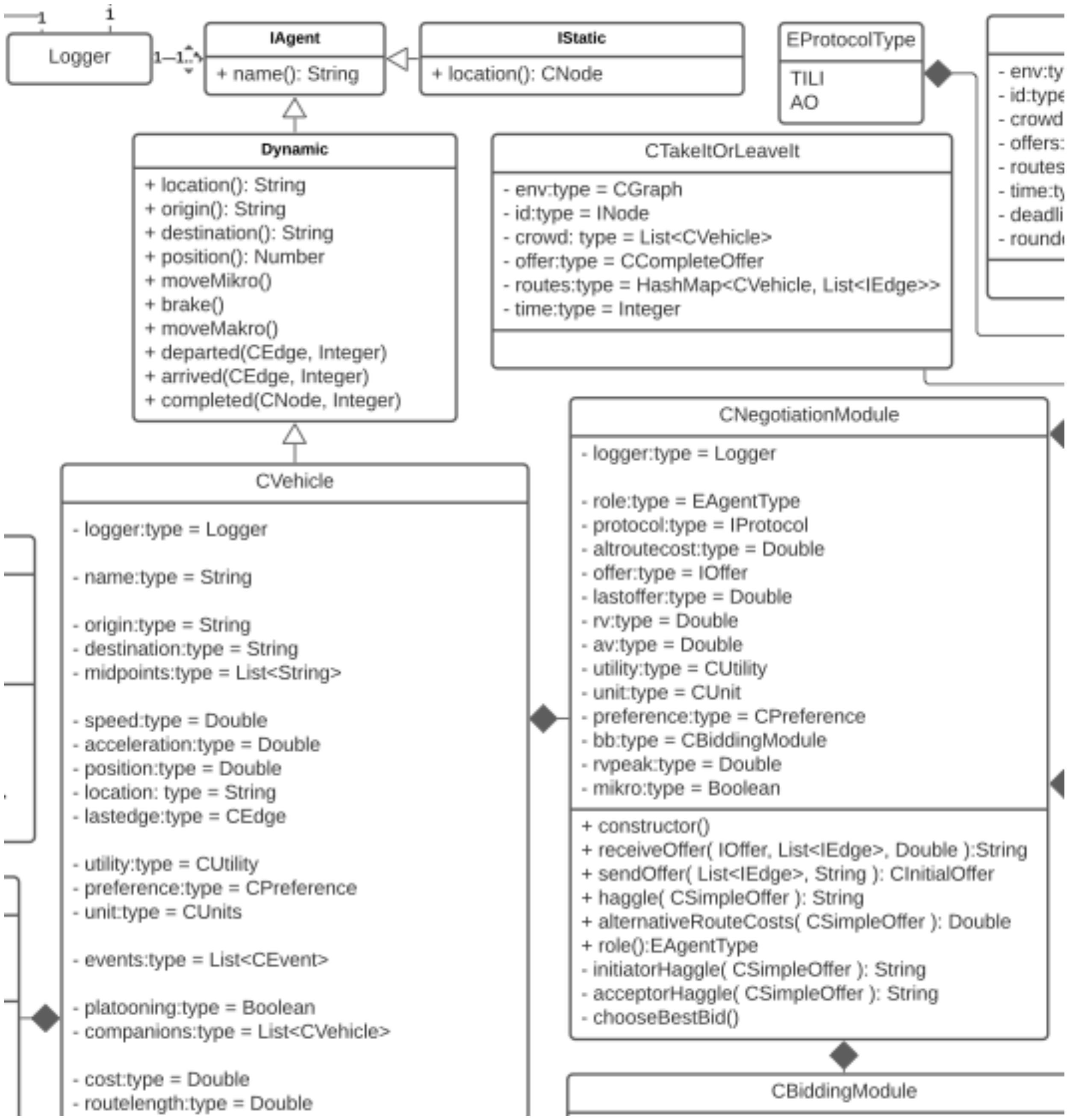

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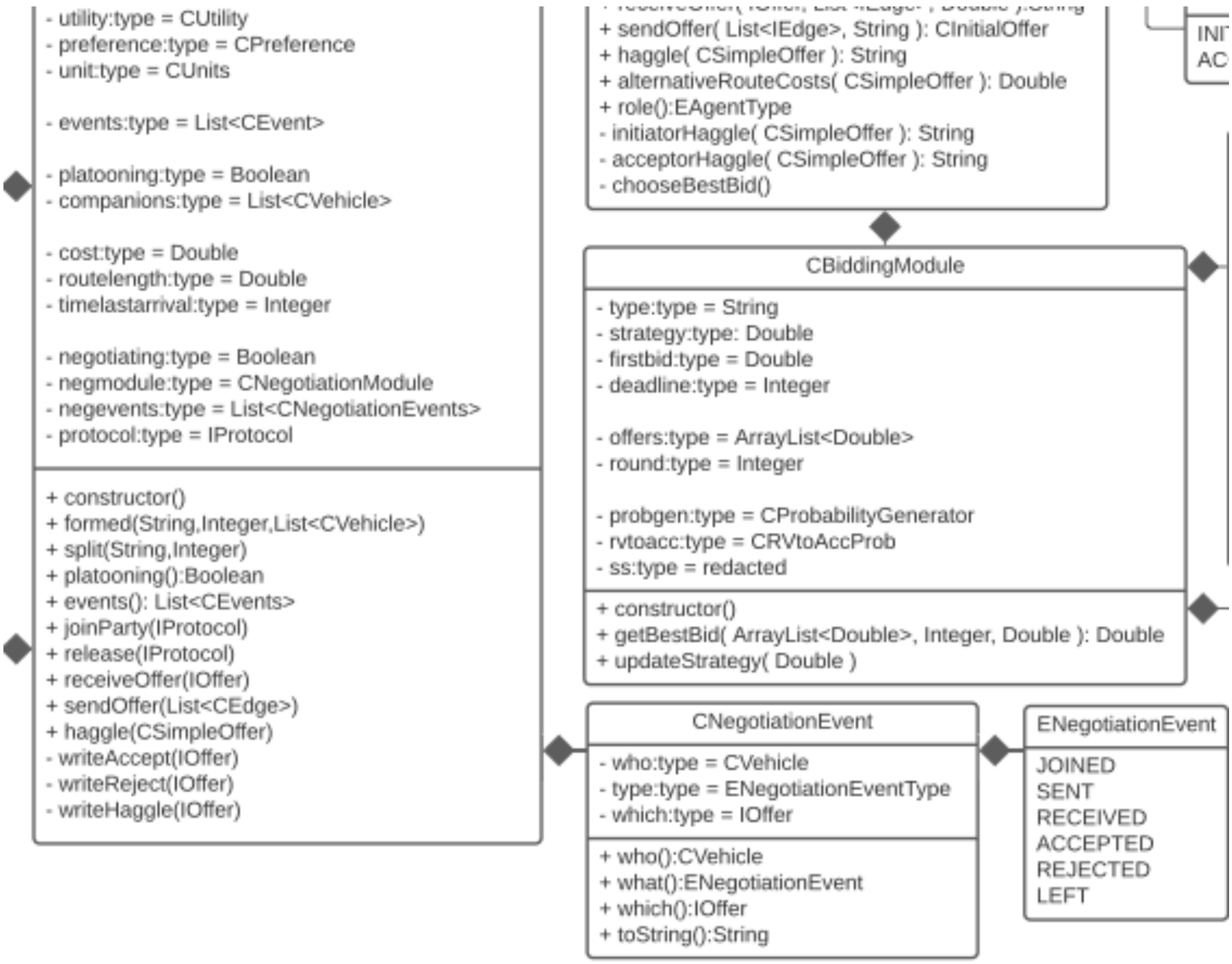

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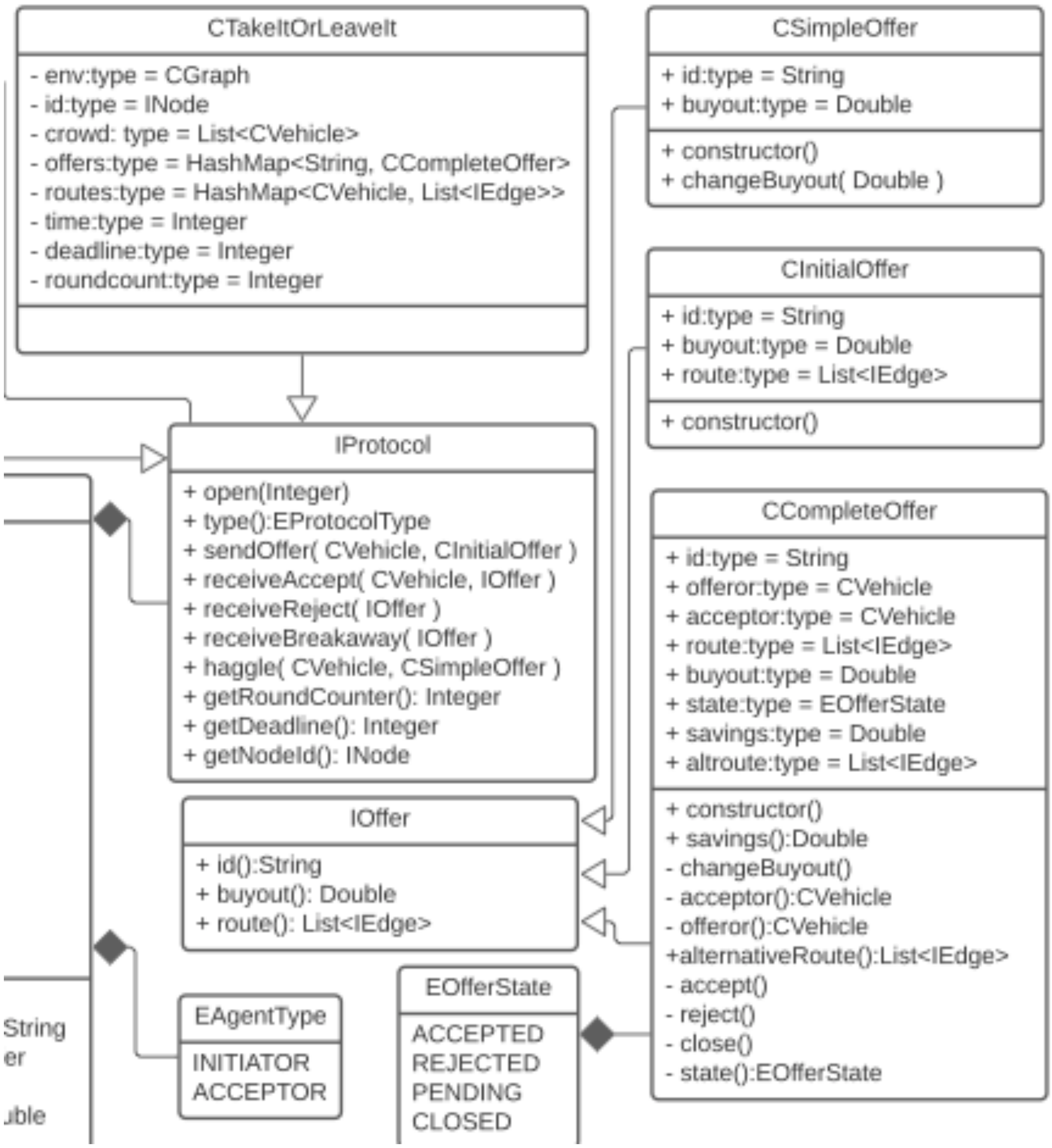

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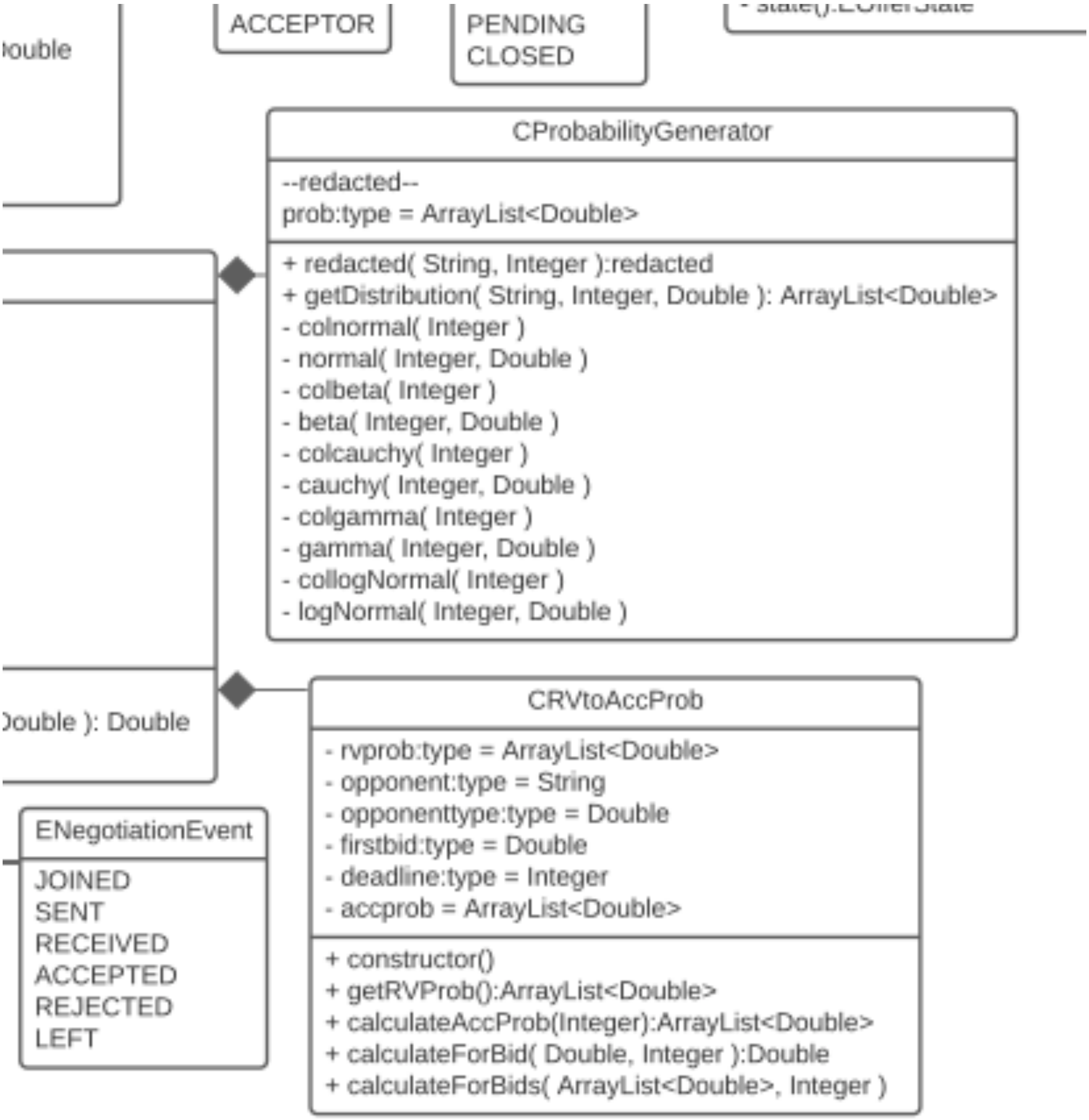

Figure 10.6: Detailed UML Diagram part 6