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Traffic Information Dissemination in Road Transportation Systems

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Abstract

The common belief is that Intelligent Transportation Systems (ITS) using advanced information dissemination techniques can steer the transportation systems into a more efficient operational state. However, it is important to analyze the consequences of providing traffic information to drivers, who are, simultaneously, participants in the data collection process. This informational feedback loop impacts the ITS systems because it can introduce unexpected dynamics with potentially detrimental effects. The main contributions of this work are the identification of several phenomena related to the information flow process. This is done by performing a set of experiments using an agent-based simulation. The first contribution of the thesis is a logical framework describing the informational flow in transportation systems, used to classify the experiments considering the step of the process where the underlying cause of the phenomenon of interest appears. The experiments demonstrate that the amount of drivers using real-time traffic information influences the transportation systems. The traffic performance, when all drivers receive information, is no different from, and perhaps even worse than, when no driver has access to information. However, in transportation systems with traffic lights, more drivers receiving navigation recommendations is beneficial. Moreover, it was also demonstrated that the content of the information influences the traffic. A lower precision of information presented to drivers is sufficient and, in some cases, better for the overall performance. The counter-intuitive positive effect of information inaccuracy manifests when drivers massively use navigation recommendations. In this case, the inaccuracy introduces a level of stabilization into the transportation system. In addition, the minimal amount of drivers that need to be data sources for optimal system performance was identified. Furthermore, the experiments show that a dynamic traffic infrastructure interacting with drivers that use navigation recommendations can have beneficial effects in some circumstances. For example, dynamic traffic lights produce positive results for rapid roads with high traffic intensity, while static control is better in other cases. More results show that the network utilization can be improved by partially closing specific road segments for a fraction of informed drivers. This concept is called soft closing of roads. This way, the traffic information can be used as a steering tool to turn the previously static infrastructure into a dynamic, more efficient road network. The findings of this thesis are relevant in the context of information-based solutions for ITS systems.

Zusammenfassung

Eine weit verbreitete Auffassung besagt, dass Intelligente Transportsysteme (ITS), welche fortgeschrittene Techniken zur Informationsverbreitung nutzen, zu effizienteren Betriebszuständen führen. Allerdings ist es wichtig, die Konsequenzen einer Bereitstellung von Verkehrsinformation an Fahrer zu analysieren, wobei letztere gleichzeitig an der Datenerfassung teilnehmen. Diese informationelle Rückkopplung beeinflusst die ITS insofern, da es eine unerwartete Dynamik mit nachteiligen Effekten einleiten kann. Grundsätzlich behandelt die vorliegende Arbeit die Identifizierung diverser Phänomene, die den Ablauf des Informationsflusses betreffen. Die Untersuchung basiert auf einer Reihe von Experimenten die eine agentenbasierte Simulation nutzen. Der erste Beitrag ist ein logisches Rahmenwerk, welches den Informationsfluss in Verkehrssystemen beschreibt. Dieses wird für die Klassifizierung von Experimenten verwendet und berücksichtigt den Prozessschritt, bei dem die eigentliche Ursache eines betrachteten Phänomens auftaucht. Versuche zeigen, dass das Verkehrssystem durch die Anzahl der Fahrer welche Echtzeit-Verkehrsinformationen benutzen, beeinflusst wird. Der Verkehrsdurchsatz für den Fall, bei dem alle Fahrer Informationen beziehen, ist der selbe oder sogar niedriger als für den Fall, bei dem die Fahrer keinen Zugang zu den Informationen haben. Allerdings kann in Verkehrssystemen mit Ampelanlagen eine höhere Zahl an Fahrern, welche Navigationsempfehlungen erhalten, von Vorteil sein. Darüber hinaus wurde gezeigt, dass der Nachrichteninhalt den Verkehr beeinflusst. Eine niedrigere Genauigkeit der Information die Fahrern präsentiert wird ist ausreichend und, in einigen Fällen, besser für den Gesamtdurchsatz. Der nicht intuitive positive Effekt der Informationsungenauigkeit manifestiert sich bei einer massiven Nutzung an Navigationsempfehlungen. In diesem Fall fügt die Ungenauigkeit dem Verkehrssystem eine stabilisierende Komponente bei. Auch wurde die minimale Anzahl an Fahrern ermittelt, die für ein optimale Systemleistung als Datenquelle benötigt werden. Zusätzlich zeigen die Experimente, dass eine dynamische Verkehrsinfrastruktur unter bestimmten Umständen von Vorteil sein kann, wenn sie mit Fahrern interagiert, die Navigationsempfehlungen nutzen. Dynamische Ampelanlagen wirken sich zum Beispiel positiv auf Schnellstraßen mit hoher Verkehrsdichte aus, während in anderen Fällen eine statische Kontrolle besser ist. Weitere Ergebnisse zeigen, dass die Strassennetzauslastung verbessert werden kann, wenn für einen Teil informierter Fahrer bestimmte Straßensegmente teilweise gesperrt werden. Dieses Konzept wird als weiches Absperren von Strassen bezeichnet. Auf diese Weise kann die Information als Kontrollmittel benutzt werden, um eine vormals statische Infrastruktur in ein dynamischer, effizienteres Strassennetz zu verwandeln. Die Forschungsergebnisse in dieser Arbeit sind insbesondere im Kontext informationsbasierter Lösungskonzepte für ITS relevant.

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Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background and motivation

With an increasing urbanization in our modern industrialized societies [2], the transportation systems are growing as well, playing an essential role in sustaining urban activities. However, this manifests in a higher traffic demand and often congestion on the vast majority of roads. The traffic infrastructure is not fully utilized by commuters not only because of an unoptimised road network design but also because of inefficient routing choices. This results in some of the roads exceeding capacity while others being underutilized. Building new roads is impractical because of the cost, the environmental impact and because of the scarcity of space in urban areas [3]. For example, in Singapore city, roads take up to 12% of the total land area and the trade-off between using the land for roads or other purposes will become more critical in the coming years [4].

Therefore, engineers are now seeking solutions to the question of how the capacity of the existing road infrastructure could be used more efficiently and how the operations can be improved [5] [6]. To address such problems, Intelligent Transportation Systems (ITS) have become one of the most dynamic areas in transportation [7]. Currently, ITS systems consisting of information processing, communication, sensing, and control technologies are more advanced and are expected to play a key role in improving transportation [8, 9, 10]. ITS systems combine several components such as driver information, telematics, motorways and rail management or electronic tolling. Building such systems implies cooperative efforts and financial investments from governments, private industry and academia to integrate information and communication technologies to transportation.

The operation and efficiency of ITS systems are achieved by using components such as Advanced Traffic Management Systems (ATMS) and Advanced Traveller Information Systems (ATIS). At the same time, novel technologies and applications on smart devices not only enable commuters to access real-time information, forecasts and navigation guidance but also to contribute with their traffic data. This creates a feedback loop that can have significant consequences on the overall system performance. Even when this information is highly detailed and accurate, complex and unexpected dynamics can emerge in such transportation systems.

As a consequence of the context, modern transportation systems have become extremely complex, interconnecting not only large infrastructures and informational layers, maintained by traffic sensors and navigation devices, but also the human factor. Moreover, information dissemination with feedback loops is a fundamental topic in all human complex systems in general, where people make decisions by accessing real-time information. Knowing details of future problems modifies people's behavior, and this possibly affects the entire system.

The effect of information dissemination in systems with feedback loops has been studied in several areas of human activity. For example, in financial markets, the effect of private and public information has been analyzed in detail. In [11], the market dynamics is explained by phases: boom, euphoria (informational cascades), trigger and panic (information avalanches). Another example is analyzing the effect of transaction costs on the overall market efficiency when aggregating private information [12].

On the one hand, this complexity makes the design and the operation of such systems challenging [7]. On the other hand, the system's complexity makes it possible that, in many cases, small changes in initial conditions can produce much bigger effects in magnitude [13], also known as the butterfly effect [14]. Therefore, it is important to analyze the positive and negative implications of traffic information dissemination techniques by exploring the complexity of transportation systems.

1.2 Problem statement and research questions

The common belief is that ITS systems using modern information dissemination techniques and providing the right recommendations to drivers trough their navigation devices can steer the transportation system into a more efficient operational state [8, 9, 10]. Literature discusses many strategies of steering transportation systems using real-time traffic information that effectively increase traffic performance such as self-organizing traffic lights based on adaptation [15, 16, 17, 18, 19], information dissemination techniques as in [20, 21, 22, 23, 24, 25], where commuters receive real-time information about congestion in the network and adapt their routes accordingly. Nevertheless, specific aspects related to the possible effects introduced by information dissemination in ITS systems have not been analyzed in much detail. Moreover, the fact that drivers are, at the same time, both sources and receivers of information or the fact that they interact with an intelligent adaptive infrastructure have not been investigated thoroughly.

It is necessary that the transportation engineers understand the implications of commuters massively using navigation guidance for their trips. The Annual Traffic Report released in 2014 by the navigation device maker, TomTom, after analyzing real-world traffic data, reveals that the travel time is increased by 50% because of the common traffic shortcuts drivers take to avoid congestion [26]. The effect can be empirically observed, for instance, during daily commutes, when multiple drivers make the simultaneous decision to take the same alternative route, thus simply moving the congestion to the new road. News reports from 2016 mention numerous problems for the streets that parallel Los Angeles County's freeways, where the traffic is diverted by navigation applications such as Waze or Google Maps [27] [28]. The streets are designed to serve residential neighborhoods and are too small to accommodate the large amounts of redirected traffic. Therefore, these roads are affected by high congestion and discomfort for the residents (i.e. often the congestion is blocking many driveways). Such matters are currently in the attention of the local authorities [29] [30].

Surveys show that in most cases, drivers trust traffic information from smart devices and follow navigation recommendations provided to them [31]. Moreover, the recent developments in autonomous vehicles technology show that that the navigation guidance will be adopted completely in the future transportation systems [32] [33]. Due to this fact, it is possible that, by integrating appropriate information control strategies within ITS systems, the traffic can become more efficient and more robust.

Therefore, the problem addressed in this thesis manifests in the context of ITS systems with traffic information dissemination and informational feedback loops, created by drivers or traffic infrastructure, simultaneously, being sources for data collection and users of the information. Moreover, these drivers interact with an intelligent infrastructure also adapting based on real-time traffic information. This problem impacts the current and future ITS systems because it can introduce unexpected dynamics with potentially detrimental effects on the overall traffic performance. The present thesis contributes to the body of knowledge needed to address this type of problems by answering the following general research questions:

- What is the effect of massively using real-time traffic information on a transportation system where the traffic infrastructure and the traffic participants are simultaneously sources and users of the information?

- Can the traffic information presented to traffic participants as navigation recommendations be used as a steering tool to improve the overall performance of a transportation system?

The investigation of such research questions can have a great significance in the context of ITS systems, producing many insights on how to develop more efficient information control strategies.

1.3 Methodology

The research questions are investigated using simulations of a transportation system, where microscopic interactions between the traffic participants and the infrastructure produce macroscopic emergent phenomena. For this, agent-based models are designed, an approach commonly used for researching complex systems (i.e. transportation or socio-economic systems [34]). This methodology is used in computational science, combining modern technologies to address real world problems that are harder to solve with the traditional numerical methods.

The traditional approach used by transportation engineers first isolates smaller components of the transportation system [35]. This approach is sufficient when the changes in the transportation system are local, in the sense that they don't produce a significant impact on the adjacent components. Therefore, parking regulations, intersection designs, and other changes in the urban transportation system typically create a small effect. For example, in the case of traffic lights, there are situations when the fixed timing of the phases is optimized by fine-tuning a set of intersections along the arterial road, rather than looking at the entire system [6].

However, there are situations when the change produced by a certain policy or design is more substantial or situations when a small change in one component has a significant effect on the elements around. One example can be congestion formation when an event, such as an accident, can perturb the traffic flow in vast areas [36, 37, 38]. In this case, only a highly detailed simulation can capture the correct effects of the change.

The agent-based simulation has been successful in reproducing the observed collective phenomena necessary for the experimental setups performed in this thesis [5], (i.e. self-organized traffic dynamics such as breakdowns of traffic flow, the propagation of stop-and-go waves, the capacity drop, and different spatiotemporal patterns of congested traffic due to instabilities and nonlinear interactions). Moreover, in the presence of increasing computing power, the agent-based simulation practice is even more appropriate for the type of problems tackled in this research.

As described in Section 1.2, this thesis investigates different aspects associated with the information flow process in transportation systems. The two general research questions are further broken down into more specific topics related to what is the effect of information dissemination on a transportation system when different shares of drivers use navigation recommendations. Other aspects investigated in this work look at what is the impact of information content and how the information can be used as a steering tool for *soft changing* the infrastructure to improve the overall system's performance.

For the types of problems investigated in this research, a real world scenario for studying the impact of real-time traffic information is difficult to implement as it requires, among others, a massive rate of participation of the drivers both as sources and users of traffic information. Therefore, the experimental setups of this thesis are a primary application for agent-based traffic simulations in general, as they evaluate hypothetical scenarios and their impact on traffic. These scenarios either don't exist in reality or are too hard or dangerous to be implemented.

Moreover, using an agent-based simulation of the traffic makes it possible to observe the desired phenomena by controlling the level of details of the model trough selected parameters.

1.4 Contributions and significance of the study

The literature review and analysis of the current state of the art on traffic information dissemination in transportation systems serves two important purposes. Firstly, the multi-disciplinary review offers an exhaustive description of the current understanding of traffic information dissemination and information control strategies that are part of intelligent transportation systems. This provides the general context and the clarity necessary to identify the important research questions that still have not been addressed in detail or which don't have very efficient solutions. Secondly, it also determines the methodology appropriate to analyze and answer such questions.

The key contributions of this thesis are:

- **A logical framework describing the information flow process in transportation systems**. This framework facilitates not only novel ways of exposing the problems but also a systematic understanding of the research questions by analyzing them from different perspectives. The experimental setups are classified based on the steps of the information flow process where the underlying cause of the problem is or by where the problem manifests. Also, the experiments are classified by the information details used or by the scale of the road network. This way, the questions related to who receives the information, how the information content impacts the traffic performance or how information can be used to change the infrastructure dynamically, can be investigated from different perspectives. Due to the classification based on the flow information framework, the problems become simpler but not trivial. The subset of problems was made more concrete and could be tackled in a more efficient manner.

- **Identification trough experiments of several phenomena occurring in the process of information flow with feedback loops**. First, an analysis of such phenomena was performed and subsequently an explanation of the possible causes was provided. The phenomena are described and analyzed in four studies.

- The first study provides an analysis of the effect of traffic information on transportation systems. The experiments investigate how the global system's performance is influenced by the number of traffic participants that have access to real-time information and also by the length of the alternative road they take to avoid congestion.
- In transportation systems, data and information are usually affected by errors or noise, as presented in the second study. The contributions of this work are two-fold: Firstly, the different sources of inaccuracy are categorized into three groups based on the underlying cause of occurrence: sparsity of data sources, collection and presentation inaccuracy. Subsequently, the effect that different types of information inaccuracy can have on the overall system's performance is investigated.
- Moreover, the traffic infrastructure (i.e. road segments or traffic lights systems) can also be operated and controlled using traffic information. The contributions of this research determine how drivers and traffic lights systems interact and influence each other when they are informed one about another's behavior.
- Since completely removing roads can be considered a rather extreme measure, the concept of *soft closing of roads* was introduced to control capacity on roads by using traffic information as a steering tool. The soft closing of a road, in this context, means that the road segment is not accessible for a share of informed drivers. The city of Singapore was used as a case study for the traffic assignment which was calibrated and validated using both survey and GPS tracking devices data. The main contribution of this study is the reduction of average travel time achieved by identifying and soft closing one road segment from the entire Singaporean road network.

The findings of these studies are relevant in the context of information-based solutions for ITS systems [8], involving information processing, advanced communication, and sensing. There are significant amounts of money that governments and private industry invest in developing such systems. ITS are expected to play even a more important role in the future [9]. It is useful to anticipate the impact that the massive use of real-time information can have on traffic.

Particularly, understanding the effect of real-time information disseminated in traffic can help solving problems related to congestion by building efficient control strategies for ITS systems. Providing the appropriate navigation recommendations to the right share of the traffic participants can have a positive influence on the traffic performance. Furthermore, this work has important implications on how information is displayed on navigation devices and also for building efficient, intelligent traffic lights systems.

1.5 Outline of the thesis

The thesis starts with two introductory chapters, describing the general context where the research problems occur and the state of the art in dealing with such problems. Chapter 2 presents a multi-disciplinary survey and also a critical analysis of the concept of information dissemination in the context of ITS systems regarded from the complex systems point of view. Transportation systems, ITS systems and an overview of different models of information dissemination and the trade-off between using a centralized and a decentralized information control strategy is presented. Moreover, the state of the art for modeling and simulation of transportation systems is addressed. Chapter 3 introduces the logical framework of the information flow process in transportation systems. Based on this framework, the research questions related to information dissemination in transportation systems can be investigated from different perspectives. In addition, a general description of the computational models used for the experimental setups is presented in Chapter 4.

Furthermore, Chapter 5 investigates how system's performance is influenced by the number of participants that have access to real-time information (i.e. trough navigation tools and applications on personal smart devices). In a real transportation system, data and information are usually affected by errors or noise, this having different implications on the system performance. Chapter 6 describes how the content details of the information can impact the traffic situation. Chapter 7 explores the effect of information dissemination when the actions of the traffic participants temporarily change or influence a responsive infrastructure (i.e. road segments or traffic lights systems). Lastly, Chapter 8 presents the conclusion and the relevance of the studied and also possible direction for future work.

Chapter 2

Literature Review

2.1 Introduction

Modern societies face new transportation challenges due to the massive urbanization. In this context, the integration of ITS systems and communication technologies enable an efficient information flow within transportation systems. As previously mentioned in Chapter 1, the feedback loop created by the fact that the traffic participants are at the same time contributors to the data collection process and users of the information may introduce unexpected dynamics.

In this chapter, the current state of research in the understanding of the different aspects related to the information flow with feedback loops in transportation systems is introduced. This led to formulating relevant research questions that can address the gaps in knowledge and help to build more efficient transportation systems. Also based on the literature review, a holistic approach, characteristic of complex systems, is taken towards understanding and modeling the transportation systems. It is important to choose to use an appropriate methodology to ensure that, the local actions can create the emergent macroscopic phenomena of interest. A suitable approach for investigating these phenomena is by using an agent-based traffic simulation.

Section 2.2 talks about transportation systems described from the transportation engineers' point of view, presenting the main components, recurring problems (i.e. traffic congestion, traffic efficiency, pollution, etc.) and traditional ways of tackling such issues. Trends of development and evolution together with methods of evaluating performance in transportation are introduced as well.

One of the most dynamic areas in transportation is Intelligent Transportation Systems (presented in Section 2.3). These systems integrate the human factor intervention with intelligent information dissemination strategies or dynamic infrastructure. Particularly, components such as Advanced Transportation Management Systems (ATMS), operating with central control strategies or Advanced Traveler Information Systems (ATIS), supplying real-time traffic information to drivers are relevant for the current research. Moreover, an overview of different models of traffic information dissemination used in transportation research is done. These models use specific information local or global details, specific route or speed recommendations. The models choose different shares of drivers to be informed or particular recommendation updates frequency. Also, several concepts related to the price of anarchy or the trade-off between using a centralized or a decentralized information control strategy are addressed.

Due to the complexity of transportation systems, a holistic approach for the evaluation of such systems is recommended. This can be achieved by choosing a multidisciplinary approach, where transportation systems are defined as human complex systems. In Section 2.4, a definition of complex systems is introduced together with the motivation why transportation systems are seen as complex systems. Concepts related to feedback loops and controllability of complex systems are also reviewed in this section.

Moreover, Section 2.5 introduces the state of the art related to modeling and simulation of transportation systems. An overview of the primary models used in traffic simulation is done. Depending on the level of details considered, these models are categorized as macroscopic, mesoscopic or microscopic.

2.2 Transportation systems in engineering

Transportation systems have pervasive and extensive effects in the economic and social live of cities [39]. Urban environments have been regarded over history as trading posts dependent on transportation technology for their growth. The economists discovered that the ideal location for various urban businesses was a function of the cost to overcome the distance between suppliers and the buyers of products. During the 19th century, the reduction of transportation costs resulting from the availability of railroad transportation technology made it possible for large manufacturing centers to operate and develop. In the current times, the rapid advancements in highway construction, automobile manufacturing, and information communication technologies provide even more efficient modern transportation solutions [40].

However, at the same time with the technological revolution, the major cities of the world are expanding and growing in population, this producing an increase in the transportation needs as well [2]. It can be seen that, despite their positive effects, modern transportation systems can often have large negative consequences such as traffic congestion, air and noise pollution too much land space used for transport infrastructure and so on. Finding solutions for such problems is an ongoing effort made by transportation engineers, electrical engineers, computer scientist, governments and the private sector.

Traffic engineering deals with the functional part of a transportation system, except the infrastructures provided (i.e. designing traffic control device installations and modifications, including traffic signals, signs, and pavement markings, investigating locations with high crash rates and developing countermeasures to reduce crashes, etc.)[41]. In this particular section, the transportation systems are presented from the traffic engineering point of view. Particularly, the focus is on the urban road traffic for private vehicles, excluding the public, freight transport or the pedestrian movements.

Transportation systems or modes are defined in the literature as systems for moving persons or goods consisting of three components: vehicles moving the individuals or the goods, the guideways or what the cars driving along (i.e. roads) and the operation plans (i.e. schedules, timetables or control systems) that move the vehicle on the guideways. Based on these components and the relations between them, the transportation systems can be classified to larger economic, social and physical systems [39], depending on the type of problem investigated.

The traditional approach used by transportation engineers to deal with problems, first isolates the smaller components of the system [35]. Such components may be either the fixed infrastructure containing roads or traffic light systems, or conveyances to support mobility for passengers of freight. The network offers a functional and spatial organization of the transportation system while the flows refer to movements of people, freight, and information over the networks [7]. This approach is appropriate when the changes in the system are not major, in the sense that they don't produce a big impact on the adjacent components. There are situations when parking regulations, intersection designs, and other changes in the urban transportation system typically produce a small impact. For example, in the case of traffic lights, there are situations when the fixed timing of the phases is optimized by fine-tuning a set of intersections along an arterial road, rather than looking at the entire system [6].

However, when the change produced by a certain policy or design is more substantial, a small change in one component can have a significant effect on the elements around. One example can be congestion formation when an event, such as an accident, can perturb the traffic flow on large areas [36, 37, 38]. Other significant impact may occur if transportation policies change road prices, develop a new road segment or a new transportation service. New flow dynamics may be introduced by changes in the urban activities (i.e. the opening of a new shopping center) [7]. Other high impact phenomena are related to environmental conservation, transport efficiency etc.

Consequently, depending on the type of problem investigated, either a solution where the components of the transportation system are isolated and examined in more detail or a holistic approach is more appropriate. For this particular research, the effect of traffic information dissemination is evaluated on the global scale of the transportation system. Complexity science discipline proposes a suitable methodology for investigating the transportation system in a more holistic manner. Section 2.4 discusses in detail transportation systems regarded as complex systems.

One of the most dynamic areas in transportation systems is the integration of information technologies together with communications hardware and software at critical points in the ecosystem. These components create the Intelligent Transportation Systems (ITS). By integrating ITS systems, the transportation systems are envisioned by researchers and policy makers to make 21st-century traffic more efficient, reliable, safe, and eco-conscious [42]. A detailed presentation of ITS systems and their implications is provided in Section 2.3. Besides the advancements in ITS systems, the pervasiveness of smart device applications that assist drivers in their trips (i.e. Waze, Google Maps, HERE Maps, Scout GPS Navigation, BackCountry Navigator GPS Pro, GPS Essentials, MapFactor, GPS Navigation etc.) is another important aspect of a modern transportation system.

To investigate different aspects of the transportation systems or ITS systems, either for isolated components or the entire system in a holistic approach, it is important to define a set of metrics and indicators. These metrics applied to traffic data are used by agencies and practitioners to collect data that can support monitoring, managing, and measuring performance [43].

In some cases, the network traffic performance is defined by combining the analysis of individual elements such as each street or each intersection. The most common variables used are speed converted in travel time or the delays defined as additional travel time experienced by the traffic participants. The level of service offered by many transportation systems is a function of the usage of these systems. Consequently, a performance function relates the travel time on each link to the flow traversing this link. Therefore, a constant travel time measure can be associated with each of the links representing the urban network [35]. The global network performance is then obtained by aggregating the individual travel times across the entire network [44]. In other studies, network performance is defined as a fundamental diagram of the mean system flux and a function of traffic load [25]. The author identifies between free-flow phase and congested-flow phase. Another approach is to calculate the relation between the filled fraction of the total network capacity and the jammed population of nodes [20]. Traffic performance can be calculated using trips duration to analyze, for example, what happens when either forecast information or real-time data is used [45]. Similar to these studies, the experiments presented in this thesis use global indicators for quantifying the system's performance.

2.2.1 Traffic congestion in transportation systems

As mentioned in Chapter 1, the current thesis addresses several phenomena related to the information flow with feedback loops in ITS systems. These phenomena can sometimes have negative implications for the traffic situation. These detrimental effects manifest as higher levels of congestion. For this reason, a review of congestion in transportation systems is provided.

Analysing empirical data from several freeways, it was shown that there are multiple causes for traffic congestion that can broadly be categorized into three groups [37][38]. The categories are high traffic flow, bottlenecks (local reduction of the road capacity) and local disturbances of individual drivers in the flow. While the bottlenecks caused by road obstructions, ramps, gradients, lane narrowing or closings are considered spatial and deterministic (predictable), the local disturbances in the flow are stochastic (spontaneously created and cannot be predicted). They can be triggered, for instance, by an abrupt break or by two trucks overtaking each other at different speeds and so on. Congestion can appear as stop and go waves, moving jams or extended jams.

However, congestion has the role in bringing the traffic demand into balance with the available infrastructure capacity [39]. In transportation studies [37], two parameters are usually taken into consideration: the amount of traffic flow and the strength or the degree of congestion. A better way of defining excessive traffic jams is: traffic congestion is excessive when the marginal costs to society of congestion exceed the marginal costs of efforts to reduce congestion (i.e. adding a road or other transport infrastructure) [9].

For this thesis, one of the objectives is to analyze the effect of traffic information dissemination to provide a solution that reduces the level of congestion on roads. The reduced levels of congestion will improve many aspects of city life such as saving travel time, reduce commuters stress levels and increase traffic comfort. There are two particular experimental setups where the traffic information dissemination is evaluated in the presence of congestion (i.e. generated by introducing local disturbances).

2.2.2 Traffic lights systems

One important component of the transportation systems is the traffic lights control as it is responsible for creating a balanced traffic flow. The concept of traffic lights appeared since ancient times, during the Roman Empire when citizens notice a conflict between pedestrian and equine travelers. Not until the 1860s a practical solution was implemented in London. The first traffic control device had arms that commanded drivers at an intersection [46].

The modern traffic light was invented in America. In 1918, New York had a three color system operated manually from a tower in the middle of the street. In 1923, an electric traffic light system with STOP and GO words illuminated was patented. In 1926, the first automatic signals depending on a timer were installed in London [46]. The control of traffic lights started a new stage with the rise of computers in

America in the 1950s. In 1952, in Denver, analog computers were first used to switch between different control plans using detector information [47]. The first use of a digital computer for controlling traffic occurred in 1959, in Toronto [48] [46].

In current transportation systems, the traffic light control is categorized as static, fixed time control and dynamic control. Usually, for static traffic lights, the phases have a fixed duration based on historical traffic data. The green time can be varied between pre-timed minimum and maximum lengths depending on flows. The fixed timing of the phases is optimized by fine-tuning a set of intersections along the arterial road, but there are a few attempts of optimizing the timing by looking at a broader scale. For example, in the case of the city of Lausanne, signal times at intersections are distributed across the entire city, improving the traffic globally [6].

In the case of dynamic control, the controller uses input from traffic sensors reporting the state of the traffic (i.e. the number or the frequency of traffic participants approaching the intersection). Based on this information, dynamic traffic lights adjust the signal timing and phasing to optimize different aspects (i.e. prioritize public transport, emergency vehicles, larger groups of cars, groups of cars that have been waiting for longer, etc.).

Currently, the responsive traffic solutions have gathered more attention while the fixed-time strategies are used more for understanding the traffic conditions. With recent advances in communication networks, computers, and sensor technologies, there is an increased interest in the development of optimizing traffic signal control systems [48]. However, there are still numerous statical traffic lights control in operation [48].

There are studies where fixed-time strategies are proposed as robust control solutions [6]. The real-time responsive optimization is achieved by extending the capabilities of basic traffic lights to either communicate with each other or communicate with vehicles. In [49] the authors use micro-auctions as the organizing principle for incorporating local induction loop information. When a phase change is permitted, each light conducts a decentralized, weighted, micro-auction to determine the next phase. Other studies deal with the prediction of traffic signals enabling innovative functionalities such as Green Light Optimal Speed Advisory (GLOSA) or efficient start-stop control [18].

Modern traffic light control is based on self-organization and seems to perform better than the traditional methods. In [15], the authors use short sighted anticipation of vehicle flows and platoons. It is achieved a decentralized emergent coordination based on local interactions traffic light control. In [16] and [17], traffic light control is considered more as an adaptation problem than as an optimization problem. These methods are based on local rules and no communication between traffic lights. Self-organization is achieved by probabilistic formation of car platoons. In turn, the platoons affect the behavior of traffic lights, prompting them to turn green before they have reached the intersection. Groups of cars that have been waiting for longer and larger groups of cars are prioritized.

Moreover, making traffic lights adaptable to the current traffic flow is one of the main applications of modern dynamic control. For example, the simulation of public transport or emergency vehicle prioritization at intersections [50] [51] or groups of vehicles that are prone to create congestion (i.e. the green phase duration is increased when the traffic jam length is longer than a threshold) [52].

On the one hand, new technological developments such as real time responsive traffic lights are implemented in major cities [48]. On the other hand, Dedicated Short-Range Communication (DSRC) systems, navigation devices or smart phone applications communicate and assist drivers in their trips. DSRC systems have already been installed on many roadways by the US Department of Transportation [53] and are expected become ubiquitous in the future [54]. For example EnLighten [55] is a stanalone smartphone application that connects to the traffic signal network and predicts the behaviour of traffic lights by communicating to DSRC systems on the roads. Using such technology, BMW drivers are informed when a stoplight changes [53].

2.3 Intelligent Transportation Systems

Intelligent Transportation Systems (ITS) are major parts of modern transportation systems. They refer to the integration of information and communication technologies with transportation infrastructure to improve economic performance, safety, mobility and environmental sustainability for the benefit of all citizens [56]. ITS systems include Road Transport but also include the use of Information and Communication Technologies (ICT) for rail, water and air transport, including navigation systems [57]. However, the main focus of this thesis is on the implications of information and communication technologies on the Road Transport component.

The ability of transportation systems to provide efficient mobility solutions to citizens is constantly challenged by the increase in traffic demand and population growth. Some of the unpleasant repercussions are congestion, increasing travel times air pollution and fuel consumption. At the September 2009 ITS World Congress in Stockholm was estimated that the widespread introduction of intelligent systems and services could reduce congestion by up to 15 %, CO2 emissions by 20 %, and road fatalities by up to 15 %. This is achieved by integrating existing technologies that produce more reliable, real-time traffic information and better routing strategies that consequently would make more efficient use of the existing infrastructure [56].

An ITS system in composed of the following major technological constituents: wireless communication for short-range or long-range data exchange (i.e. Dedicated Short Range Communication DRSC), computational technologies for model-based process control, artificial intelligence and sensing technology. These constituents provide the ITS control systems with both vehicle-based data (i.e. from radars, infrared or visible-band cameras) and with infrastructure-based data (i.e. from similar devices and inductive or pressure sensors around the roads). Communication in ITS systems is done not only between vehicles but also between vehicles and infrastructure. Transportation systems with such communication capabilities are called Cooperative ITS systems [56].

Transportation engineers envision the future of transportation to integrate various components of ITS systems to deliver more holistic solutions [56]. Using a systemic, centralized approach, they provide advanced technologies to control the road capacity by creating more intelligent infrastructure and sending appropriate navigation recommendations to vehicles and drivers. Traditionally, traffic improvements were based mainly on building additional infrastructure. However, dynamic elements are now being introduced into traffic management [41]. Dynamic elements have long been used in rail transport in the past, but currently such components are integrated in all transportation modes (i.e. urban public transport, urban road transport, highway traffic, rail transportation, air transportation, water transportation, etc.).

ITS systems first appeared around the 1930s, and hey have been developing with high speed. The major developments on ITS systems were made in Europe, U.S., and Japan in three phases: preparation (1930-1980), feasibility study (1980-1995) and product development with the primary focus on large-scale integration and deployment (1995-present) [3]. However, several major problems are expected to occur when merging the information from different sources into a comprehensive system able to communicate with all interested users: considerations related to vehicles, infrastructures, drivers' behavior, and legislation [56].

ITS models are implemented at national scale and are composed of several layers connected with each other. These models start with the highest layers which are the national control ITS centers and regional control ITS centers and end with the lowest layers such as toll lanes [58].

From a functionality perspective, an ITS system comprises of three types of components: sensor networks formed by vehicles of a particular vicinity that exchange traffic-related information, cognitive management functionality placed inside the cars for inferring knowledge, experience and cognitive management functionality in the overall transportation infrastructure [59].

2.3.1 ITS components

ITS systems have six main components [3] [60]. The first component is the Advanced Transportation Management System (ATMS) which responds to traffic conditions in real time. ATMS provide central control strategies such as adaptive traffic signal control, dynamic message signs or ramp metering using centralized traffic data.

The Advanced Traveler Information System (ATIS) supplies real-time traffic information to drivers. This information contains route guidance for navigation systems, parking details, roadside weather updates, etc. The information collected by ATMS is also supplied to the ATIS. ATMS technology has been in use for several years in some metropolitan areas (i.e. in ramp metering which are red-green stoplights placed at the head of onramps for highways that can be timed for certain periods of the day or controlled by a detector positioned upstream).

The rest of the components are Commercial Vehicles Operation (CVO) used to increase safety and efficiency of commercial vehicles and fleets, Advanced Public Transportation System (APTS) designed to improve the operation and efficiency of public transport, Advanced Vehicles Control System (AVCS) using joint sensors, computers and control systems to assist and alert commuters while driving and Advanced Rural Transports System (ARTS) is designed to solve the problems arising in rural zones.

According to [60], the main technologies used by the ITS components for data collection are Global Positioning System (GPS), Dedicated-Short Range Communications (DSRC), probe vehicles, wireless networks, telephone networks, Vehicle Information Communications System (VICS).

The embedded GPS receivers within vehicles receive satellite signals and calculate the vehicle's position (location can be determined within 10 meters). GPS is the core technology behind several in-vehicle navigation and route guidance systems. DSRC is a short- to-medium-range wireless communication channel, operating in the 5.8 or 5.9 GHz wireless spectrum, expressly designed for automotive uses.

DSRC systems provide two-way wireless communication between the vehicles and roadside equipment (RSE) (i.e. communication vehicle-to-vehicle, vehicle-to-infrastructure, adaptive traffic signal timing, electronic toll collection, congestion charging, electronic road pricing, information provision, etc.). There are several mobile applications developed on top of DSRC technology (i.e. EnLighten [55] connects to the traffic signal network and predicts the behavior of traffic lights by communicating to DSRC systems on the roads, Electronic Fee Collection (EFC) [57]).

Another technology commonly used in ITS systems for wireless Internet access, are wireless networks that allow rapid communications between vehicles and the roadside within a range of a few hundred meters. More disadvantageous solutions for data collection and information communication use mobile telephone networks. VICS systems use radio wave beacons on expressways and infrared beacons on trunk and arterial roadways to communicate real-time traffic information (implemented in Japan).

Data collection in ITS systems is done using also probe vehicles or devices. In several countries, there are already government-owned vehicles or a number of taxis, equipped with DSRC technology that travels trough the city and reports their speed and location at a central traffic operation center. For real-time data collection, mobile phones are used to provide GPS locations (i.e. more than 10,000 taxis and commercial vehicles provide GPS coordinates translated to travel speed information to a satellite, which then sends the data to Beijing Transportation Information Center) [60].

The sensors can be fixed (i.e. inductive loop detectors, radars, infra-red or acoustic) or mobile devices within vehicles (i.e. smartphones, navigation devices, etc.). The collected data is further processed to provide intelligible recommendations to traffic participants throughout their navigation devices or to obtain information for the responsive traffic infrastructure. It is important to note that the traffic participants and the road infrastructure are at the same time sources for data collection and users of the traffic information.

2.3.2 Information dissemination in ITS and the Price of Anarchy

This section presents the existing work done on the effect of information dissemination over transportation systems or ITS systems in urban environments. A set of studies present innovative strategies of steering transportation systems with the use of information showing good results. For example, the traffic flow has been improved using modern traffic light control based on self-organization and adaptation using information about the local traffic conditions rather than optimization [15, 16, 17].

Moreover, previous research shows that there are many ways of using different types of information details as part of an information control strategy. Studies done in [20] and [25], analyze the traffic network performance when using information control systems for traffic planning in the presence of congestion.

Congestion-aware routing strategies comparing global and local information dissemination models have been studied in [25]. Information about congested links is used to influence the routing choice for vehicles by applying a penalty function. Congestion is defined as the fraction of occupied cells in a link and uses this measure in the mechanism of choosing the best route to avoid traffic jams. Urban street models for various city topology were implemented, ranging from self-organized ones such as Bologna, London to grid-like cities such as Los Angeles, Washington. The authors showed that the best performance is achieved when limited local knowledge is used.

Similar results presented in [20] indicate that systems with heavy loads perform better when local information dissemination models are used and when the number of links connecting the jammed nodes with the non-congested ones is reduced. In [20], the authors have studied a minimal network flow model with congested and uncongested nodes affected by two types of information dissemination models. In the first case, each node received local information (i.e. details such as congestion, flow or occupancy) only about the neighbors. The information is used to control the traffic flow for the outgoing nodes. This mechanism helps to prevent the congestion of the nodes. Besides different traffic loads, various networks topology were also considered. The simulations for this study were performed on random graphs and scale-free networks. The authors have analyzed the congestion formation, persistence, and elimination also in the case of information being disseminated in the transportation system.

Other examples show that a complete view of the network leads to a faster coordination and that the effect of information view depends on the network structure [61]. In [62], the authors demonstrated that increasing the weights of particular links that are active early in a cascade crush worsens the bottlenecks. In contrast, strengthening only links that propagated the activity just prior to cascade termination (i.e. links that point into bottlenecks), removes bottlenecks and improves accessibility to other pathways in the network.

Studies about information, congestion and route guidance were done in [45] and [63]. However, in this case, no models for information dissemination were used. In this approach, the authors use a delegate multi-agents system with agents that communicate [63]. The infrastructure agents represent the road elements, and the vehicle agents represent the vehicles in the system. The vehicle agent knows the destination of the trip, asks the environment for routing options and informs the road agent of its intention. Based on these details, the road agent estimates the future traffic intensity on the road and gives a better recommendation to the vehicle agent [63]. These multi-agents systems are inspired by biological systems where the cooperation vehicle and the infrastructure resemble the way ants behave. The infrastructure agent is informed of the current and past situation of the traffic by the exploration ants and the future situation by the intention ants. It is demonstrated that such mechanisms provide a better routing choice to drivers [45].

Systems for traffic planning in the presence of congestion have been researched in [21, 22, 23, 24] by controlling the information given to each participant (proposing certain routes) to achieve individual or global social optimum performance. In [21], a fleet of taxi drivers from Singapore used a web-based application to specify the origin, the destination and the departure time of the trip. Based on this input data, the drivers receive a route recommendation in order to avoid the congested areas. Congestion is modeled as the relationship between flow and delay (Bureau of Public Roads (BPR) function). This function for Singapore is estimated using traffic volume data from loop detectors and GPS location and time data from a roving fleet of taxis. The learned congestion model is used in the navigation recommendations in two ways. In the first case, the recommendations are determined by computing socially optimal paths in a multi-agents system while in the second case, the recommendations are calculated by computing greedy path planning in a single agents system. The study proposes an experimental comparison between actual taxi paths, with socially optimal congestion-aware routing and greedy path planning. The results show that socially-optimal congestion-aware routing performs better, achieving 15% reduction in the overall travel time.

Price of anarchy in transportation systems

It is important to note that, the information dissemination models provide route navigation recommendations determined either by computing socially global optimum paths or by computing individual, selfish, greedy paths. In the first case, a centralized mechanism is used to generate routes that achieve global social optimum while in the second case, a decentralized mechanism is used to produce the selfish routes.

Studies presented in [64] show that the modern society pays a Price of Anarchy (POA) for lack of coordination and cooperation of the traffic participants. This means that providing traffic information that optimizes the individual selfish route due to decentralization is less efficient than providing a route that optimizes the social optimum. Nevertheless, in a transportation system, the global social optimum is not always achieved. Therefore, POA is defined as the ratio between the total cost of the Nash equilibrium (actual travel time) and the total cost of the social optimum (the possible minimum travel time). In transportation systems where selfish, uncoordinated actors interact, inefficiency may appear due to suboptimal Nash equilibrium. In this case, the selfish drivers can create congestion, causing undesired delays to the other traffic participants and also to themselves. The authors have analyzed the POA for road structure containing the major roads and intersections in Boston, London, and New York but also in four constructed ensembles of bidirectional model networks with distinct underlying structures.

The experiments presented in [65] quantify the degradation in system performance due to the inefficient selfish routing. In [66], it was proven that a network with two parallel links achieves the worst ratio between total latency of a Nash equilibrium and a minimum-latency routing for any multicommodity flow network. Moreover, in [67] the authors evaluate the price of stability for network design with fair cost allocation by calculating the ratio between centrally enforced solutions and unregulated anarchy.

More research on the price of anarchy studied full information games, where all players have complete common knowledge. In [68], the goal is to develop a useful general theory for bounding the price of anarchy in games of incomplete information, where players are uncertain about each others' payoffs. Incomplete information refers to routing games with uncertain origin-destination pairs or routing games with unknown weights.

The problem of selfish routing versus social optimum routing in congested networks is relevant in other areas besides transportation. For example, the future development of the Internet as well as the behavior of commonly used routing algorithms was studied in [69].

2.3.3 ITS and the human factor

The previous sections introduced the ITS components and communication technologies used for the information transfer in transportation. Although a substantial effort is put in practice to integrate the sophisticated systems to compute and present the traffic information to navigation devices, only the traffic participants decide to follow or not this information.

Understanding traveler response to potential ATIS services is critical for designing such services and evaluating their effectiveness [70]. For instance, it is interesting to know to what extent the traffic participants use this information. There are a few studies addressing such problems from different perspectives.

In most of the cases, drivers trust the real-time information and follow the navigation recommendations as stated in a survey from DLR Institute of Transport Research [31]. However, there are more factors that may influence the human decision-making process.

In [71], it was shown that the decision of following the traffic recommendations might depend on perceived system capabilities, trust in the system and the confidence the driver has in his perception, knowledge, and intuition. Trust is considered to be crucial in people's decision to rely on automated systems to perform tasks for them [72]. Moreover, self-confidence plays a role in how drivers decide to use the recommendations. It was shown that future estimates are accepted with a level of overconfidence even in cases of less expert judgment [73].

It is interesting to note the fact that there were cases when drivers disregarded the navigational advice that did not match their intentions. After performing empirical studies, it was shown that when the route deviated significantly from the straight line, it was rejected 44% of the time compared to 9% where it was more closely aligned. The traffic participants accept the recommendations if they optimize their individual goal rather than a global performance [71].

Furthermore, the authors show that another reason for rejection was the quality of advice. When the recommendation was close to the theoretical optimum, there was only 20% rejection. However, when the recommendations were twice as long as the theoretical minimum, the drivers rejected 80% of the time.

Moreover, learning about the accuracy of the recommendations from ATIS systems was also an important factor. It is interesting to note that drivers will accept some degree of inaccuracy (less 29%). According to this research, when the information accuracy drops to 43% both drivers will not trust the advice [71].

More studies investigate the levels of information accuracy necessary in in-vehicle information systems to have positive behavioral and attitudinal responses from the driver. Results show that decreasing the accuracy of the system decreased both driving performance and trust and liking of car and in-vehicle system. For this research, the authors also consider the gender's differences and show that female drivers in particular benefit from the in-vehicle system and show higher tolerance of inaccuracies [74].

Looking from a different perspective, the extent to which the traffic participants choose to respond to the route navigation advice depends on the characteristics of the traffic information. For instance, quantitative information has more influence on route choice than the qualitative information. This research shows that drivers value delay time (in this case, information concerning delay time in terms of travel time) more highly and they become increasingly sensitive to delay time as the values become higher [75].

2.4 Complex systems and multidisciplinary research

Complex systems are formed by nonsimple, nonreducible heterogeneous elements that interact with each other and with their environment in a nontrivial manner. The interactions exhibit a great deal of noise, tension and fluctuation [76] and generate multiple layers of collective structure that form a self-organization without a centralized control [77]. The separate components of a complex system can be categorized as structural, behavioral, contextual, temporal and perceptual [78]. These elements if disconnected would produce the system to lose its complexity.

It is important to note that complex systems differentiate from complicated or simple systems. Simple systems have few components, and their behavior is deterministic and easy to understand. An example would be following a recipe. The complicated systems are composed of a subset of simple components but are not merely reducible to them. Their complicated nature is related to the level of coordination and specialized expertise required to use or understand them. Also, in this case, the behavior of the system is fully predictable and understandable. For example airplanes, electrical circuits, computers or rocket sent to the moon can be considered complicated systems. On the other hand, complex problems can encompass both complicated and simple subsidiary problems, but are not reducible to either. The complex systems require more levels of comprehansion, including the unique local conditions [76].

Complex systems are common in nature and human societies [79] [77]. For this research, the transportation systems can be regarded as complex systems as they consist of several layers that interact and influence each other. For example, the physical road network interacts with an informational layer maintained by sensors and navigation devices and with the traffic participants.

This nontrivial interaction between components introduces new, emergent dynamics in the traffic flow. On the one hand, in transportation systems, the elements are complicated. For example, a car has a deterministic behavior, reacting to the driver's actions on the wheel, acceleration or breaks. On the other hand, the transportation system is complex because of the interaction of the elements combined with the presence of human factors and the choices they make while driving on the road network.

2.4.1 Feedback loops in complex systems

Feedback is an important condition for complex dynamical systems. A system has feedback if the way its components interact at a later time depends on how it interacts at an earlier time [80]. However, the presence of feedback in a system is not sufficient for complexity. For this to happen, the feedback needs to give rise to higher-level order. For example, in the case of ants, the behavior of ants who are able to undertake complex tasks such as building bridges or farms even though no individual ant is aware of what it is doing [80]. This feedback is maintained by informational transfer with the purpose of error correction or improving the system's performance.

Moreover, information dissemination with feedback loops is a fundamental topic in all human complex systems in general, where people make decisions by accessing real-time information. Knowing details of future problems modifies people's behavior, and this possibly affects the entire system. This effect has been studied in several areas of human activity. For example, in financial markets, the effect of private and public information has been analyzed. In [11], the market dynamics is explained by phases: boom, euphoria (with informational cascades), trigger and panic (with information avalanches). Another example is analyzing the effect of transaction costs on the overall market efficiency when aggregating private information [12]. Feedback between human and natural systems can have a positive role (i.e. local residents in Wolong, China use bamboo forests as fuelwood for cooking and heating leading to deterioration in forests and panda habitat. To prevent further degradation and restore panda habitat, the Chinese government implemented major conservation policies, which help both local residents and panda habitat [81].

The current thesis addresses the concept of feedback loops in a complex system. In the case of transportation systems, such loops are created by the fact that traffic participants are at the same time sources and users of the traffic information. Unlike the current state of the art, the studies presented here evaluate different aspects of the information flow starting with the process of data collection, data processing, information dissemination and how the information is displayed back to drivers trough their navigation devices.

2.4.2 Controllability of complex systems

Inefficiency in complex systems can be avoided by constructing adequate steering mechanisms. However, understanding and controlling complex systems is a very hard goal in natural or man-made systems. It was shown that both the system's architecture, represented by the network and the time-dependent dynamical interactions between the components make the steering of complex systems a very difficult task. It has been shown that sparse inhomogeneous networks, which emerge in many real complex systems, are the most difficult to control in comparison to dense and homogeneous networks that can be controlled using a few driver nodes [82].

In complex systems, it is typically neither feasible nor necessary to control the entire network, but rather a selected subset of targeted nodes. It was demonstrated that the degree of heterogeneous networks is target controllable with higher efficiency than homogeneous networks and that the structure of many real-world networks is suitable for efficient target control [83]. The mean degree of the network is a major factor in determining the robustness of random networks. However, in realistic situations, the set of control nodes may not overlap with the set of externally accessible nodes. Nonetheless, the authors determine a small set of critical nodes to obtain maximum possible control of the network to achieve the highest possible energy efficiency. This is done by using a theory that provides a method and algorithms that identify efficiently the nodes that possess the strongest possible control centrality [84].

Moreover, the mean degree of the network is a major factor in determining the robustness of random networks [85]. However, the random networks are statistically significantly different from the real complex networks and have additional factors that influence their robustness of control. It was shown that for real networks, more subtle and, potentially, local structures are involved in implementing robust control. A complex network can be decomposed into the structural elements (control profile) that induce the need for specific control, sources, external dilations, and internal dilations (a dilation requires an expansion point in the network, a region where a smaller number of nodes link into a larger number of nodes) [84].

Therefore, one characteristic of complex systems is the emergence of the butterfly effect [14], where small changes in initial conditions can lead to performance alterations that are much bigger in magnitude [13]. On the one hand, there are cases when a simple event can perturb the entire network (i.e. in the case of transportation systems, one simple traffic disturbance such as an accident can produce a generalized congestion). On the other hand, a simple intervention in one component can improve the overall system's performance (i.e. intelligent traffic lights control system can prevent a big congestion, opening or closing certain roads can help distributing the overall traffic in a more efficient manner).

2.5 Modelling and simulation of transportation systems

A methodology appropriate for analyzing the complexity of transporatation systems trough simulation uses Agent-Based Modelling (ABM). The system is modeled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions by a set of rules. ABM has been successful in reproducing the collective phenomena of self-organized traffic dynamics such as breakdowns of traffic flow, the propagation of stop-and-go waves, the capacity drop, and different spatiotemporal patterns of congested traffic due to instabilities and nonlinear interactions [5]. ABM models execute various behaviors appropriate for the system they represent, for example producing, consuming, or selling [34].

This methodology is part of the new discipline of computational science, combining modern technologies to address problems in complex systems. The primary application for traffic simulations is the evaluation of hypothetical scenarios for their impact on traffic. For example, a real world scenario for studying the traffic impact information is difficult to implement as it requires, among others, a high rate of participation of the drivers both as sources and users of traffic information.

In transportation systems, different aspects of road traffic have been studied. Depending on the purpose of the study, different types of models can be chosen. Each model has a set of advantages and disadvantages regarding available resources (i.e. input data, computational power, the level of modeling details needed, etc.). Next, a summary of the common models classified by the level of details is presented.

2.5.1 Macroscopic traffic simulation

Macroscopic traffic simulations contain the least level of details. Macroscopic traffic models are based on the fluid dynamic aggregating traffic flow properties: density, speed, and flow with respect to time and space [86] [87]. For this type of models, the time-space diagrams illustrate the propagation of congested traffic and traffic waves in small and large scale traffic scenarios. The disadvantage of macroscopic models is the fact that they don't capture the detailed individual behavior of the simulated vehicles. However, this property of the model requires less computational resources and thus larger scale experiments can be performed. For example, macroscopic models can generate short-term traffic predictions for route guidance or traffic flow optimization. A popular macroscopic traffic simulation is METANET [88].

2.5.2 Mesoscopic traffic simulation

The second type of models concerning the level of details used in traffic simulation are mesoscopic traffic models. In contrast to macroscopic models, mesoscopic models capture individual vehicles details to a certain extent using speed-density relationship and queuing theory [89]. The disadvantage of mesoscopic models is the fact that the level of details does not contain information about the exact speed and position of the vehicle. However, for this reason, the computational requirements are still not very high, making it possible to simulate both small scale and large scale traffic scenarios. The mesoscopic traffic model is suitable for applications which require traffic demand modeling and short-term predictions [90][91]. For example, the following simulation tools are based on mesoscopic traffic simulation DynaMIT [89] and SUMO [92].

2.5.3 Microscopic traffic simulation

Furthermore, microscopic traffic simulations provide a higher level of details than the previous models. Similar to the mesoscopic model, the microscopic models capture details for each vehicle. However, unlike the mesoscopic model, the microscopic models provide information about the speed and position on the roads. Another difference consists in the time scale resolution. While for some mesoscopic models, the time step can be up to a few min, for the microscopic models, the time step can be less than 1s.

Microscopic traffic models describe individual details regarding acceleration, deceleration or lane changing. Because the microscopic actions manifest in an emergent macroscopic system behavior, they are successful in reproducing the observed collective, self-organized traffic dynamics. For instance, such emergent phenomena are breakdowns of traffic flow, the propagation of stop-and-go waves, the capacity drop, and different spatiotemporal patterns of congested traffic due to instabilities and nonlinear interactions [5]. Also because they allow for a low-level individual integration, the microscopic traffic models are used in applications where heterogeneous traffic flows consisting in different types of vehicles or driver behaviors are investigated or in applications where different properties of an individual vehicle can influence the traffic.

The disadvantages of microscopic traffic simulation, comparing to macroscopic and mesoscopic traffic simulation, are the high necessity of computing power but also calibration and validation. Because the large scale microscopic traffic simulation can be computationally challenging, the traffic evaluation can be done offline in some cases.

The microscopic traffic models can be categorized into three groups [5]. The first category consists of time-continuous models where space and time are treated as continuous variables. Car-following models are examples of continuous time models. One of the most popular car following models is Intelligent Driver Model (IDM) [93, 5]

The second category of microscopic traffic models id based on Cellular Automata (CA). For these models, the time is discretized, and the road is divided into cells which can be either occupied by a vehicle or empty. Comparing to the time-continuous models, they are less accurate and thus simpler, requiring less computational resources. However, CA models reproduce well emergent traffic phenomena and also, can be used in applications with large road networks.

The third category of microscopic traffic models is discrete-time models. In this case the time-discretized while the spatial coordinate remains continuous. One of the most used examples is the Gipps model [94]. However, these models are typically associated with car-following models as well [5].

Examples of commercial software applications used are SUMO [92], MITSIM [90], PTV-VISSIM TM [95], TRANSIMS [96], AIMSUN2 [97], PARAMICS [98].

2.6 Conclusion

This chapter first introduced the main components of a transportation system and the transportation challenges that appear in modern societies. Section 2.3, presents Intelligent Transportation Systems (ITS), one of the most dynamic areas in transportation, integrating the human factor intervention or the intelligent dynamic infrastructure with information control strategies. An overview of different models of traffic information dissemination used in transportation research and considerations about the Price of Anarchy concept are also presented. Section 2.4 provides a definition of complex systems is introduced together with the motivation why transportation systems are seen as complex systems. The methodology used to tackle this type of transportation problems and the state of the art related to modeling and simulation of transportation systems is presented in Section 2.5.

This chapter has provided an overview of existing state of the art related to information control strategies in the context of ITS systems. Based on this review, a set of transportation problems were identified but also gaps in the knowledge that needs to be explored by formulating the appropriate research questions. The problem addressed in this thesis manifests in the context of traffic information dissemination and feedback loops created by the traffic participants simultaneously being sources for data collection and users of information in ITS systems. Such novel technologies provide numerous benefits but may also introduce some new transportation challenges. These research questions are suitable to be addressed from the complex systems point of view. To answer this type of research questions, the state of the art proposes an agent-based traffic simulation. The experiments use a microscopic traffic model for small scale networks scenarios and a mesoscopic traffic model in the case of large scale traffic models.

Chapter 3

Information flow in transportation systems

3.1 Introduction

The current section introduces the logical framework used for describing the information flow process in ITS systems. This framework facilitates not only novel ways of exposing the transportation problems but also a systematic understanding of the research questions presented in Chapter 1. This way, issues related to who receives the information, how the information content impacts the traffic performance or how it is used to change infrastructure dynamically, can be investigated from different perspectives.

The experimental setups used for this thesis are classified based on the steps of the information flow process where the problem manifests. The possible benefits and challenges associated with each step of this information flow process are described in detail. Also, the experiments can be classified by the information details provided to the traffic participants or by the scale of the road network used. This way, a complete view of the investigated phenomena is achieved. At the same time, due to the classification based on the information flow framework, the problems become simpler but not trivial. The subset of problems was made more concrete and could be tackled more efficiently.

The experimental setups used in this thesis can be classified based on the details contained in the traffic information. The information can be presented to the traffic participants on their navigation devices as route recommendations or speed recommendations to avoid stopping at the red color of traffic lights systems. Also, the traffic information contains details about the traffic situation on roads and can be used by the intelligent, responsive infrastructure.

The information in this system flows through three stages: *input stage, processing stage* and *output stage*. Due to this categorization, different possible challenges associated with each step can be tackled in standalone studies. For instance, experiments are analyzing potential problems related to the process of data collection, different models of information dissemination or the interaction between an adaptive traffic infrastructure and drivers using navigation recommendations.

Moreover, based on the type of problems investigated and the size of the network chosen for the experimental setup, the studies can be classified as small scale using a *block* type network and a more realistic large scale or *city* scale network.

3.2 Logical framework for the information flow process

As described in Chapter 1, ITS systems become more advanced and are expected to provide solutions for the transportation challenges emerging in our modern societies. Such systems collect data, process information and provide navigation recommendations to traffic participants. However, the consequences of providing this information in real time, to drivers who are themselves participants in the data collection process, has not been investigated in much detail. The experiments performed for this thesis evaluate different hypotheses related to these possible new dynamics created by the modern ITS systems.

Moreover, as mentioned in Chapter 2, the literature review does not contain enough detailed studies related to this problem, despite the fact that there are several articles presenting information control strategies.

Based on these considerations, a set of experiments where several phenomena associated with information flow in transportation systems with feedback loops are first identified and sequentially analyzed. Using the results of this analysis, transportation engineers can build appropriate steering mechanisms as part of ITS systems.

Due to a high level of connectivity between components combined with the human factor intervention, transportation systems are also defined as human complex systems. Such systems comprise of roads and traffic infrastructure, traffic participants, vehicles sensors, navigation devices, in-vehicle entertainment systems, communication technology and so on.

In general, the vehicles are equipped with several sensors and navigation devices. Vehicle sensors are capable of enabling the ad hoc formation of networks to allow the communication and information exchange [59] [58]. In such a system, the communication can be either vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I) or infrastructure-to-vehicle (I2V). These systems are also called cooperative ITS systems [56]. Therefore, the components are interconnected and communicate with each other, this way creating an informational flow within the transportation system. Traffic data gathered from sensors from the transportation system is transmitted back as traffic information to drivers or the traffic infrastructure.

From a functional perspective, an ITS system comprises of three main components: sensor networks formed by vehicles of a particular vicinity that exchange traffic-related information, cognitive management functionality placed inside the vehicles and cognitive management functionality in the overall transportation infrastructure [59]. Chapter 2 describes in more detail the ITS components and how they interact.

However, from a logical perspective, the functionality of an ITS system, in the context of this research, is grouped into two parts: the human complex system (HCS) and the information control system (ICS). The ICS, working at the back-end of the transportation system, is responsible for cleaning the raw data from the HCS, aggregating it, processing it and present it to the traffic participants on their navigation devices.

Therefore, HCS sends data to the ICS and also eventually utilizes the information that the ICS provides. It is important to note that in this categorization, the processing system of the *information presentation devices* like smartphones or in-vehicle information displays are also part of the ICS as they determine how information is received by the traffic participants.

During the *input stage*, the real world traffic status is converted into raw data by the different kinds of sensors as mentioned above. Raw data is collected from the sensors and sent to the preprocessing and processing block. The sensors can be fixed (i.e. inductive loop detectors, radars, infra-red or acoustic, etc.) or mobile devices within vehicles (i.e. smartphones, navigation devices, etc.). The vehicles used by data collection are called probe vehicles or devices.

The preprocessing stage consists of preparing the raw data set for the processing stage trough procedures of cleaning, normalization or fusion. During the *processing stage*, raw data is converted into information that can be used to reconstruct the traffic state and, eventually, to a form that is presented back to the HCS. In the final step of the process, this traffic state information is displayed back to the commuters through their smart devices.

It is important to note that that a feedback loop between HCS and ICS is formed. Figure 3.1 illustrates the information flow process and the feedback loop created between the transportation system and the information control system [56]. The traffic participants can be at the same time sources for data collection and also users of the information displayed back to them. The fact the drivers know about possible problems that may occur in the transportation system changes the way they decide to react in certain situations (i.e. select different routes to avoid congestion or adapt the speed to avoid stopping at the red light of a traffic lights system). Unexpected new phenomena may occur in such transportation systems. For this reason, the experimental setup is designed first to determine and sequentially analyze the dynamics associated with the information flow process in a transportation system.

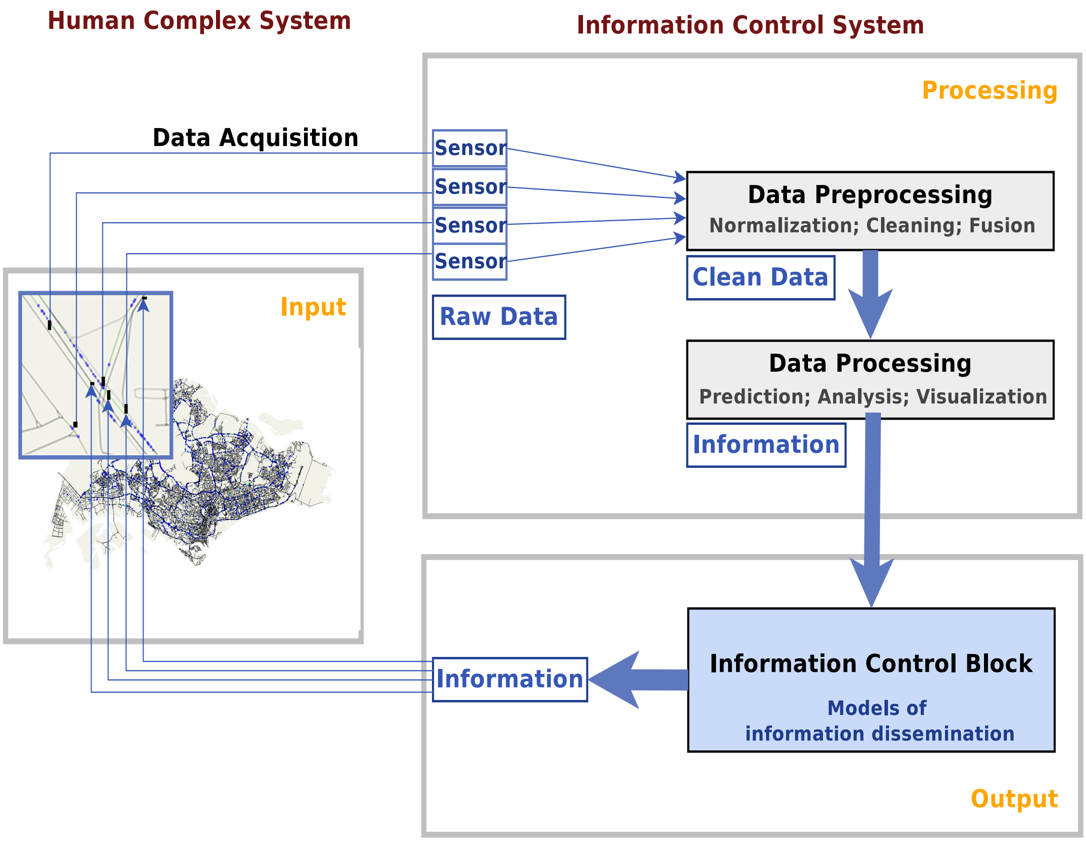

Figure 3.1: The figure illustrates the information flow process in a transportation system with the following steps: *data acquisition*, *data preprocessing*, *data processing* and *information dissemination*. The information control system (*ICS*) and the transportation system that is also called human complex system (*HCS*) interact and influence each other, creating a feedback loop. The information in this system can be seen to flow through three stages: *input*, *processing* and *output*. In the final step of the process, this traffic state information is displayed back to the commuters through their smart devices or in-vehicle navigation systems.

3.3 Traffic information in the context of ITS systems

Data exchanged among vehicles can be classified into high- and low-level data [59]. High-level data refers to details on the congestion level, emergencies, characterization of driver's behavior, information on the road condition (i.e. slippery roads), information on neighboring vehicles and their cruising behavior, etc. The low-level data includes details on the vehicles such as their accurate position, velocities and directions, capabilities braking distances, and acceleration driver's profiles, driving habits, capabilities, and preferences.

According to [60], the main technologies used by the ITS components are Global Positioning System (GPS), Dedicated-Short Range Communications (DSRC), probe vehicles or devices, wireless networks a Vehicle Information Communications System (VICS), camera- or tag-based schemes, and so on.

For this research, the traffic simulation output includes details reported at the end of each trip: total travel time, total trip distance and trip average speed. Other experimental indicators use vehicle specific information reported with a certain frequency during the simulation run: current speed, current position, distance to traffic lights systems. A category of indicators uses traffic data, collected from infrastructure sensor readings reported at a particular frequency during the simulation: traffic counts for each road, average speed on each road, information about traffic lights. Furthermore, the emergent phenomena analyzed in the experiments can be observed on a visual presentation of the traffic simulation with the road network, moving agents or traffic lights color phases. The output provided by simulation of transportation systems allows the calculation of several types of indicators used for traffic performance analysis. The specific performance indicators are defined and described in detail for each study.

Depending on the scenario investigated, traffic information presented to the traffic participants as navigation recommendations may refer to different aspects of the traffic situation. The navigation recommendations are presented to only a share of the traffic participants either as regular updates or as route recommendation at the beginning of the trip. Also, the traffic information can be provided as regular updates to a responsive traffic infrastructure.

In some of the scenarios, the navigation recommendations contain details about the speed the drivers need to use to avoid stopping at the red color of a traffic lights system. Drivers receive speed recommendations only if they are in a range distance, called adjustment distance, to the traffic lights system. These scenarios are inspired by the technological advancements in communication systems such as Dedicated Short-Range Communication (DSRC) and by navigation apps that can interact with DSRC systems. For example, EnLighten is a smartphone application that connects to the traffic signal network and predicts the behavior of traffic lights by communicating to DSRC systems on the roads [55].

Moreover, the navigation recommendations can contain updates about what routes to provide to the agents selected to be informed. The purpose of using the route recommendations is either to avoid the congested areas in the network or to temporarily exclude some harmful road segments determined for the global network level. Data used for determining the routes contains details about the current travel times on roads and is inferred from speed and position updates provided by probe vehicles or by fixed sensors on the side of the roads.

For other types of scenarios, the traffic information can be used by an adaptive infrastructure as well. For example, dynamic traffic lights adapt the phase duration to prioritize public transport, emergency vehicles, larger groups of cars, groups of cars that have been waiting for longer, etc. This information can be obtained from data collected by traffic sensors containing details about the number of vehicles or other road users approaching a particular intersection.

3.4 Information flow process in ITS systems

The experiments presented in this thesis are classified based on the step of the information flow process where the phenomena of interest are caused or where it manifests. The three stages trough which the information flow process goes through in an ITS system are the following: *input stage, processing stage* and *output stage*.

The role of the *input stage* is to collect raw data by using different kinds of sensors. This data is transmitted to a central database for storage and further processing and analysis. It would be practically impossible to observe every single point of the real world system due to a large number of high-quality sensors that would be required. Because of this reason, a certain level of data inaccuracy that arises due to this lack of coverage of sensor networks may appear. This inaccuracy would be impossible to avoid completely in practice; however, it is useful, even vital, to discover the minimum coverage required for optimal system performance. A set of experiments is performed in this regard. The global transportation system's performance is evaluated for different proportions of drivers participating to data collection process with their trip details.

Next, the raw data is sent to the preprocessing and processing blocks. Further inaccuracy may appear from low-resolution sensors, improper cleaning and inefficient algorithms for aggregation or traffic state reconstruction. During the *processing stage*, the raw data is converted into information about the traffic state that eventually is presented back to the HCS. Each type of sensor presents specific error causes. Data may be affected by inefficient traffic state estimation for solving the missing data problem [99]. The processing block can introduce inaccuracy among other by the using an oversimplified or even wrong model of the transportation system, inefficient algorithms for matching traffic patterns [99] or not enough processing power that can delay the real-time forecast. This uncertainty is difficult to avoid, but they become smaller over time as technology advances. A series of experiments are performed to investigate the effect of different levels of inaccuracy arising in the processing stage.

In the *output stage*, this traffic state information is presented back to the commuters through their smart devices. At this step of the information flow process, different models of information dissemination can be implemented. A set of experiments aims at understanding the impact of providing information to drivers by using several models of information dissemination as evaluating the overall traffic performance for dynamic route guidance systems where the alternative routes have a different length. In these models, only a share of the traffic participants is informed. The navigation updates can be regular, recalculated with a certain frequency or they can be presented only once at the beginning of the trips.

Moreover, the traffic information can be used to dynamically change the infrastructure by using the traffic information as a steering tool to improve the overall performance. This mechanism is *soft changing* the infrastructure. For instance, dynamic traffic lights adapt the phase duration. Another example is to partially close certain road segments by providing the traffic participants with navigation recommendations that exclude certain detrimental road segments from their routes.

At the output step, it would be impossible to display the state of the complete traffic system to the user on the navigation device. Thus, design decisions have to be taken as to what information is displayed and in what resolution. For example, when displaying a map for navigation with congestion information, the roads with a range of high speeds may be marked in green and others in red; or there could even be a color gradient from red to green for a range of speeds. Lower resolution information may mean that it is easier for the user to process a larger amount of information (i.e. several roads at the same time) and it would probably also be technically easier to display this information. Therefore, these types or errors appear due to trade-offs in how information is presented. It is crucial to understand these to create better smart devices for ITS systems. A set of experiments investigates the impact of displaying to drivers different levels of inaccurate traffic information.

3.5 Information flow for block and city scale road networks

The experiments can be classified based on the information details contained, on where the phenomena occur in the information flow process but also on the scale of the scenario. There are two types of scenarios that the experimental setups are based on, depending on the size of the network. One set of experiments uses a simple, controlled scenario where all unnecessary factors that may introduce further complexity are eliminated. The second set of experiments is performed using realistic travel patterns and realistic network setting where the dynamic route guidance systems are evaluated for the city of Singapore. Therefore, the small-scale scenarios, referred as *Case A scenarios*, are performed on a *block* network, while the large-scale scenarios, referred as *Case B scenarios*, are performed on a realistic *city* network.

Experimental setups for block and city level scenarios

Case A scenarios are designed to use a small scale network so that the observed complex phenomena could be analyzed and explained in isolation, without other interfering factors. In this case, the network topology contains a simple geometry, resembling a regular block roads structure from a city. This network model is simple but yet representative in capturing the complex dynamics responsible for the emergent phenomena. Besides eliminating the unnecessary interfering factors, using simulating smaller setups has the advantages of using less computing resources, which can be vital in some cases.

Case An experimental setups are suitable, for instance, to analyze and explain the effect of drivers using error-free navigation recommendations in the presence of traffic congestion. In this case, the real-time information recommends what routes are suitable for the traffic participants to avoid congestion. The overall objective is to understand the impact of providing information to different shares of drivers as well as evaluating the overall traffic performance for dynamic route guidance systems where the alternative routes have a different length. The second study extends the experimental setup from the previous one by adding uncertainty or inaccuracy to the provided information. The objectives of this study are two-fold: firstly, a general source-based classification of different kinds of this inaccuracy is introduced; secondly, a detailed analysis of the effects that these different types of inaccuracy sources can have on the system is performed. Another study analyses how drivers and traffic lights systems interact and influence each other when they are informed one about another's behavior. In this case, the drivers receive information about how to adapt the speed to avoid stopping for the red light when possible. The overall purpose of this study is to evaluate how the overall traffic performance is impacted by the responsiveness of the traffic lights and the usage of speed recommendation by different shares of the drivers.

Experimental setups for city level scenarios

Case A, block level scenarios can be used for many types of applications, as explained in the previously. However, there are cases when the phenomena of interest appear to a very large network. For example, there are several circumstances when a small change in the system's components can produce a big impact on a large scale (i.e. the butterfly effect [14]). Such scenarios need to be evaluated on a large scale network.

Case B experimental setups proposed in this thesis investigate an information control strategy providing route guidance for the informed drivers. In contrast to Case A scenarios, the current guidance methods are based on simulated outcomes of closing specific roads segments optimized for achieving socially optimum performance in a realistic city network. The purpose of routing is to improve the overall traffic performance by partially eliminating the harmful segments from the routes of the informed drivers. Partially closing a road means that, instead of informing the whole population to avoid a certain road, only a share of the drivers receive route recommendations. This strategy is *soft changing* the infrastructure so that a small change (partially closing a road segment from the city network) has a significant effect on the global traffic performance.

3.6 Conclusion

It is important to analyze different aspects related to the information flow in transportation systems to design efficient ITS components. This chapter provided a systematic approach for tackling such issues. First, a logical framework in which the information flow process goes trough a ITS system is presented. The information in this system can be seen to flow through three stages: data *input*, data *processing* and information *output*. Possible benefits and possible problems associated with each particular step of the information flow process are evaluated. For this, a set of studies were selected for this thesis to investigate different problems are related to this process of information flow in transportation systems from different perspectives. For example, studies investigate aspects related to data collection, different models of information dissemination or the interaction between an adaptive traffic infrastructure and drivers using navigation recommendations.

To efficiently tackle the research questions described in Chapter 1, a systematic approach for designing and performing the experiments is used. The experimental setups are classified based on several criteria. The first categorization is done based on the type of information content used. The information can be presented as route or speed recommendations to drivers or can be used by the intelligent traffic infrastructure. Moreover, the experiments are categorized based on the step of the information flow process where the underlying cause of the investigated phenomena appears or where the phenomena manifests (i.e. data collection step, data processing step, the process of information dissemination or the information display step). Another classification of experiments is done based on the scale of the infrastructure network used, i.e., Class A block level networks or Class B city scale networks.

Therefore this thesis investigates how different models of information dissemination used by information control strategies can impact the traffic performance. In addition, the thesis investigates how the traffic information can be used to dynamically change a responsive traffic infrastructure in order to avoid inefficiency. Moreover, uncertainty and inaccuracy that may appear at each of the steps of the information flow can impact the traffic situation. First, a classification of the uncertainty based on the stage of the data processing that the inaccuracy originates from to enable a more general analysis. A series of experiments evaluate the effect produced when different shares of the probe vehicles provide data for collection. Sequentially, the studies identify the minimum amount of probe vehicles necessary to provide data to determine an acceptable level of information inaccuracy. The possible errors introduced during the collection step, preprocessing/ processing step or presentation step are also analyzed.

Chapter 4

Computational model

4.1 Introduction

In order to study different aspects related to the information flow in transportation systems, it is necessary to model the traffic infrastructure, traffic flow, and information dissemination. For this, and Agent-Based Model (ABM) is used as a representation of the transportation system which is conceptualized as a multiagent system. The active components or decision makers are defined as agents, who are autonomous with respect to the other entities within the simulated environment. For this traffic simulation, the agents represent Driver-Vehicle Units (DVU). The rules and the specifications of the interactions of agents among themselves and with their shared environment are implemented. Therefore, the phenomenon can be generated from the actions and interactions of agents rather than describing it globally [100].

The traffic infrastructure components are, for instance, roads or traffic lights systems. The traffic flow is modeled by agents and their movement on the roads infrastructure. The agents are created by a model of agents generation and are assigned with an itinerary consisting of an Origin and Destination (OD) pair. Based on the OD pair, routes are calculated by a routing model.

As mentioned in Chapter 3, depending on the research questions investigated and on the level of details needed for modeling the agents, there are two types of models used for the traffic flow. There are cases when it is necessary to use controlled scenarios with a smaller network setup based on a microscopic traffic model. There are also cases when the experiments require larger realistic city scale based on a mesoscopic traffic model. On top of the traffic flow, an information flow model with models of information dissemination is also designed. The general characteristics of these models are described in the following sections.

4.1.1 Modelling the traffic infrastructure

Road network model

The physical structure of the streets and the intersections is represented as a network, naturally associated with a graph representation of nodes (vertices) and edges (links). The links are associated with segments of roads, and nodes define decision points at which a road may split or merge with another one. Therefore, links are road segments that connect two nodes, and an intersection is represented by a collection of nodes. A link can have more lanes.

Traffic lights model

Traffic lights are simulated as part of the road network infrastructure, located at a certain intersection of roads. They contain a collection of links that can be either *active* or *inactive*. As mentioned above, the links are roads that connect two road sections in an intersection. A traffic light system consists of a set of mutually compatible phases. The green or red color of phases is modeled by controlling the accessibility of the links. While for the green color of the traffic lights system, the set of links associated with this phase are active, for red color the links are inactive. A cycle of the traffic lights system contains all the phases associated with the intersection active at least once.

4.1.2 Modeling the traffic flow

At the beginning of the simulation, each agent is assigned an itinerary generated by a routing technique. The agents travel trough their routes that can be either fixed, with predetermined OD pairs or probabilistic. Therefore, the traffic demand is determined by the agent generation, itinerary assignment and the agent's movement on its route.

Agents generation modelling

There are two techniques used for generating agents and traffic demand, each suitable for a type of scenario and experimental setup. For experiments requiring a controlled scenario with simple traffic patterns, the agents are created by a Poisson process with a specific mean inter-arrival times (I_A). The traffic intensity determined by the number of agents N_{total} and the frequency of creating agents: the mean inter-arrival time I_A.

The second technique of agent generation is based on a time-dependent origin-destination OD table, matching realistic traffic patterns. The road network was derived from Navteq 2009 data [101] which provides information on the road infrastructure in Singapore. Data from the Household Interview Travel Survey 2012 (HITS) [102] was used for initializing the time-dependent OD assignment. The specific details of the agent generation model are described for each set of experiments.

Routing modelling

For a vehicle to traverse between the origin and destination, a route needs to be calculated based on the provided graph. In this thesis, there are two models for route generation. Some sets of experiments calculate the shortest path between the origin and destination points based on Dijkstra's algorithm. In this case, the algorithm uses different weight systems so that each driver can have a preference for route choice optimized in terms of distance, travel time, speed, distance or comfort.

Other sets of experiments use the probabilistic routing technique. In this case, the origins of trips are peripheral the lanes, without predecessors. A route is generated based on the turning probability for each intersection (equally distributed in this case). When the vehicle reaches a lane without successors, this link is marked as the destination and the vehicle is removed from the simulation.

Agent motion modelling

The agents know the road network infrastructure, perform route calculations using the routing model and move forward on their route. The system consists of agents operating and interacting in a shared environment (road network) this making that the behavior of the entire system to be the emergent behavior of all its interacting elements. Depending on the level of details required for the agent modeling, the traffic flow is determined by two types of models: microscopic and mesoscopic traffic model.

For the microscopic traffic model, the agents move forward on their routes with a certain speed and acceleration determined by a time-stepped car following model [103]. For this, the Intelligent Driver Model (IDM) is used [93, 5]. This setup is suitable for understanding and explaining certain phenomena associate with information dissemination in a simplified and controlled traffic scenario.

Other sets of experiments are suited for mesoscopic traffic model as it requires less detail for the agent model. In the mesoscopic traffic modeling, after the generation of the origin, destination and starting time of every agent, the traverse time calculation is implemented. In this case, it is not necessary to consider details regarding the speed and acceleration at each time step. This setup is suitable to optimize traffic control and generate consistent route guidance for a realistic traffic situation (i.e. realistic city scale roads network and realistic agent population).

4.1.3 Modelling the information flow

The traffic information is obtained from data collected from individual agents, which in this context are called *sources* for data collection. For specific scenarios, only a fraction of the traffic participants is selected by a model of data collection to provide details such as origin and destination of the trip, or current speed and position.

This data is aggregated and processed, sometimes through several layers before it is presented back to traffic participants on their information systems as navigation recommendations. There are two types of agents: *informed* and *uninformed*. The informed agents differ from the uninformed ones as they receive navigation recommendations with different details, depending on the experimental setup. For specific scenarios, similar to the data collection process, only a share of the traffic participants is selected by a model of information dissemination to receive navigation recommendations.

These navigation recommendations can refer to different aspects of the traffic situation. In some of the experiments, the traffic information contains details about the speed they need to use to avoid stopping at the red color of the traffic lights system. The agents receive speed recommendations only if they are in a range distance, called adjustment distance, to the traffic lights system. The recommended speed takes into consideration the remaining distance to the traffic lights system but also the minimum and maximum speed of the specific roads (v_Y^{min}, v_Y^{max}).

In another set of experiments, information dissemination is simulated by sending updates about what routes to provide to agents selected to be informed. In this case, the purpose of using route recommendations is to avoid the congested areas in the network. The information contains details about the current travel times on links and is used by informed agents to estimate the fastest path (as defined by travel time). As mentioned above, the route calculation is done using Dijkstra's algorithm. The difference between informed and uninformed agents is that one calculates the best route using a road network of *current* travel time (these are the informed agents). The other agents calculate the best route, assuming free flowing traffic, i.e., they estimate travel time by dividing the length of the road by the maximum speed of that road: $\frac{L_Y}{v_Y^{max}}$. This way, the congested roads may have a lower priority in the informed driver's choice.

For the third category of experiments, the informed agents are recommended a route that excludes the harmful roads calculated for the global network level. Therefore, when implementing the soft closing strategy, the group of informed agents is sampled from all drivers that initially need to use the examined road segment. This is how the harmful roads are selected. Also, in this case, the routes are calculated with Dijkstra's algorithm using the preference choice for each individual optimized in terms of speed, distance or comfort.

4.1.4 Model calibration and validation

In a real world scenario, it would be necessary to run multiple iterations of the proposed process with realistic, calibrated data sets. For this thesis, there are two types of calibration used. One is by setting the proper parameter values for the presented models described in the literature (i.e. parameters for the IDM).

The second calibration was done for the specific the scenarios using realistic data sets. For example, the parameters from the transverse time calculation are calibrated for different types of roads depending on their speed limits using both GPS tracking data and a travel time distribution of the population for a period of the day of interest.

The particular details of each model will be described in detail in the next sections when presenting the computational model of each study. The parameter values and the experimental setup particularities will also be introduced for each study.

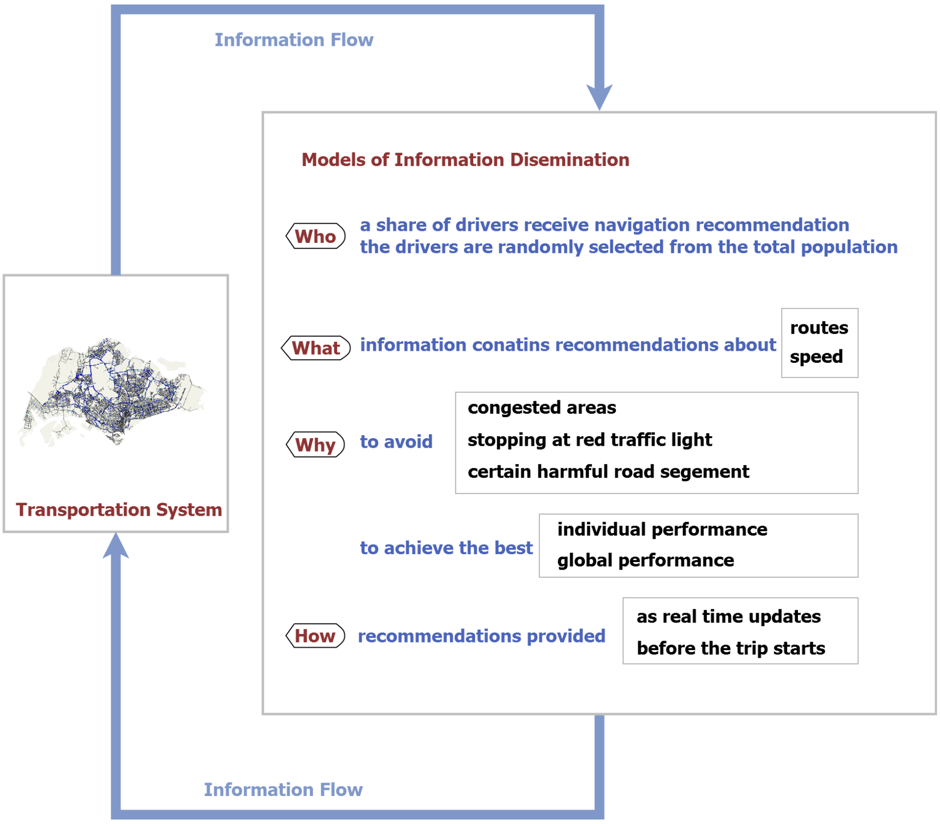

Figure 4.1: Illustration of models of information dissemination. The information is presented to drivers as recommendations on their navigation devices. From the total amount of drivers only a share is selected to be informed. The recommendations can refer to what routes to choose in order to avoid congested areas in the city or certain roads segments that are harmful to the overall performance. The recommendations can also refer to what speed are appropriate to avoid stopping at the red light of the next traffic lights system. Information is provided as regular updates or once, at the beginning of the simulation. The first category optimizes the individual performance, while, in the second case, the global performance is achieved.

4.2 Conclusion

This chapter introduced the methodology used to investigate different aspects related to the information flow in transportation systems. To perform the experiments necessary to explore the phenomena of interest, an Agent-Based Model (ABM) of traffic is used. This model has three components: the traffic infrastructure model, the traffic flow model, and the information dissemination model. The agents, which in this case are Driver-Vehicle Units (DVU), interact with each other or with the shared traffic infrastructure. This way, their local actions create an emergent macroscopic phenomenon. Depending on the level of detail necessary for each scenario, either microscopic or mesoscopic models are used.

Chapter 5

The impact of different shares of drivers using navigation recommendations

5.1 Introduction

With a larger distribution of personal smart devices and navigation tools, there are several novel sources for real-time data collection and better means for information transmission. At the same time, Intelligent Transportation Systems (ITS), applying information processing, communication, sensing, and control technologies [8], have become more advanced and play a fundamental role in improving transportation [9]. In this context, large amounts of data are processed and presented to the participant vehicles through their navigation systems. Surveys show that, in most cases, drivers trust the traffic information and follow the navigation recommendations [31]. However, the consequences of providing real-time information to drivers, who are themselves participants in the data collection process, has not been investigated in much detail. Moreover, in an ITS system, these drivers interact with an intelligent adaptive traffic infrastructure (for instance dynamic traffic lights systems).

This chapter presents a detailed analysis of the effect of real-time information on a transportation system when different proportions of the traffic participants receive traffic navigation recommendations. Knowing details about possible traffic problems influences the traffic participant's driving behavior, and this may have consequences on the overall traffic situation. In this regard, a sweep of the percentage of informed agents is performed during simulation and, for every case, the overall traffic performance is evaluated. The percentage of informed agents is varied from 0 to 100 in steps of 10%.

Two studies are presented to provide evidence for or against the impact on the overall performance of informing different shares of traffic participants about the traffic situation. In the first study, the navigation recommendations details are in the form of route recommendations for congestion avoidance given to informed agents. In the second case, the informed agents receive speed recommendations about how to adapt their speed and acceleration to avoid stopping at the red light of a traffic lights system.

The objective of this chapter is to find out if there are cases when different shares of traffic participants, using navigation recommendations can be detrimental to the overall traffic performance. Also, it is important to investigate if there is an extent to which the ITS systems can become better by being smarter.

5.2 Computational model

In order to perform the two sets of experiments, the transportation system is simulated using an agent-based microscopic model. The system consists of Driver Vehicle Units (DVUs) as agents operating and interacting in a shared environment (road network infrastructure). The behavior of the entire system is the emergent behavior of all its interacting elements.

The agents perform route calculations taking into consideration the road network topology in the current traffic situation. They move forward on their path with a certain speed and acceleration determined by a time-stepped car following model [103]. The simulation uses a model of the traffic infrastructure, containing roads and traffic lights systems. The traffic flow is simulated using a microscopic traffic model with the Intelligent Driver Model (IDM) [93, 5]. In addition, the information flow is also modeled, with the focus on the models of information dissemination.

An overview of the computational models used in experimental setups is described in Chapter 3. The main characteristics but also the reason for selecting this methodology are presented in that dedicated chapter. In the next sections, the specific details of each model used for the particular set of experiments performed for the current chapter are introduced.

	parameter description	min value
Y	road identifier	
v_Y^{min}	minimum speed	$[m/s]$
v_Y^{max}	maximum speed	$[m/s]$
$Length_Y$	road length	$[m]$
N_{Lanes}	number of lanes	$lanes$

Table 5.1: Road link model parameters

5.2.1 Infrastructure model

The infrastructure components are either roads in the network infrastructure or traffic lights systems as the intersection of two roads.

Road network model

Each road contains a set of attributes. Therefore, a road Y from the road network is characterized by a minimum and maximum speed (i.e. this can correspond for instance to the legal speed limits on roads), the number of lanes and length of the road segment: $Road_Y =< v_Y^{min}, v_Y^{max}, N_{Lanes}, Length_Y >$. Table 5.1 summarizes the main parameters in the road network model. Figure 5.1 illustrates the model parameters for a road link.

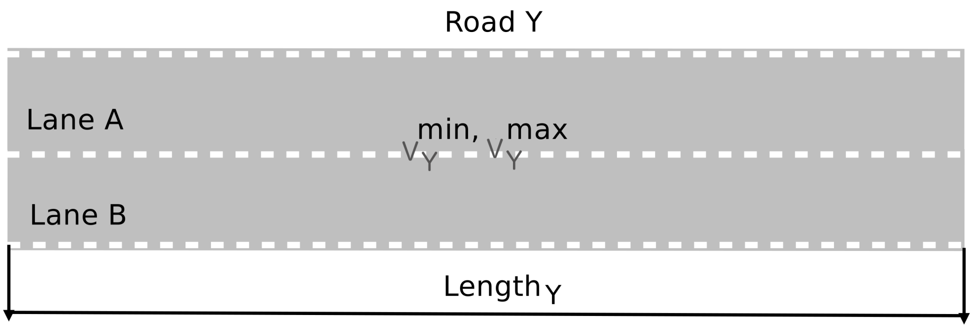

Figure 5.1: Illustration of the model parameters for a road link. A road link Y is characterised by minimum and maximum speed, number of lanes and length: $Road_Y =< v_Y^{min}, v_Y^{max}, N_{Lanes}, Length_Y >$.

Traffic lights model

Traffic lights systems are modeled as part of the road infrastructure placed, at the certain intersection of roads. Links are special roads that connect two road sections in an intersection. The traffic lights systems contain links, and the links have a set of lanes. Links can be either *active* or *inactive*. A traffic light system consists of a set of mutually exclusive phases. The green or red color of phases are simulated by controlling the accessibility of the links. A phase is characterized by duration and a set of lanes that are active: $Phase_x =< \delta^{Phase}, Lanes >$

For example, Figure 5.2 illustrates a traffic light intersection with traffic lights. There are three groups of links marked with different colors, corresponding to three distinct phases. At any given point, only one group of links is active [1].

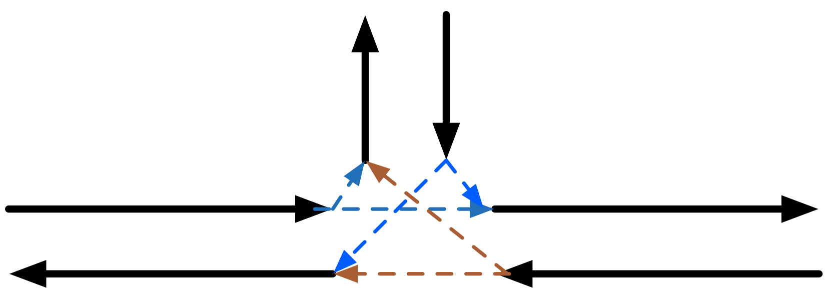

Figure 5.2: Illustration of the traffic lights model. There are three groups of links marked with different colours. At one point only one group of links is active [1].

Traffic lights systems used in the experimental setups are either static or dynamic, depending on how the phase duration δ^{Phase} is calculated. For one intersection, a cycle of the traffic lights systems contains all the phases associated with the intersection active at only once. The traffic lights systems complete a cycle.

Static traffic lights have the active phase duration fixed at the start of the simulation $\delta^{Phase} = k$. Dynamic traffic lights have a variable duration, determined at each timestep

	parameter description	min value	max value	incremental step
D^{Adj}	adjustment distance	$0[m]$	$900[m]$	$100[m]$
δ^{Phase}	phase duration	$11[s]$	$135[s]$	$1[s]$

Table 5.2: Traffic lights system model parameters

based on the number of cars that pass trough the intersection link. The phase weight (w^{Phase}) considers the number of cars passing trough the link at the current time. All the phases of a cycle are taken into consideration, and each duration is a ratio of the weight to the sum of total weights of phases of a cycle (w^{Total}): $\delta^{Phase} = w^{Phase}/w^{Total}$.

Furthermore, this computational model contains an adjustment distance (D^{Adj}) parameter, which represents the distance to the traffic lights system from which the cars receive speed recommendations. Table 5.2 introduces the main parameters used for modelling traffic lights systems. Figure 5.3 illustrates a traffic lights system with two parameters, adjustment distance D^{adj} and phase duration δ^{Phase}.

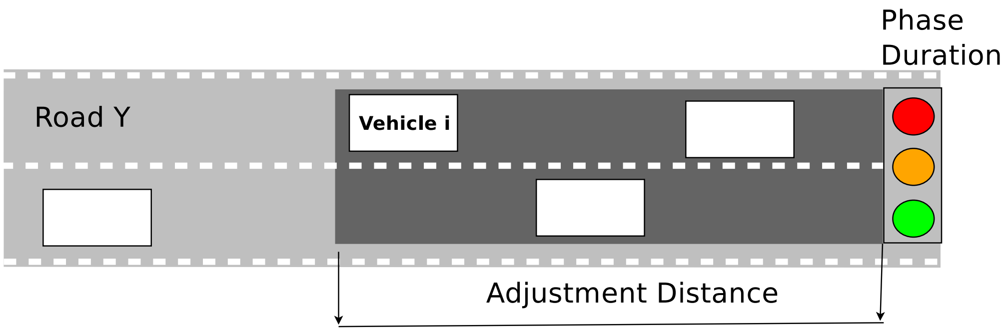

Figure 5.3: Illustration of the traffic lights model. The traffic lights systems are characterised by two parameters: adjustment distance D^{adj} and phase duration δ^{Phase}

5.2.2 Traffic flow model

Drive-Vehicle Unit model

The agents or Drive-Vehicle Units (DVU) move on roads with an acceleration and deceleration using Intelligent Driver Model (IDM) and lane-changing models. These models describe the position and velocity of each car in the simulation and can then be compared much easier with empirical data than in macroscopic models. IDM is a car-following model and belongs to the deterministic kind of microscopic models [5, 93, 104], as presented in more detail in Chapter 2.

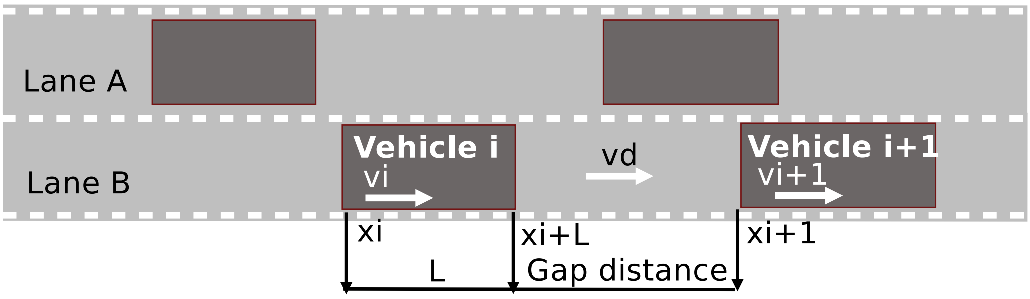

Figure 5.4: Illustration of the IDM model parameters. In an IDM scenario, a vehicle i is characterised by the current position x_i and the current speed v_i. D_{gap} is the gap distance between vehicles. The road is characterised by minimum and maximum speed, length and desired speed v_d: $Road_Y =< v_Y^{min}, v_Y^{max}, N_{Lanes}, Length_Y >$.

- **Acceleration model**

  Next, IDM [5, 93, 104, 105] is used to model the acceleration and deceleration. A vehicle i (v_i) follows the car in front vehicle $i + 1$ (v_{i+1}) at a speed less than the desired speed of the road v_d, which is a value between v^{min} and v^{max}. The current speed of car i, v_i is adapted to the speed of car $i + 1$, v_{i+1} in order to maintain a gap distance greater than D_{gap}, where D_{gap} is a parameter of the IDM model that specifies the preferred distance between cars.

  IDM calculates a realistic instantaneous acceleration (or deceleration) and displacement of vehicle i for a time step δt by taking into consideration its current

Parameter	Description	Unit
v_d	desired velocity	$[m/s]$
v_i	current speed	$[m/s]$
x_i	current position	$[m]$
t_h	safe time headway	$[s]$
a	maximum acceleration	m/s^2
b	desired deceleration	m/s^2
s	gap distance between vehicles	$[m]$
D_{gap}	proffered gap distance between vehicles	$[m]$
δ	acceleration exponent	
$L_{vehicle}$	vehicle length	$[m]$
Δt	update interval	$[s]$

Table 5.3: Main parameters of the IDM model.

speed and position (v_i and x_i), the desired speed (v_d), the current speed and the position of the car in front (v_{i+1} and x_{i+1}). In addition, there are parameters that specify vehicle length ($L_{vehicle}$), time headway (t_h) for safe acceleration and deceleration (to avoid collisions), and maximum acceleration and deceleration (a, b). The main parameters of the IDM model are described in Table 5.3.

For a vehicle i, the acceleration is assumed to be a continuous function described by the velocity v_i and the distance to the car in front s_i. The equation for acceleration then becomes:

$$\dot{v}_i = a[1 - (\frac{v_i}{v_d})^\delta - (\frac{s^*}{s_d})^2] \tag{5.1}$$

where v_d and effective desired distance s^*.

The desired distance between cars s^* is calculated from minimum distance s_d, time headway t_h and difference in velocity Δv:

$$s^* = s_d + max(v_i t_h + \frac{v_i \Delta v}{2\sqrt{ab}}) \tag{5.2}$$

$$\Delta v = v_i - v_{i+1}$$

Equation 5.1 consists of two terms: a free road acceleration term and a braking deceleration term. The free traffic state dominates when s is very large, causing the interaction term to become negligible. The free traffic term is then:

$$\dot{v}_{\text{free}}(v_i) = a\left[1 - \left(\frac{v_i}{v_d}\right)^{\delta}\right] \tag{5.3}$$

It can be noticed that as $v \to v_d$, the acceleration $\dot{v}_{i\text{free}}(v_i) \to 0$. This models the tendency for a driver to gradually decrease their acceleration as they approach their desired velocity v_d.

The braking or interaction term of Equation (5.1) governs the braking and following driving states. The braking term is given by:

$$\dot{v}_{i\text{brake}}(s_i, v_i, \Delta v) = -a\left(\frac{s^*}{s}\right)^2 \tag{5.4}$$

$$s^*(v_i, \Delta v_i) = s_d + v_i t_h + \frac{v_i \Delta v}{2\sqrt{ab}}$$

In normal driving conditions, the $v_i t_h$ term dominates. The $v_i \Delta v / 2\sqrt{ab}$ term dominates when approaching a car at a high rate of speed. The model limits braking decelerations to the comfortable deceleration b. However, that the IDM brakes stronger than b if the gap becomes too small.

The positions of vehicles are calculated with the equations of motion similar to [104]. The acceleration is commonly assumed to be constant within an update interval. The velocity and the position of a vehicle at the end of an update interval are given by following the update rules:

$$v_i\left(t + \Delta t\right) = v_i(t) + \dot{v}_i(t)\Delta t \tag{5.5}$$

$$x\left(t + \Delta t\right) = x(t) + v(t)\Delta t + \frac{1}{2}\dot{v}_i \Delta t^2 \tag{5.6}$$

$v(t)$ and $x(t)$ are the velocity and position of the vehicle at time t, and Δt is the update interval of the vehicle.

- **Lane changing model**

  Moreover, in order to capture a more realistic traffic behavior, a lane changing model is also implemented. There are a two situations when vehicles need to change the lanes. The first situation is when vehicles need to turn in order to follow their route itinerary. The second case when vehicles change lanes is when faster vehicles need to overtake the slower vehicles by shifting to faster lanes.

- **Congestion model**

  Generally, congestion is an emergent phenomenon that occurs naturally in microscopic traffic simulations [5]. However, as the congestion appears in certain circumstances, it can also resolve by itself. For some the experimental setups used in this chapter, the hypothesis is that the fact that traffic participants use route navigation recommendations in order to avoid congested area can significantly impact the traffic situation. For this reason, the information dissemination strategies are evaluated in a controlled scenario with a constant level of congestion on a specific area.

  Therefore, congestion is created by introducing disturbances in the *disturbance area*, marked on Figure 5.5. In order to create a disturbance, a random vehicle i driving on the disturbance segment of the road is chosen every $2[s]$ and forced to break immediately ($v_i = 0[m/s]$). The car takes some time to accelerate and once again reach full speed, thus causing a temporary congestion on the link.

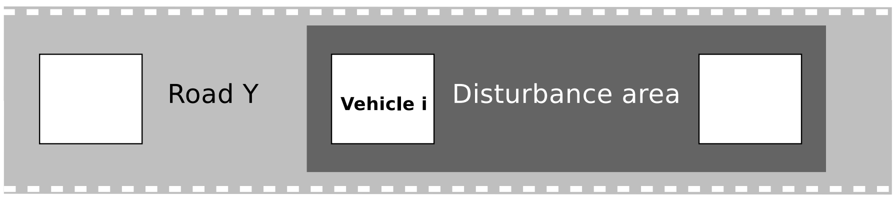

Figure 5.5: The figure illustrates how a constant level of congestion is modelled by randomly stopping a vehicle travelling on the *disturbance area* marked on the image.

5.2.3 Information flow model

As mentioned in Chapter 4, the computational model includes two type of agents: *informed* and *uninformed*. The informed agents differ from the uninformed ones as they receive navigation recommendations in order to avoid the congested areas on a network or to avoid stopping at the red color of traffic lights. In both cases, the recommendations updates are sent regularly, to only a share of the informed agents. Every time they receive an update, the agents will follow the recommendation.

In the first set of experiments, information dissemination is simulated by sending updates about what routes to choose to only a fraction of the agents. For this study, the purpose of using route recommendations is to avoid the congested areas in the network. The information contains details about current travel times on links and is used by informed agents to estimate the fastest path (as defined by travel time).

Route calculation is done using Dijkstra's algorithm. The difference between informed and uninformed agents is that one calculates the best route using a road network of *current* travel time (these are the informed agents). The other agents calculate the best route assuming free flowing traffic, i.e., they estimate travel time by dividing the length of the road by the maximum speed of that road: $\frac{L_Y}{v_Y^{max}}$. This way, the congested roads may have a lower priority in the informed driver's choice.

In the second set of experiments, the information contains details about the speed the traffic participants need to use in order to avoid stopping at the red color of the traffic lights system. The drivers receive speed recommendations only if they are within a range distance to the traffic lights system, defined as the adjustment distance.

5.3 Studies

5.3.1 Route recommendations for congested traffic flow

This study investigates the effect of information dissemination on ITS systems. Intuitively, the more drivers are informed, the better the traffic situation should be. The conditions under which, different shares of drivers having knowledge of the current statuses of the transportation system are detrimental to the system as a whole is investigated. For this, an experimental set-up based on a microscopic traffic model is implemented. The transportation system and the effect of information dissemination are modeled and analyzed through the agent based model.

As discussed in more detail in Section 2.3.2, there are some relevant studies on information dissemination in transportation systems using simulations. Similar to the current study, the information details refer to routing recommendations provided for the purpose of avoiding congested areas. One category of studies looks at how either local information (only about the neighbors) or global information (about the entire network) affects the overall system performance [20][25].

Moreover, information control systems for traffic planning in the presence of congestion has been researched by [21, 22, 23, 24]. In [21], a fleet of taxi drivers from Singapore used a web-based application to specify trip origin, destination and departure time and receive route recommendations. The study proposes an experimental comparison between actual taxi paths, with socially optimal and greedy path congestion-aware planning. The results show that socially-optimal congestion-aware routing achieves a reduction in travel time. Other similar studies analyzing the effect of information on a traffic simulation are inspired from biological ants systems [63, 45].

The approach presented in the current study [1] is similar because we also select a fraction of drivers to receive recommendations. However, in the previous studies, the number of informed drivers is fixed to the taxi fleet. This study investigates in more detail what happens when different percentages of traffic participants receive information. Another difference is that it does not estimate congestion, because, the fact that traffic participants use information makes the congestion prediction invalid.

[1] The content of this study is based on the published in article [1], referenced in Appendix A.1

5.3.1.1 Experimental setup

This study evaluates the effect caused on traffic by real-time information dissemination in the presence of congestion, generated by local disturbances. The computational model of the microscopic traffic simulation containing the road network model, routing mechanism, congestion formation and agent generation is described in detail in Section 5.2. Next, this section will define the experimental setup with the network graph, parameters, metrics, and indicators.

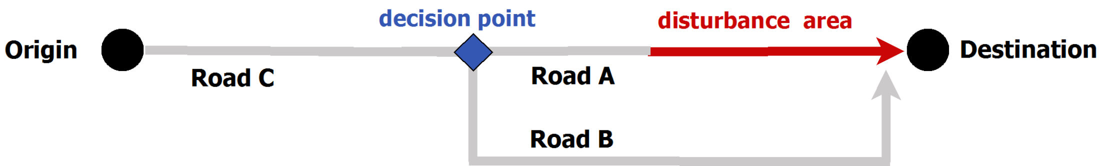

Figure 5.6: Illustration of the network graph used in the experimental setup. Agents travel from origin to destination on the fastest recommended option. Agents select either Route A or Route B at the *decision point*. Congestion is obtained by introducing disturbances on *disturbance area* (the last 150[m] of Road A). L_A is fixed to 500[m], while L_B varies between 500[m] to 1250[m].

The experiments consider a controlled scenario using a simplified road network as shown in Figure 5.6. Every agent starts at the origin and moves towards the destination, as marked on the figure. Considering the road network topology, the agents have two choices in terms of the routes they take: $Road_A =< 11[m/s], 19[m/s], 1lane, L_A >$ and $Road_B =< 11[m/s], 19[m], 1lane, L_B >$, where L_A is fixed at $500[m]$ and $L_B \geq L_A$. In this scenario, both roads are single lane.

As described in Section 5.2, each vehicle applies a car-following model and the IDM model to determine the speed and acceleration for moving forward on its route at each time step. The main parameters used by the IDM model are: $L_{vehicle} = 3[m]$, $a_{max} = 3[m/s^2]$, $b_{max} = 5[m/s^2]$, $t_h = 1.5[s]$, $\Delta t = 250[ms]$.

	parameter description	min value	max value
p	percentage of informed agents	0%	100%
L_B	length of Road B	$625[m]$	$1250[m]$

Table 5.4: Main parameters used in one experiment E_{p,L_B}.

Agents are created by a Poisson process with a mean inter-arrival time of $1700[ms]$. This value is chosen as the minimum inter-arrival time so as to maximize traffic, while not causing congestion on Road C (i.e. before the decision point, marked in Figure 5.6). Each informed agent receives updates about the traffic situation every $2[s]$. At the *decision point*, the agents select either Road A or Road B, whichever gives the fastest route time. Each experiment simulates 40 minutes of traffic which implies about $N = 1000$ agents in total that finish trips. From this amount, the last 800 vehicles to complete their trip N_c were considered, giving a warm-up period of 10 minutes after which the system reaches a steady state.

Congestion is created by introducing disturbances in the *disturbance area* (the last $150[m]$ of Road A), marked on Figure 5.6. In order to create a disturbance, a random vehicle i driving on the disturbance segment of the road is chosen every $2[s]$ and forced to break immediately ($v_i = 0[m/s]$). The car takes some time to accelerate and once again reach full speed, thus causing a temporary congestion on the link.

Each experiment E_{p,L_B} is characterized by two parameters: L_B, the length of is the length of the alternative road (Road B) and p, the percentage of informed agents. The main parameters used for the experiments are defined in Table 7.7. The values for the length of the alternative road, L_B, varies from $500[m]$ to $1250[m]$, while the length of Road A, L_A, is fixed to $500[m]$. The percentage of informed agents, p, varies from 0% (no agent is informed) to 100% (all agents receive information) in steps of 10%. Each experiment E_{p,L_B} is repeated 10 times.

To quantify the effect of information dissemination, the network performance is characterize as T, the average travel time of all agents in one experiment E_{p,L_B},

$$T = \frac{1}{N_c} \sum_{i=0}^{N_c} t_i, \tag{5.7}$$

where t_i is the trip duration of an agent i and N_c is the last 800 agents to complete their trip by the end of the simulation.

In order to evaluate different aspects of information dissemination, T is analyzed for different groups of agents. T is the global indicator of performance calculated over all agents. Moreover, T_U, T_A, and T_B is the global performance indicator calculated for the different groups of agents: uninformed, informed agents on Road A and informed agents on Road B.

For each L_B we can calculate the maximum improvement across all levels of informed agents, i.e., $p \in (0, 100]$. The information impact indicator for a road length L_B, I_{L_B}, quantifies the maximum improvement (negative change) on T when compared to the case of no information. This is actually the value of p at which we see the smallest value of T, which is defined as p_{min}.

$$I_{L_B} = max(T_{0,L_B} - T_{p_{min},L_B}), \tag{5.8}$$

where T_{p_{min},L_B} is the minimum T, obtained for p_{min}. T_{0,L_B} is T for $p = 0\%$.

As p is increased, for some road lengths L_B the average trip time will initially decrease (i.e. performance improves) to a minimum at p_{min}, beyond which average trip time will increase. This degradation in performance (increase in average travel time) is defined as D_{L_B}.

$$D_{L_B} = max(T_{p_{max},L_B} - T_{p_{min},L_B}), \tag{5.9}$$

where p_{max} gives the longest average trip time and $p_{max} > p_{min}$. It is important to note that for $L_B = 625[m]$, $p_{max} = 100\%$ and $p_{min} = 60\%$, $I_{625} = 98.1 - 85.8 = 12.3[s]$ and $D_{625} = 91.06 - 85.85 = 5.21[s]$.

5.3.1.2 Results

This section presents the experimental results for scenarios when the traffic participants use route navigation recommendations in order to avoid congested areas on the map. It is important to investigate how the length of the alternative roads influences the overall traffic performance and also how the fact that different shares of drivers are informed affects the overall traffic performance.

The length of the alternative road influences traffic performance

It is interesting to note that the performance T is influenced both by the percentage of informed agents p and by the length of the alternative road L_B. This phenomenon is shown in Figure 5.7. When the alternative Road B is equal to the reference Road A, T does not have a significant modification when increasing the share of informed agents. Increasing L_B to $625[m]$, T has an abrupt improvement. In this case, more information makes the traffic better. This happens because some parts of the traffic are moved on the alternative road. This way, the congestion on the reference Road A is also diminished but at the same time, the distance on the alternative road is not too big. It can also be observed that the overall trip duration T takes about 13% less when all agent are informed than when none is informed.

When increasing L_B between $750[m]$ and $1125[m]$, it can be observed that first the traffic is getting better (for less than 40% of the agents being informed) and for more informed agents T gets worse. When the length of the alternative road is long enough ($1250m$), very few agents select the alternative road, and T is not much affected. In this case, the shape of the plotted graph (T depending on p) is almost straight. However, it can be noticed that the standard deviation is high because Road B is very long.

In order to better illustrate this effect, the impact of information on T as we vary L_B was illustrated in Figure 5.8. For this, the Improvement Indicator I_{L_B} (defined in Equation 5.8) and the Degradation Indicator D_{L_B} (defined in Equation 5.9) was calculated. It is interesting to notice that the information produces the biggest improvement, $I_{L_B} = 12.3[s]$, for $L_B = 625[m]$ and the most significant degradation, $D_{L_B} = 6.7[s]$, for $L_B = 875[m]$. Because of this reason, further analysis was performed for $L_B = 625[m]$ and $L_B = 875[m]$.

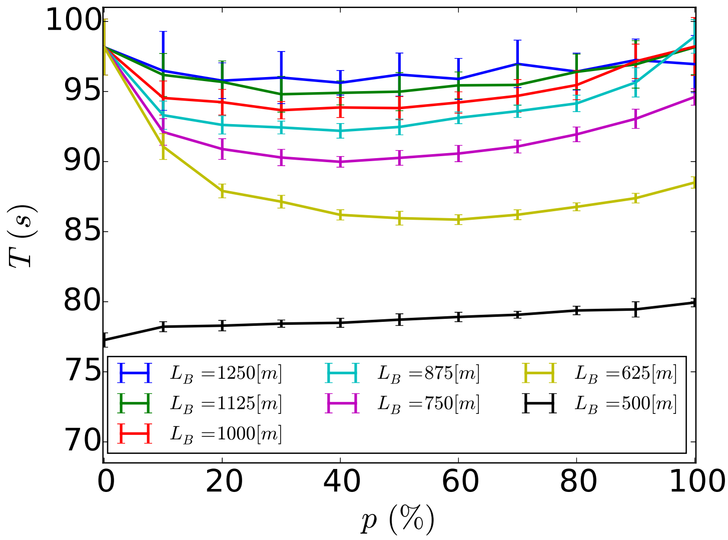

Figure 5.7: Illustration of the information impact on the traffic performance (T defined in Equation 5.7, expressed in s) depending on p and L_B. T is the performance indicator is calculated for each L_B depending on p. It shows how p influences the average travel time of all agents for a particular L_B.

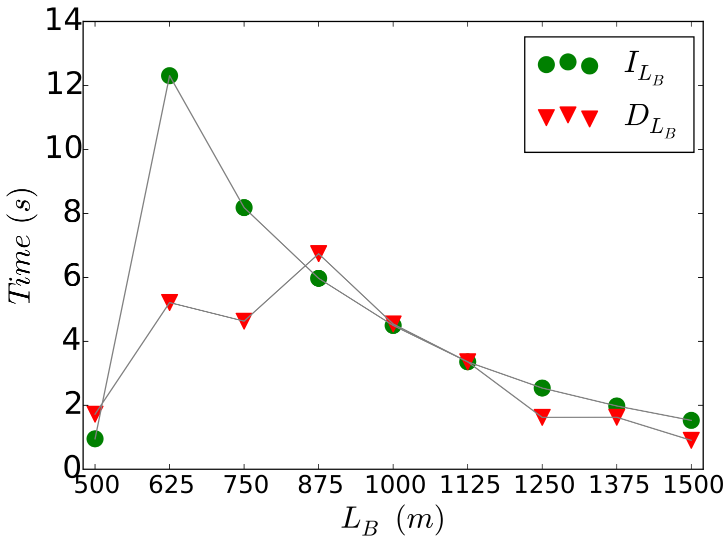

Figure 5.8: Illustration of the information impact indicators I_{L_B} and D_{L_B} depending on p and L_B. I_{L_B}, (defined in Equation 5.8) shows the improvement that information produces on T. D_{L_B}, (defined in Equation 5.9) shows the degradation that information produces on T.

The share of informed agents influences the global performance

It is interesting to analyze and explain why there is a significant improvement on the overall traffic performance T for $L_B = 625[m]$ and a significant degradation on T for $L_B = 875[m]$. For this, the indicator F_Y defined as the fraction of informed agents that select Road Y is defined:

$$F_Y = N_Y/N_I, \tag{5.10}$$

where N_Y is the number of informed agents that select Road Y and N_I is the total number of informed agents.

In the next section, it is shown how the percentage of informed agents p affects F_A and F_B for the two values of L_B. In Figure 5.9, it can be observed that, for $L_B = 625[m]$, $F_A < F_B$. This happens because Road A is congested and therefore Road B, with $L_B = 625[m]$, is the fastest option. Artificial disturbances are introduced on Road A to create a controlled scenario where information dissemination is done in the presence of congestion.

The agents that select Road B will not experience a significant increase in distance and therefore no severe degradation on travel times. In this case, T has an important improvement. On the other hand, in Figure 5.10, it can be seen that, for $L_B = 875[m]$, $F_A \geq F_B$. The reason is that L_B is long enough that it is better to choose Road A, even though this road is congested. The informed agents that select Road B experience longer trip duration producing a significant degradation on T.

Based on the results illustrated in Figures 5.7 and 5.8, further investigation is provided for the case of $L_B = 875[m]$. As illustrated in Figures 5.7 and 5.8, this case is interesting as it contains a significant improvement ($I_{875} = 6[s]$ for $p_{min} = 40\%$) but also a significant degradation ($D_{875} = 6.7[s]$ for $p_{max} = 100\%$).

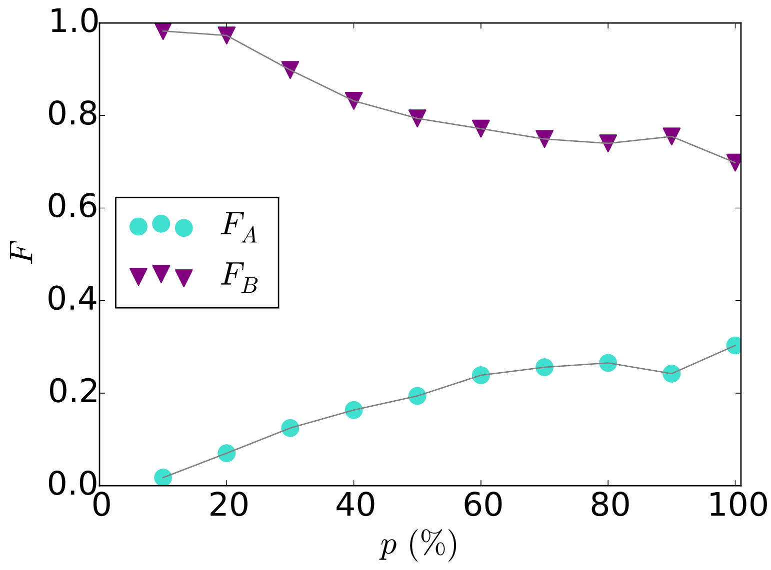

Figure 5.9: Illustration of F_A and F_B indicators (as defined in Equation 5.10) showing the fraction of informed agents that select either Road A or Road B, depending on p. The F_A and F_B indicators are calculated for $L_B = 625m$

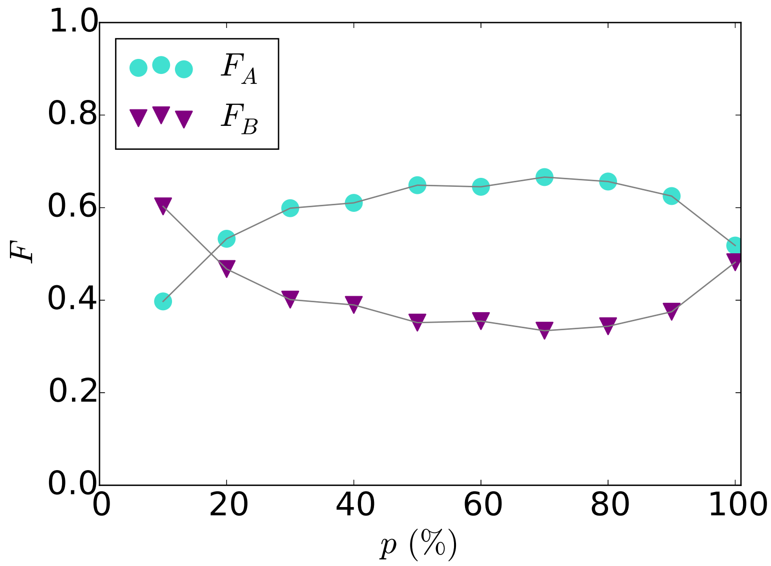

Figure 5.10: Illustration of F_A and F_B indicators (as defined in Equation 5.10) showing the fraction of informed agents that select either Road A or Road B, depending on p. The F_A and F_B indicators are calculated for $L_B = 875m$

Even though intuitively, one would expect that more agents using information would improve traffic conditions, the results show the opposite in some cases. Figure 5.11 shows T as a function of p in the case of $L_B = 875[m]$. It can be noticed that by increasing the percentage of informed agents p, first the performance indicator T improves, and afterward it decreases to almost the same level as if no agent is informed.

To explain this effect, the average speed for roads A and B is analyzed. The performance indicator calculated for different groups of agents in the simulation is evaluated: T_U, T_A and T_B for uninformed, informed agents that select Road A and informed agents that select Road B. In Figure 5.11, it can be observed that T_U and T_A have smaller values than T_B. The uninformed agents and the agents who select Road A perform better than the agents who select Road B.

The informed agents select Road B because Dijkstra's algorithm recommends it as the best route at that moment in terms of duration of the estimated trip. After a while, the situation improves on Road A, the informed agents find out about this change, and a new route evaluation is done for the new traffic situation. The agents from Road B are not able to return to Road A because of the roads topology and their trips take significantly longer, causing a severe degradation of the global performance T.

Furthermore, S_A and S_B indicators are defined as the average speed of Road A and on Road B for one experiment. In Figure 5.12 it can be seen that S_B decreases for higher values of p (when more agents are informed). This effect is caused by the increasing number of agents that select Road B as illustrated in Figure 5.10. Also, it can be observed that S_A remains almost the same, regardless of the fact that the number of agents on Road A is getting smaller as p increases. This values on the speed on Road A remain almost the same because on Road A is generated a constant level of congestion by introducing disturbances based on the model of congestion generation.

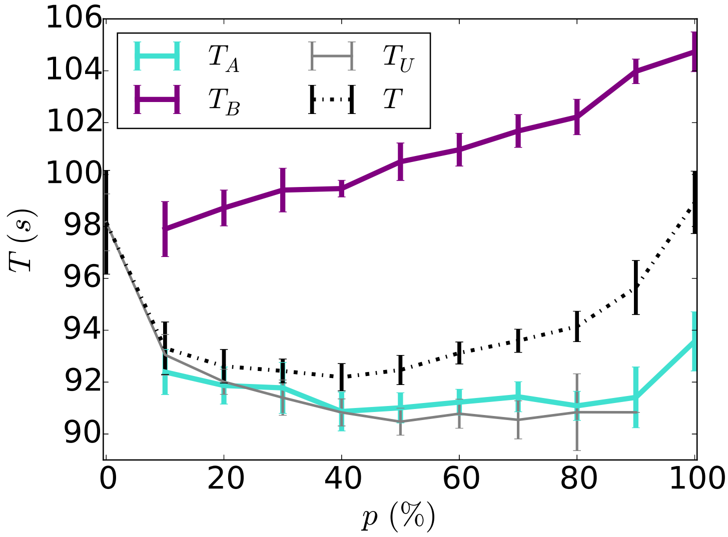

Figure 5.11: Illustration of T, T_U, T_A and T_B performance indicators (defined in Equation 5.7, expressed in s) are calculated for $L_B = 875m$. It can be seen that, for p higher than 40%, the group of informed agents that select Road B experience worse T_B than the ones that select Road A causing the global T to decrease.

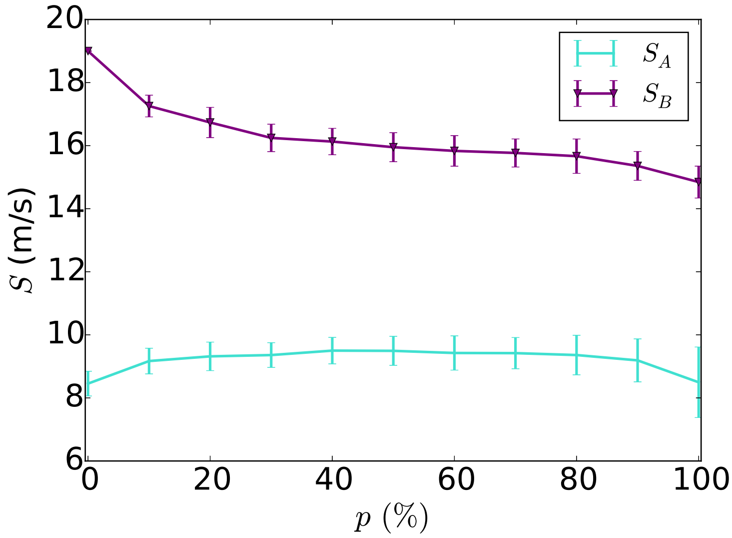

Figure 5.12: Illustration of S_A and S_B indicators defined as the average speed on Road A and on Road B. Information impact on S (average speed on roads) depending on p. The S_A and S_B indicators are calculated for $L_B = 875[m]$.

The average speed on roads influences the way Dijkstra's algorithm produces route recommendations. In Figure 5.13 it is shown that the standard deviation SD of the numbers of the informed agents that select Road A and Road B (N_A, N_B) becomes bigger when p increases. Similarly, in Figure 5.14 is shown that the standard deviation SD of the average speed of Road A and Road B (S_A, S_B) increases with p. This means that the recommendations from Dijkstra's algorithm change more frequently for bigger p. Therefore, some informed agents are recommended to select Road B, even though very soon afterward, the recommendation is no longer valid. Nevertheless, the agents that choose Road B are not able to move on Road A, even though they may receive new recommendations later.

Furthermore, in order to better explain how the groups of informed agents select the two roads, a congestion indicator C_Y for a Road Y is defined as follows:

$$C_Y = (1 - v_Y^{avg}/v_Y^{max}), \tag{5.11}$$

where v_Y^{avg} is the average speed on Road Y at the moment when agents select their route (the route is selected at *decision point* marked on Figure 5.6) and v_Y^{max} is the maximum speed for Road Y.

Figures 5.15 and 5.16 illustrate F_A and F_B (defined in Equation 5.10) depending on C_A. It can be noticed in Figures 5.15 and 5.16 that for higher p, agents experience $C_A \in (0, 1)$, while for smaller p, C_A interval is narrower. Road A is selected when C_A has smaller values (the congestion is smaller on Road A), while Road B is selected when C_A is bigger (the congestion on Road A is higher).

It is important to notice that traffic is influenced both by the percentage of informed agents p and by the lengths of the alternative road L_B. Contrary to the common intuition, there are cases when more information becomes detrimental. Also, it is shown that among the informed agents, some experience worse travel time or performance T than others, even though one would expect to have similar performances.

This phenomenon is explained in an abstract manner as follows: the transportation system provides data coming from fixed or mobile sensors. Information is processed from data and sent back into the system in real time. People make new routing decisions and change their behavior. These new routing decisions, result in the original model of the transportation system, which produced the routing recommendations, to be invalid because the participants changed their behavior.

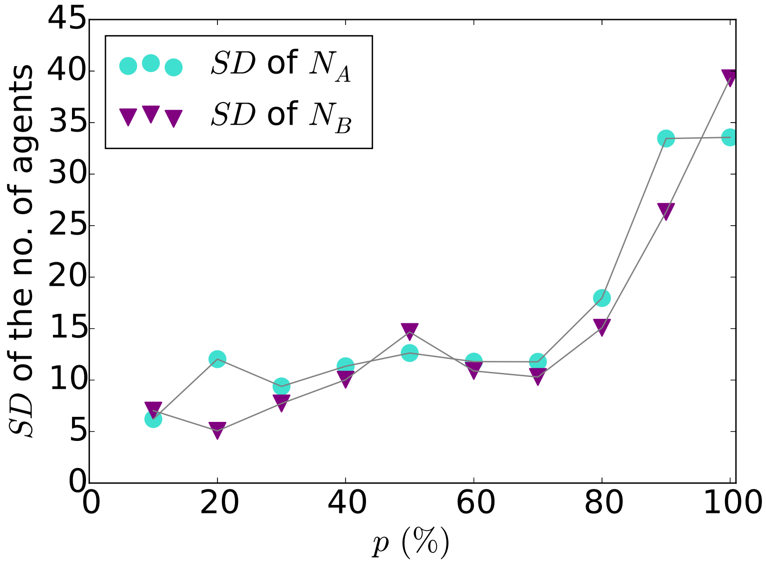

Figure 5.13: Illustration of SD (standard deviation) of N_A and N_B (numbers of the informed agents that select Road A and Road B) depending on the p calculated for $L_B = 875[m]$. It proves that the amount of informed agents influences traffic.

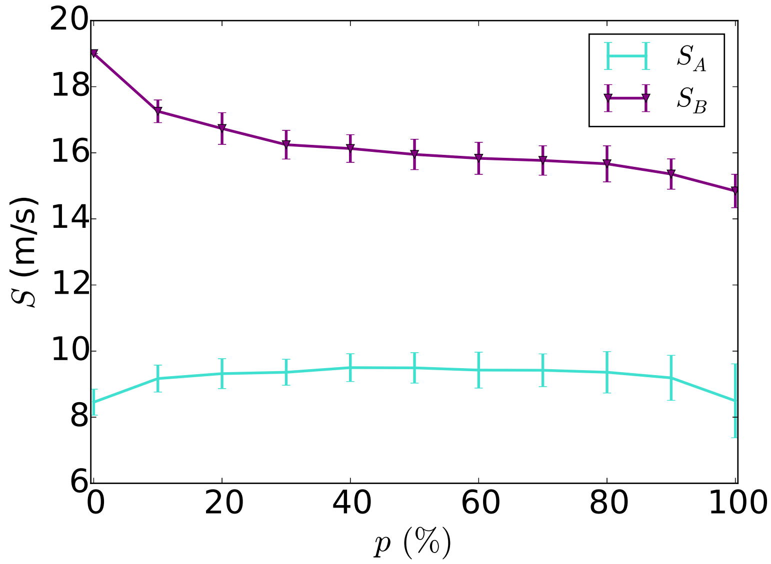

Figure 5.14: Illustration of SD (standard deviation) of S_A and S_B (average speed on Road A and Road B), depending on the p calculated for $L_B = 875[m]$. It proves that the amount of informed agents influences the speed on roads and implicitly the traffic performance.

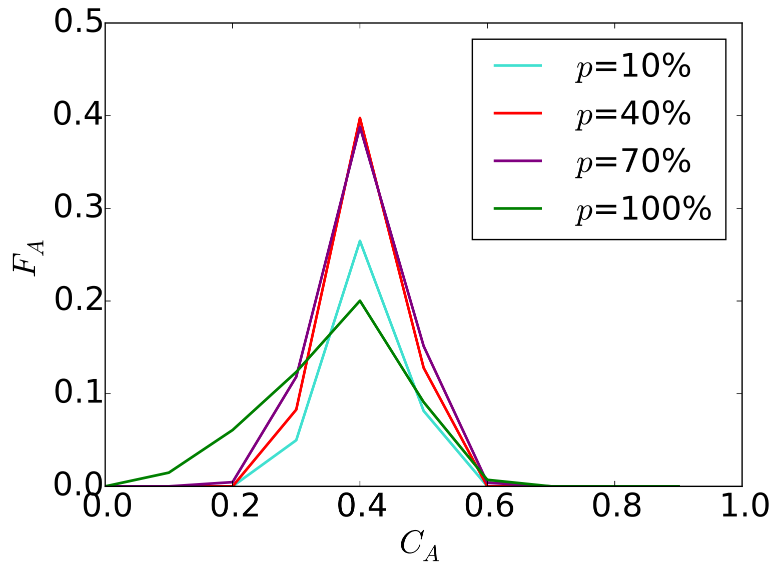

Figure 5.15: Illustration of F_A indicator for Road A depending on C_A congestion indicator for Road A (defined in Equation 5.11). The F_A indicators represent the fraction of informed agents that select Road A (defined in Equation 5.10) are calculated for C_A indicator for Road A. It shows F_A for Road A depending on C_A for $L_B = 875[m]$.

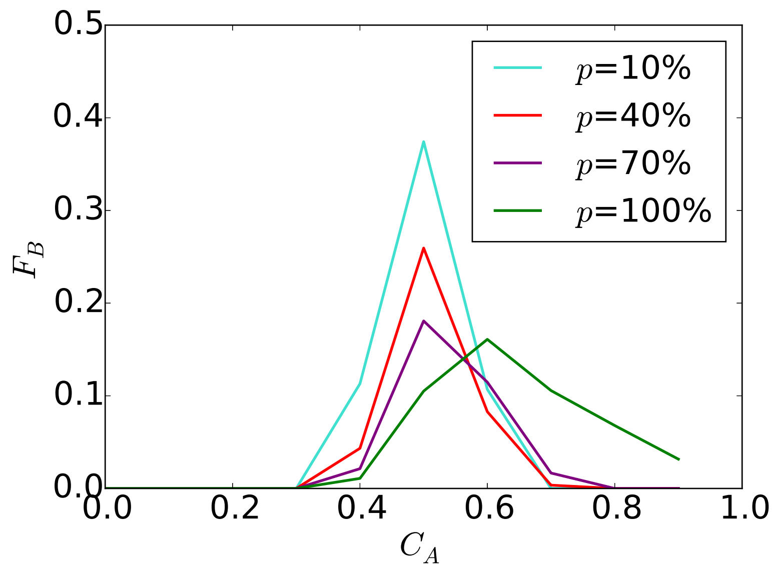

Figure 5.16: Illustration of the F_B indicator, representing the fraction of informed agents that select Road B (defined in Equation 5.10), calculated for the congestion indicator C_A indicator for Road A (defined in Equation 5.11). It shows F_B for Road B depending on C_A for $L_B = 875[m]$.

5.3.2 Speed recommendations for vehicles approaching traffic lights

In the context of ITS systems, there are different information strategies used for steering the traffic situation. The previous section introduced the effect of using route navigation recommendations to avoid congested areas. Another way of steering the traffic is by creating an efficient, intelligent traffic lights control systems. Nevertheless, in many situations, traffic lights can cause discomfort to drivers. Surveys state that there are cases when drivers prefer to change their routes to avoid stopping to multiple traffic lights on the way [106] [107].

The current study [1] proposes a systematic analysis of the interaction between drivers and traffic lights systems. The drivers receive information about what speeds they need to use to avoid stopping for the red light. Additionally, the study evaluates on how different shares of drivers being informed can impact the overall traffic state for both cases of static and dynamic traffic lights systems.

With the recent advancements in communication networks, computers, and sensor technologies, there is an increasing interest in developing optimized traffic lights control systems. New technological developments such as real-time responsive traffic lights are implemented in major cities [48]. Moreover, Dedicated Short-Range Communication (DSRC) systems, navigation devices or smart phone applications communicate and assist drivers in their trips. DSRC systems have already been installed on many roadways by the US Department of Transportation [53] and are expected to become ubiquitous in the future [54]. For example EnLighten [55] is a smartphone application that connects to the traffic signal network and predicts the behavior of traffic lights by communicating to DSRC systems on the roads. Using such technology, BMW drivers are informed when a stoplight changes [53]. More details about the state of the art in traffic lights systems is presented in Section 2.2.2.

The interaction of these new technologies not only offer new possibilities for improving the traffic but, at the same time, it may introduce new, unexpected, complex

[1] The content of this study is based on the published in article [2], referenced in Appendix A.1

consequences. Receiving information about the next traffic light color can have many advantages, mostly regarding safety, but also convenience. The drivers are less surprised by the sudden change in red color, and they try less to accelerate so that they catch green light before it turns red. However, it is interesting to understand what is the effect on the traffic performance when a massive amount of drivers react simultaneously to information about the traffic lights.

In this section, an agent-based model of a transportation system is used to analyze how drivers and traffic lights systems interact and influence each other when they are informed one about another's behavior. The drivers receive information about how to adapt the speed to avoid stopping for the red color when possible. Traffic lights have two types of control: static, with a fixed phase duration and dynamic, optimized the phase duration to prioritize directions for larger groups of cars [6].

5.3.2.1 Experimental setup

The primary purpose of the experiments is to investigate how the fact that drivers use speed recommendations can impact the performance. For this, two case studies are identified. In the first case, all drivers receive traffic lights information, but the traffic lights are static. In the second scenario, both the drivers and the traffic lights have information about each other and react accordingly.

For the experiments, a simplified scenario of the road network and traffic lights was used. This setup is illustrated in Figures 5.17 and 5.18. A detailed description of the computational model used is described in detail in Section 5.2 of this chapter. The main parameters used by the IDM model are: $L_{vehicle} = 3[m]$, $a_{max} = 1.2[m/s^2]$, $b_{max} = 2.2[m/s^2]$, $t_h = 1.5[s]$, $\Delta t = 100[ms]$.

In the next paragraph, only the details related to the specific experimental setup presented in this chapter are described. The main parameters used in the current study are defined in Table 7.2.

	parameter description	min value	max value	incremental step
IA_{time}	inter-arrival time	$1[s]$	$5[s]$	$1[s]$
N_{total}	total number of agents	$500[agents]$	$2500[agents]$	$1000[agents]$
v^{max}	roads speed range	$15[m/s]$	$20[m/s]$	$5[m/s]$
p	percentage of informed agents	0%	100%	10%
D^{Adj}	adjustment distance	$0[m]$	$900[m]$	$100[m]$
δ^{Phase}	phase duration	$11[s]$	$135[s]$	$1[s]$

Table 5.5: Main parameters used in one experiment $E_{p,I_{traffic},v^{max},D^{Adj},\delta^{Phase}}$.

$I_{traffic}$ represents the traffic intensity described as it follows:

- *Low* traffic intensity is generated for $IA_{time} = 5[s]$ and $N_{total} = 500[agents]$
- *Medium* traffic intensity is generated for $IA_{time} = 3[s]$ and $N_{total} = 1500[agents]$
- *High* traffic intensity is generated for $IA_{time} = 1[s]$ and $N_{total} = 2500[agents]$

In order to capture the overall performance of the transportation system, the global indicator is defined as it follows:

$$I_P = \frac{1}{N_c} \sum_{i=0}^{N_c} \frac{d_i}{t_i}, \tag{5.12}$$

where t_i is the trip duration and d_i is the trip distance of an agent i. N_c is the total number of agents to complete their trip.

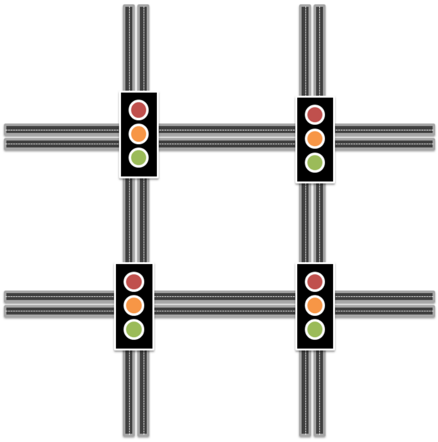

Figure 5.17: Illustration of the network graph used in the experimental setups. Each road has 4 lanes (2 in each direction), a fixed $Length_Y = 900m$ and a maximum speed v_Y^{max} with different values(for each scenario).

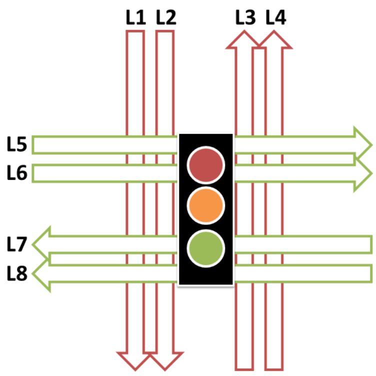

Figure 5.18: Illustration of a traffic lights intersection with two roads, $Road_A$ and $Road_B$. $Lanes$ L_1, L_2, L_3 and L_4 from $Road_A$ are associated to $Phase_1$ and lanes L_5 ,L_6,L_7 and L_8 from $Road_B$ are associated to $Phase_2$.

5.3.2.2 Results

This section presents the experimental results for scenarios where the traffic participants use speed recommendations to avoid stopping at the red color of a traffic lights system. It is important to investigate how the fact that drivers adapt their speeds based on navigation recommendations influences the overall traffic performance and also how the fact that different shares of informed drivers interact with intelligent adaptive traffic lights control systems.

Drivers adapt their speeds based on navigation recommendations

The studies presented here analyze what is the effect on the overall traffic when a massive amount of drivers are using speed recommendations. In this case, the traffic lights are *static* and all the agents are informed ($p = 100\%$, $\delta^{Phase} = 45[s]$, $v^{max} = 20[m/s]$). It is important to note that our scenario implies that traffic is generated symmetrically in both directions (north-south/ south-north and east-west/ west-east). The waiting time in one direction is compensated by the fact that more cars are going on the green wave in the other direction.

The main attributes of traffic lights systems (in this case D^{Adj}, v^{max}, δ^{Phase}) are varied in order to obtain detailed insights on their influence on the overall traffic situation. An analysis on how the adjustment distance D^{Adj} influences the traffic was performed. For this, the following indicator was defined:

$$I_{Adj} = (I_P^{D^{Adj}} - I_P^0)/(I_P^0), \tag{5.13}$$

where $I_P^{D^{Adj}}$ is the performance indicator defined in Equation 5.7 and I_P^0 is the performance indicator for the reference case of $D_{Adj} = 0[m]$.

Figure 5.19 illustrates the effect of drivers using speed recommendations for different values of D^{Adj}. The adjustment distance indicator I_{Adj}, defined in Equation 5.13, is affected even by small values of the $D_{Adj} = 100[m]$. Nevertheless, for higher D_{Adj}, I_{Adj} does not have a significant variation. This effect is explained by observing how much time the drivers stop at the traffic lights. Even for small D_{Adj}, some drivers manage to avoid stopping at the red light when using the speed recommendation.

Figure 5.20 shows how much time the cars stop at the red light by using the waiting indicator I_W, which shows the total number of timesteps when agents are stopped.

$$I_W = \sum_{i=0}^{T_{end}} t_i^{stopped}, \tag{5.14}$$

where T_{end} is the time when simulation ends, and $t_i^{stopped}$ is the timestep when the car is waiting for the red color of the traffic lights systems.

In Figure 5.20, it can be observed that that I_W is improved even for small values of D_{Adj} ($D_{Adj} = 100[m]$). It is important to note that, the fact that agents adapt their speed does not cause a significant difference on the traffic performance I_P instead this is caused by the fact that they avoid stopping at the red light.

Further, an analysis on how the phase duration influences the traffic situation was done. Figure 5.21 illustrates the effect of drivers using speed recommendations for different phase duration δ^{Phase}. In this case $D^{Adj} = 900[m]$ and $v^{max} = 20[m]$. I_P, defined in Equation 5.12, has better values for smaller δ^{Phase} ($< 11s$). For high values, δ^{Phase} does not have a significant impact on the traffic performance. This effect is explained in Figure 5.22 using the waiting indicator I_W (defined in Equation 5.14) which shows the total number of timesteps when the agents are stopped. It can be observed that for higher δ^{Phase}, I_W increases.

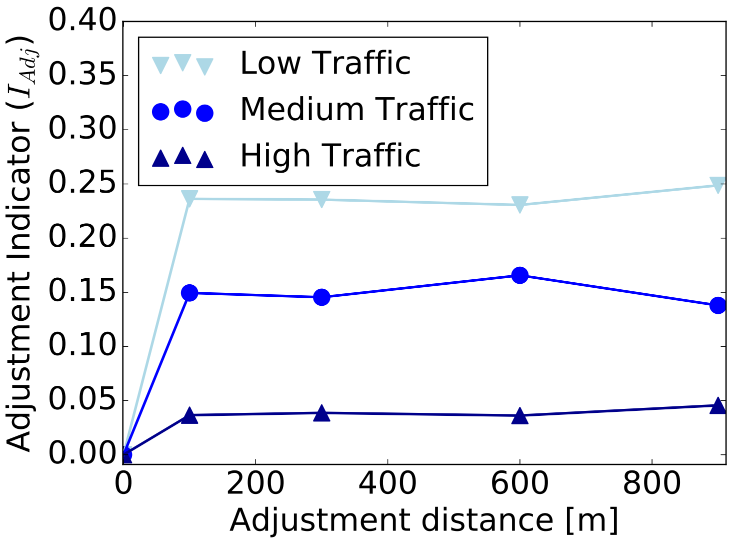

Figure 5.19: Illustration of the effect of drivers adapting their speed for different values of the adjustment distance D^{Adj} for *static* traffic lights. I_{Adj} (Equation 5.13) is calculated for low, medium and high traffic intensity.

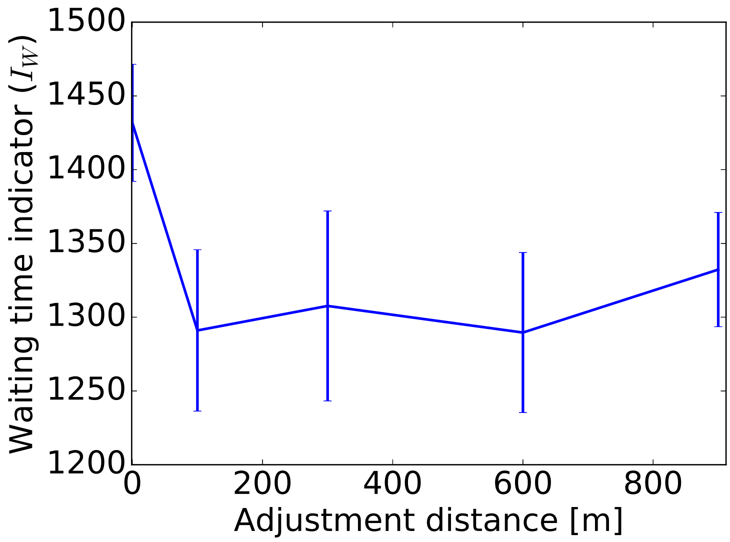

Figure 5.20: Illustration of the effect of drivers adapting their speed for different values of the adjustment distance D^{Adj} for *static* traffic lights. The waiting Indicator I_W (defined in Equation 5.14, expressed in *number of timesteps*) is calculated for medium traffic intensity.

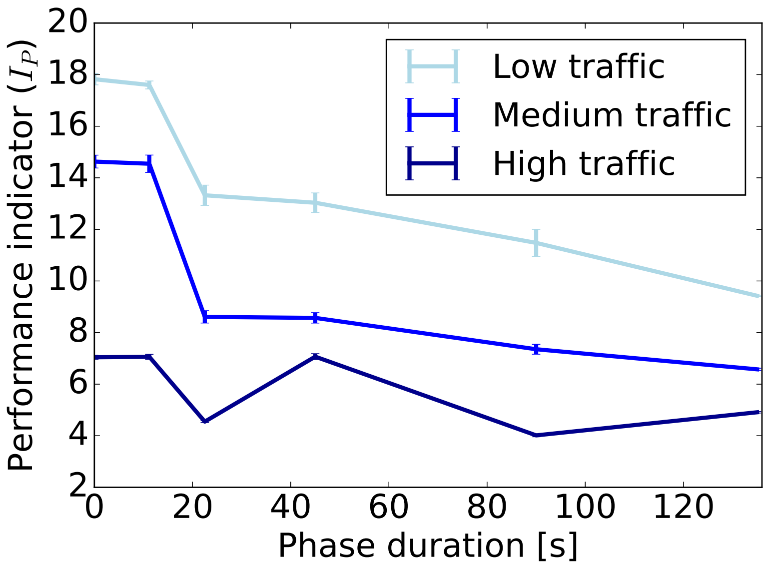

Figure 5.21: Illustration of the he effect of drivers using speed recommendations for different phase duration δ^{Phase} of *static* traffic lights. I_P expressed in m/s (defined in Equation 5.12) is calculated for low, medium and high traffic intensity.

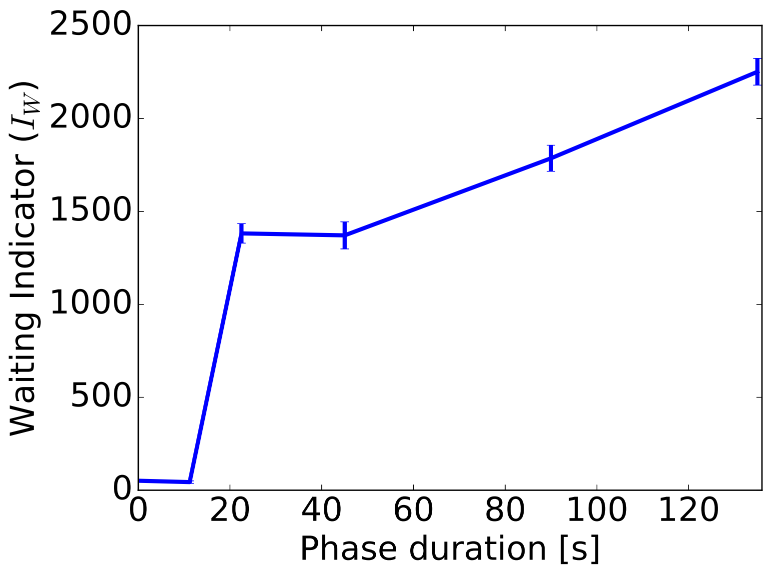

Figure 5.22: Illustration of the effect of drivers using speed recommendations for different phase duration δ^{Phase} of *static* traffic lights. The waiting Indicator I_W (defined in Equation 5.14, expressed in *number of timesteps*) is calculated for medium traffic intensity.

Both drivers and the traffic lights adapt to traffic

In this scenario, different shares of agents receive navigation recommendations about how to adapt their speed in order to avoid stopping for the red light ($p \in [0, 100]\%$, $D^{Adj} = 900[m]$, $\delta^{Phase} = 45[s]$, $v^{max} = 20[m]$). For this, the information impact indicator was defined as it follows:

$$I_{Info} = (I_P^p - I_P^0)/(I_P^0), \tag{5.15}$$

where I_P^p is the performance indicator defined in Equation 5.7 and I_P^0 is the performance indicator for the reference case of $p = 0\%$.

In Figures 5.24 and 5.25, it can be noticed that the traffic is improved when more agents are using information both in the case of static and dynamic traffic lights. For static traffic lights, the reference I_P^0 for low, medium and high traffic intensity have the following values: $10.1[m/s]$, $7.4[m/s]$ and $4.2[m/s]$. For dynamic traffic lights I_P^0 are $9.8[m/s]$, $6.1[m/s]$ and $4.4[m/s]$. Therefore, the reference cases for static and dynamic traffic lights have similar values.

However, it is worth noting that the increase rate of the impact information indicator I_{Info} (defined in Equation 5.15) is smaller for dynamic traffic lights than for the static traffic lights. This effect appears because, in the case of dynamic traffic lights systems, the instability of the system is growing when more agents receive speed recommendations. This effect is illustrated in Figure 5.23 by the coefficient of variation (C_V) of the average speeds on roads.

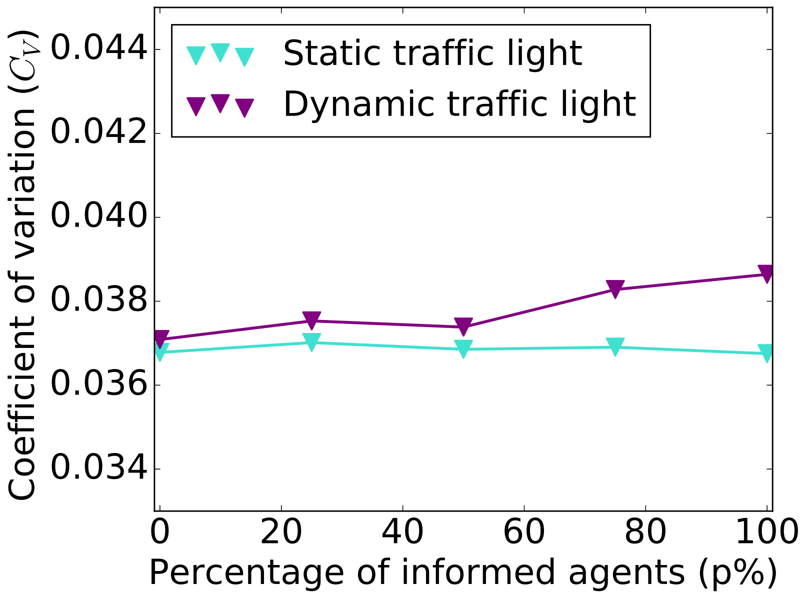

Figure 5.23: Illustration of the effect of different shares of drivers using speed recommendations. Coefficient of variation of the average speeds on roads C_V for medium traffic for *static* and *dynamic* traffic lights.

The coefficient of variation indicator C_V is defined as it follows:

$$C_V = \frac{\sigma}{\mu}, \tag{5.16}$$

where σ is the standard deviation of the total speed on roads and μ is mean of the total speed on roads.

In conclusion, informing more agents is beneficial for both static and dynamic traffic lights systems. Nevertheless, in the case of dynamic control, the transportation system is affected by a higher level of instability.

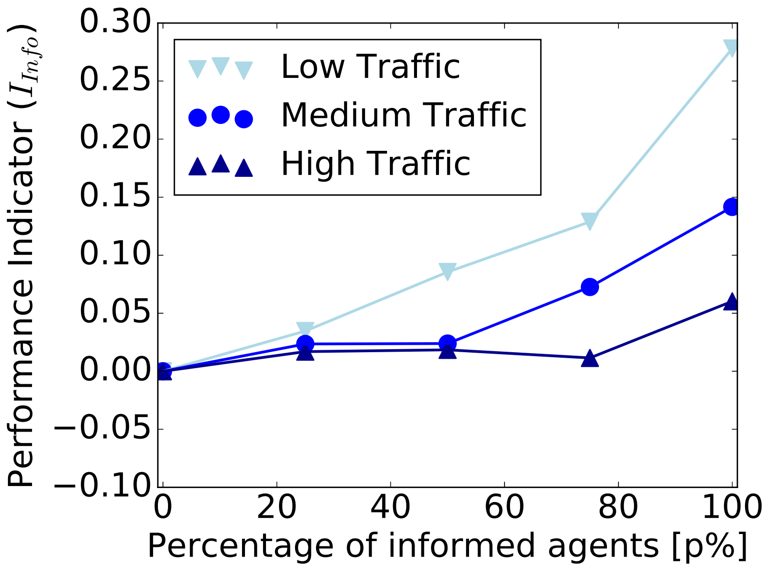

Figure 5.24: Illustration of the effect of different shares of drivers using speed recommendations. I_{Info} indicator (defined in Equation 5.15) is calculated for *static* traffic lights.

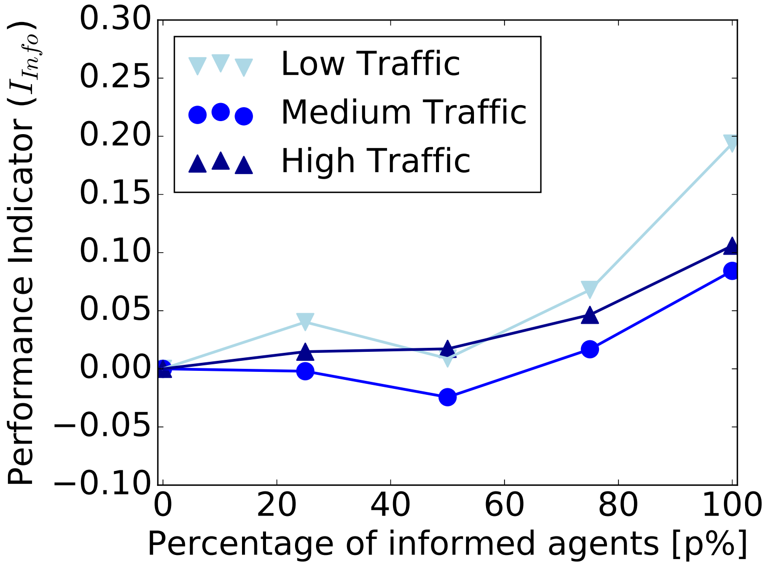

Figure 5.25: Illustration of the effect of different shares of drivers using speed recommendations. I_{Info} (defined in Equation 5.15) is calculated for *dynamic* traffic lights.

5.4 Conclusions

This chapter presented the experimental results involving information dissemination in transportation systems when the traffic participants are at the same time sources for data collection and users of the traffic navigation recommendations. Two studies were presented to demonstrate the fact that drivers, using real-time traffic information, has a significant impact on the transportation system.

For this, an agent-based model of a transportation system was used to simulate different aspects of the urban road traffic: traffic infrastructure with roads and traffic lights systems, traffic flow and information flow with models of information dissemination. The traffic flow uses a car-following model based on IDM model and the model of disseminating information consists of selecting different shares of drivers to receive details about congestion on roads or about how to adapt the speed to avoid stopping at the red color of a traffic lights system.

The first study evaluated the effect caused on traffic by real-time information dissemination in the presence of congestion (generated by local disturbances). The informed traffic participants receive updates about what route to follow to avoid the congested areas in the network. The global traffic network performance is calculated when varying a number of informed agents and the length of the alternative road selected to avoid the congested area. The results show that in some cases, if most of the traffic participants receive information (i.e. trough navigation tools and applications on personal smart devices), traffic can become worse, contrary to common expectation. There are cases when giving more information does not make a difference on the network performance and cases when it gets improved.

In the second study, drivers used the recommendations on how to adapt the speed to avoid stopping at the red color of a traffic lights system only if they were closer than a specified adjustment distance to the traffic lights. Two types of traffic lights were considered: static and dynamic traffic lights control. The static traffic lights have a pre-defined fix phase duration. The dynamic traffic lights have smarter adaptive mechanisms for reacting to the traffic situation. The results show that when all drivers receive information, the distance to the traffic lights system within they adapt their speeds does not influence significantly the performance. The fact that cars do not wait for the red light decreases the travel time even for low values of adjustment distance.

For fixed phase duration smaller than 11s, drivers adapting speeds produces a bigger effect on traffic than for higher phase duration. Moreover, different shares of drivers that receive information about the traffic lights behavior produce different effects on the traffic performance for both static and dynamic traffic lights control. More drivers receiving information is beneficial for the overall traffic performance.

For the two studies, it was assumed that all informed agents are rational and decide to use the navigation recommendations to improve their traveling time. Also, all the traffic participants provide data about their trips to process the navigation recommendations. Future work will aim at extending the existing models of information dissemination by introducing among others time delays and information errors. Another plan is to introduce more realistic city networks and human behavior models to determine how agents decide to use the real-time congestion awareness information. For the traffic lights systems, the future work can extend the existing models of the responsive traffic lights by considering more details when determining the phase duration.

The findings presented in this chapter are relevant in the context of information-based solutions for ITS [8], involving intelligent traffic lights control, information processing, advanced communication and sensing. There are significant amounts of money that governments and private industry invest in developing such systems. ITS are expected to play even a bigger role in the future [9]. It is useful to anticipate the impact that the massive use of real-time information can have on traffic.

Particularly, understanding the effect of real-time information disseminated in traffic can help solving problems related to congestion by providing appropriate navigation recommendations to the correct share of the traffic participants. However, a practical solution to improve congestion in the ITS systems should take into consideration not only the travel time but also reliability, predictability, recurrence,peak-spreading or the geographic extent [108]. This can be analyzed in future work.

Moreover, it is useful to understand what impact can have the fact that a massive amount of drivers use real-time information about the traffic lights behavior. At the same time, the main challenge in optimizing the traffic lights control consists in minimizing the time spent on the network by agents [6]. This means determining the most efficient proportion of green allocated to each phase. A practical solution to improve traffic should take into consideration not only the travel time but also the comfort and safety of drivers while approaching traffic lights.

Chapter 6

Information impact depending on the content details

6.1 Introduction

ITS systems with their most popular components, Advanced Traffic Management Systems (ATMS) and Advanced Traveller Information Systems (ATIS), are expected to play a fundamental role in managing the future transportation systems [8] [9] [10]. ATMS and ATIS systems are considered to be promising technologies for achieving efficiency in the operation of ITS systems as they aim at providing minimum but relevant details as navigation recommendations which can assist drivers in their trips. The information is presented to traffic participants using novel technologies and applications trough their smart devices or in-vehicle navigation devices. Such systems and technologies, not only enable commuters to access real-time information, forecasts and navigation guidance but also to contribute with their travel data.

In an ITS system, even when this information is highly detailed, and accurate, complex and unexpected dynamics can emerge. This is due to the massive participation of commuters as both sources for collecting data and consumers of the traffic information. In addition, uncertainty, sometimes called inaccuracy or noise, can arise in the information passing flow through the transportation system either at the time of collection, processing or presentation.

In this particular chapter, the aim is to analyze how the information content presented to traffic participants as navigation recommendations impacts the overall traffic performance. The current study [1] explores the different kinds of noise or inaccuracy present in the information content, and the effect that they can have on an ITS system.

The current research comes together with more studies in the logical framework of the information flow process in ITS systems (described in detail in Chapter 3). This systematic description of the information flow steps facilitates novel ways of exposing the transportation problems from different perspectives. For instance, aspects related to the effect of various proportions of drivers using the traffic information are investigated in Chapter 5 or how information can be used to steer a responsive infrastructure is investigated in Chapter 7.

During the input stage of the information flow process in ITS systems, data is collected from different types of sensors (such details are presented in Section 6.1). This data is then aggregated and processed to recreate a model of the traffic state. Eventually, the relevant parts of this traffic state information are transmitted to commuters through their in-vehicle information systems or personal smart devices. There are several points in this process in which information inaccuracy may occur either because the collected data produces incomplete information or because the information loses some of the precision during processing and display. This is discussed in more detail in Section 6.3. It is important to understand the impact that inaccuracy can have as it can affect not just the actions of a few individual commuters but also the performance of the transportation system as a whole.

The effect of information inaccuracy and noise has been the subject of several research studies. It is interesting to note that some counter-intuitive discoveries are suggesting that noise can have a potentially beneficial effect in many non-linear systems, both artificial or natural. An example of the former is the constructive effect of

[1] The content of this study is based on the published in article [3], referenced in Appendix A.1

inaccuracy shown in technical systems where noise enhances the information transfer efficiency [109]; similar examples in natural systems include discoveries in brain function, carrier signals, animal avoidance and feeding [110]. Section 6.2 provides a more detailed discussion of some of these studies.

Traditionally, when building ITS systems and navigation devices, the effort consists of providing faster and more accurate traffic recommendations and real-time predictions [111]. In general, improving the accuracy comes at a certain cost. For example, to get more precise information, either more sensors have to be installed, or more high-quality sensors have to be used. Both of these come at a financial cost. In another example, consider the information that is displayed on a traditional navigation device. The designer has to take care to present information in a way that can be easily understood [112][113] and within the constraints of the display device. This means that trade-offs have to be made regarding what roads are displayed and what information regarding these roads is displayed (elevation, speed, etc.). To be able to make these decisions in areas ranging from sensor infrastructure development to navigation devices design, it is important to understand the acceptable levels of noise in traffic information.

The objectives of this study are two-fold: firstly, the study introduces a general source-based classification of different kinds of inaccuracy that can occur in data processing in an ITS system; secondly, the study does a microscopic simulation based analysis into the effects that these different types of inaccuracy sources can have on the system and identify the acceptable levels for different types of uncertainty. The following sections explore how noise can be introduced in the information that passes through a transportation system and what is the impact that it can have on the traffic.

6.2 Related work

Previous research has analyzed the effect of traffic information on a transportation system. It has been shown that the information content has a significant effect on the traffic. For example, the content consists of certain routes proposed for the traffic participants to achieve either individual or global social optimum performance [21, 24] or of using local or global details of the traffic network when determining the routes [20, 25]. More studies about the effect of traffic information dissemination in transportation systems are presented in Section 2.3.2.

An important aspect related to information dissemination is the level of accuracy that the recommendations or the initial set of data have. It was shown that providing inappropriate information to the traffic participants sometimes leads to undesirable situations such as one-sided congestion [114]. In [115], the authors, analyze how the information quality and its accuracy influences traffic. It was shown that drivers using forecast information, even with inaccuracy, produces a better impact on the traffic performance than present information. When predicted information containing errors is provided to a larger share of traffic participants, an even bigger improvement in performance is observed. In the current study, this issue is further explored by first categorizing different errors and analyzing the effect that each error can have. In the case of large dynamic congestion games, learning by players ensures low social cost even with a dynamically changing player population [116].

A set of studies investigates the problem of routing vehicles in transportation networks. The routes have deadlines imposed at a subset of nodes, and with uncertain arc travel times that can be characterized by exact distributions, or by a distributional uncertainty incorporating ambiguity [117]. The main challenge consists of simultaneously coping with limited knowledge on random fluctuations in traffic congestion (i.e. caused by traffic incidents, the variability of travel demand, etc.) and the users' desire to arrive on time. The arc cost probability distributions are known trough confidence intervals on some statistics such as the mean, the mean absolute deviation and so on. An approximate optimal strategy for providing routes when the driver is constrained by a travel-time budget [118]. Another precise mathematical framework for defining and solving routing problems with deadlines imposed at a subset of nodes, and with uncertain arc travel times is provided in [119]. In this work, the solutions find optimal routing policies such that arrival times at nodes respect deadlines as much as possible.

Several studies challenge the traditional view in information processing that noise degrades efficiency, and show that controllable noise can even be considered an additional engineering tool [120]. Such findings correspond to Stochastic Resonance (SR), a nonlinear phenomenon in which the transmission of a coherent signal by certain systems can be improved by the addition of noise to the system [121] [122].

The influence of noise from information transmitted in the form of packages shipped between nodes of hierarchical networks is presented in [123]. The experiments were performed on artificial tree networks, scale-free networks and in a real network formed by email addresses of employees. Two types of noise are considered and shown to have a positive influence: one type dealing with a random part of packets paths and one originating from random changes in the initial network topology. In a similar vein, this study deconstructs the different kinds of noise that can arise in a transportation system and analyze both their positive and negative implications.

SR is possible also in discrete-time dynamical threshold-crossing systems driven by the subthreshold periodic signal which is too weak to cause the system to cross the assumed threshold [124]. In the case of a nonlinear second order dynamic system, feedback control is applied to change conditions of a noise-induced transition. It is found that under conditions when the noise is effective in determining the destructive dynamics of the system without control, a proper feedback control can suppress the role of noise. The control efficiency depends on the amplitude of control signal in a non-monotonic way, demonstrating a resonance-like regularity [125].

Besides artificial systems, noise affects the natural complex systems as well. An example of noise influencing pedestrian movement simulation is presented in [126]. The authors describe the formation of pedestrian lanes. The number of lanes depends on the width of the street, on the pedestrian density, and also on the noise level. In techno-socio-economic-environmental systems, a significant noise or fluctuations usually have a destructive influence on a system, but small noise intensities can trigger structure formation or increase system performance [122]. For example, besides the ability for strategic interactions and learning, the capacity to move has played a crucial role in the evolution of large-scale cooperation and social behavior. Noise can trigger frequent cooperation, even if individuals would behave selfishly in the vast majority of interaction [127]. Animal behaviour is also influenced by the existence of noise, as explained in [128], [129] and [130]. Counter-intuitively, locusts increase the noisiness of their movements in response to a loss of alignment by the group.

In [110], it is shown that Stochastic Resonance is compatible also with neural models and brain functions. In [131], the potential benefits of noise in nervous systems (human motor behavior) were examined. Neural networks formed in the presence of noise are more robust and explore more states; this facilitates learning and adaptation. Moreover, noise induces stochastic facilitations in auditory brainstem neuron models [132]. In [133] the authors discuss how nature has actively exploited the beneficial effect of noise by creating noise-assisted processes for achieving robust and efficient energy transfer.

A review of existing literature shows that errors and noise present in complex systems can have significant effects on its performance. Inspired by such observations, [120] introduced a new paradigm of noise-engineering. The following sections explore how noise can be introduced in the information that passes through a transportation system and the impact that it can have.

6.3 Information uncertainty in transportation systems

As discussed in in more detail in Chapter 3, in a transportation system, traffic information is obtained from data collected by sensors. This data is further aggregated and processed, sometimes through several layers, before it is presented back to the commuters on their different information systems (in-vehicle entertainment systems or smart-phones). This forms a feedback loop since commuters are both consumers and producers of the information.

The left side of Figure 7.16 illustrates a Human Complex System (*HCS*) consisting of roads, traffic participants, vehicles sensors, navigation devices and so on. On the right side, the Information Control System (*ICS*) that works at the back-end of the transportation system is illustrated. HCS provides data to the ICS and also eventually utilizes the information that the ICS provides.

Information inaccuracy can occur in different forms. The information in a transportation system can be seen to flow through three stages: input, processing, and output. Inaccuracy can arise in any or all of these stages. In this study, the uncertainty is classified based on the stage of the data processing that the inaccuracy originates from to enable a more general analysis. Based on their most common underlying cause, uncertainty is classified as inaccuracy due to sparsity, processing, and display.

During the *input stage*, the real world traffic status is converted into raw data by the different kinds of sensors. It would be practically impossible to observe every single point of the actual world system due to a large number of high-quality sensors that would be required. The inaccuracy that arises due to this lack of coverage of sensor networks is termed as *sparsity inaccuracy.* Sparsity inaccuracy would be impossible to avoid entirely in practice; however, it is useful, even vital, to discover the minimum coverage required for optimal system performance. Raw data is collected from the sensors and sent to the preprocessing and processing blocks. Further inaccuracy may appear from low-resolution sensors, improper cleaning and inefficient algorithms for aggregation or traffic state reconstruction. During the *processing stage*, the raw data is converted into information that can be used to reconstruct the traffic state and, eventually, to a form that is presented back to the HCS (i.e. on the navigation devices).

Each type of sensor has specific error causes. For example, in the case of GPS, there are many sources of errors such as dilution of precision, satellite geometry, multipath, ionosphere delays, the signal reflected by objects, etc. [134]. Besides deviations in the sensor records, data may be affected by inefficient traffic state estimation for solving the missing data problem [99]. The processing block can introduce inaccuracy among other by using an oversimplified or even wrong model of the transportation system, inefficient algorithms for matching traffic patterns [99] or not enough processing power that can delay the real-time forecast. Since the uncertainty manifests in the information system in the same way as inaccurate traffic state reconstruction, they are classified together as *collection inaccuracy*. This uncertainty is difficult to avoid, but they are expected to become smaller over time as technology advances.

In the final step of the process, this traffic state information is presented back to the commuters through their smart devices. It would be impossible to display the state of the complete traffic system to the user. Thus design decisions have to be taken about what information is displayed and in what resolution. For example, when displaying a map for navigation with congestion information, the roads with a range of high speeds may be marked in green and others in red; or there could even be a color gradient from red to green for a range of speeds. Lower resolution information may mean that it is easier for the user to process a larger amount of information (several roads at the same time) and it would probably also be technically easier to display this information. These types or errors that appear due to trade-offs in how information is presented are termed as *presentation inaccuracy*. It is crucial to understand this type of inaccuracy impact to create better smart devices for ITS systems.

Previously [115], traffic errors in the case of predicted information have been categorized as routes not precisely estimated, simulation model imperfection, current traffic condition not be exactly monitored, driver's route choice behavior not understood. The new categorization of inaccuracy based on sources proposed in this study is essential to investigate the impact of information uncertainty and noise on modern transportation systems that consist of mobile sensors, ITS, and smart navigation devices. Furthermore, this categorization can help in gaining a better understanding of the current and future transportation systems. Engineering solutions can eventually be developed that leverage on information as a control tool integrated into ITS systems. Next sections will present a methodology for exploring in more detail the different types of inaccuracy.

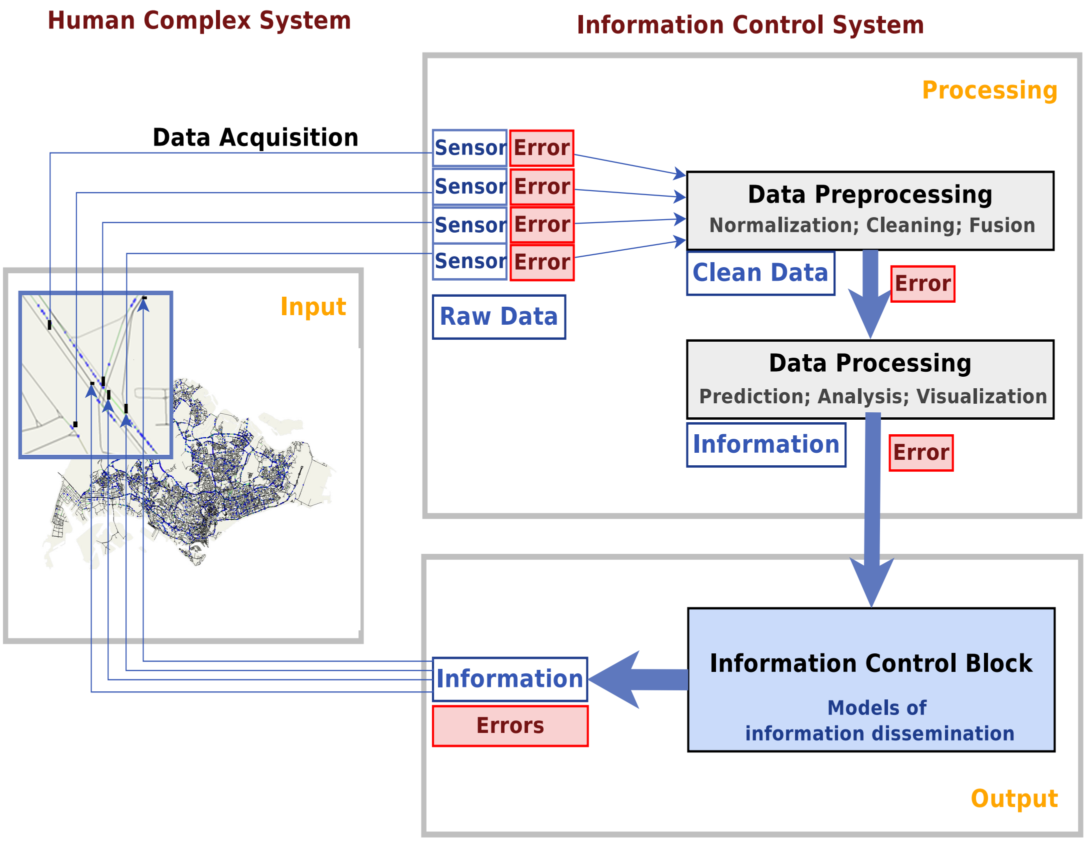

Figure 6.1: Illustration of the information flow process in a transportation system with the following steps: *data acquisition*, *data preprocessing*, *data processing* and *information dissemination*. The information content is affected by uncertainty due to *sparsity inaccuracy*, *collection inaccuracy* and *presentation inaccuracy*. The information control system (*ICS*) and the transportation system that is also called human complex system (*HCS*) interact and influence each other, creating a feedback loop. The information in this system can be seen to flow through three stages: *input*, *processing* and *output*. In the final step of the process, this traffic state information is displayed back to the commuters through their smart devices or in-vehicle navigation systems.

6.4 Computational model

Modeling the traffic infrastructure, traffic flow, and information flow

A real world scenario for studying the impact of noise is difficult to implement as it requires, among others, a massive rate of participation of the drivers both as sources and users of traffic information. It would also be difficult to study each of the different types of errors in isolation. For this, a simulation based approach is used, a methodology suited for transportation or socio-economic systems. The traffic flow is simulated using an agent-based microscopic traffic model for a bottom-up approach.

In the current section, first a brief overview of this model is presented, and subsequently, the new components of the computational model are introduced. The computational model that we use for the traffic infrastructure, traffic flow and congestion formation, information flow with data collection and information dissemination has been described in detail in the previous Section 5.2.

As mentioned in Section 5.2, the agents are represented by Drive-Vehicle-Units (DVU) that know the road network, perform route calculations and move forward on their route with a certain speed and acceleration determined by a time-stepped car following model (Intelligent Driver Model IDM). Also, a model of information dissemination consisting of sending regular route recommendations updates to only a share of informed agents. The recommendations optimize the travel time by avoiding the congested areas on the network. These congested areas are created by introducing artificial disturbance on a specific road segment. This initial setup from Section 5.2 is extended to simulate different types of information inaccuracy sources or noise.

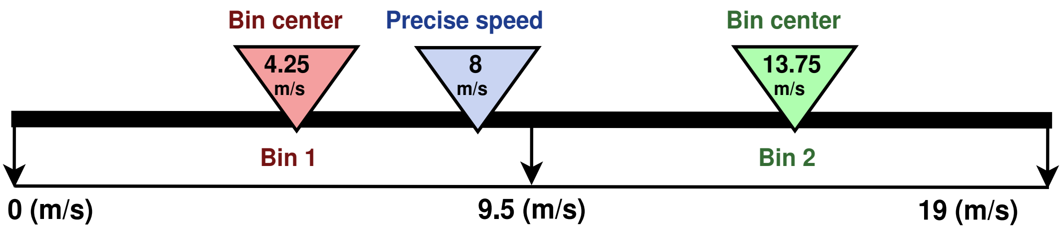

Figure 6.2: Example of information uncertainty introduced by using 2 error bins. The precise speed value ($8m/s$) is approximated with a bin center value ($4.25m/s$) from the corresponding bin ($Bin1$ in this case).

Modelling the information uncertainty

Additionally, the effect of the three types of inaccuracy introduced in Section 6.3 is modeled. *Sparsity inaccuracy* is simulated by varying the percentage s of agents that provide information about their current situation (sources for data collection). *Collection inaccuracy* and *presentation inaccuracy* generally manifest in the form of lower resolution information.

For this study, the three types of inaccuracy are modeled by dividing the speed range $[0, v_{max}]$ into n $[bins]$ and reporting the middle value of the chosen bin rather than the actual value. As the number of bins increases the information resolution and accuracy increases. The collection inaccuracy bins are called n_c and the presentation inaccuracy bins is called n_p. The main parameters of the experiments and their values are presented in Table 6.1.

An example of how the real values are affected by 2 error bins is shown in Figure 6.2. First, the interval (bin) in which the actual value belongs is identified. Instead of using the real value ($8[m/s]$) , a value equal to the *bin center* is used (for $Bin1$, the bin center value is $4.25[m/s]$). For instance, in a real world example, consider how information about average speed on roads is reflected on a traffic map. For values corresponding to the first *bin*, the roads are colored in red and for values in the second bin, the roads are colored green.

6.5 Studies

6.5.1 Experimental Setup

The experimental setup is similar to the one described in the previous Chapter 5 and is based on the computational model described above. The simplified scenario uses the road network shown in Figure 5.6 presented previously in Section 5.3.1.1. Agents move from origin to destination. They have two route choices: $Road_A =< 11[m/s], 19[m/s], 500[m] >$ and $Road_B =< 11[m/s], 19[m/s], L_B >$

A constant level of congestion is simulated by introducing local disturbances. To create a disturbance, a random vehicle i driving on the *disturbance segment* (marked on Figure 5.6) of the road is chosen every $2[s]$ and forced to brake ($v_i = 0[m/s]$). The car accelerates gradually and once again reaches full speed, thus causing congestion.

Similar to the previous study, the agents are created by a Poisson process (a technique traditionally used in simulations for traffic generation [135]) with a mean interarrival time of $1700[ms]$. The experiments simulate 40 minutes of traffic situation (approximately 1000 agents simulated). From this amount, the last 800 trips are considered, giving a warm-up period of 10 minutes. The specific values of the parameters were chosen empirically so that the congestions remains localized on $Road_A$.

Additionally, the effect of the three types of inaccuracy is simulated: *Sparsity inaccuracy* is simulated by varying the percentage s of agents that provide information about their current situation. *Collection inaccuracy* and *presentation inaccuracy* generally manifest in the form of lower resolution information. This is simulated by dividing the speed range $[0, v_{max}]$ into n bins and reporting the middle value of the chosen bin rather than the actual value. As the number of bins increases the information resolution and accuracy increases as well. The collection inaccuracy bins are called n_c and the presentation inaccuracy bins is called n_p.

An example of how the real values are affected by 2 error bins is presented in Figure 6.2. First, the interval (bin) in which the real value belongs is identified. Instead of using the real value, a value equal to the *bin center* is used. For instance, in a real world example, consider how information about average speed on roads is reflected on a traffic map. For values corresponding to the first *bin*, the roads are colored in red and for values in the second bin, the roads are colored in green.

	parameter description	min value	max value
s	percentage of sources	0%	100%
n_c	number of bins for collection inaccuracy	$1[bin]$	$19[bins]$
n_p	number of bins for presentation inaccuracy	$1[bin]$	$19[bins]$
p	percentage of informed agents	0%	100%
L_B	length of Road B	$625[m]$	$1250[m]$

Table 6.1: The main parameters used for one experiment E_{p,L_B,s,n_c,n_p}.

Table 6.1 presents the main parameters of the experiments and the range of values used. One experiment is characterised by the following set of parameters: E_{p,L_B,s,n_c,n_p}. Each experiment is repeated ten times. Next, the main indicators used to evaluate the global, and local impact of these parameters are defined.

To quantify the effect of information dissemination, the network performance T is defined as the average travel time of all agents in one experiment.

$$T = \frac{1}{F_t} \sum_{i=0}^{F_t} t_i, \tag{6.1}$$

where t_i is the trip duration of agent i, F_t is the fraction of agents (last 800 agents) that complete their trip.

The information impact indicator is defined to quantify the impact that each of the three types of inaccuracy produces on T. For the experiments, it is considered that information is affected only by one type of inaccuracy at a time.

$$I_{L_B} = max(T_{ref}(L_B) - T_{i,p}(L_B)), \tag{6.2}$$

where $i \in (i_{min}, i_{max}]$, $p \in (0, 100]$.

In the case of sparsity errors, collection errors and presentation errors e refers to s, n_c and n_p, respectively. For each L_B we calculate the maximum impact across all levels of informed agents and all values of e. $T_{ref}(L_B)$ is calculated for $i = i_{min}$ and $p = 0\%$. I_{L_B} quantifies the maximum change on T when compared to T_{ref}.

For sparsity errors, $i_{min} = 0\%$ (no sources) and $i_{max} = 100\%$ (all vehicles are sources). For collection and presentation errors, $i_{min} = 19[bins]$ (error free information) and $i_{max} = 1[bin]$. No noise corresponds to $19[bins]$, as this is maximum speed on roads.

6.5.2 Results

This section shows the results of evaluating the metrics and indicators introduced previously in Section 6.5.1 to analyze the impact that different types of inaccuracy have on the traffic performance. First, the impact that the variation in the network topology (i.e. varying the length of the alternative road L_B) can have on different types of information inaccuracy. Next, the influence that different kinds of errors have on the traffic performance is explored.

Network topology can impact the various kinds of inaccuracy

In this section, the effect that route recommendation based on inaccurate information can have on the traffic is evaluated. In particular, the impact that a range of values of the length of the alternative road (L_B) can have on performance introducing inaccuracy to information are analyzed. Also, the percentage of traffic participants being informed ($p\%$) is evaluated.

It is interesting to note that, all three types of inaccuracy produce an effect on T (defined in Equation 6.1) for these particular values of L_B, as illustrated in Figure 6.3. For this, the information impact indicator I_{L_B} (defined in Equation 6.2) was calculated. Figure 6.3 shows that the information impact is decreasing for a bigger length of the alternative road for all types of error. It is surprising to note that sparsity inaccuracy produces a bigger impact on the overall performance than the presentation and collection inaccuracy.

Moreover, collection and presentation inaccuracy have a similar impact on the traffic situation. However, this is only natural as both these types of inaccuracy manifest in the same way i.e., the speed based on which decision is made is quantised (just to different degrees).

Inaccuracy can influence the global traffic performance

Next, the case of $L_B = 875[m]$ was chosen for further analyzing the effect of information uncertainty as this case provides a significant improvement when we vary s, n_c and n_p (as shown in Figure 6.3).

The effect of information sparsity inaccuracy

Figure 6.4 illustrates the effect of varying the percentage of traffic participants selected to be sources for data collection $s\%$. It can be seen that, in most cases, having more than 20% agents as sources produces marginal to no improvement in the global traffic performance T. The only exception is when $p = 100\%$ where we see the surprising effect that decreasing the inaccuracy produces a reduction in traffic performance. The former is referred to as Case A and the latter as Case B.

In the previous study presented in Section 5.3.1, it was observed that the biggest effect on performance was seen for $p = 40\%$ of the drivers using information (error free in that case). Thus, to explain Case A, the same scenario where $p = 40\%$ was chosen.

Further, the indicators are defined F_A and F_B as the fraction of agents that select either Road A or Road B. In Figure 6.5, it can be noticed that, for $s = 0\%$ (when it is assumed that the speed on the roads is maximum), most of the traffic participants select Road A. As s increases, the accuracy of the recommendations increase and more drivers are redirected to Road B; this results in improving T. As the percentage of sources increases above 20%, there is an only marginal improvement in the additional information gained and as such T does not change much.

To explain Case B, the standard deviation (STD) of F_A and F_B is calculated. In Figure 6.6, it can be observed that STD of F_A and F_B increases with an increasing number of sources. A higher STD for F_A and F_B is reflected in a destabilization of the transportation system; this is due to an extensive use of information. The higher values of STD mean that the recommendations from Dijkstra's algorithm change more frequently for a higher level of resolution. Some informed agents are recommended to select Road B, even though this recommendation becomes invalid very soon. Nevertheless, despite receiving newer information, agents that are already on Road B are unable to change to Road A. So, there are too many agents that are stuck on the long route, resulting in a negative impact on the traffic performance T.

To summarize, modifying a number of sources for data collection affects data precision and this is reflected in traffic recommendations. The recommendations determine the number of agents that select one route or the other thus influencing the global traffic performance T. The fact that a massive number of drivers using navigation recommendations produces a destabilization of the system and an increase in T manifested in a deterioration in the traffic situation.

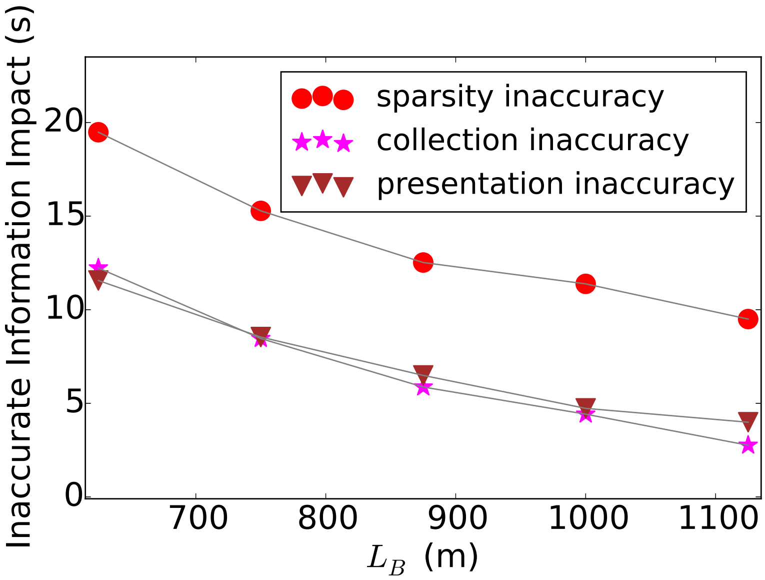

Figure 6.3: Illustration of the inaccurate information impact on T when varying L_B (I_{L_B} defined in equation 6.2, for s, n_c or n_p, depending on the type of inaccuracy considered).

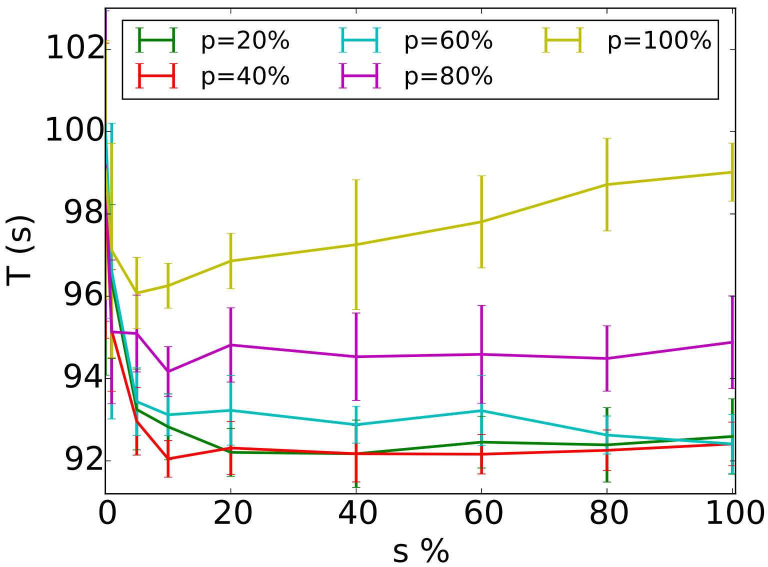

Figure 6.4: Illustration of the average travel T (performance defined in Equation 6.1) depending on s. It reflects the effect of *sparsity inaccuracy* on the traffic situation. $L_B = 875(m)$. No collection or presentation errors are considered.

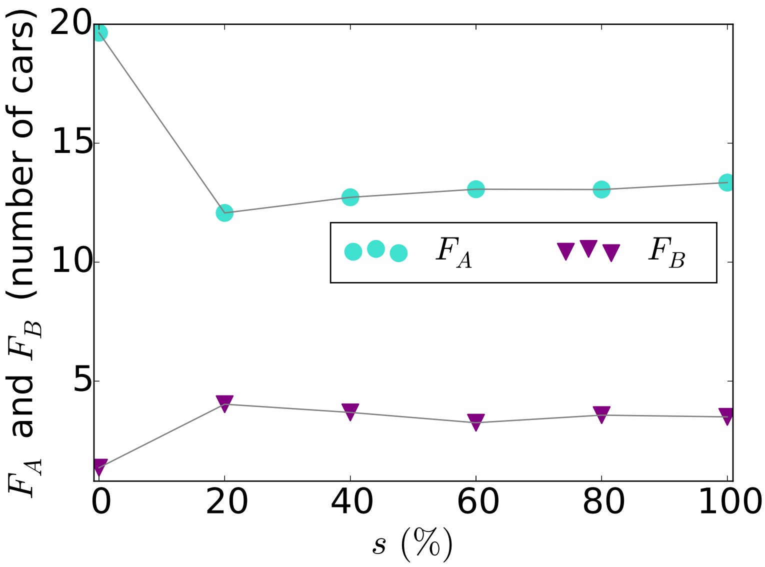

Figure 6.5: Explanation of the effect of information *sparsity inaccuracy* on T for $p = 40\%$. F_A and F_B depending on s for $p = 40\%$. F_A and F_B represent the fraction of agents that select RoadA or RoadB.

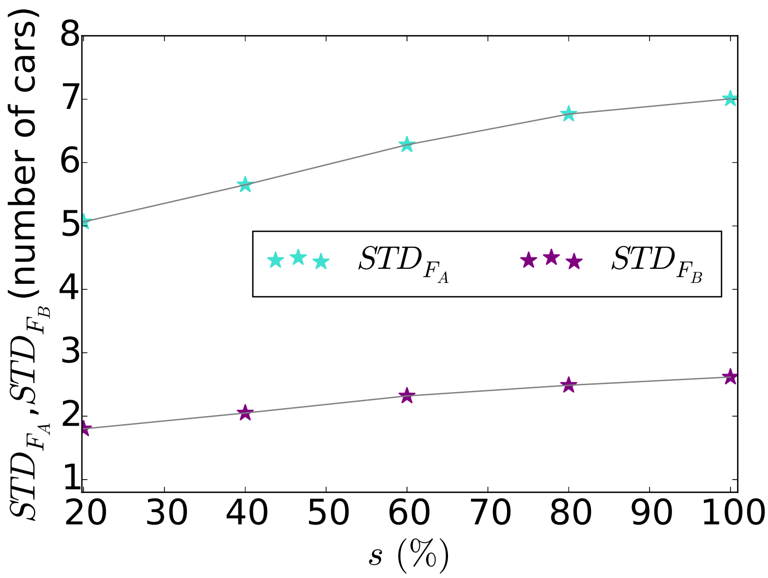

Figure 6.6: Explanation of the effect of information *sparsity inaccuracy* on T for $p = 100\%$. The figure illustrates the STD (standard deviation) of F_A and F_B (fraction of drivers that select Road A or Road B) depending on s for $p = 100\%$.

The effect of information collection and presentation inaccuracy

Next, the effect of *collection inaccuracy* and *presentation inaccuracy* on the overall traffic performance T is investigated. For this, the case of $s = 100\%$ for $L_B = 875[m]$ are considered. Figurs 6.8 and 6.7, illustrates how increasing precision or the number of bins n_c and n_p for the collected data and for the displayed information affects T. In most of the cases, the increase in precision produces either a small improvement ($< 2s$) or it has no effect on T.

However, for the case of $p = 100\%$ where there is a large usage of information, it can be noticed some counter-intuitive behavior: for better precision in information (less inaccuracy) the overall global performance T decreases. This means that when most participants have access to information, then a better precision (in both n_c and n_p) reduces the system performance (T increases).

In this case, it is also interesting to observe that, for collection inaccuracy, increasing the precision beyond a certain value (i.e. $n_c > 4[bins]$) has almost no effect on the system performance. In the case of presentation inaccuracy, the same effect appears only for $n_p > 10[bins]$. The higher value of this threshold for presentation errors manifests because the same level of resolution or precision in information that is used by the participant is obtained for fewer numbers of bins in the case of collection inaccuracy.

To better understand this effect, consider the case of there being two bins for collection, i.e. the processing stage gives a value of either $NC1$ or $NC2$. The speed that is reported to and used by an informed participant is the average of this value across all participants with sensors. Thus, if there are two drivers, the value of n_p for the informed driver would be three, as there are three values $NC1$, $NC2$ or $\frac{NC1+NC2}{2}$ that may be reported. Thus, a collection inaccuracy of n_c translates to a much smaller presentation inaccuracy.

In order to better quantify the impact of a massive usage of traffic information ($p = 100\%$) affected by *collection inaccuracy* and *presentation inaccuracy* on the overall traffic performance T, the following indicator was defined:

$$IC_{Impact} = (T^n - T^{19})/(T^{19}), \tag{6.3}$$

where T^n is the performance indicator defined in Equation 6.1 in the presence of noise (n refers to either n_c and n_p) and T^{19} is the performance indicator for the reference case of error free information $n = 19[bins]$ ($n_c = 19[bins]$ or $n_p = 19[bins]$).

Figure 6.9 illustrates the effect of *collection inaccuracy* and *presentation inaccuracy* when $p = 100\%$. It can be noticed that both types of inaccuracy can be beneficial for the overall traffic performance when a massive amount of drivers receive navigation recommendations. In this case, the higher the inaccuracy, the better the effect is on T.

This effect can be observed also in Figure 6.10. This figure illustrates a comparison between the case when the information is error-free and the cases when information contains the highest level of collection and presentation inaccuracy. For this, IC_{Impact} indicator (defined in Equation 6.3) is used.

Next, to explain the counter-intuitive effect of noise for the case of $p = 100\%$, F_A, and F_B indicators are defined as the fraction of agents that select either Road A or Road B for the entire simulation.

Figure 6.11 illustrates the standard deviation (STD) of F_A and F_B. It can be noticed that STD increases with increasing the number of bins both for F_A and F_B. This means that the higher level of noise produces stabilization in the overall traffic situation. This stabilization also induces a positive effect on the overall traffic performance T. In Section 5.3.1, it was shown that a massive amount of traffic participants ($p = 100\%$) using navigation recommendations produce more frequent changes in the recommendations updates. This is a consequence of a destabilization of the traffic situation when a massive amount of drivers are simultaneously users of the traffic information, thus changing traffic conditions, and sources for data collection, thus constructing the traffic information.

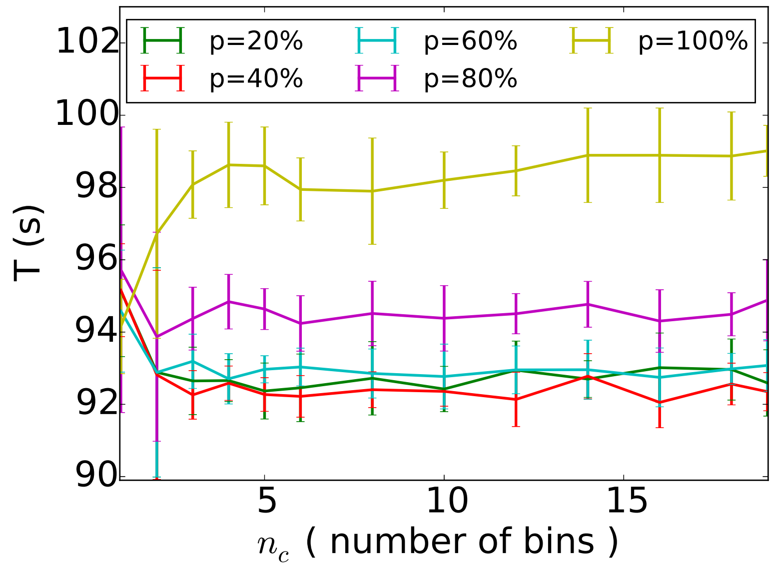

Figure 6.7: Illustration of the average travel T (performance defined in Equation 6.1) depending on the inaccuracy or noise introduced at data collection, $L_B = 875(m)$, $s = 100\%$. T depending on n_c (*collection inaccuracy*).

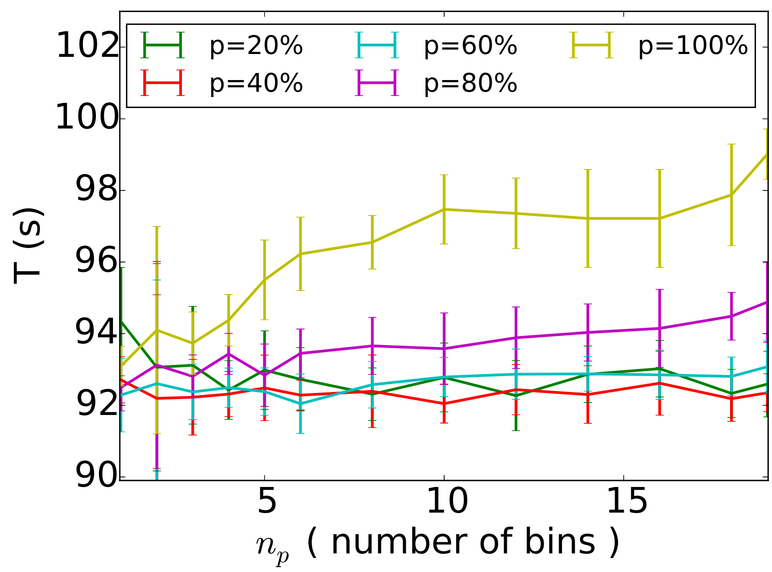

Figure 6.8: Illustration of the average travel T (performance defined in Equation 6.1) depending on the inaccuracy or noise introduced at the information display, $L_B = 875(m)$, $s = 100\%$. T depending on n_p (*presentation inaccuracy*).

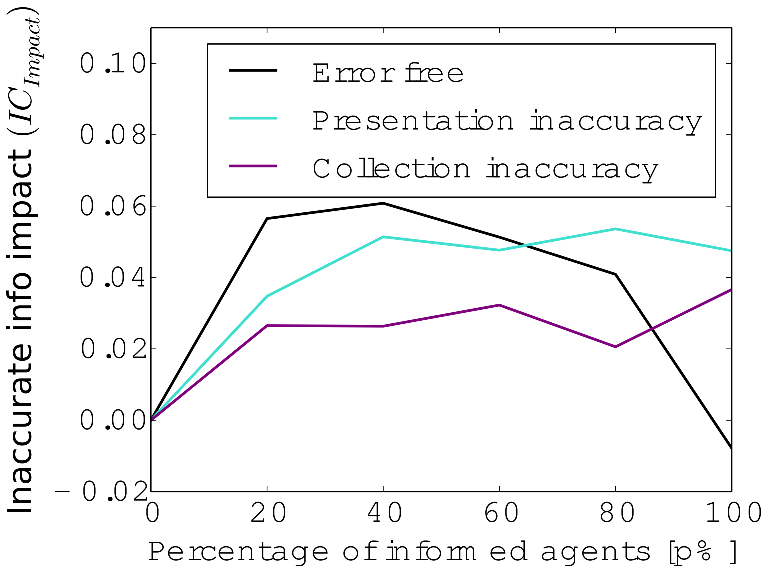

Figure 6.9: Illustration of the impact of introducing a high collection and presentation inaccuracy on the informational content on traffic situation. For this, the Information Impact Indicator I_{Impact} defined in Equation 6.3 is calculated for different percentages of informed agents $p\%$.

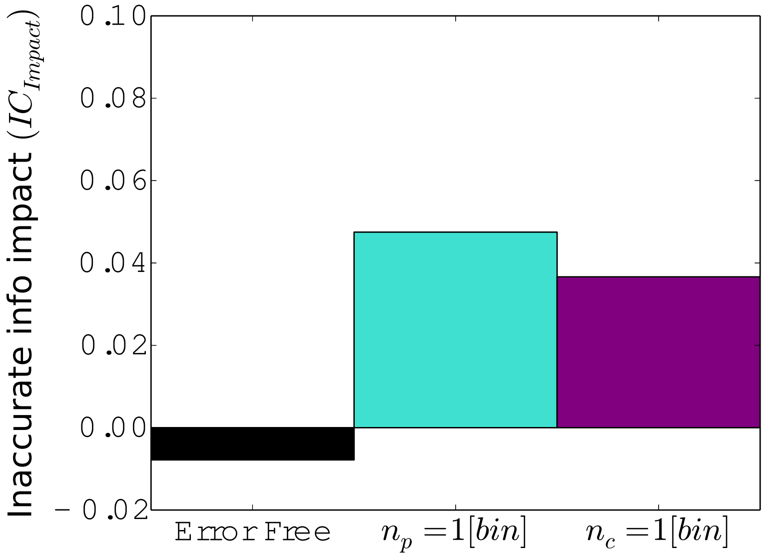

Figure 6.10: Illustration of the impact of introducing a high collection and presentation inaccuracy on the informational content on traffic situation when all drivers are informed ($p = 100\%$). For this, the Information Impact Indicator I_{Impact} defined in Equation 6.3 is used.

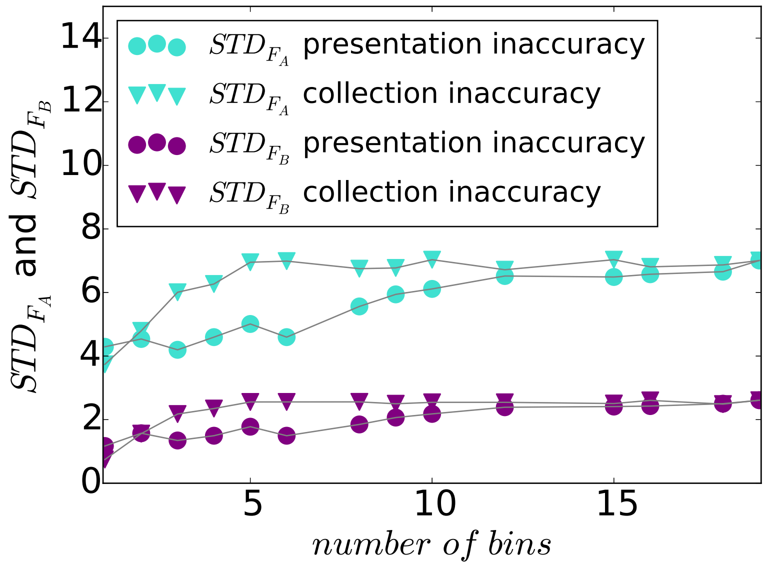

Figure 6.11: Explanation of the effect of collection and presentation inaccuracy on T (performance defined in Equation 6.1) for $p = 100\%$. The figure illustrates how the STD (standard deviation) of F_A and F_B (the fraction of agents that select Road A or Road B) varies with increasing precision (number of bins).

6.6 Conclusions

New advancements in ITS systems and navigation devices enable commuters to access real-time traffic recommendations and at the same time provide data about their trips. This creates a feedback loop that can introduce unforeseen challenges into the transportation system. ITS systems process collected traffic data and provide information to drivers as navigation recommendations. Each step of this feedback process can be affected by different kinds of errors, this having an additional impact on the overall traffic performance. Starting with the collection of data, data processing and the way the information is presented to the traffic participants it can be affected by different levels of errors or uncertainty.

In this study, first the data and the information inaccuracy present in modern transportation systems are classified as *sparsity*, *collection* and *presentation inaccuracy*.

Subsequently, an analysis on how each type of inaccuracy source affects the overall performance of a transportation system is provided. Furthermore, an investigation on how some traffic participants that use inaccurate information can influence the overall performance. This reveals an interesting insight into how information dissemination strategies and smart devices should be developed.

Interestingly, the results show that in most of the cases, only a small fraction ($< 20\%$) of the traffic participants is necessary to provide data for collection to have the best traffic performance. For the case when there is a massive participation both as sources and consumers of information, the traffic performance decreases. In general, noise in the form of collection or presentation inaccuracy decreases the traffic performance. However, when the traffic participants massively use the navigation recommendations, that noise can produce an improvement in the traffic situation. Beyond a certain limit, increased precision of information does not have a corresponding increase in traffic performance.

The findings of this study are relevant in the context of ITS, where a major effort is invested in providing information with higher precision. Such systems are are designed to solve major traffic problems in cities [8, 9]. This study helps to improve ITS systems by offering relevant insights on how different levels of information inaccuracy can impact the overall traffic performance. The experiments reveal the amount of sensors or probe vehicles necessary to collect data that provides the best traffic performance. Moreover, the acceptable level of inaccuracy during information processing are determined. The study on presentation inaccuracy gives a target for improving the design of information dissemination devices.

In future studies, more advanced experiments dealing with information and uncertainty can be performed using realistic traffic networks and travel patterns. Future studies can analyze more types of inaccuracy overlapping (i.e. a certain level of sparsity, collection and presentation errors can be present simultaneously in the information content). Also, more detailed human behavior models may reveal the exact way in which people choose to use traffic recommendations.

Chapter 7

Soft control of traffic infrastructure trough information

7.1 Introduction

The rapid expansion of mega-cities caused by the increasing urbanization from the last century has numerous positive implications regarding economic growth and quality of life but, at the same time, it confronts the city planners and the operators with new challenges. One of the biggest problems in modern cities is traffic congestion. The road network infrastructure in urban environments has been evolving over decades, and, in many cases, is no longer compatible with the requirements for an efficient transportation system. In the majority of cities, the travel patterns are changing faster than the physical infrastructure can adapt. In such a situation, the transportation engineers propose building new roads or increasing the traffic capacity, in the hope of alleviating congestion in specific city areas.

Nevertheless, an extension of road network infrastructure is no longer a suitable or an accepted option in the current city environments, not only because of the scarcity of the urban space but also because it requires high investments and costly maintenance. Therefore, engineers are now seeking more appropriate solutions to the questions of how the capacity of the road network could be used more efficiently and how operations can be improved without significant changes in the infrastructure [5]. ITS systems are designed to deal with such challenges. Using modern technology to transfer information between infrastructure, vehicle, and drivers, they have become one of the most dynamic areas in transportation [7].

The previous chapters looked at different aspects related to the effect of information dissemination in transportation systems. These topics investigate the effect of traffic information when only a share of drivers is informed or when the content is affected by different levels uncertainty. In the current chapter, two studies are presented to explore the possibility of using traffic information, navigation recommendations, and ITS systems to transform the static infrastructure into a more dynamic and efficient network, this way improving the traffic performance. These studies use different road network scales, first a smaller block topology and subsequently a more realistic, large city scale network.

The first study investigates how the system's performance is affected by the level of responsiveness of the traffic lights. Dynamic traffic lights systems represent the traditional technique of soft changing the infrastructure by using real-time traffic information. In this case, the dynamic traffic lights systems optimize and adapt the phase duration to prioritize directions for larger groups of cars as opposed to static control with a fixed phase duration. This initial experimental setup uses a block scale road network (presented in Section 5.3.2). The study analyses the effect of speed navigation recommendations on the overall traffic performance for dynamic traffic lights systems in comparison to unresponsive, static traffic lights control.

The second study introduces the concept of *soft closing* of roads. This concept means that route navigation recommendations, sent to different shares of the traffic participants, are used as a steering mechanism to prevent the informed drivers from using certain detrimental road segments. This way, the roads become partially closed, creating an intelligent dynamic traffic infrastructure. The road segments are previously determined based on the simulated outcome of removing each of the segments of the network. The study investigates how soft closing of roads can impact the overall traffic performance on a city level in the sense of reduced average travel time.

The objective of this chapter is to prove that the *soft changing of the infrastructure*, when using the traffic information as a steering tool can be beneficial for the overall traffic situation. Therefore, ITS systems with information control strategies and a profusion of navigation devices that assist the traffic participants in their trips can be instrumental in leading the transportation systems towards better performance.

7.2 Computational Model

The experiments performed for the two studies use the computational model presented in more detail in Chapter 4. Here, only a general overview is provided. As explained in Chapter 4, the transportation system is modeled trough components: traffic infrastructure, traffic flow, and information flow. The traffic infrastructure contains roads and traffic lights systems. The traffic flow is modeled by agents and their movement on the roads. The agents are created by an agents generation model and are assigned an itinerary consisting of an Origin and Destination (OD) pair. Based on the OD pair, routes are calculated by a routing model. On top of the traffic flow, the information flow model with models of information dissemination is also added. The model of information dissemination consists of selecting a share of the traffic participants to receive navigation recommendations about the route or the traveling speed. The general characteristics of the information flow model and the information dissemination model are described in more detail in Chapter 4.

This chapter introduces the two types of traffic flow models used, depending on the research questions investigated and on the level of details needed for describing the agents: microscopic and mesoscopic traffic model. The microscopic model has been presented in Chapter 5 and will not be outlined in this chapter. However, the mesoscopic model will be presented in detail as it has not been presented before.

The experiments performed for the first study use a microscopic traffic model and a block scale network to create simplified controlled scenarios where the specific research questions can be investigated. However, The experiments performed in the second study are based on a mesoscopic traffic model. This setup optimizes traffic control and generates consistent route guidance for a realistic traffic situation with city scale roads network and agent population. The specific values of the parameters are described in Section 7.3.2.1.

It is important to note that the mesoscopic traffic model, similar to the microscopic model, take individual vehicles into account, but in a different way. In this case, the traffic dynamics are represented using speed density relationships. Due to the fact that mesoscopic models don't take into consideration detailed movement on the route (i.e. exact position, speed, and acceleration for each agent), it is possible to simulate realistic city scale scenarios at an acceptable computational cost.

Variable	Description	Unit
t_i	time it takes to traverse road segment i	$[s]$
l_i	length of road segment i	$[m]$
v_f^s	free flow velocity on segment with speed limit s	[m/s]
F_i	flow on segment i	
w_i	number of lanes on road i	
t	simulation time from which the flow is calculated	$[hours]$
v_{min}	minimum flow velocity at link i at extreme congestion levels	[m/s]
$I(i)$	function that checks if there is an intersection at the end of link i	
d^s	intersection added delay for roads with speed limit s	[s]
α^s	parameter from the BPR function for roads with speed limit s	
β^s	parameter from the BPR function for roads with speed limit s	
$S(i)$	number of successors of road segment i	
$P(i)$	number of predecessors of road segment i	

Table 7.1: Main parameters for the traverse times calculation

In this mesoscopic traffic simulation, the first step is the generation of the origin, destination and starting time for every agent. In the second step, the traverse time on each road is calculated. After determining the routes of all agents, the number of vehicles that pass through each link in the network can be extracted.

The time needed to traverse a link t_i for the link i is calculated by using an extended version of the Bureau of Public Roads (BPR) [136] function defined as it follows:

$$t_i = \min\left(\frac{l_i}{v_f^s}\left(1+\alpha^s\left(\frac{F_i}{2000w_it}\right)^{\beta^s}\right), \frac{l_i}{v_{min}}\right) + I(i)d^s \tag{7.1}$$

and

$$I(i) = \begin{cases} 1 & \text{if } S(i)+P(i) > 2 \\ 0 & \text{otherwise} \end{cases} \tag{7.2}$$

where t_i is the time it takes to traverse road segment i, F_i determines the flow on segment i and $I(i)$ is the function that checks if there is an intersection at the end of link i. It was assumed that the minimum possible velocity for a link in extreme congestion is set to 5 km/h. Table 7.1 presents all parameter notation used to describe the calculation of traverse times.

7.3 Studies

7.3.1 Soft control of dynamic traffic lights trough information

The objective of this study [1] is to investigate the impact of *soft changing the infrastructure* components by using the traffic information as a steering tool. One of the simplest infrastructure components that adapt based on traffic information are the dynamic traffic lights systems. Due to recent advancements in communication technologies between traffic infrastructure, vehicles, and drivers, the control and responsiveness of traffic lights systems can be approached in novel ways. However, this may introduce new, unforeseen phenomena in the traffic situation.

In a modern transportation system, the traffic lights systems are categorized as static and dynamic. The static traffic lights have a predefined fixed phase duration. In real situations, these fixed phases are based on historical traffic data. The green time is varied between pre-timed minimum and maximum lengths depending on flows [6].

For dynamic traffic lights control, a traffic-actuated controller operates based on traffic demands as registered by the actuation of a vehicle and/or pedestrian detectors [6]. However, lately, the responsive traffic solutions have gathered more attention while the fixed-time strategies are used more for understanding the traffic conditions. There are studies where fixed-time strategies are proposed as robust control solutions or used directly or indirectly to infer the real-time strategies [6].

The real-time responsive optimization is achieved by extending the capabilities of basic traffic lights to either communicate with each other or communicate with vehicles. Traffic lights control systems can be centralised (i.e. SCOOT [19], an adaptive system based on information on traffic flow from detectors) or decentralised (i.e. [15] [16] [17]).

Modern traffic lights based on self-organization perform better than the traditional methods [15]. In this study, the authors use short sighted anticipation of vehicle flows and platoons. A decentralized emergent coordination based on local interactions traffic lights control is achieved. This manifested in a reduction of the average travel time and the emergence of green waves.

In [16] and [17] the self-organization is achieved as well by probabilistic formation of car platoons. In turn, the platoons affect the behavior of traffic lights, prompting them to turn green before they have reached the intersection. These methods are based on local rules and no communication between traffic lights which mean that the

[1]The content of this study is based on the published in article [2], referenced in Appendix A.1

decentralized coordination is based on local interactions of traffic lights control and the traffic flow. The cars that have been waiting for longer and larger groups of cars are prioritized to cross the intersection. In this case, the traffic lights control is considered rather an adaptation problem than an optimization problem.

In [49] the authors use micro-auctions as the organizing principle for incorporating local induction loop information. When a phase change is permitted, each light conducts a decentralized, weighted, micro-auction to determine the next phase. Other studies deal with the prediction of traffic signals enabling innovative functionalities such as Green Light Optimal Speed Advisory (GLOSA) or efficient start-stop control [18]. A detailed description of the state of the art in traffic lights is presented in Section 2.2.2.

It is interesting to note that, the dynamic traffic lights systems presented in the current study also take into consideration the number of vehicles that pass trough the link. The dynamic control is optimized to prioritize larger groups of cars. Unlike the previous research, this study proposes a systematic analysis of the interaction between drivers and traffic lights systems. The current study investigates how the fact that the infrastructure, in this case, traffic lights systems, using information about the traffic situation can impact the overall system's performance. It aims to evaluate how dynamic traffic lights systems perform in comparison to static traffic lights systems. To perform this set of experiments, an agent-based model is used to simulate transportation systems with static and dynamic traffic lights.

7.3.1.1 Experimental setup

The current study uses the computational model presented in Chapter 5. A detailed description of the experimental setup is presented in Section 5.3.2.1. In the previous chapter, other experiments related to traffic lights and information used to adapt the driving speed are performed using the same setup. Unlike to the previous study, the main purpose of the experiments is to analyze how the traffic performance is affected by traffic lights being responsive to the traffic situation. The main parameters used in the current study are defined in Table 7.2.

$I_{traffic}$ represents the traffic intensity described as it follows:

- *Low* traffic intensity is generated for $IA_{time} = 5[s]$ and $N_{total} = 500[agents]$,
- *Medium* traffic intensity is generated for $IA_{time} = 3[s]$ and $N_{total} = 1500[agents]$
- *High* traffic intensity is generated for $IA_{time} = 1[s]$ and $N_{total} = 2500[agents]$.

	parameter description	min value	max value	incremental step
IA_{time}	inter-arrival time	$1[s]$	$5[s]$	$1[s]$
N_{total}	total number of agents	$500[agents]$	$2500[agents]$	$1000[agents]$
v^{max}	roads speed range	$15[m/s]$	$20[m/s]$	$5[m/s]$

Table 7.2: Main parameters used in one experiment $E_{I_{traffic},v^{max}}$

The global performance indicator is defined as it follows:

$$I_P = \frac{1}{N_c}\sum_{i=0}^{N_c}\frac{d_i}{t_i}, \tag{7.3}$$

where t_i is the trip duration and d_i is the trip distance of an agent i. N_c is the total number of agents to complete their trip.

7.3.1.2 Results

In this study the aim is to determine how the real-time traffic responsiveness of the traffic lights can impact the overall traffic performance (I_P defined in Equation 7.3). Both traffic lights systems (*static* and *dynamic*) are evaluated. The agents are not informed and for the static case $\delta^{Phase} = 45[s]$. The experiments consider three levels of traffic intensity *low, medium and high* and three values of the maximum speed on roads ($v^{max} = 10m/s$, $v^{max} = 15m/s$, $v^{max} = 20m/s$).

In order to quantify the impact of responsive traffic lights on the system's responsiveness indicator I_R is defined. I_R shows the impact on I_P of the *dynamic* traffic lights control in comparison to the *static* traffic lights control:

$$I_R = (I_P^{Dynamic} - I_P^{Static})/I_P^{Static} \tag{7.4}$$

where I_P^{Static} is the reference performance indicator.

Figures 7.1, 7.2 and 7.3 show that dynamic traffic lights control produces a worse effect on the traffic than the static one for lower levels of traffic intensity. However, there are cases when the dynamic traffic lights control outperforms the static one for high traffic and high speed roads ($v^{max} = 20[m/s]$).

Therefore, it can be concluded that traffic information can be used by a dynamic traffic infrastructure in order to achieve an improvement in the overall performance. It is important to identify the circumstances that are favorable for such an improvement.

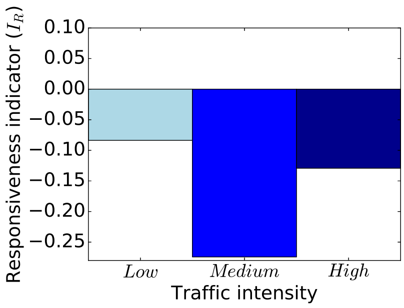

Figure 7.1: $v^{max} = 10m/s$. Illustration of the he effect of dynamic traffic lights in the traffic using responsiveness indicator I_R (defined in Equation 7.4). None of the agents have information, only the traffic lights are responsive to the traffic situation for roads with different v^{max}.

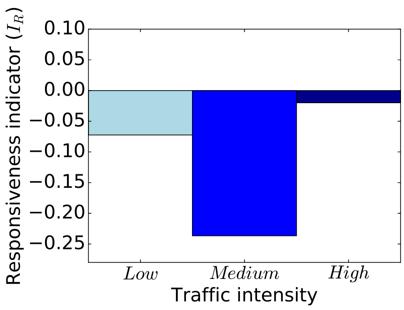

Figure 7.2: $v^{max} = 15m/s$. Illustration of the he effect of dynamic traffic lights in the traffic using responsiveness indicator I_R (defined in Equation 7.4). None of the agents have information, only the traffic lights are responsive to the traffic situation for roads with different v^{max}.

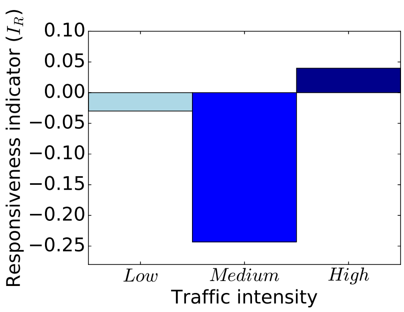

Figure 7.3: $v^{max} = 20m/s$. Illustration of the he effect of dynamic traffic lights in the traffic using responsiveness indicator I_R (defined in Equation 7.4). None of the agents have information, only the traffic lights are responsive to the traffic situation for roads with different v^{max}.

7.3.2 Soft closing of road segments using navigation recommendations

With increasing urbanization, traffic demand is growing as well. This leads to numerous challenges for different aspects of a city. In this context, complex transportation systems face a major problem regarding the traffic congestion despite a laborious attempt to control the traffic flow. Understanding and controlling complex systems (such as the transportation systems) is a very hard goal in natural or man-made systems. The difficulty appears because of the system's architecture, consisting of the physical network, and because of the dynamical rules that capture the time-dependent interactions between the network components [82].

The road network infrastructure in most cities has evolved over decades, being optimized to serve the transportation needs of the specific period. For this reason, in many cases, the physical road network is sub-optimal when considering the today's traffic demand. Congestion has become a significant challenge in our society. The solution commonly used to improve congestion consists of building new roads or increasing road capacity in some road sections. Nonetheless, this type of strategy is often impossible to implement because of the costs and of the scarcity of space in urban areas [3] [4].

Moreover, there is evidence that closing a road can, as counter-intuitive as it may seem, actually improve the traffic situation. This phenomenon is known in the literature as Braess paradox [137]. This states that adding extra capacity to a four-node network where drivers act selfishly, can in some cases, decrease performance. Also, a generalization of the Braess paradox was done in [138]: Removing edges for large networks can produce an arbitrarily large improvement. Also, it is possible that in some real situations, closing a road may result in drivers taking fewer trips. This phenomenon is called the disappearing traffic paradox [139].

In [140], it was shown that adding a link between the source and destination may lead to an increase in both total price and total cost. On the other hand, multiplying the capacity of some specific links by a constant factor decreases the total cost. Another study shows that an increased provision of highways and major urban roads is unlikely to relieve congestion of highways and major urban roads in metropolitan areas [141].

There are many examples in real life confirming the existence of Braess and disappearing traffic paradoxes in cities as Stuttgart [142] or New York [143], where streets were closed for renovation or on purpose and better traffic conditions were observed. There are 70 more case studies from 11 countries showing such conditions [139].

However, closing a road permanently can have the disadvantage of being rather an extreme measure, that can isolate some of the traffic participants. A better approach can be a more dynamic solution: temporarily closing some harmful road segments for only a fraction of the traffic participants. This approach, proposed in this study is termed *soft closing of roads*. The soft closing of roads is done by using a centralized control system that provides route navigation recommendations to the informed group of drivers. The recommended routes exclude the particular road segments only for the informed traffic participants. This way, the harmful roads segments are partially closed. The roads segments which are detrimental are determined based on the simulated outcome of removing certain road segments from the network.

ITS systems are instrumental in realizing the soft closing of roads by using information control strategies. For this, a share of traffic participants is selected to receive route information as navigation recommendations. Section 2.3.2 presents several studies dealing with the effect of using navigation recommendations by drivers. The way the routes are calculated either optimise the individual performance (selfish routing) or a global performance (socially optimum routing) [20], [25, 21, 45, 63].

Other examples show that a complete view of the network leads to a faster coordination, and the effect of information depends on the network structure [61]. In [62] it was shown that increasing the weights of particular links that are active early in a cascade crush worsens the bottlenecks. In contrast, strengthening only links that propagated the activity just before cascade termination (i.e. links that point into bottlenecks), removes bottlenecks and improves accessibility to other pathways in the network.

Similar to the presented state of the art, this study [1] investigates methods of improving congestion by controlling the traffic flow on certain roads segments with the use of navigation recommendations. Unlike the presented papers, the current study evaluates the soft closing technique for a realistic transportation network and traffic patterns. Another difference is the method which identifies what road segments to be partially removed (the segments are chosen based on simulated outcomes of removing each road). Therefore, an information control strategy based on route recommendations that partially excludes the selected roads that can be easily implemented in the real world is proposed.

[1]The content of this study is based on the published in article [4], referenced in Appendix A.1

7.3.2.1 Experimental setup

As mentioned in Section 7.2, the experimental setup uses a computational model with three main components: the infrastructure model, the traffic flow model, and the information flow model. Next, the specific details of the implementation and the parameter values are presented.

Figure 7.4: Illustration of a city scale road network infrastructure based on the Singapore map

Modelling the infrastructure

The road network infrastructure uses the infrastructure model for a realistic city scale scenarios. For this, the road network was derived from Navteq 2009 data [101] which contains information on the roads and intersections in the city of Singapore, including the number of lanes on roads.

The road network is modeled as a unidirectional graph, where one edge or link connect two nodes. Intersections are collections of nodes. For this experimental setup, the road network of the Singapore city is formed from 240,000 links and 160,000 of nodes. The Singapore road network is illustrated in Figure 7.4.

Modelling the traffic flow

The current study examines the realistic travel patterns from the city of Singapore. The traffic flow in the simulation is generated by creating a realistic population of agents that move on the roads from their trip's origin to the destination point. The traffic demand is based on a time-dependent origin-destination (OD) table, matching realistic traffic patterns deferred from survey data. For this particular scenario, the initialization of time-dependent OD assignment was done using data from the Household Interview Travel Survey (HITS) conducted in 2012 by the Singapore Land Transport Authority (LTA) [102]. According to LTA reports, the population of Singapore is around 5.4 million people, and there are approximately 1 million registered vehicles including taxis, delivery vans, and public transportation vehicles.

HITS data contains a set of questions regarding traveling habits of the approximately 0.67% population of Singapore, which accounts to 35715 participants. Each person has answered 108 questions about demographics, commuting preferences and capabilities. From this dataset, only the information that deals with travel patterns is considered. Data includes details about various travel model such as private cars, taxi, public transportation, motorbike, etc. The HITS data is described in the following format:

Origin Postal Code	Destination Postal Code	Time of Start (hh:mm)	Duration (mins)	Means of Transportation

The experiments simulate the traffic conditions during the morning rush hour, which is the most intense period of the day for Singapore. This can be seen in Figure 7.7 illustrating the distribution of trip starts throughout the day calculated from HITS data. Therefore, a one hour period from $7:00$ $a.m.$ to $8:00$ $a.m.$ is chosen because of the peak time when most of the agents are starting their trips is around $7:30$ $a.m.$. In total, there are roughly $309,000$ agents that start their trips during the examined period. It is important to note that this interval is large enough to have enough samples from the HITS data (this is useful for an accurate agent generation) and also has a homogeneous trip generation. The two conditions are necessary for the assumptions of the traffic model to hold.

$$\text{Car Users} = \text{Population} \times \frac{\text{Car Users in HITS}}{\text{Surveyed People in HITS}} \tag{7.5}$$

At the beginning of the simulation, each agent is assigned an itinerary from the itinerary dataset containing origin-destination (OD) pairs and journey start time. The start time is extrapolated the from HITS dataset as it follows: the original set of origin and destination locations specified by a postal code are generated from the filtered entries for the time interval from $7:00$ *a.m.* to $8:00$ *a.m.*. Singapore has a unique six-digit postal code system for every building. A counter is incremented each time the postal code is encountered in the filtered dataset. This counter is further used to estimate the probability of the location being an origin or a destination point. From the original set, each pair of origin and destination postal codes are selected, and the first two digits of the postal codes are considered. The rest of the digits are generated so that more postal codes are created, and the whole number of agents receive an OD pair. Temporally, the start time of trips is uniformly distributed over an hour period.

Routing

After each agent is assigned to an OD pair and a start time, a route is calculated based on the provided network. In this study, the route is calculated as the shortest path between the origin and destination points based on Dijkstra's algorithm. In this case, the algorithm uses different weight systems so that each driver can have a preference for route choice optimized in terms of distance, travel time or comfort. There are three types of weights:

1. $w_d = \text{road length}$ (minimizing distance)

2. $w_t = \dfrac{\text{road length}}{\text{road speed}}$ (minimizing time)

3. $w_c = \dfrac{\text{road length}}{\text{road speed} \times \text{number of lanes}}$ (maximizing comfort)

When generating each route, one of the three preferences is chosen at random with probabilities p_d, p_t and p_c respectively. The values of these three probabilities are calibrated since the preferences of routing choices vary from nation to nation as mentioned in the literature. In [144] [145], it is shown that roughly one-third of the agents prefer the shortest routes and the rest have a preference for fastest paths and wide roads,

Parameter	Calibrated Value
p_d	0.31
p_t	0.33
p_c	0.36

Table 7.3: Calibrated route choice parameters and their values

which may, in some cases, coincide. This information is derived from choice route data from the Transportation Survey of the Faculty and Staff conducted in 1997 by the MIT Planning Office. Drivers were asked to provide a written description of their habitual route. When route descriptions contained gaps, the least-distance path was used to connect known portions of the survey respondent's route. A total of 188 respondents met the screening criteria and thus formed the origin-destination pairs on which the various route generation algorithms described above were performed. The results show that the majority of the respondents prefer to minimize the travel time. Also important aspects in route choice are minimizing free flow (stop lights), maximize capacity-weighted time path (main roads), maximize time in secure neighborhoods (safety), least distance and maximize arterial path. Table 7.3 presents the calibrated route choice parameters and their values chosen based on the literature.

It is important to note that there is no re-routing in the routing model. For this particular experimental setup it was assumed that once the route of an agent is chosen, there will be no changes to it throughout the trip.

Identifying the harmful roads segments for soft closing

Identifying the segments that, if used for routes (even partially), produce a decrease in the overall traffic performance. This was done by partially removing from the routing graph each of the 260,000 links. It is important to note that the removal of this segment is done for 50% of the traffic participants. The value of 50% closure was chosen since it is the middle ground between completely closed and opened. The top two roads whose closure produced the highest improvement are selected for the experiments and are referred to as $Road_a$ and $Road_b$.

Parameter	Calibrated Value
α^{50}	0.8
β^{50}	2
α^{70}	1
β^{70}	3
α^{90}	1.2
β^{90}	5

Table 7.4: Calibrated parameters α and β and their values for the traverse time calculation

Parameter	Calibrated Value
d^{50}	$1[s]$
d^{70}	$4[s]$
d^{90}	$1[s]$

Table 7.5: Calibrated parameters delays due to intersections and their values for the traverse time calculation

Traverse Time Calculation

Next, the number of vehicles that pass through every link in the network can be extracted using the information about the agents and their routes. The time needed to traverse a link t_i for the link i is calculated using an extended version of the Bureau of Public Roads (BPR) function defined in Equation 7.1. There are a few calibrations steps used for the traverse time calculation.

The first calibration step done for the transverse time parameters uses a GPS trajectory dataset from the city of Singapore from a commercial fleet, with tracking system [146]. This data is referred to as Quantum Inventions (QI) data. The size of the fleet is around $20,000$ vehicles. It comprises mainly of goods vehicles, truck and small lorries. However, there is also data included from car leasing companies and personal trackers installed on private vehicles. The information about trip duration, origins, and destinations, therefore, cannot be used to extract travel patterns reliably, since it is not representative of the commuting population. It can be utilized, however, to estimate average speeds on the roads with a good coverage of the whole network. The available data is for the duration of two months in 2014.

Each entry has the following format:

Track id	Latitude	Longitude	Heading	Ground speed	Time stamp

The time difference between two consecutive signals (sampling period) from the same vehicle can vary between 1[s] and 30[min]. There are more data points when a vehicle is turning and fewer data points when the vehicle is going in a straight line. Vehicles reduce speeds at turns and move faster when going in a straight line. Therefore, there possibly is a slight bias towards lower speed values being recorded (this can be seen in Table 7.6). On straight congested roads, it is possible that the number of samples is smaller than if there were a fixed sampling frequency. Data is collected for the entire day (24 hours), including when the vehicles are parked. To exclude the samples from the parked vehicles, all data points where there is no change in the position and velocity in the last 15 samples are removed. After this preprocessing step, the size of the dataset is around 120 million points. The next step consists of using, a map matching algorithm [147] on every trajectory to assign every sample point to an actual link on the road map of Singapore. All samples are regrouped according to links speed limits and time stamp to identify the speeds profile on links throughout the day.

This first set of calibrated parameters based on QI data is the α and β of the BPR function. These parameter values depend on the network infrastructure characteristics and drivers' behavior profile. The calibrated values are in the range of accepted values for these parameters, as mentioned in the literature [148]. The calibration parameters and their values are presented in Table 7.4.

Another calibration step performed for the transverse time parameters refers to adding delays due to intersections for the three groups of roads. The calibrated values show that the most time on average is lost at major road intersections (i.e. due to traffic lights), while smaller roads and high-speed roads or highways the delays are less significant. The calibration parameters and their values are presented in Table 7.5.

Modelling the information flow

To simulate the information flow, a few assumptions are made. The first assumption is that all the agents are sources for data collection. They participate with travel data such as current speed, location, origin and destination and route information. This data together with details about the road network infrastructure is used to calculate the routes recommendations for the agents.

There are two types of agents: *informed* and *uninformed*. On the one hand, the agents selected to be informed receive the route navigation recommendations aiming at optimizing the overall traffic performance. This optimization of the overall global performance is done by partially excluding some well-determined road segments from these routes. It is important to note that the route calculation mechanism is centralized and aims at achieving a global social optimum for the overall transportation system and, not the individual performance. In this case, each agent follows the route recommendations that gives the shortest travel time, using the road network that excludes the segments determined as being detrimental for the global traffic performance.

On the other hand, the uninformed agents receive route recommendations that are optimized to achieve individual performance and not a global optimum performance like for the informed agents. In this case, each agent has a selfish behavior and follows the route that gives the shortest travel time, using the entire road network, including the segments that are determined as being harmful to the overall traffic performance.

The informed agents are chosen to receive route navigation recommendations based on a model of information dissemination. It is important to note that this model of information dissemination is randomly selecting a share of the traffic participants to be informed and receive route recommendations that optimize the traffic globally. It is assumed that all agents are rational when they decide how to react to the traffic information presented to them. This means that each agent chooses the best possible route with respect to their preferences (i.e. time, distance or comfort) and will follow it without cheating.

Simulation validation

Table 7.6 presents a comparison between simulation and real world speed values on roads used for transverse time calculation. To validate the values, the three most congested road segments (according to the simulation) are chosen to be evaluated. The speed on those sections calculated using the traverse function reaches the minimum of 5 km/h. All three examined roads have a speed limit of 90 km/h. The samples of vehicles are extracted from the QI data. They passed on those roads between $7:00$ $a.m.$ and $8:00$ $a.m.$ the interval on weekdays. It can be observed from the table that all three road segments that are severely congested in the simulation are also congested in reality as well according to the GPS tracking data. Therefore, it can be said that the traffic flow model gives an appropriate approximation of reality for the desired level of detail.

Parameter	Value in Simulation	Value from Data
v^{50} [km/h]	22.4	22.8
v^{70} [km/h]	39.1	35.5
v^{90} [km/h]	64.3	59.3

Table 7.6: Comparison between simulation speeds on roads and real world values from QI data

Furthermore, Figures 7.5 and 7.6 show that the simulated trip lengths distribution resembles the real world values obtained from HITS data. It is interesting to note that, for both real and simulated data, the peak traffic intensity in the morning and evening rush hours are observed in the same hour intervals. Moreover, the simulated trip start distribution throughout the day shows the same traffic patterns like the one generated with HITS data. This is illustrated in Figures 7.7 and 7.8. Therefore, the agent generation and the traffic assignment used in the simulation provide realistic travel patterns derived from real world datasets.

The mechanism for agent generation from the current study has been validated and described in a previous study [1]. Similar results are obtained in the current experiments and because of this reason, some of the figures illustrating the results from the validation of the traffic generation mechanism from the previous study are presented in this section.

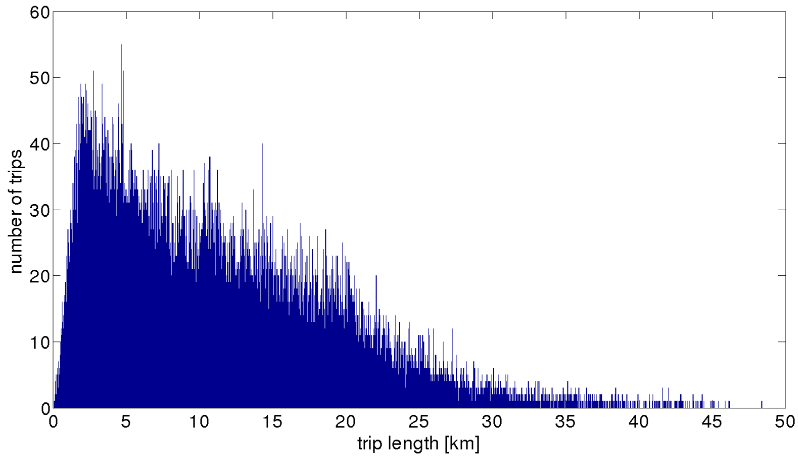

Figure 7.5: Illustration of the trip length distribution according to HITS data for Singapore traffic patterns [1]

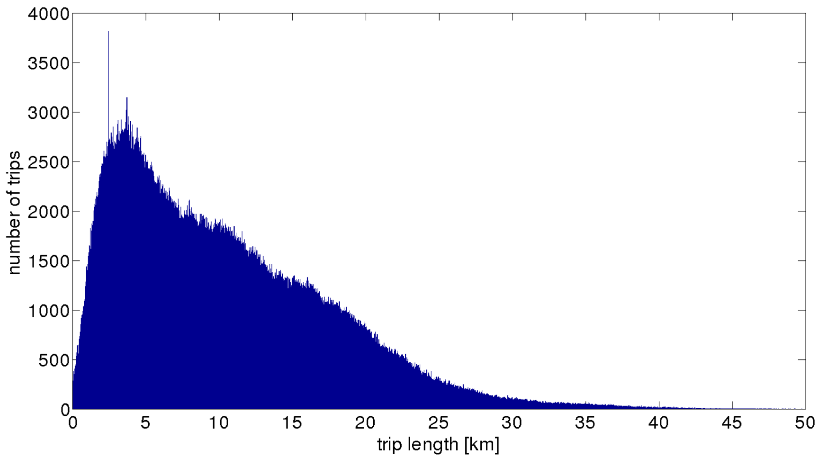

Figure 7.6: Simulated trip length distribution for Singapore city [1]

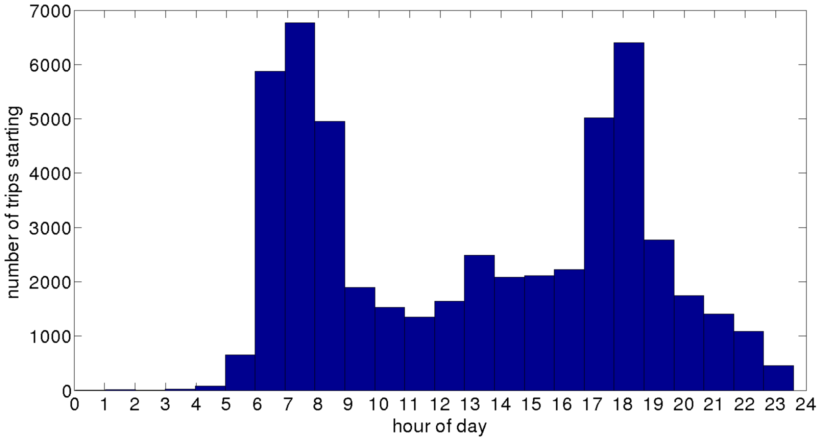

Figure 7.7: Illustration of the start time histogram for trips according to HITS data for Singapore city [1]. The highest traffic intensity is observed at rush hour between 7:00 to 8:00 a.m.

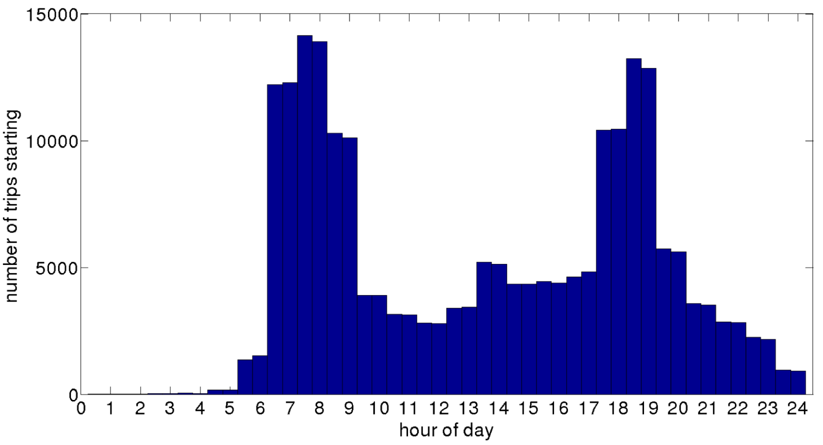

Figure 7.8: Illustration of the simulated start time histogram for Singapore city [1]. Similar to the real world data histogram, the highest traffic intensity is observed at rush hour between 7:00 to 8:00 a.m.

Performance indicators

To quantify the effect of information dissemination, the network performance is characterized as T, the average travel time of all agents in one experiment $E_{p,Road_{Id}}$.

$$T = \frac{1}{N_c} \sum_{i=0}^{N_c} t_i, \tag{7.6}$$

where t_i is the trip duration of an agent i and N_c is the total number of agents to complete their trip by the end of the simulation. To evaluate different aspects of information dissemination, T is analyzed for various groups of agents. T is the global indicator of performance calculated over all agents. Moreover, T_U and T_I are the global performance indicators calculated for the groups of uninformed and informed agents.

The second indicator used to quantify the effect of information dissemination is defined as S, the average trip speed of all agents in one experiment $E_{p,Road_{Id}}$.

$$S = \frac{1}{N_c} \sum_{i=0}^{N_c} d_i/t_i, \tag{7.7}$$

where t_i is the trip duration of an agent i, d_i is the trip length of an agent i and N_c is the total number of agents to complete their trip by the end of the simulation. Similar to T, also for S, the performance for the two groups of informed and uninformed agents S_I and S_U is evaluated. Observing these indicators is necessary to better analyze and explain the effect of soft closing certain road segments.

Each experiment $E_{p,Road_{Id}}$ is characterised by two parameters: $Road_{Id}$, the id of the road segment selected to be removed and p, the percentage of informed agents. The main parameters used for the experiments are defined in Table 7.7. Parameter p varies from 0% (no agent is informed) to 100% (all agents receive information) in steps of 10%. Each experiment $E_{p,Road_{Id}}$ is repeated 10 times.

	parameter description	min value	max value
p	percentage of informed agents	0%	100%
$Road_{Id}$	the id of the road segment to be closed	$Road_a$	$Road_b$

Table 7.7: Main parameters used in one experiment $E_{p,Road_{Id}}$.

7.3.2.2 Results

The contributions presented in this study are related to the concept of soft closing of links. As mentioned previously, soft closing of roads means that rather than removing a link from the road network completely, this segment is closed only for a fraction of the informed agents. The road segment is removed by providing route recommendations that exclude this segment to the group of informed traffic participants. These drivers are redirected to alternative routes, and this fact produces an intelligent redistribution of the traffic demand.

Figure 7.9 illustrates an example of one of the two roads segments shown in the context of the entire road network of the Singapore city. Moreover, Figure 7.10 shows the same example but in a zoomed area. In these figures, the road segment that is chosen to be soft closed is marked in green. It is interesting to note that the two figures illustrate how a rather small the change in comparison to the entire magnitude of the system can produce significant beneficial results for the overall system. This characteristic of the soft closing of roads represents an important factor that can be utilized to steer the transportation system into the desired state, with a very simple but efficient strategy.

The literature describes how the complete removal of certain roads from the road network in several cities lead to a surprising improvement in the traffic situation (i.e. Braess's paradox and disappearing traffic paradox). However, the complete removal is an extreme measure that can produce a great discomfort to some of the traffic participants (i.e. to the commuters who don't have an acceptable alternative when trying to avoid a certain road segment).

In the current study, the aim is at evaluating what is the effect of partially closing roads by using a centralized technique for providing effective route navigation recommendations to traffic participants. This strategy is more practical as it can exploit more efficiently the current infrastructure without creating extreme situations for some of the traffic participants.

The first step in the soft closing strategy consists of identifying the segments that, if used for routes (even partially), produces a decrease in the overall traffic performance. This technique is described in more detail in Section 7.3.2.1.

The experimental results show that, from the total number of 260,000 links from the Singapore city network, there are 64 links whose partial closure leads to more than 1-minute decrease of average trip duration. The top two segments whose partial closure produces the highest improvement on the overall performance are $Road_a$ and $Road_b$.

It is important to note that, the link that shows the best performance if partially closed gives 100 seconds decrease of the average travel time of the total amount of traffic participants. This amounts to 6.25% increase in overall traffic performance, which shows that the impact produced by this closure on the performance is significantly high for a city scale level.

To further evaluate the effect of partially closing of roads, different levels of closure are evaluated for $Road_a$ and $Road_b$, selected at the previous step. For this, the percentage of informed agents (or percentage of closure), p is varied from 0 to 100 in 10% steps. For every step, the global traffic performance indicators such as the average trip duration (T defined in Equation 7.6) and the average trip speed (S defined in Equation 7.7) for the total amount of completed trips are evaluated.

Figure 7.9: Illustration of a road segment chosen for soft closing on the Singapore map

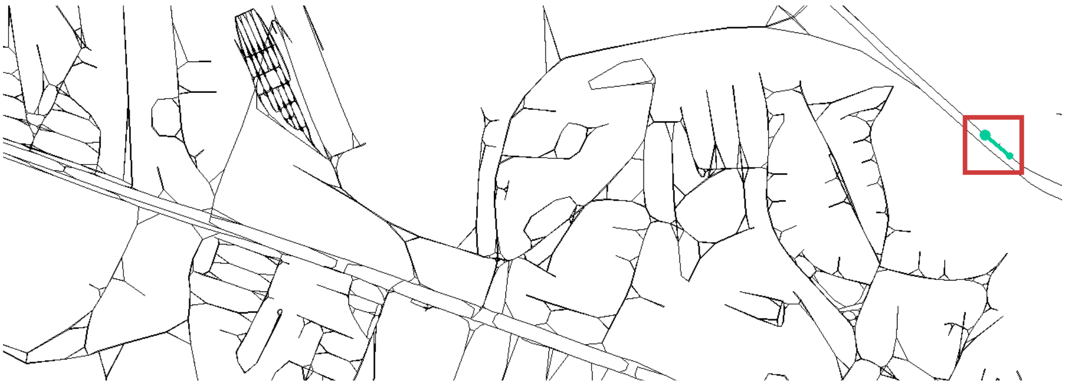

Figure 7.10: Illustration of the zoomed version of Figure 7.9 showing a road segment chosen for soft closing on the Singapore map

Soft closing of roads

Figure 7.11 illustrates the information impact on the total average duration for the completed trips (T defined by Equation 7.6) depending on the percentage of informed agents, p, for the two most harmful links, $Road_a$ and $Road_b$. In this case, T represents a global performance indicator quantifying the effect of partially closing the specific road segment.

It can be observed that the best performance for both selected roads is achieved when only a share of the traffic participants (p around 40% and 50%) are prohibited from using the specific road. T first is increased (the traffic situations becomes better). For increasing more the amount of drivers that avoid the two road segment the traffic performance degrades until it becomes even worse than when all agents are uninformed.

The same phenomenon is observed when examining the information impact on the total average speed for the completed trips (S defined in Equation 7.7) depending on the percentage of informed agents, p, again for most harmful links, $Road_a$ and $Road_b$. Similar to the previous case, Figure 7.12 shows that the traffic performance is first improved (S is getting higher) by increasing by the number of informed agents up to an extent (p around 40% and 50%). After this point, S decreases abruptly even more than when the roads are not closed.

It can be concluded that different shares of traffic participants using navigation recommendations that exclude certain road segments impacts the overall traffic performance. There is an optimal percentage of traffic participants that need to be informed (around 40% and 50%) to achieve the maximum improvement in the overall traffic performance.

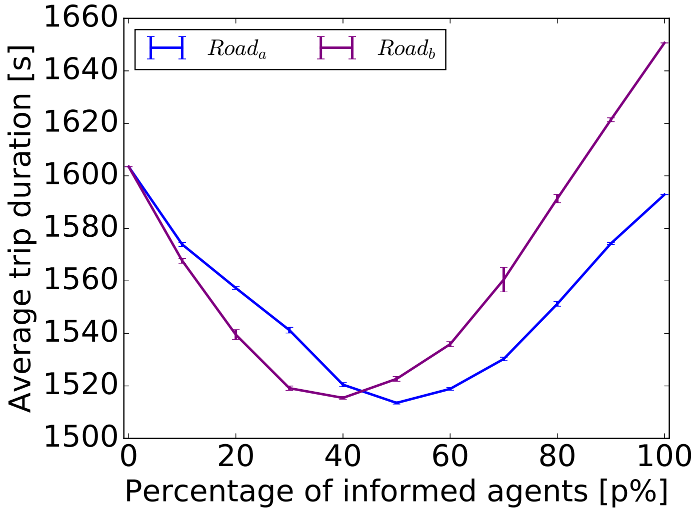

Figure 7.11: Information impact on the total average duration for the completed trips T (defined in Equation 7.6) depending on p, for tot most harmful links $Road_a$ and $Raod_b$

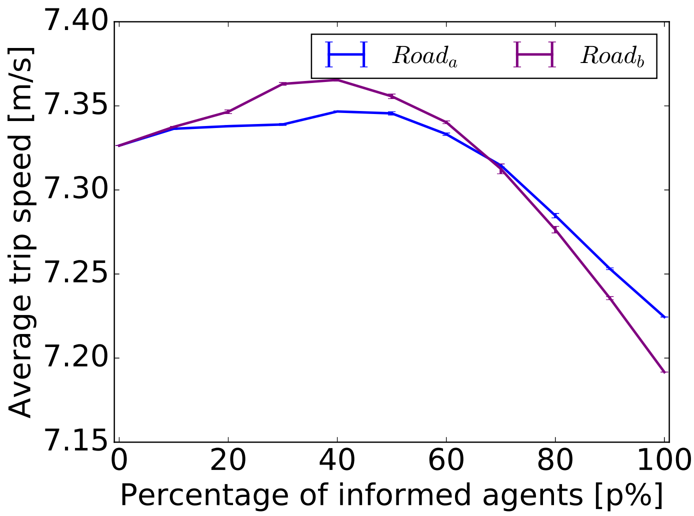

Figure 7.12: Information impact on the total average speed for the completed trips S (defined in Equation 7.7) depending on p for tot most harmful links $Road_a$ and $Raod_b$.

Local effects of information propagation and equilibria analysis

In order to evaluate different aspects of information dissemination, T (defined in Equation 7.6) is analysed for different groups of agents: uninformed (agents that receive route recommendations without excluding any segments) and informed (agents that receive route recommendations with the excluded road segments) as T_U and T_I.

Figure 7.13 displays how the informed and uninformed agents perform for different values of p in terms of average travel time. It can be observed that at the point of global social optimum, T_I is decreased by 23% and 41% while T_U is decreased by 23% and 50%. Therefore, in this case, both groups of informed and uninformed manage to save travel time by implementing the soft closing strategy.

Nevertheless, the slope of the informed group is negative with the increasing percentage of informed agents while the slope of the uninformed agents is positive with more people being informed. This phenomenon happens because the redirection of a group of informed drivers relieves the congestion on the particular roads. However, this redirection is detrimental for the group of informed agents, who need to drive a longer distance to the desired destination. Though, because the agents that need to exclude the roads segments are chosen randomly, it can be considered a fair solution that can be accepted by the traffic participants.

Similar results are observed when examining S_U and S_I, the average speed on roads S (defined in Equation 7.7), calculated for the uninformed and the informed groups of agents. The experimental results are presented in Figure 7.14. It can be seen that S_I is decreased with about 19% and 24%, and S_U is decreased by about 18% and 31%.

Therefore, the surprising improvement obtained by soft closing certain road segments is explained by the fact that traffic flow in the city is re-directed more homogeneously. The partial closing of roads produces a correction in the network topology. Figures 7.17 and 7.18 illustrate how traffic is re-distributed on the network. The blue roads have a decrease in the traffic flow while the red segments have an increase in the traffic flow. The thicker the line is, the higher the change in the traffic flow is.

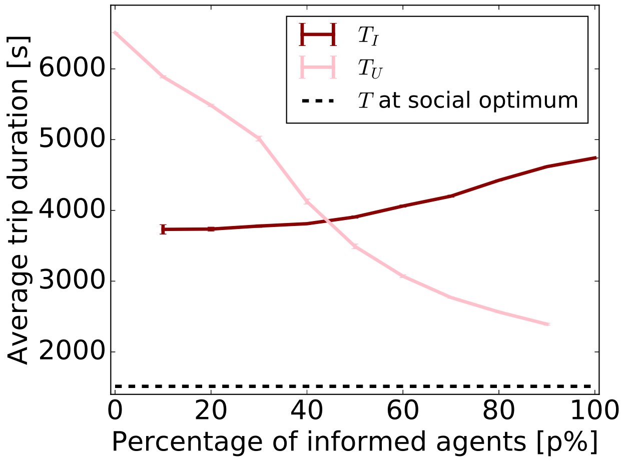

Figure 7.13: Comparison of T_U and T_I (defined by Equation 7.6) calculated for the group of uniformed agents and the group of informed agents respectively, when $Raod_a$ is soft closed. The dashed line illustrates T value at the social optimum point. Soft closing of $Raod_a$ is done for different percentages of p. The uninformed agents use the harmful road segment while the informed ones receive route recommendations that avoid the specific road segment.

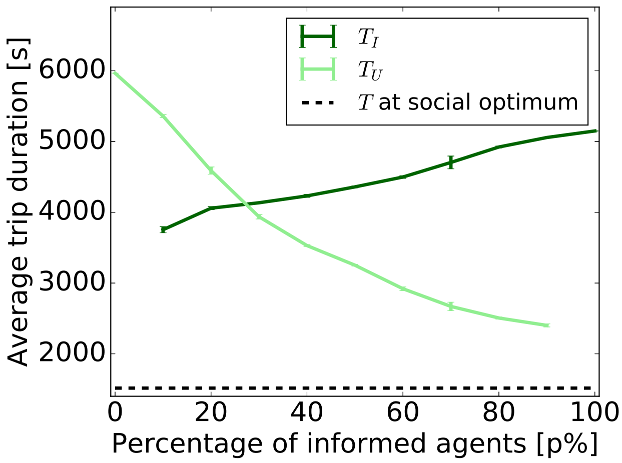

Figure 7.14: Comparison of T_U and T_I (defined by Equation 7.6) calculated for the group of uniformed agents and the group of informed agents respectively, when $Raod_a$ is soft closed. The dashed line illustrates T value at the social optimum point. Soft closing of $Raod_b$ is done for different percentages of p. The uninformed agents use the harmful road segment while the informed ones receive route recommendations that avoid the specific road segment.

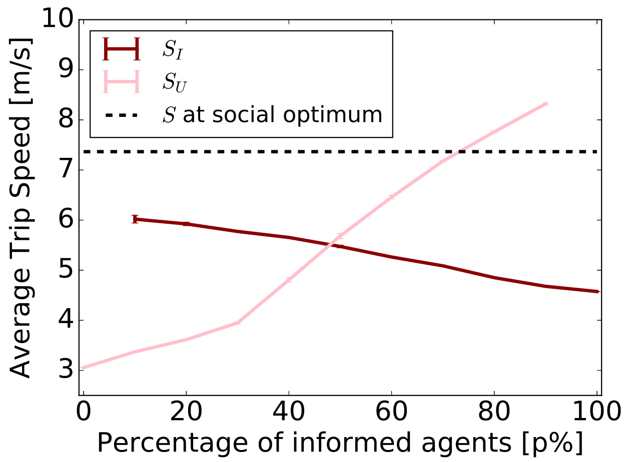

Figure 7.15: Comparison of S_U and S_I (defined by Equation 7.7) calculated for the group of uniformed agents and the group of informed agents respectively. The dashed line illustrates S value at the social optimum point. Soft closing of $Raod_a$ is done for different percentages of p. The uninformed agents use the harmful road segment while the informed ones receive route recommendations that avoid the specific road segment

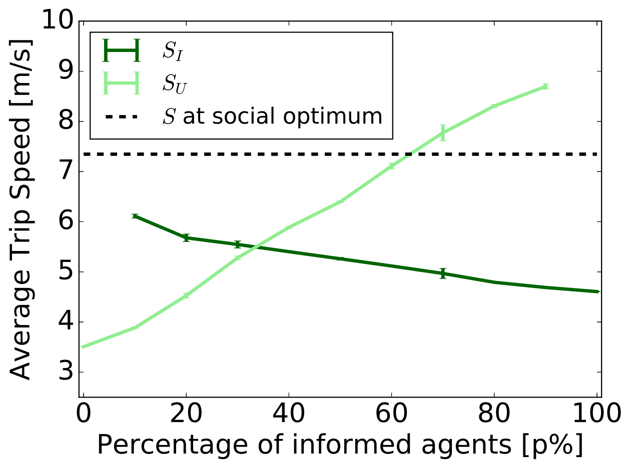

Figure 7.16: Comparison of S_U and S_I (defined by Equation 7.7) calculated for the group of uniformed agents and the group of informed agents respectively. The dashed line illustrates S value for the social optimum point. Soft closing of $Raod_a$ is done for different percentages of p. The uninformed agents use the harmful road segment while the informed ones receive route recommendations that avoid the specific road segment

Figure 7.17: Illustration of the traffic flow redistribution caused by the soft closing strategy. The road segments colored in red represent roads that achieve an increase in the average travel time while the blue segments achieve an improvement of the average travel time. The thicker the line is, the bigger the change produced by soft closing is. Gray roads segments are not affected by the partial closure of the road segment

Figure 7.18: Zoomed version of Figure 7.17 in order to observe in more details the effect of soft closing of roads on the so-rounding area

7.4 Conclusion

This chapter has confirmed that traffic information can be used as a steering tool to control certain aspects of the infrastructure. It was shown that dynamically changing the road network or the responsive traffic lights control leads to an improvement in the overall traffic performance. For this, two studies are presented.

The first study introduced an example where the traffic infrastructure is soft changing based on the current traffic state by using real-time traffic information. The intelligent infrastructure adapting to traffic situation produces a significant effect on the overall performance. First, a typical example with traffic lights systems is presented. In this case, two types of traffic lights are considered: static and dynamic traffic lights control. The static traffic lights have a pre-defined fix phase duration while the dynamic traffic lights have smarter adaptive mechanisms for reacting to the traffic situation. The experimental results show that the system's performance is affected by the level of responsiveness of the traffic lights. Dynamic traffic lights perform worse than the static ones for roads with smaller speeds limits. However, for rapid roads with high traffic intensity, the responsive traffic lights control can produce positive effects.

The second study proposed the concept of soft closing of roads, which consists of partially closing certain road segments by providing well-determined route navigation recommendation to the traffic participants. The road segments are obtained based on the simulated outcomes of systematically removing each of the links in the graph network and evaluating the system's performance. The segments, which if they are eliminated produce the best improvement in performance, are considered for the next step of partial removal. This is done by providing to the share of informed drivers routes that avoid the harmful road segments. The experiments are based on a realistic, large-scale simulation using the complete road network of Singapore city and the travel patterns. The specific details of the simulation are deferred from real world data that is also used for the calibration and validation of the model.

It is important to note that this closure is partial, as the navigation recommendations are provided to only a fraction of the traffic participants. It was shown that this strategy improves the traffic conditions by as much as 6% which corresponds to thousands of saved hours on a daily basis.

Exploring the possibilities introduced by the increasing computing power and the advancements in traffic simulations can provide valuable insights about how to design the future smart cities in general and the ITS systems in particular. Soft closing strategies are excellent examples that make use of simulations and can be easily implemented into the real world. These strategies manage to create a more intelligent redistribution of the traffic demand to avoid congestion by using information as route navigation recommendations. The main advantage is the flexibility, instant adaptation to the traffic conditions and also law costs of implementation. For designing the future traffic lights systems and for integrating them efficiently with the future ITS systems, it is necessary to consider the negative and the positive effects that the responsiveness of the infrastructure can introduce.

The two studies presented in this chapter illustrate that the real-time traffic information dissemination has a significant impact on a transportation system. For the future transportation, it is important to study further such information dissemination techniques as they can transform the previously static infrastructure into a more dynamic and efficient one. Understanding what the effect is and why it occurs can help utilizing the network infrastructure more efficiently, this way reducing the likelihood of congestion or simply bringing more comfort in the driving experience.

Chapter 8

Conclusion

8.1 Discussion and conclusions

The common belief is that ITS systems, integrating information dissemination techniques and providing the right recommendations to drivers trough their navigation devices can steer the transportation system into a more efficient operational state. Intuitively, it is expected that more the drivers using traffic information improves the system's performance. The infrastructure and the drivers, who are both participants in the data collection process and users of the recommendations, create an informational feedback loop within the information flow process of the transportation system.

However, the consequences of providing real-time navigation recommendations to a massive amount of traffic participants or a responsive infrastructure in a transportation system with informational feedback loops have not been the subject of extensive literature prior to the current thesis. Moreover, the implications of these drivers interacting with an intelligent, responsive traffic infrastructure have not been investigated in much detail by the previous literature either.

Therefore, it is necessary to understand the consequences of drivers massively using navigation guidance for their trips and also the effect of interacting with an adaptive, dynamic traffic infrastructure. Thus, by using an agent-based simulation of the infrastructure, traffic and information flow in a transportation system, this thesis investigated the following research questions:

- What is the effect of massively using real-time traffic information on a transportation system where the traffic infrastructure and the traffic participants are simultaneously sources and users of the information?
- Can the traffic information presented to traffic participants as navigation recommendations be used as a steering tool to improve the overall performance of a transportation system?

The two general research questions were further broken down into more specific topics related to what is the effect of information on a transportation system when different shares of drivers use navigation recommendations to assist their trips, what is the impact of the information content and how information can be used as a steering tool for soft changing the infrastructure. Each of these topics was addressed in more detail in individual chapters as it follows:

Chapter 5 analyzed and explained phenomena related to different shares of traffic participants receiving navigation recommendations. The experiments show that there are cases when giving routing information to a bigger share of drivers does not make a difference on the network performance and cases when it gets improved. In particular circumstances, the system performance when all participants have information is no different from, and perhaps even worse than, when no participant has access to information. When taking into account traffic light systems, in general, more drivers receiving information is beneficial for the overall traffic performance. Different shares of drivers that receive information about the traffic lights behavior produce different effects on the overall performance depending on what type of traffic light system is used (i.e. static and dynamic traffic lights control).

The focus of analysis in Chapter 6 was the information content and the specific details of the recommendations. The experimental results show that the content of the information can influence the traffic performance. The minimal amount of vehicles that need to be data sources for optimal system performance was identified. Furthermore, it was also discovered that lower precision of information presented to participants is sufficient and, in particular cases, better for the system performance. In the case of drivers massively using the navigation recommendations, inaccuracy can have a positive influence by introducing a level of stabilization. This can have significant implications on how information is processed and displayed on navigation devices.

Chapter 7 investigated the effect of information dissemination when the actions of the traffic participants temporarily change or influence a responsive infrastructure (i.e.

road segments or traffic lights systems). The results show that dynamic, adaptive traffic lights can produce positive effects for rapid roads with high traffic intensity, while in the rest of the cases static control is better. The fact that drivers massively use information about the traffic lights influences the traffic situation. Moreover, it was demonstrated that the concept of *soft closing* of roads, which refers to partially closing certain roads for a fraction of informed drivers improves the network utilization. This way, information can be used as a steering tool to turn the previously static infrastructure into a dynamically changing intelligent roads network.

This thesis contributes to the literature related to information control strategies in the context of ITS systems with informational feedback loops by providing answers to the transportation research questions mentioned above using an agent based simulation approach. This methodology applied to solving the transportation problems is commonly used in complex systems research, having numerous advantages as described in Chapter 4.

Several previous studies analized the system's performance when a fraction of commuters receive real-time information about congestion in the network and adapt their routes accordingly [20, 21, 22, 23, 24, 25]. For the case studies analyzed, the authors found out that using navigation recommendations produces an improvement on the traffic situation. Nevertheless, the current thesis showed that this improvement is influenced by the amount of drivers receiving information and that a massive usage of recommendations can be even detrimental for the overall performance.

Furthermore, the literature provided evidence for the beneficial effect of noise or errors in natural or man-made systems [120, 123, 124, 125, 126, 128, 129, 130, 132, 133]. This thesis has confirmed the existence of positive effects in transportation systems where the traffic participants receive inaccurate navigation recommendations. The reason for such a phenomenon occurring in transportation system were identified and also insights on what levels of inaccuracy are acceptable when designing future navigation devices and recommendations strategies.

The effect of a responsive traffic lights was studied in [15, 16, 17, 18, 19, 49]. However the current research investigates how the system's performance is affected by a responsive traffic lights interacting with traffic participants that use also traffic information recommendations.

Moreover, this work introduced a novel concept of *soft closing* of roads, which uses the traffic information as a steering tool to partially close certain detrimental roads. Previous work has proven that certain segments being removed from a network can produce beneficial effects on either a small network [137, 138, 140] or by coincidentally closing some roads on a city [141, 142, 143]. However, for the soft closing of roads strategy, the segments to be removed were systematically determined using traffic simulations on a city scale level. The work proposes also a strategy for soft closing of roads using route navigation recommendations that avoid the detrimental segments. This way the traffic information is used as a steering tool to redistribute the traffic flow.

The findings of this thesis are relevant in the context of ITS systems, where a major effort is invested in providing traffic information with higher precision. Governments, private companies, and academic researchers are all involved in building efficient ITS systems to provide modern transportation solutions for cities. Such systems are expected to play a key role in solving major traffic problems in cities [8, 9].

Therefore, it is useful to anticipate the impact that the massive use of real-time information can have on the traffic situation. Moreover, when building ITS systems, it is important to consider the impact that different models of information dissemination implemented in the ITS systems can have on the traffic situation.

This thesis helps improving ITS systems by offering relevant insights on how different shares of traffic participants using several types of navigation recommendations can affect the transportation systems. Also, varying levels of information inaccuracy can impact the overall traffic performance. Giving a target for improving the design of information dissemination devices and identifying the minimum amount of sensors or probe vehicles necessary to collect data that provides the best traffic performance can produce a substantial improvement for the ITS systems. Moreover, the ITS systems can be improved by designing traffic lights with the appropriate level of responsiveness or intelligent soft closing of roads strategies to efficiently redistribute the traffic load.

For planning efficient future ITS, it is necessary to consider the negative and the positive effects that real-time congestion awareness information can have. This work illustrates that the real-time information has a great impact on transportation systems. Understanding what the effect is and why it occurs can help decreasing the likelihood of congestion. Therefore it is worth exploring further details.

The current chapter summarizes the primary contributions of the thesis and thereby the conclusion and the significance of the work. These conclusions also include the observed shortcomings in the approach used for solving the research problems. With respect to these observations, future work is proposed in order to overcome the current limitations.

8.2 Shortcomings of the system

Although the studies presented in this thesis provide interesting insights regarding the information flow process in ITS systems, there are a few aspects which need further optimization. This section introduces the limitations that this research has on the basis of which the research plan for the future will be formulated.

The first contribution of the thesis is a logical framework describing the steps involved in the information flow process. This framework was useful for classifying the experimental setups based on the step where the phenomena of interest manifest. Numerous more transportation problems can be further investigated within the current framework, besides the ones presented in this thesis. For example, an investigation of the robustness of different models of information dissemination for various network topology. Both synthetic and realistic networks can be considered. Another study can investigate the effect of time delays that may occur on each of the information flow steps (i.e. in data collection, processing, or information dissemination). Moreover, the integration of a realistic behavior of the agents when receiving the information can be the subject of another study. However, for identifying and tackling a bigger range of transportation problems, the current framework can be extended by adding more details and breaking the logical flow into more intermediate steps.

The experiments presented in the current thesis use the state of the art models for traffic simulations. The experimental setups were designed to be sufficient and to capture the necessary details for the research questions investigated. Nonetheless, as a direct consequence of this methodology, a set of limitations need to be considered. For instance, the road network model has a set of simplifications. For the experimental setups using a block scale network, the roads are single lane and the topology has a simple geometric structure. The city scale network model can contain a small level of error for a few of the road segments, because of some faulty entries in the Navteq data used for the Singapore network generation. Additional data sets can be used to calibrate the model parameters, and also a more advanced preprocessing methods can be implemented. Besides Singapore, data sets for other cities can be considered.

Moreover, the constant level of congestion necessary for the controlled scenario is generated by introducing disturbances on a certain road segment. Nonetheless, congestion can be achieved in many different ways (i.e. by increasing the traffic intensity, or by adding traffic lights systems in the setup).

For the experiments using controlled scenarios, the agents are generated using a Poisson process with a particular mean inter-arrival time. Even though, in the literature is considered a traditional way of generating agents, a more realistic model can be implemented. The traffic assignment model used in the large scale scenarios is based on a time-dependent origin-destination (OD) table, matching realistic traffic patterns derived from HITS data. Even though the results look realistic (according to the validation outcome), by using additional surveys or real word data sources, the OD table can be made even more accurate and precise.

Furthermore, the experimental setups contain a series of assumptions about how the agents react when provided with routing navigation recommendations. A common assumption in all the studies is that the agents are rational, in the sense that they choose the best possible route with respect to their preferences. The agents don't have behavioral models for reacting when they are provided with navigation recommendations, meaning that they follow all the time the recommendations without cheating. Such behavioral models can be made based on survey data or using serious games to capture the player's reaction when they receive information and need to make a decision. Nonetheless, the future ITS may not relay as much on drivers' behavior when provided to route recommendations as the autonomous vehicles industry is making progress, and these vehicles may become very popular in future transportation systems [32] [33].

Another type of routing assumption was made in the soft closing of roads study where agents are assigned to the appropriate route at the beginning of their trips. This is done mainly because the computation power needed for simulation that can perform re-routing for a large city scale would be too high. However, for the experiments based on small-scale scenarios, the agents are updated with traffic information very often and they choose to follow this recommendation every time by rerouting. Future research can be done to build more realistic routing models, with an adequate re-routing parameters values. This model can account for the realistic amount of routes that remain static during trips and also for realistic dynamic rerouting.

The models of information dissemination consists of sending different recommendations to a share of randomly selected agents. It is important to note that the results show a small standard deviation of the performance indicator when the informed agents are selected randomly, which suggest that it does not make a difference what agents are chosen. Nevertheless, the fact that the agents are randomly chosen can be considered as fair action and this may lead to a better acceptance of the recommendations among drivers. However, even more, advanced information dissemination models can be implemented to target specific goals for the transportation system (i.e. in toll pricing research).

Furthermore, the current models of information dissemination contain details about *what* information is provided or to *whom*. For a new set of studies, the models can be extended to contain details about *how* the information is displayed (i.e. how frequent, how accurate or how far from a certain spot that is affected by problems). Moreover, the models of information dissemination can be extended to use more details when calculating the recommendations (i.e. about what speed the agents to use to avoid stopping at red color of the traffic lights can use information not only counting the cars that locally approach the traffic lights systems but also about cars situated further from the traffic lights system and on a larger areas on the network).

The use of traffic simulations has numerous benefits such as giving control over the environments of the experimental setup, creating scenarios that are too dangerous or don't exist in reality or even for testing different hypothesis at a lower cost. However, validating the results by performing the experiments in a holistic city scale real traffic situation can be very interesting. Confirming findings such as: only about 15% of the traffic participants need to provide data to construct an accurate state of the traffic situation, soft closing certain road segments using an information control strategy is beneficial for the overall system, testing different levels of data accuracy or the effect of traffic lights responsiveness on a city scale level. Nevertheless, it is not possible to perform some of the experiments in a city scale magnitude (i.e. providing navigation recommendations to all traffic participants).

8.3 Proposed future work

From the conclusions drawn and the observed shortcomings, the future work to improve the performance of the transportation system in certain aspects where it is currently not explored will be discussed in this section. The following are the possible areas for future research: Based on the logical framework provided by this work, new research questions can be formulated and investigated. Additional studies can examine the effect of time delays that may occur at different steps of the information flow process or the robustness of the information control strategies for various network topology.

Not only new types of research questions can be investigated in this context but also the current studies can be further extended. For instance, the small-scale block network can be extended to use more complicated network topology and more realistic travel patterns and congestion formation models. For the studies using the large scale network and realistic travel patterns from the city of Singapore, additional real-world data sets can be used to calibrate the parameters further and validate the results.

In addition, an extension of the experimental setups to cover more cities besides Singapore can be done. Moreover, the models of information dissemination can be extended to use more details and consider more vehicles when calculating the speed recommendations. Further validation of the results can be done by performing some of the experiments (where this is possible) in a real world traffic situation.

The current agent based model can be further refined and extended to integrate new models that create an even more advanced traffic simulation. This can be done by calibrating some of the parameters with additional real-world data sources. Another improvement can be achieved by integrating new models (i.e. behavioral models for agents dealing with how they decide to follow the navigation recommendations. These models can be build by using survey data or data recorded from serious games).

Since the transportation system is abstracted and modeled by an agent-based simulation, a methodology used in complex systems, the current experiments can be implemented in more fields that contain an information flow process with feedback loops. These conditions are present in complex systems such as financial markets, biological, social or technological systems.

The current thesis contributed to the body of knowledge by providing answers to several research questions related to the information flow process in ITS systems with feedback loops. One of the most noteworthy issues to consider is the proof that the way in which the traffic information is disseminated to the traffic participants influences the overall system's performance and the fact that a "smarter" transportation system does not necessarily mean a more efficient system. Therefore, the results of this research indicate that is worth exploring furthermore possible phenomena caused by the fact that a massive amount of drivers use navigation recommendations and by the fact that drivers and the infrastructure are simultaneously providers of traffic data and users of the information creating an informational feedback loop within the ITS systems. Moreover, it was demonstrated that the complexity of transportation systems can be exploited by designing efficient steering mechanisms which use the traffic information as a control tool. It is possible that a small controlled change in the systems produces a significant effect on the overall performance. Such insights are very important for building more efficient future ITS systems.

Appendix A

Appendix

A.1 Published articles used in the content of the thesis

[1] (Costache) Litescu, Sorina, Vaisagh Viswanathan, Michael Lees, Alois Knoll, and Heiko Aydt. "Information impact on transportation systems." Journal of Computational Science 9 (2015): 88-93.

[2] (Costache) Litescu, Sorina Costache, Vaisagh Viswanathan, Heiko Aydt, and Alois Knoll. "Information Dynamics in Transportation Systems with Traffic Lights Control." Procedia Computer Science 80 (2016): 2019-2029.

[3] (Costache) Litescu, Sorina Costache, Vaisagh Viswanathan, Heiko Aydt, and Alois Knoll. "The Effect of Information Uncertainty in Road Transportation Systems." Journal of Computational Science (2016).

[4] Ivanchev, Jordan, Sorina (Costache) Litescu, Daniel Zehe, Michael Lees, Heiko Aydt, and Alois Knoll."Determining the Most Harmful Roads in Search for System Optimal Routing". "Technischer."

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