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Hierarchical and Hybrid Decisional Control Architecture for Cooperative Navigation of Autonomous Vehicles in Complex Environments/Situations

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Abstract

Cooperative navigation (CN) is a frequently used technique for ensuring the effective navigation of Intelligent Vehicles (IVs). In this background, efforts to establish a Connected Autonomous Vehicles (CAVs)-based traffic control system via vehicular communications technology have accelerated in recent decades. Safe and flexible multi-vehicle coordination (MVC) technology, in particular, has attracted considerable interest for its ability to deal with complicated environments/situations. Additionally, a feasible hierarchical architecture is critical for cooperative driving with numerous control goals in autonomous vehicles. Thus, the objective of this PhD thesis is to develop reliable MVC technology (e.g., trajectory planning and decision-making for motion planning) and CAVs-based frameworks for use in complex environments/situations. To achieve this goal, this thesis first presented a safe and flexible cooperative navigation technique with risk assessment for cramped local locations (defined as single intersection/roundabout). The ε-constraint Probability Collectives (PC) algorithm, which is based on the distributed Collective Intelligence (CI) theory, is developed to offer proper solutions for cooperative driving. More precisely, IVs can compute their optimal/sub-optimal and risk-sensitive (i.e., invasive or conservative) cooperative navigation strategies base on the decentralized ε-PC framework, enabling collision-free trajectories in the decision-making level. Next, it is suggested a global supervisor responsible for scheduling and improving vehicle navigation routes while also proposing well-suited trade-offs between speed and risk to achieve the targeted tasks. To better deal with the inhere complexity of CN system in a transportation network (e.g., intersection/roundabout and the expended intersection network), the second part of the thesis addresses the potentialities of adopting Multi-layer Hybrid Control Policy and Motion Planning (MHCP-MP) framework. Given the fluctuating road traffic, it was recommended that local supervisors be in control of the urban network's intersections (tricky regions). Specifically, the local supervisor works as a mediator between the global traffic management level and the CAVs decision level, sending instructions to regulate vehicles' trajectories and improve the mobility and safety of the overall transportation system. To accomplish the aim, a Macroscopic Fundamental Diagram (MFD)-based approach in the proposed MHCP-MP framework is designed with concise urban traffic data (e.g., vehicle position, speed, etc.). Further, the Micro-Macro Flow Control (MiMaFC) strategy is proposed to demonstrate the advantages of establishing a link between the suggested local collective optimization framework and macro traffic model for improving the fluidity of the overall transportation system. Following that, the suggested intersection navigation protocols in a deep relationship with our established intelligent intersection management system are designed to permit an uncertain traffic flow. Finally, the proposed CN management architecture in this thesis has been proven in a dedicated transportation network through intensive simulation.

Keywords: Cooperative navigation, Multi-vehicle coordination, Hierarchical architecture, Risk assessment, Probability collectives, Traffic management.

Résumé

La Navigation Coopérative (NC) est une technique fréquemment utilisée pour assurer la navigation efficace des Véhicules Intelligents (VI). Dans ce contexte, les efforts visant à établir un système de contrôle du trafic basé sur les véhicules autonomes connectés (CAVs) par le biais des technologies de communication entre véhicules se sont accélérés au cours des dernières décennies. La technologie de coordination multi-véhicules (MVC) sûre et flexible a suscité, en particulier, un intérêt considérable grâce à sa capacité à gérer des environnements/situations complexes. En outre, une architecture hiérarchique faisable est essentielle pour la conduite coopérative avec de nombreux objectifs de contrôle des véhicules autonomes. Ainsi, l'objectif de cette thèse est de développer une technologie MVC fiable (e.g., la prise de décision pour la planification) et des cadres basés sur les CAVs pour une utilisation dans des environnements/situations complexes. Pour atteindre cet objectif, cette thèse présente, tout d'abord, une technique de NC sûre et flexible avec une évaluation des risques pour les emplacements locaux encombrés (définis comme une seule intersection et/ou un rond-point). L'algorithme ε-Probabilté Collective (PC) à contrainte, qui est basé sur la théorie de l'Intelligence Collective (IC) distribuée, est développé pour offrir des solutions appropriées pour la conduite coopérative. Plus précisément, les VI peuvent calculer leurs stratégies de navigation coopérative optimales/sous-optimales et sensibles au risque (invasives ou conservatrices) en se basant sur le cadre décentralisé ε-PC, ce qui garantit des trajectoires sans collision. Ensuite, nous suggérons d'utiliser un superviseur global responsable de l'ordonnancement et de l'amélioration des trajectoires de navigation des véhicules, tout en proposant des compromis adaptés entre la vitesse et le risque de la réalisation des tâches visées. Afin de mieux gérer la complexité inhérente aux systèmes NC dans un réseau de transport (e.g., les intersections/ronds-points et le réseau étendu d'intersections), la deuxième partie de la thèse aborde le potentiel de l'adoption d'une architecture de contrôle hybride multicouches et de planification du mouvement (CHM-PM). Compte tenu de la fluctuation du trafic routier, il a été recommandé que des superviseurs locaux contrôlent les intersections du réseau urbain (régions dangereuses). Plus précisément, le superviseur local joue le rôle intermédiaire entre le niveau de gestion global du trafic et le niveau de décision des CAVs, en envoyant des instructions pour réguler les trajectoires des véhicules et améliorer la mobilité et la sécurité du système de transport globale. Pour atteindre cet objectif, une approche basée sur le Diagramme Fondamental Macroscopique (DFM) dans l'architecture CHM-PM proposée est conçue avec des données de trafic urbain concises (par exemple, la position du véhicule, la vitesse, etc.). En outre, la stratégie de contrôle des flux micro-macro (MiMaFC) est proposée pour démontrer les avantages de l'établissement d'un lien entre l'architecture d'optimisation collective locale proposée et le macro modèle de trafic pour améliorer la fluidité du système de transport global. Ensuite, les protocoles suggérés de navigation aux intersections, en forte relation avec notre système de gestion intelligente des intersections, sont conçus pour permettre un flux de trafic incertain. Enfin, l'architecture de gestion des NC proposée dans cette thèse a été évaluée dans un réseau de transport par un travail de simulation intensive.

Mots-clés : Navigation coopérative, Coordination multi-véhicules, Architecture hiérarchique, Évaluation des risques, Probabilté Collective, Gestion du trafic.

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Glossary

- **AGVs:** Autonomous Guided Vehicles.
- **AHS:** Automated Highway Systems.
- **AI:** Artificial Intelligence.
- **AIM:** Autonomous Intersection Management.
- **CACC:** Cooperative Adaptive Cruise Control.
- **CAVs:** Connected Autonomous/Automated Vehicles.
- **CIC:** Cooperative Intersection Control.
- **CN:** Cooperative Navigation.
- **CVs:** Connected Vehicles.
- **FIFO:** First In First Out.
- **I2I:** Infrastructure-to-infrastructure.
- **I2V:** Infrastructure-to-vehicle.
- **ITS:** Intelligent Transportation Systems.
- **IVs:** Intelligent Vehicles.
- **MFD:** Macroscopic Fundamental Diagram.
- **MRS:** Multi-Robot System.
- **MVC:** Multi-Vehicle Coordination.
- **MVN:** Multi-Vehicle Navigation.
- **MVS:** Multi-Vehicle System.
- **NFD:** Network Fundamental Diagram.
- **PAVIN:** Plate-forme d'Auvergne pour Véhicules INtelligents.
- **PC:** Probability Collectives.
- **RL:** Reinforcement learning.
- **SPaT:** Signal Phase and Time.

- **SPR:** Shortest Path under Risk constraint.
- **TTC:** Time-To-Collision.
- **UGV:** Unmanned Ground Vehicle.
- **UTC:** Urban Traffic Control.
- **UVS:** Unmanned Vehicle System.
- **V2I:** Vehicle-to-infrastructure.
- **V2V:** Vehicle-to-vehicle.
- **V2X:** Vehicle-to-everything.
- **VIPALAB:** Véhicule Individuel Public et Autonome.

General introduction

Context of the PhD thesis

Over the last few years, the development of fully autonomous vehicles for transportation tasks has received even more attention from different laboratories/companies throughout the world [8], [71]. The focus of the proposed PhD subject is passengers' transportation in midtown or in closed/dedicated areas like inside big companies, amusement parks, airports, etc., which need autonomous shuttles between their different areas. Within the context of a complex task in such a constrained region, multi-vehicle navigation and coordination need very precise design and management of the vehicle interaction [8]. The applicative focus of the proposed PhD thesis corresponds to the field of autonomous public transportation. Nevertheless, it is important to mention that several of the targeted scientific developments and targeted experiments can be easily transferred to other economics sectors, such as agriculture or to the general domain of Industry of the future, with for instance the task of autonomous goods transportation in warehouses.

In particular, safe and accurate coordination of Multi-Robot System (MRS) is a field of research of high effervescence. Indeed, this kind of system of large potentialities makes possible to carry out for example tasks which are unfeasible for only one robot (e.g., to move a too heavy or bulky object [199]) or improve certain criteria related to the velocity, the robustness or the flexibility of the task to achieve [368]. Inspired by these scientific challenges, this PhD work deals with cooperative autonomous vehicles management and navigation in complex environments/situations (mainly in terms of cooperative scheduling, planning and control).

The proposed PhD thesis in this manuscript is done and a combined effort in two laboratories: LIMOS (https://limos.fr/) and Institut Pascal (http://www.institutpascal.uca.fr/) in Université Clermont Auvergne (UCA). The collaboration was initiated and supervised by Prof. Alain Quilliot from LIMOS/Université Clermont Auvergne (UCA) and Prof. Lounis Adouane associated with Institut Pascal from Université de Technologie de Compiègne (UTC). Both of them made equal contribution to this PhD manuscript.

LIMOS (le Laboratoire d'Informatique, de Modélisation et d'Optimisation des Systèmes) is a collaborative research unit which is focused on computer science, and more generally in information and communication sciences and technologies. The scientific mission of the author's group which named *Outils Décisionnels pour la Production et les Services* (Decision-making Tools for Production and Services, ODPS) is concerned with management of operations in modes of transport with very different characteristics (road, rail, sea, air). The lab members are also committed to process issues as network design, time planning or calculating best routes in transportation network at different time horizons (strategic, tactical, operational, real-time, etc.) [38, 47, 48, 109, 119, 386].

Institut Pascal is a multi-disciplinary laboratory including several team clusters and addressing various engineer issues relating next generation transports, hospitals and factories. The author is one of the members in the *Modélisation, Autonomie et Contrôle dans les Systèmes Complexes* (Modeling, Autonomy and Control in Complex Systems, MACCS) team. It is worth mention that the robotics application especially for ground vehicles and intelligent passenger transportation systems are gained high research interests in Institut Pascal [51, 470, 473, 474]. The research theme covers a wide variety of perspectives, for instance, robotics for agricultural applications, Lyapunov based navigation of autonomous vehicles, platooning [52, 472, 474], Bayesian reasoning for decision making [217, 218], risk assessment/management for reliable navigation [45, 46] and decentralized multi-vehicle collaboration techniques [373].

It is worth also noting that both of LIMOS and Institut Pascal are highly involved in the LABEX (Laboratory of Excellence) IMobS3 (http://www.imobs3.uca.fr/), dedicated to innovative mobility. The IMobS3 LABEX project has novel features that are of considerable implementation of sustainable mobility solutions through cooperative approaches combining various subjects. The goal of this research is to exploit a hierarchical and hybrid decisional control architecture for improving the mobility/safety of Multi-vehicle cooperative navigation in a cramped, cluttered environment.

Main objectives and Theoretical approach

Safe, efficient and flexible coordination of a group of autonomous vehicles in dynamical environments requires taking into account both inter-connected aspects: high-level (e.g., supervision for optimal progression of the mission; management of the existing interactions between the multi-vehicle systems) and low-level (e.g., control of the vehicles while taking into account their structural constraints: non-holonomy, maximum torque, avoiding encountered obstacles, etc.). The architecture of control/management that will be able to guaranty simultaneously these two aspects should be elaborated with modular and bottom-up manner (e.g., subsumption architecture like what has been introduced in [65]). The aim of following this methodology is to permit us to break the inherent complexity of the coordination of a high number of vehicles (autonomous agents) which must achieve efficiently the assigned mission. In addition, the application of the MVS is strongly influenced by many potential disturbing factors (sensor measured errors, communication congestion/packet losses, speed oscillations, etc.). The flexible and efficient strategic planning need to be properly designed so that will reduce the uncertainty and run a low navigation cost in such a multi-level configuration.

A MVS is controlled either while adopting a centralized approach (characterized by: global information on the environment, trajectories and/or missions planning, etc.) or while using a distributed approach that only uses local information of the environment. Each of these two approaches presents strong points and shortcomings. The centralized aspect of the control allows having more robust and reliable control; however, it requires quasi-complete information on the environment and on the task to achieve. Nevertheless, this is not always possible in the context of the MVS. Otherwise, it is in this context that distributed approaches take their full interest, because they only require partial information on the environment. Unfortunately, these last approaches have generally no prove on their convergence toward the global optimum that characterizes the cooperative task to achieve. However, it is possible to centralize only a part of the cooperative system to dispose the current state of the system and its short term evolution whilst preserving the decentralized part to perform cooperative navigation strategies [8, 146]. The works of this PhD thesis consists in proposing suitable control/management architecture to obtain optimal and sub-optimal balance between centralized and distributed functionalities in order to enhance the overall efficiency of the MVS. Moreover, global performance metrics of the MVS were entailed by the developed hierarchical motion planning/control architecture, which allow the improvement of traffic stream mobility for an overall transportation task.

The high-level aspect of the control concerns the management of the inter-vehicles interactions that will permits us the right cohesion and efficiency of the MVS to achieve a desired global task. For this, the wireless communication network between vehicles serves an important role. Indeed, this support of communication will permit, according to the local perception of each vehicle, to synchronize global information on the evolution of the whole MVS [339]. From this information, each vehicle will be able to tack in a distributed manner, the most suitable decision/action according to the current system configuration. Nevertheless, this requires having suitable communication protocols that will be able to adapt to the different configurations of the environment, and to the possibilities of eclipses and failings of the wireless emission-reception. It will be proposed thus, and validated during this thesis appropriate communication protocols/architecture that should be perfectly integrated into the architecture of control/management of the MVS while allowing for rapid interaction (to acknowledge time scales and purposes of the inter-vehicles) [472].

Among the important items that will be addressed in this PhD thesis, one can mention:

- *Safe and flexible cooperative navigation strategy for both optimizing progression of the collaboration task and reducing the likely risks between inter-vehicles (the main bibliographic part and contribution regarding to this aspect are given in Chapter 1 and Chapter 3 respectively).*
- *Appropriate construction of a hierarchical control architecture for the management/control of the MVS in constrained and dynamical environments (the main bibliographic part and contribution regarding to this aspect are given in Chapter 1 and Chapter 4 respectively).*
- *Global versus Local Planning-re-planning of multi-vehicle tasks and the influence of the local strategies adopted by the entities on the global evolution of the MVS (the main bibliographic part and contribution regarding to this aspect are given in Chapter 2 and Chapter 4 respectively).*
- *Eligible procedures/protocols in the proposed interaction network (the main contributions regarding this aspect are given both in Chapter 3 and Chapter 4.).*

The main topics given above are gathered to belong to the main scientific topics of this PhD thesis. We further highlighted below the main research objectives and theoretical approaches in this manuscript:

- **Safe and reliable Multi-Vehicle Coordination (MVC) and decision-making under uncertainties:** The challenge consists of guaranteeing safe and reliable navigation of a MVS at critical time to manage in-road risks [45, 218, 470]. This will make it possible to deal with the uncertainties in real-time for such a critical cooperative system according to the context of navigation. One of the aims of this

PhD thesis is to develop concepts, which should be enough generic in order to be applied for complex intersection/roundabout coordination. This could be resolved while taking inspiration from the already developed MVC techniques [470] and collective intelligence theory [261, 262, 263, 373], while having always flexible and robust collision avoidance functionalities [9] in order to manage any risky situations. It is also expected that an algorithm can guaranty the flexibility and the safety of the MVS at the time of transitions between the individual controls of each vehicle to the phase of coordinating the MVS when performing the complex maneuvers. The developed concepts/methods in this work should serve also several merged/separated platoons or single-vehicle dynamic w.r.t. the overall fluidity of traffic state. This could be resolved while taking inspiration from the already developed car-following/formation reconfiguration approach and the proposed techniques of traffic flow control [259, 472].

- **Risk management of autonomous vehicles in a transit network:** The target in this part is to deal with a group of collaborative vehicles which are required to perform transportation tasks in a transit network (see [53, 137, 269, 477]). As previously said, when autonomous vehicles are engaged, safety is a concern. Further, it is discussed in this PhD manuscript the risk management of autonomous navigation in a high level. It is preferred that the top level agent (also known as a global supervisor) in the PhD thesis can be deployed in such restricted areas for professional purposes in a foreseeable term. More precisely, the global supervisor must compute and schedule routes in such a way that not only tasks are completed quickly, but also risk can be appropriately limited. The issue can be viewed as a Shortest Path under Risk constraint (SPR) problem [137, 401]. An important challenge in the field of SPR is guaranteeing rapid traversal time while ensuring the safety of traversal of any arc at a given time in an overall transit network. As a result, a common requirement for SPR is the need of a time dependent estimation of the risk induced by the traversal strategy even in uncertain environment [401, 533]. Thus, it is proposed a middle agent (called local supervisor) to be in charge of the small tricky areas which are risk sensitive. The local supervisor acts as a mediator, sending instructions to the vehicles in order to regulate their transit and avoid the risk of traffic congestion. Nevertheless, our goal is to compute and schedule the route of MVS, in such a way that its riding time is minimized and that induced risk estimation does not exceed some threshold. Therefore, motivated by vehicle routing problems in [356] and [430], the heuristic local search algorithm was further refined in the PhD manuscript.

- **Robust and generic hierarchical and hybrid decisional control architecture:** The inherent complexity of the cooperation/coordination of the movements between autonomous entities will be addressed while deeply investigating the potentialities of multi-vehicle hierarchical and hybrid decisional control architecture [8, 469, 476] (e.g., Figure 1 for example of a decentralized hierarchical architecture). Indeed, an autonomous MVS can compute feasible trajectories in a very complex physical network and requires, in addition, accurate and safe coordination between the vehicles (to cross an intersection for instance or to take a roundabout in cramped tricky areas). Thus, to control this complexity, it is planned to implement a hierarchical supervision architecture dedicated to managing such a system. The goal in this PhD thesis is to develop a robust and generic control architecture in 3 levels (see also Figure 1). A group of accurate and reliable strategies (collision avoid-

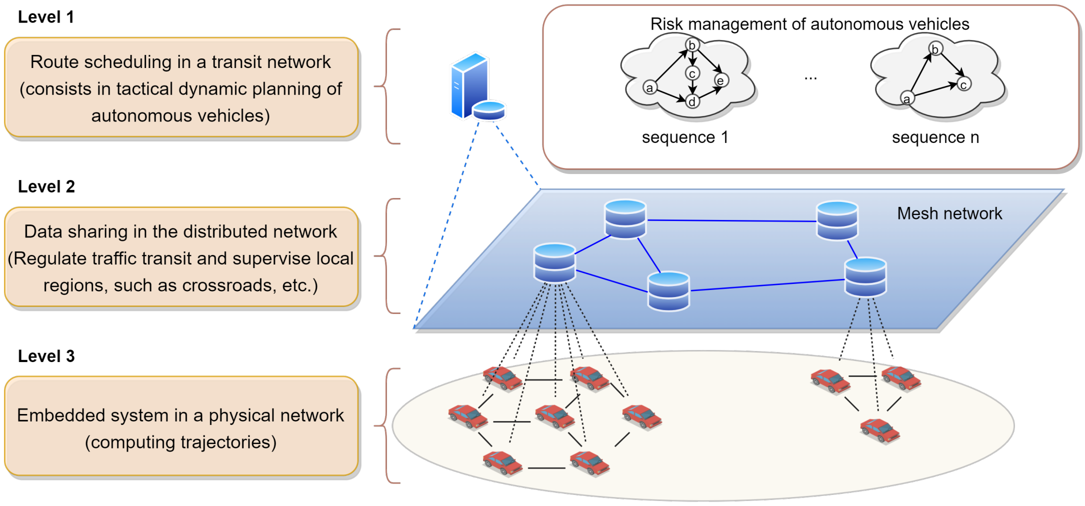


Figure 1: Multi-vehicle hierarchical and hybrid decisional control architecture.

ance [212, 264, 373], coordination and motion planning in multiple intersections [52, 470, 474], etc.) which link different traffic fundamental information (e.g., flow, density given by sensors in a mesh network) is involved for the interests of the decision-making of a MVS. An important part of the targeted work corresponds to finding the optimal/sub-optimal balance between control demands among unevenly distributed traffic demand and the control of the group of vehicles relevant for intersection crossing or roundabout navigation. Effectiveness in such a hierarchical and hybrid decisional scheme will be evaluated by safety, mobility and scalability of the MVS both in micro tricky areas and macro intersection networks.

Manuscript organization

According to the above mentioned PhD subjects, the manuscript are comprehensively divided into two parts. The outlines of the PhD manuscript is depicted in Figure 2. More precisely, the first part, which contains two chapters, targets to discuss the state of the art — in particular, the current research gap for autonomous entities cooperative motion planning and decision-making for the MVS in a complex transportation network — as follows.

- **Chapter 1 - Cooperative motion planning for autonomous vehicles**
  This chapter clarifies the main developments and control structures for MVS and makes the focus on the development of advanced cooperative motion techniques in cluttered/complex environments. More precisely, much focus has been paid on the effectiveness of the control system coping with single intersection driving strategies. The methods related to round-about and highway entrance/exit ramps are also delivered. The main challenges for multi-vehicle navigation in protected logistic regions and even urban areas are considered as well.

- **Chapter 2 - Decision-making for multi-vehicle navigation in a transportation network**

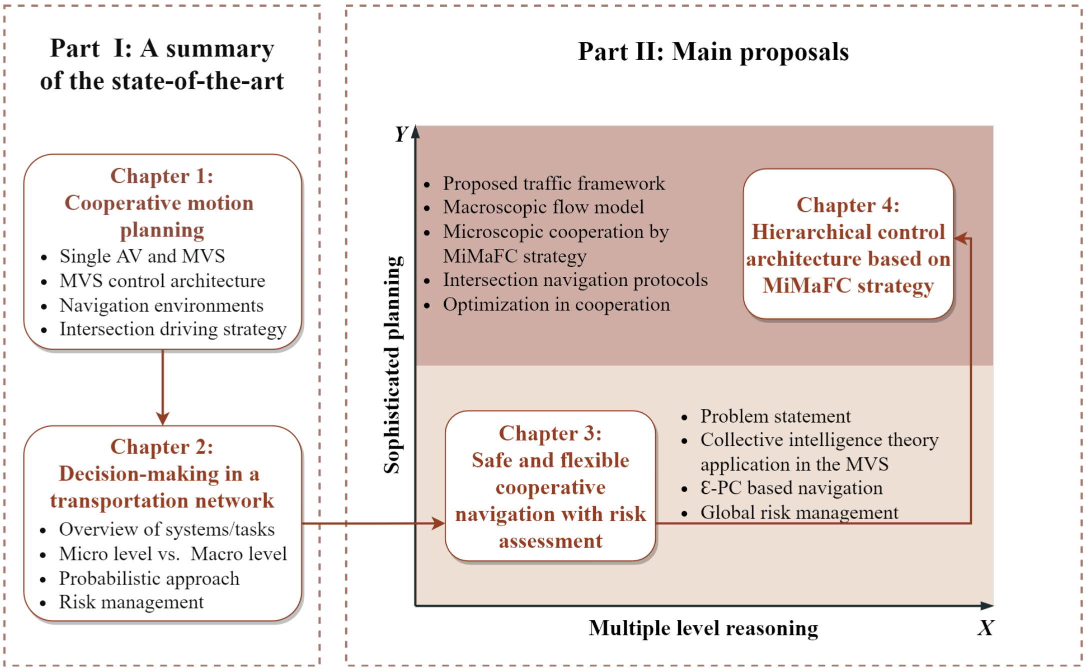


Figure 2: The outline of the PhD manuscript.

Through a broad analysis of published literature, this chapter investigates the MVS navigation management systems/tasks in a transportation network. Further, this chapter is dedicated to the related work for decision-making in multiple intersection networks. Particular attention is paid to the link between macroscopic traffic perturbation and ego-vehicle navigation strategy making based on statistic (and/or probabilistic) models. The commonly used techniques/algorithms to the fluidity of traffic in cities and the system limit of different mainstream traffic flow control models are presented. Additionally, an introduction of the promising approaches to resolve risk constraint decision-making issues in road networks is performed.

The latter part of the PhD manuscript is focused on the dissertation's main addressed approaches/proposals which can be categorized into two chapters (as can be seen also in Figure 2).

- **Chapter 3 - Safe and flexible cooperative navigation with risk assessment**
  The state of the art can lead to a conclusion that a safe and flexible cooperative navigation scheme is crucial for a MVS to deal with in-road risks. In this aim, this chapter presents the reliable single intersection crossing strategy for the proposed cooperative navigation system. Particularly, collective intelligence theory applied in the mobile system will be further explained. Next, the ε-constrained Probability Collective (PC) algorithm is used to obtain safe and flexible solutions for determining the proper intersection crossing speeds. The robustness, scalability and flexibility of the proposed algorithm will be demonstrated as well. In addition, we extend the risk management problem from a global perspective. A local search heuristic algorithm is proposed in this chapter to deal with the SPR problem in mobile systems.

- **Chapter 4 - Proposed hierarchical traffic management architecture based on**

Micro-Macro Flow Control (MiMaFC) strategy in traffic network
This chapter considers the problem of multi-vehicle cooperative navigation within the hierarchical control architecture. The main ideas in this chapter are: to extend the addressed algorithm in Chapter 3 while enabling its functionalities (e.g., collision-free, mobility, risk management) in the scaled network; to explore the influence of high traffic density that induces the decrease of the flow, or to show thus the limit of the system, which will validate at the same time the macroscopic flow modeling of the system; further, to demonstrate the advantages of establishing a link between the suggested local collective optimization and the macro model (i.e., the Micro-Macro Flow Control strategy: MiMaFC in micro model). Following that, it is proposed intersection navigation protocols in a deep relationship to our established intersection crossing methods. Finally, based on the proposed MiMaFC technique, the optimization procedures are integrated into the entire traffic navigation scheme for MVS. The suggested cooperative navigation management architecture is illustrated through a multitude and various simulation results in dedicated traffic networks.

General conclusion and main contributions in the PhD thesis are summarized at the end of the manuscript as well as several PhD prospects.

I

Context and state of the art

1

COOPERATIVE MOTION PLANNING FOR MULTI-VEHICLE NAVIGATION

This chapter is dedicated to introduce the development and control structures of MVS. The main focus will be paid on the cooperative technologies for a group of autonomous vehicles in cluttered environments. The multi-vehicle navigation scenarios are introduced in detail. The important characteristics/requirements for collaborated vehicles operating in various environments are underlined even further. We also bring up the issue of intersection motion planning. The related reactive/cognitive strategies to crossing an intersection are discussed by comparing to current scientific literature. Finally, the major challenges of multi-vehicle navigation in urban areas are summarized.

1.1/ INTRODUCTION

Over the past few decades, advanced technologies for Intelligent Vehicles (IVs) have gained considerable attention in research communities, industry managers and regulators. IVs provide with an ability to assist humans in achieving a higher level of maneuverability [21], [131]. Nevertheless, determining what the new generation of autonomous/semi-autonomous vehicles can exactly perform remains a critical topic. The idea to validate Artificial Intelligence (AI) techniques in autonomous vehicles system is also one of the most promising directions to develop intelligent driving. However, in order to successfully implement public transportation service with a sophisticated IVs system, other relevant automotive sector fields must also undergo adjustments and development (e.g., automotive design, advanced electronic and electrical products and policy setting). In densely populated metropolitan areas, the public's trust in such vehicles driving without external guidance remains low. Therefore, autonomous vehicles are identified currently at the "rock bottom" of the hype cycle from a perspective of the commercial institutions, as seen in Figure 1.1.

Instead, semi-autonomous or fully-autonomous vehicles are more likely to be restricted in the protected area in the near future, which includes professional purposes and/or dedicated operational conditions. In terms of the taxonomy of vehicles, SAE INTERNATIONAL's Standard J3016202104 provides six levels of driving automation [98], ranging from no driving automation (Level 0) to full driving automation (Level 5). Vehicles with Levels 3 (conditional driving automation) and 4 (high driving automation), in particular, still require a human driver in a supervisory capacity who is prepared to retake control in

Figure 1.1: 2021 Gartner hyper cycle for Artificial Intelligence (AI) [151]: Autonomous Vehicles at the "rock bottom" before entering the plateau of productivity.

certain situations. Additionally, each Level 3 and Level 4 vehicle will have its own Operational Design Domain (ODD)[1] [98, 144, 401] (see Figure 1.2). Consequently, autonomous vehicles are favored to travel freely inside some limited locations, such as vast parking lots, and to execute rural or urban logistics in lieu of the overly constricted Autonomous Guided Vehicles (AGVs) (tied to any kind of cable/rail track) deployed in warehouses or industrial structures.

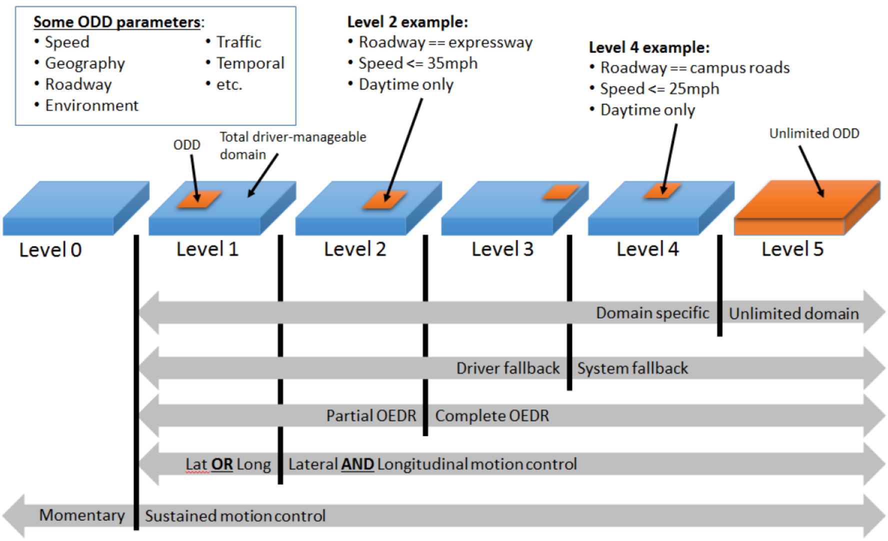


Figure 1.2: Operational Design Domain (ODD) relative to driving automation [98].

[1] "Operating conditions under which a given driving automation system or feature thereof is specifically designed to function, including, but not limited to, environmental, geographical and time-of-day restrictions, and/or the requisite presence or absence of certain traffic or roadway characteristics." ([98], Page 17)

Under this circumstance, one of the critical scientific issues for intelligent vehicles will be to govern and maintain a collection of autonomous vehicles that must accomplish navigation duties while safely engaging with collaborators in dynamic environments. The focus of the associated problem will be on using related decision approaches linked to MRS and Operational Research to satisfy the industrial and/or public transportation needs.

In this section, the essential characteristics of intelligent mobile robots and the transition process to build a multi-vehicle system will be discussed. In addition, different cooperative navigation control structures are evaluated in order to determine the most efficient and safe way to handle such a complicated system. The high-level automated vehicles that cooperative driving in common-yet-difficult conditions are then investigated further.

1.1.1/ From single-vehicle intelligence to multi-vehicle collaboration

One of the goals of an intelligent unmanned system is to expand human geographical reach while decreasing risk of collision. The majority of robotic mobile systems are required to do jobs that are repetitive, unpleasant or dangerous [139]. In general, autonomous and Unmanned Vehicle System (UVS) may be described and categorized according to their operating environments (land, sea and air) with the most representative being [8]: Autonomous Underwater Vehicles (AUVs), Unmanned Surface Vehicles(USVs), Unmanned Maritime Vehicles (UMV)[1], Unmanned(or Uninhabited) Aerial Vehicles (UAVs) and Unmanned Ground Vehicles (UGVs)[2]. Moreover, UGVs may move using various devices, like legs, wheels or specialized mobile robot wheels for planetary exploration (for more details, see chapter 1 in [8]). In particularly, the problems and primary works in this PhD manuscript are interpreted mainly in terms of UGVs with wheels. Apart from the application scenarios, a sophisticated UVS system must meet the following generic demands/requirements [139, 147, 349]:

- Persistence, low cost, stealth, and ready deploy/retrieve-ability;
- The capacity to detect, locate, track, identify and engage targets autonomously;
- The ability to gather, disseminate and act on several types of information;
- That they are networked together and to the high-value, manned assets;
- That the individual platform and sensor elements can be self-organized;
- That they do not impose significant risk or burden upon the operators.

UGVs are also known as mobile robots in the research community, which differs from traditional robotics (oriented to the control of industrial manipulators [147]). More specifically, mobile robots are preferred to deal with problem related to path planning, obstacle avoidance, and perceptual control. The involved navigation tasks/control issues in the application domain of UGVs can be categorized, for instance, in terms of surveillance

[1] Unmanned Maritime Vehicles (UMV) are “Comprising Unmanned Underwater Vehicles (UUVs) and Unmanned Surface Vehicles (USVs).” ([139], Page 2)

[2] “An Unmanned Ground Vehicle (UGV) is any piece of mechanized equipment that moves across the surface of the ground and serves as a means of carrying or transporting something, but explicitly does not carry a human being.” ([147], Page 1)

[63, 350, 528], visual navigation [227] [267], human search and rescue (disaster robotics) [237] [343], solar tracking [15] [185], military [390], precision agriculture/farming [384] [385], service robotics [108, 173, 370] or transportation/automated guided [36, 436, 470]. Nevertheless, it is worth mention that UGVs can also deal with tasks incorporating both mobility and manipulation as seen in NASA's space robotics project: Robonaut [22], Regolith Advanced Surface Systems Operations Robot (RASSOR) Excavator [340], Curiosity (mars rover) [411] and Valkeyrie (robot) [387]. Despite the fact that the generated UGVs control method/concepts might be applied to the various tasks/domains listed above, the transportation domain (both for passengers and for products) remains our primary focus.

Indeed, one of the most important areas of UGVs research is intelligent vehicles (also known as self-driving cars, autonomous vehicles, driver-less car or robotic car) for public/private transit. The deployment of a fully (SAE Level 5) or semi-autonomous system (SAE Level 3/Level 4) in the surface transportation system have drawn much attendance/efforts from government institutions, universities, commercial Big Tech companies and car manufacturers. The early research efforts for developing intelligent vehicles are referred to the numerous interesting publications in the literature [8, 143, 297, 443, 456, 474, 478, 489]. In this PhD manuscript, a short view of autonomous vehicle development is presented in a timeline covering the recent two decades (as seen in Figure 1.3) and thereby follows a brief summary.

In the 2000s, large-scale self-driving activities fueled the development of intelligent vehicle technology. The DARPA (Defense Advanced Research Projects Agency) Grand Challenge [68], which was held in 2004, 2005 and 2007, had a significant impact on future self-driving automobile development. Further, other autonomous vehicle events, such as the European Land Robot Trial (ELROB) [407], Intelligent Vehicle Future Challenge (IVFC) [503], and SparkFun Autonomous Vehicle Competition (AVC) [120], were held on a yearly basis in the last two decades. Moreover, the early development of self-driving testing datasets (for object detection and recognition) was founded mostly for individual naturalistic driving data. See the 100-Car Naturalistic Driving Studying [254], Strategic Highway Research Program 2 (SHRP 2) [60] and European Field Operational Test (EuroFOT) [50] for instance. Google's self-driving project which is the best-known as Waymo later [303] was performed initially in 2009.

From the 2010s till now (2021), single intelligent vehicles' technologies were in a new age of rapid progress. The startup technology companies supported by/combined with academia aimed to develop their own self-driving vehicles. We don't aim to exhaust all the lists of technology companies developing self-driving cars. One can find the most notable examples in the Figure 1.3 (like: Transdev, Lyft, Cruise, Zoox, NAVYA, Uber, Argo AI, AutoX, Pony.ai, JD, Aurora, Zenuity, Aptiv and Didi among others). Particularly, the aforementioned technology companies, hardware developers and research institutes have released advanced simulation tools (e.g., Gazebo [256], TORCS [500], CARLA [115] and others) as well as self-driving frameworks (e.g., Autoware [242], Nvidia DriveWorks [361], openpilot [97] and Apollo [128], etc.), which are very useful for developing intelligent vehicles. Furthermore, various training datasets have been utilized to improve computer vision technology in self-driving cars, due to the application of machine learning to large-scale data. This study also list the most remarkable ones as: ImageNet [110], KITTI Vision Benchmark [157], MS COCO [294], Oxford RobotCar [313], DAVIS Driving Dataset (DDD17) [59], CommonRoad [20], LiDAR-Video Driving Dataset (LiVi-Set) [89], ApolloScape [211], UC Berkeley DeepDrive (BDD) [523], nuScenes datasets [73] and

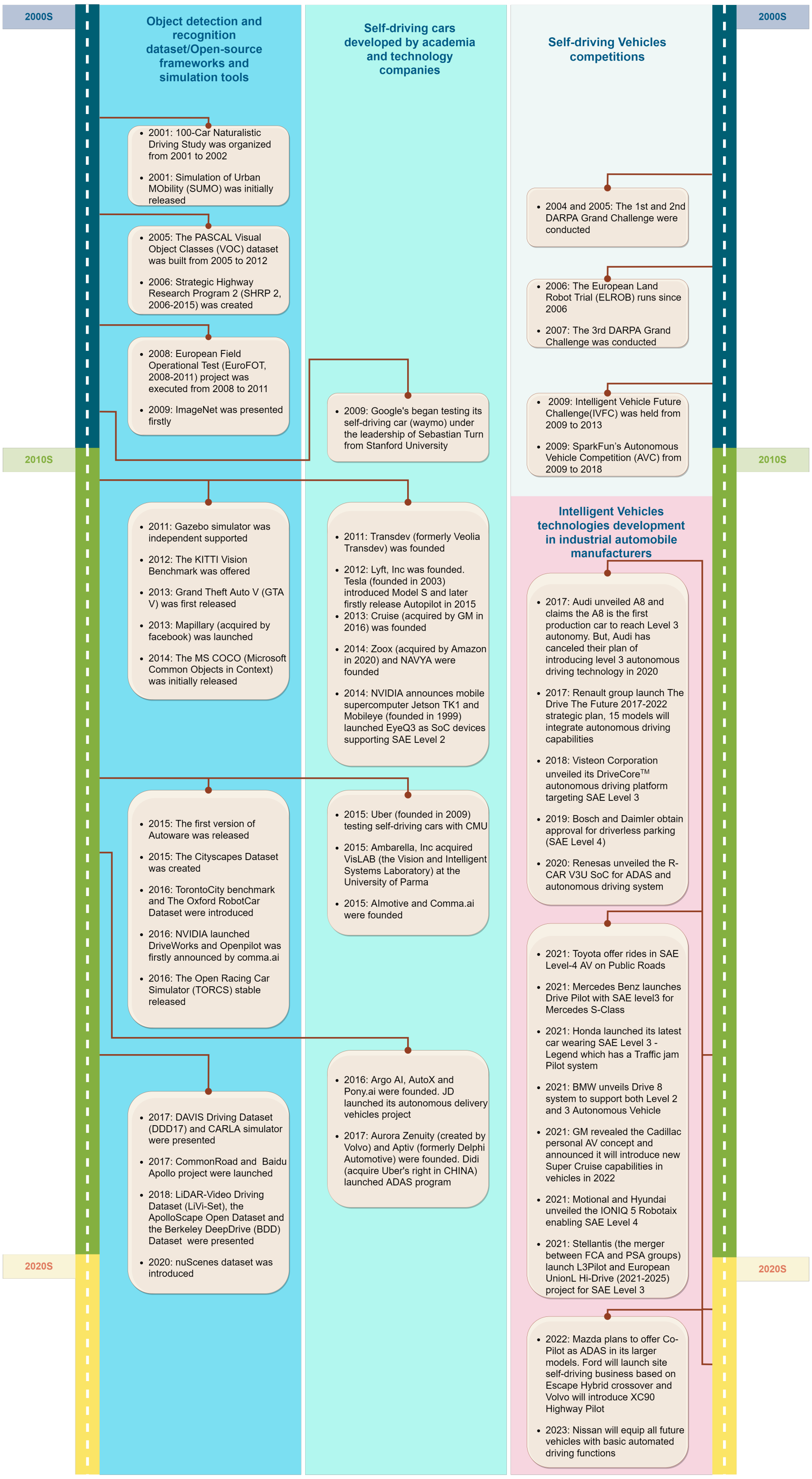


Figure 1.3: A brief view of autonomous vehicle development in the last two decades.

others. Traditional vehicle manufacturers, on the other hand, further unveiled their new-generation private sedans claiming to enable SAE Level 2 to 4. However, because of the ambiguous policy obligations for self-driving car accidents, automobile manufacturers have had to abandon or postpone their plans to provide customers with full autonomous driving technology on roads. More information on Audi, Renault, Toyota, Mercedes Benz, Honda, BMW, and General Motors, among other companies, can be also found in Figure 1.3. For further information on the development of single-vehicle intelligence, interested readers are referred to [37, 170, 371, 409, 512, 526].

A natural extension of a single intelligent vehicle is to deal with Multiple intelligent Vehicle System (still referred MVS). Recall MRS as a reference. Due to the enhancement of the dynamic interaction between robots, controlling MRS rather than a single robot significantly increases the control complexity: for instance, the amount of control variables and sub-objectives to investigate/achieve; the uncertainty associated with observing/localizing/communicating with a collection of robots [8]. The primary benefit of MRS is that it enables the completion of complicated tasks that are either too demanding for a single robot or are intrinsically distributed [26, 75, 369, 452]. Additionally, constructing several resource-constrained robots is less complicated than developing a single powerful robot [265, 325, 400]. A common categorization strategy for cooperative robotic systems is based on information exchange, which is separated into *collective swarm systems* and *intentionally cooperative systems* [420] (see Figure 1.4 for instance). In collective swarm systems, cooperative robots only interact locally to complete self-assigned tasks. Typical applications include cooperative exploration robots [276, 357] (Figure 1.4a), entertainment robots [17], localization & mapping robots [72, 279, 402] (Figure 1.4c) and warehouse robots [311, 378] (Figure 1.4f). In intentionally cooperative systems, all system agents have complete knowledge about the same aim to co-manipulate or co-transport objects [8, 134] (Figure 1.4d,1.4e). Some examples can be found in co-manipulation robots [201], load transport robots [154] and construction robots [298, 487]. Since its fast growth in the 1970s and 1980s, MRS in the form of mobile robots has been extensively utilized and tested by a variety of research goals, tasks and projects. MRS technology was encouraged in physical cooperative vehicles in the 1990s by information technology and vision-based control. A brief history of the MRS may be found in [474].

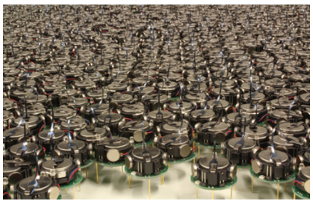
MVS is supposed to engage in cooperative navigation tasks [481], sharing certain characteristics and benefits such as MRS. As indicated before, this PhD thesis focuses on cooperative navigation for public transit. Thus, Connected Autonomous/Automated Vehicles (CAVs), which have shown immense promise as a component of future transportation systems [78, 145, 424], will be further discussed in the latter of the section. Noting that the proposed MVS makes the assumption that connection is always available, either locally or globally. As a result, we made no clear distinction between MVS and CAVs.

Similar to MRS, CAVs provide appealing benefits in terms of operating in resource-constrained environments, resolving problems concurrently, considerably reducing accidents and related costs [363, 475]. Vehicle connectivity is a new technology that enables Vehicle-to-infrastructure (V2I)/Infrastructure-to-vehicle (I2V), Vehicle-to-vehicle (V2V) and Vehicle-to-everything (V2X) communications [61, 312]. Vehicles equipped with interactive Advanced Driver Assistance Systems (ADASs) and cooperative Intelligent Transportation Systems (C-ITSs) are typically considered to be “connected” [455]. Car connection may give both the regular vehicle and the autonomous vehicle with new information and services. CAVs are capable of receiving information from V2X outside the field of vision and negotiating with other road users. Thus, CAVs may outperform the single intelligent vehicle not just in terms of safety and performance, but also in terms of traffic throughput and fuel efficiency via global route planning and cooperative driving [124]. In addition, CAVs cooperating with other road users can be classified into two types: information-based and maneuver-based cooperation [70]. In information-based cooperation, such as Cooperative Adaptive Cruise Control (CACC) [250, 286, 296] and cooperative perception/prediction [252, 253], agents communicate their own knowledge (e.g., system states, sensor data and intention) with one another, and they use the received information to maximize their own utility [62]. In maneuver-based cooperation, vehicles get sensor data, intentions or intended trajectory from other CAVs and use planning to maximize an estimated/negotiated total utility [70]. The following are the empirical applications and research works for using CAVs in both motorways and urban environments (as seen in Figure 1.5): telematics applications/devices plugged in CAVs (including Vehicle-to-broadband, telemetry services, etc.) [421]; fleet/convoy management [392, 474] (Figure 1.5a); Electronic Toll Collection (ETC) system with CAVs [95, 274] (Figure 1.5b); HD map data collection by CAVs [40, 258] (Figure 1.5c). It is difficult to test most CAVs technology on public highways, and there is a lack of experimental validation in real-world conditions [181]. Therefore, several programs based on CAVs have been established by governments or national organizations. The following highlight several interesting examples of CAVs projects around the world:

- **PATH:** Caltrans and the University of California jointly created the PATH program in more than two decades to guide the implementation of CAVs in California [417]. The PATH initiative focused on difficulties associated with navigation, automation and electrification in increasingly sophisticated traffic management systems. In 1997, the PATH project showed platoon driving and safe operations such as lane changes using numerous autos (Honda-PATH vehicles) [389, 437]. In 2011, as part of the PATH project, a platoon of autonomous trucks was driven [55, 220]. Additionally, PATH has developed a CACC system for platooning heavy trucks in partnership with the Volvo company since 2015 [221] (Figure 1.5d).

- **Google's self-driving car:** Google's CAVs have tested more than 3.5 million au-

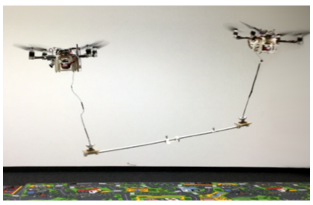
(a) Mars exploration robotics [357].



(b) A swarm of 1024 Kilobot [400].

(c) Localization robots [431].

(d) Co-manipulate robots [201] .



(e) Load and co-transport robots [154].

(f) Warehouse robots [320].

Figure 1.4: Examples of common multi-robot systems.

tonomous miles (5.63 million kilometers) since 2009 [25]. In 2012, Google demonstrated a fleet of seven automated Toyota Priuses that traveled more than 140 thousand miles (225 thousand kilometers) in California [29, 492]. The vehicle uses data from Google Street View in combination with perceptive information to determine its location and ensure safe operation in urban environments [29, 492]. In 2017, Google invested 1 billion USD in Lyft to support Waymo's Robo-taxi fleet [257] (Figure 1.5e).

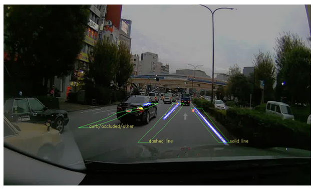
- **Energy-ITS:** Since 2008, the Japanese Ministry of Economy, Trade, and Industry has been administering the Energy-ITS program [450]. The project's objective is to save energy and avert global warming via autonomous driving. On a test vehicle, a platoon of three completely automated heavy trucks and one fully automated light truck traveled at 80 kilometers per hour with a distance of up to 4.7 meters [450] (Figure 1.5f). The lateral control was based on computer vision-based lane marker identification, while the longitudinal control was based on gap measurement using radar and LIDAR with Dedicated Short Range Communication (DSRC) and infrared inter-vehicle communications. Additionally, this research included testing on four big vehicles equipped with Cooperative Adaptive Cruise Control (CACC) [450].

- **Demo 2000:** In November 2000, "Demo 2000 Cooperative Driving" was performed with five autonomous cars to demonstrate the technology's viability and promise [243]. The vehicle uses RTK-GPS for localisation and is equipped with a laser radar, an inter-vehicle communication unit, and onboard displays to allow passengers to locate nearby cars and obstacles. On a test track, the five autonomous vehicles demonstrated scenarios such as stop-and-go, platooning, lane changing, passing and merging at speeds of $40 \sim 60$ kilometers per hour [451].

- **SARTRE:** The SARTRE program (SAfe Road TRains for the Environment) [79] evaluated platooning (Volvo vehicles and trucks) in public traffic conditions by using CACC, which has the potential to enhance traffic flow and safety. From September 2009 to September 2012, the European Commission supported this project [80, 105].

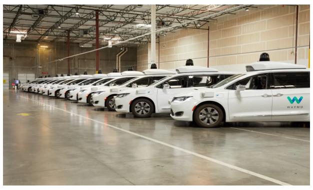
(a) Convoy of VIPLAB vehicles [474].

(b) Electronic toll collection (ETC) [442].



(c) Building HD maps [449].

(d) Heavy trucks with CACC [221].



(e) Robo-taxi fleet [192].

(f) Automated truck platoon [450].

Figure 1.5: Application of Connected Autonomous/Automated Vehicles.

- **GCDC:** The Grand Cooperative Driving Challenge (GCDC) was an international competition in which teams from universities and industry competed to maily test CACC (as seen in Netherlands' GCDC in 2011) [376]. CACC performance was evaluated using a number of parameters, including platoon gap, travel time, platoon merging behavior and damping behavior during rapid acceleration/deceleration [156]. In 2016, the Netherlands hosted another GCDC challenge aimed at achieving cooperative merging and intersection management [375].

- **SAE:** SAE International has established many standards for Dedicated Short Range Communication (DSRC) application layers, including SAE J2735 [222], SAE J2945 [223] and SAE J3067 [224]. The FCC reallocated all of DSRC's spectrum to other purposes (i.e., Wi-Fi and cellular V2X) in November 2020 [491]. In the same year, SAE introduced a revised standard for V2X communication [225].

Although decades of research and development have gone into CAVs systems, a great deal of technology has the potential to benefit road users. CAVs/MVS are still confronted with a slew of challenges as follows [124, 181, 317, 474]:

- **Accurate perception/location data:** Perception errors may be exacerbated in CAVs. A data association mechanism that is efficient for a variety of vehicle and sensor designs is required. The performance of cooperative perception is highly dependent on the accuracy of relative localisation. However, relative localisation accuracy may be limited in particular circumstances.

- **Real-time coordination:** In multi-agent situations characterized by dynamic environments, cooperative motion planning for a new maneuver frequently becomes a matter of system safety. This type of planning is highly dependent on on-board algorithms and is quite sensitive to nearby traffic. As a result, real-time coordination is required for the on-board controller.

- **Communication:** Unified communication topologies and protocols for deploying cooperative CAVs systems are lacking. A reliable control approach is required to handle communication delays, packet loss, error messages and uncooperative agents. Additionally, transmission latency and bandwidth constraints may decrease cooperative perception's efficiency. The trade-off between communication bandwidth and closed-loop performance has received less attention.

- **Accurate forecasts:** Due to the absence of an integrated CAVs control architecture that enables access to more precise forecasts, the majority of existing approaches rely only on static route data (such as road grade and speed limits). Nevertheless, CAVs prospects are often associated with improved forecasts for data and remote computations, which are highlighted as the primary technological difficulties.

- **Real-world verification** The majority of CAVs technology (e.g., CACC) has been undertaken in controlled environments, difficult to know its efficacy. Current verification issues for CAVs' advanced algorithms include real-world testing and application to non-highway scenarios.

Indeed, CAVs can eliminate (or significantly reduce) unexpected human factors and gain awareness of their surroundings via perception sensors and communication. There are numerous scenarios where V2X communication provide a significant advantages. However, CAVs running on public roads that take advantage of this benefit remain need to be fully explored and exploited. Control of CAVs system should also take into consideration the partial or total system state, rather than relying just on the perception or aims of a single intelligent vehicle [8]. One of the primary issues for CAVs cooperative navigation is developing an effective control strategy that enables all vehicles in the CAVs system to establish coherent and efficient configurations to accomplish the desired tasks. In fact, with vehicle communication, CAVs may exchange their perceptive data and current condition with other road users (for example, intended acceleration, actual acceleration or velocity) [181]. As a result, control structures for processing system information have become critical for implementing such networking technologies efficiently. An overview of CAVs/MVS control architecture will be discussed in the next section.

1.1.2/ Overview of multi-vehicle control architectures

As seen in Figure 1.6, the MVS is comprised of multiple modules deployed in each connected vehicle. More specifically, multi-vehicle control architectures addressed here refer to the system architectures that operate the communication, perception, localization and planning modules (see also in Figure 1.6). Numerous control architectures for MVS are described in the literature [10, 124, 200, 307, 471, 481]. Clearly, exhaustively classifying the control structures of MVS would not be the primary objective in this PhD thesis. Nevertheless, one of the critical concerns to address before developing the multi-vehicle control architectures is whether to use centralized or decentralized control over vehicles [8, 396]. This section will further evaluate the centralized vs. decentralized management of MVS.

1.1.2.1/ Centralized architectures

The MVS architecture is said to be centralized when a part of all the sensory and/or decisional loops of each vehicle entity is delocalized from its physical structure and governed by a central unit (referred to as a supervisor or central planner) [236, 359]. The primary benefit of this architecture is that a central unit can make decisions based on global knowledge, which is often superior than an agent making decisions based on local information

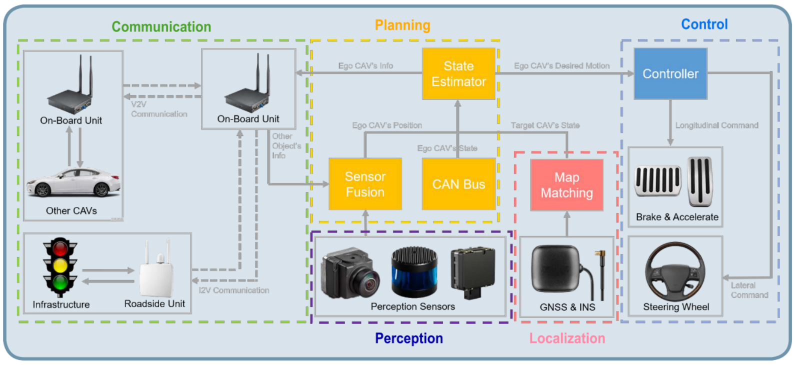


Figure 1.6: General architecture of a MVS with communication, perception, localization, planning and control modules [481].

[249]. Thus, centralized systems often need a large amount of computing power to analyze massive data through extensive communication [249, 527]. Such architecture lacks robustness as a result of its deep reliance on the central unit.

In terms of implementation, the targeted communication modules, perception/localization modules and motion modules may all be handled by centralized architecture in the fields of information flow topology design [543], sensor fusion approach [180, 490], and cooperative planning [396]. A centralized control method for MVS is explored in [86], with the purpose of minimizing a cost function that incorporates MVS safety, efficiency and ride comfort. Noting that centralized planning, based on V2V and V2I communication, may give a dependable solution that is fully aware of the states and intents of other cars. The sophisticated 5G technology standard is gaining popularity as a centralized method of V2V and V2I communication. However, its longer end-to-end latency (which may be much longer during handovers) prohibits its use in vehicle safety [312]. Numerous MVS and mathematical optimization techniques are used to address the problem of centralized planning, as described in V2V and V2I [85, 113, 126, 358]. However, V2V and V2I are not yet widely used. As a consequence, centralized planning will be difficult to implement in the near future.

1.1.2.2/ Decentralized architectures

In contrast, in the decentralized (distributed) control architecture, each on-board module (see Figure 1.6) has its own perception, localization and decision-making (planning) process among a group of vehicles [8]. Due to the fact that MVS can always conduct control on their own without receiving extra commands from outside, the benefits of this decentralized design allow robustness to system defects and failures. Additionally, decentralized control enables the parallel solutions, hence ensuring the implementation's dependability and scalability [75, 130, 138, 393]. The disadvantages of such a decentralized management need a high degree of coordination, since the given tasks of each vehicle are incorporated in the local control, and if the assigned work changes, global reconfiguration of the MVS tasks without a supervisor may be problematic.

Decentralized (distributed) control may also be used to MVS in terms of communication technology [5, 289], perception technique (decentralized fusion [180, 490]), and cooperative motion planning [396]. The research in [318] established a decentralized theoretical framework for MVS coordination. Thought has been paid to rear-end, speed-dependent safety constraints. Additionally, as compared to cellular networks such as 5G, DSRC is preferable for road safety driving because to its decentralized nature and low latency for end-to-end transmission [418]. Since maximizing the flexibility and autonomy of controlled MVS is often preferred. Some of the above-mentioned literature extensively researches decentralized multi-vehicle control systems in complex environments or situations (mainly in terms of cooperative scheduling, planning and control in industry, warehouses, hospital and urban backgrounds, etc.).

1.1.2.3/ Other architectures

Other studies with similar discussion in various control approach/architecture might also be discovered in [84, 162, 231, 379, 515, 546]. We highlight several kinds of notable control architectures as follows:

- **Hierarchical architecture:** In a global sense, this architecture is decentralized control, but it is centralized at the local level [326, 354]. More specifically, the vehicle conducts its assigned responsibilities independently while update a central planner on the status of those activities. The great majority of MVS are structured hierarchically [164, 241]. The idea is that every large-scale system's control is structured in a dispersed hierarchy [465]. With this approach, a large design challenge is partitioned into a number of smaller, more manageable sub-problems that are handled in distinct layers. Since MVS tasks become more and more complicated, it is preferable to have hierarchical architecture that can capture the complicated interactions.

- **Hybrid Centralized/Decentralized architecture:** This architecture integrates a high-level controller (centralized planner) with the local control (decentralized executor) in individual vehicles [359, 420, 474]. As a consequence, the primary advantages of this designs include: the centralized planner which can act as a high-level control over the autonomous vehicles; the decentralized executor's fault tolerance; the flexibility to reschedule the global task/control based on both (centralized/decentralized) control. As shown in [422], researchers use this architecture to conduct a high-precision docking task. In addition to vehicle navigation in formation, centralized/decentralized architecture was successfully used in [474].

Roughly, the possibility also exists to centralize only a part of the control and let the other part be decentralized (hybrid centralized/decentralized control) [146]. For example, hybrid fusion is common in CAVs systems. The Global Navigation Satellite System (GNSS) information from centralized planner is unreliable while the ego-CAV is under tunnels or bridges. So, in addition to the on-board Inertial Navigation System (INS), the CAVs location may be enhanced by incorporating perception sensor data coupled with a reference map [481]. Noting that the addressed multi-vehicle control structure must manage data from several devices, the primary challenge is to use data from the communication/perception module to complete navigation tasks in complicated environments/situations through information-based or maneuver-based cooperation (e.g., vehicle classification, vehicle tracking, lane detection [549] and cooperative navigation [124]). The primary focus of this PhD thesis is to develop a control architecture for maneuver-based collaboration that is compatible with the individual planning module of the targeted MVS. While decentralized control is always favored in our proposed control architecture for MVS, global knowledge obtained by a central planner can be used to enhance MVS control in certain scenarios (or tasks). We will further specify the research problem in the following section on exploring MVS navigation environments and situations. Notably, in the rest of the manuscript, when we mention MVS, we also refer to CAVs, since both of them perform cooperative navigation tasks and make the assumption that connectivity is always available, either locally or globally.

1.1.3/ Multi-vehicle navigation in complex environment/situations

According to literature reviews, MVS (or CAVs) coordination issues that emerge in rural and urban areas include motorway/highway speed coordination, merging at on-ramp and coordination at signalized/autonomous intersections [56, 181, 481]. Figure 1.7 depicts a visual categorization of these MVS application scenarios. Additionally, MVS platooning technology, which has a significant impact on road capacity [23, 539], has garnered considerable attention during the last decades. Moreover, the majority of the fundamental

(a) Rural freeway.

(b) Highway on-ramp.

(c) Principle/minor arterial.

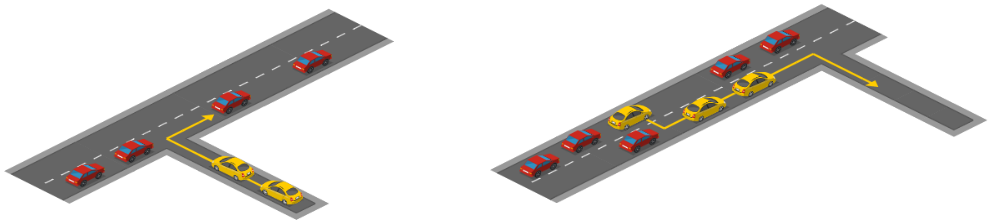
(d) Urban core/intersection area.

Figure 1.7: A classification of MVS coordination scenarios from both rural and urban areas (cite from https://www.freepik.com/).

research efforts have been devoted at MVS highway speed harmonization [197, 365], which has the potential to lower overall trip time and average energy consumption [479]. Readers interested in MVS freeway longitudinal motion control (mainly in terms of platooning and speed harmonization) may read [181, 204, 248, 481]. It should be noted that lateral maneuvers (mostly seen on principle/minor arterial, see Figure 1.7c) such as maintaining or changing lanes are not considered in this manuscript. This section will examine multi-vehicle navigation in complex environment/situations such as highway entrance/exit ramps and intersections/roundabouts.

1.1.3.1/ Highway entrance/exit ramps

Indeed, to avoid lateral collision, highway entrance/exit ramps (as seen in Figure 1.8) create issues about safety and mobility for MVS coordination. An overview of studies on highway on-ramp can be found in [396, 404, 541]. Ramp metering, for example, is a common use for highway traffic management that is mostly done using traffic lights positioned at highway entrances [366]. In contrast, the challenge of seamlessly merging or crossing two streams of vehicles without causing stop-and-go driving is similar to the problem of speed harmonization. Under this situation, vehicles on the mainline may decide to accelerate or decelerate in order to enable the merging of vehicles on the other lane, altering overall traffic flow [332]. Similarly, it has been shown that saturated exit ramp (also known as off-ramp) attract a lot of attention to creating effective traffic management to prevent the off-ramp queue spill back into the freeway [230, 342, 427]. The primary idea of generating gaps by deceleration and lane changes may also be used nearby off-ramp (at a diverging bottleneck area). However, when implemented on off-ramp, the MVS cooperative technique is primarily developed by automation and connection technology that use lane change tactics [544]. As a result, in the following text, the multi-vehicle navigation approach will be analyzed in more details in terms of entrance ramp for merging.



(a) Highway entrance ramp (on-ramp).

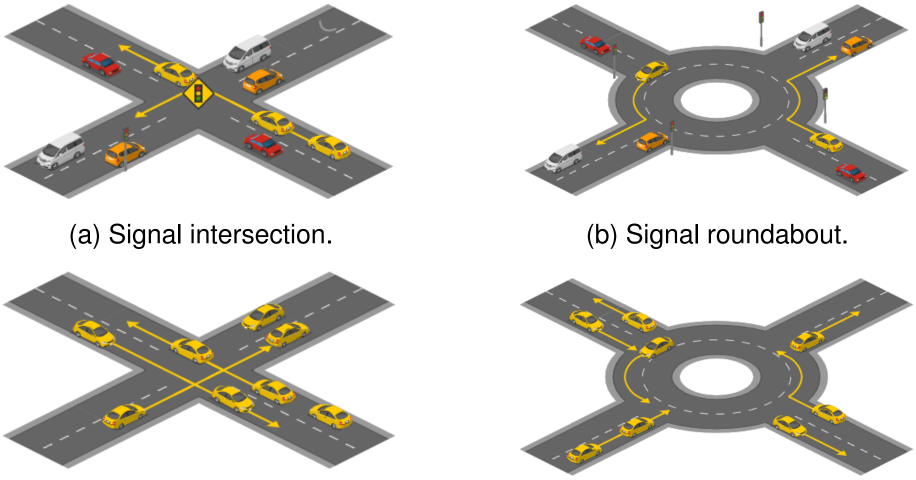
(b) Highway exit ramp (off-ramp).

Figure 1.8: Merging/splitting maneuvers at highway entrance/exit ramps (designed on https://icograms.com/).

Several algorithms for assisting on-ramp merging have been suggested, including controlling mainline vehicle deceleration to create gaps for MVS [367, 380, 403]. Additionally, cooperative control algorithms were developed between ramp and mainline vehicles to facilitate merging operations [403, 502]. In [458], a virtual vehicle is created by mapping a car on one lane to another. This enables longitudinal control between a mainline vehicle and one on a ramp, allowing for seamless merging. A distributed cooperative highway on-ramp merging system is presented in [482], which utilizes both V2V and I2V communication and involves the formation of two vehicle strings on the main line and on the on-ramp. Particularly, [169] proposes a protocol for merging vehicles from the neighboring lane, with a special emphasis on the communications exchanged between vehicles. The authors in [395] establish an optimization framework and a closed-form analytical solution for online vehicle coordination in the merging zone. Although there has been a lot of published work on autonomous highway entry ramp, there has been far less practical implementation of cooperative merging throughout the world [481]. According to a study from the PATH program, testing on cooperative automatic merging systems was done at the Richmond Field Station, U.C. Berkeley, and Crows Landing, California in the US [309]. The University of Minnesota Duluth [214], as well as East Tennessee State University [11, 12], conducted comparable experimental implementations on highway on-ramp merging situations using V2V communication [481].

1.1.3.2/ Intersection/roundabout

In urban core areas (see Figure 1.7d), multi-vehicle cooperative navigation becomes highly difficult under a variety of urban situations involving numerous road users. Several MVS applications have been explored to benefit safety, mobility and the environment with connected vehicles [460]. Among them, MVS cooperation technology for intersection or roundabout applications is particularly representative and significant effort has been done to improve traffic safety/mobility in such densely urban regions. More precisely, research on MVS cooperative driving is conducted at both signalized and unsignalized intersection/roundabout (see Figure 1.9 for instance). Roughly, V2I communication is often preferred at signalized intersections in order to get Signal Phase and Time (SPaT) information and prevent unnecessary speed changes or complete stops [7]. Within an intelligent transportation system, V2V and I2Vcommunication are often used at unsignalized intersections [181, 481]. Thus, following the planning and scheduling algorithm, MVS can be assigned specific sequences to cross the intersection/roundabout. Theoretical studies and applications are given below.



(a) Signal intersection.

(b) Signal roundabout.

(c) unsignalized intersection.

(d) unsignalized roundabout.

Figure 1.9: Signalized and unsignalized intersection/roundabout (designed on https://icograms.com/).

In fact, the research work related to MVS navigation in intersection/roundabout has gained considerable attention during the last decades. Interesting and comprehensive surveys about this problem are analyzed in [85, 121, 183, 345, 396]. Several signal-based control systems assured the efficient and economic management of intersections and aided in the alleviation of traffic congestion [111, 524]. The authors in [513] propose an Eco-CACC algorithm that computes the most fuel-efficient vehicle trajectory through a signalized intersection by guaranteeing that the vehicle arrives at the intersection stop bar as soon as the last connected vehicle in the queue is discharged. The work in [540] considers a real-time cooperative eco-driving approach for a group of vehicles with a mix of autonomous vehicles (AVs) and human-driven vehicles (HVs) crossing a signalized intersection. As a result of newly developed vehicle communication technology, a large range of unsignalized intersection management approaches are also introduced in recent literature [88, 508]. It provides promise for Cooperative Intersection Control (CIC), particularly in terms of adapting to the use of MVS. Additionally, those CIC methods can be classified into: cooperative resource reservation techniques, trajectory planning approaches and virtual traffic lights solutions [85]. In an autonomous intersection study from [117], the reservation-based technique based on a communication protocol is shown to outperform existing intersections with either traffic lights or stop signs. To develop a CIC strategy, researchers in [327] propose the notion of “virtual platooning”, which enables cars in separate lanes of the intersection with different destinations to form platoons. Similar platoon-based intersection management methods can also be found in [235, 505]. Nevertheless, MVS collaboration studies at intersections/roundabouts confront similar challenges in terms of implementation in today’s traffic/infrastructure settings. Thus, the United States Department of Transportation initiatives the Multi-Modal Intelligent Traffic Signal System (MMITSS) project to offer a series of advanced intersection control applications for MVS [459]. In Europe, INRIA (*Institut national de recherche en sciences et technologies du numérique*) in France has done many experimental implementations of automatic coordination at unsignalized intersection, including the Cybercars and Cybercars-2 projects [64, 107].

Recent research has explored these MVS cooperative navigation challenges on highway ramps and intersections/roundabouts [181, 317], assuming all cars are MVS. This issue has sparked considerable interest in the control community, with plenty of literature [396]. The challenges of merging at highway entrance/exit ramps and intersection/roundabout may be tackled similarly using comparable assumptions and ideas [360, 395, 537]. Apparently, these assumptions may be altered; for example, [534] discusses a MVS application that allows both left and right turns at intersections. In [93], the authors investigate V2V communication limitation situations for MVS cooperative merging control. Although those studies' findings are attractive, we emphasize three critical issues where application concerns need to be addressed further, as follows.

- The described MVS coordination issue mainly relies on the on-board algorithm. For deployment on public roadways, planning must be updated in real-time to respond to changing traffic circumstances.
- Automated Highway System (AHS) research has proven significant promise in freeway environment (see Figure 1.7a). Simulations and trials of varying complexity have been conducted on motorway/highway [428], further study is required to implement these MVS collaboration on urban areas (as seen in Figure 1.7d).
- MVS with intersection management has emerged as a prominent research field for the use of cooperative technology inside a specific control framework. However, the system lacks a unified communication protocol and requires a more risk-sensitive design to ensure reliability.

As a result, this PhD thesis will concentrate on the multi-vehicle navigation challenge particular to intersection/roundabouts. It is worth noting that the intersection control and highway on-ramp merging control are quite similar in nature, and that the majority of methodologies given for intersection control may simply be modified for merging coordination for an on-ramp, and vice versa [396]. Further, MVS can both apply information-based cooperation (optimized their own utility) [62] and maneuver-based cooperation (optimize the total utility in a system) [70] for intersection management. To avoid any misunderstanding, the issue we discussed in this work primarily refers to maneuver-based collaboration for the motion planning of MVS. Thus, the intersection management method and navigation strategy of MVS will be discussed in more detail in the next section.

1.2/ INTELLIGENT VEHICLE'S MOTION PLANNING AT AN INTERSECTION

This section will highlight the primary intersection model, typologies, assumptions and driving strategies enabling the application of MVS/CAVs. The purpose of this part is to explain related terms and to classify the main methodologies created for intersection/roundabout motion planning. Following that, an overview of the major challenges is given in the summary.

1.2.1/ AN OVERVIEW OF THE INTERSECTION MANAGEMENT SYSTEM

The situation shown in Figure 1.10 demonstrates how MVS may be used to cross intersections. There is a gray *Buffer area* [292] with a length of S_0 for vehicles to approach

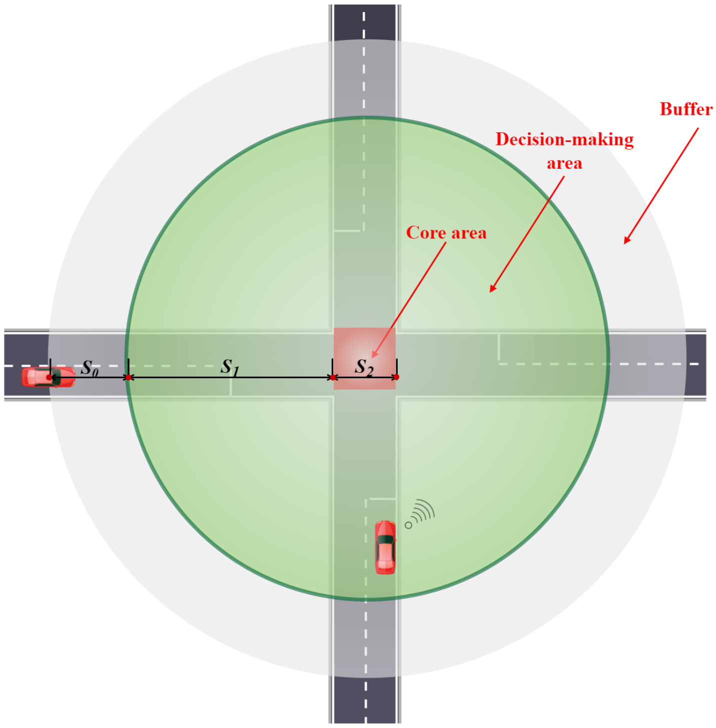


Figure 1.10: General intersection management with MVS.

the intersection. By the length of S_1, connected vehicles in the green region referred to as the *Decision-making area* may interact with other agents (vehicles or coordinators). The red *Core area* (alternatively referred to as the conflict area or intersection zone [396]) in length S_2 is located at the merging point of multiple roads. The MVS longitudinal kinematics model can be illustrated by a discrete model like the following:

$$\begin{cases} a_i(t) = u_i(t) \\ v_i(t+\Delta t) = v_i(t) + a_i(t) \times \Delta t \\ x_i(t+\Delta t) = x_i(t) + v_i(t) \times \Delta t + \frac{1}{2} a_i(t) \times \Delta t^2 \end{cases} \tag{1.1}$$

Where $x_i(t)$ and $v_i(t)$ denote respectively the displacement and velocity of the vehicle i at time instant t. $a_i(t)$ is the corresponding acceleration for a time interval Δt . Besides, $a_i(t)$ is addressed by the control input $u_i(t)$. The purpose here is likely to compute $u_i(t)$ for each vehicle to safely cross the intersection, i.e., without rear-end and/or lateral collisions.

Clearly, there are more conflicts at intersections [278]. Left-turning of MVS raises the chance of crashing much more than straightening or turning right [90]. From an intersection management perspective, the present study will concentrate on the isolated intersection driving strategy (In Chapter 2, we will examine more complex instances involving multiple intersections). Additionally, the intersection structure, other than crossroads and roundabouts, is rather sophisticated in terms of topology. A diagram generated by [485] (i.e., Figure 1.11) reveals further information regarding the intersection topology. However, the nature of these intersection management issues is extremely similar, and they may be simply transformed by referring to the crossroad (i.e., Figure 1.11a). As a consequence, the focus dedicated to the technique part of this PhD thesis will not include the intersection topology. All of the intersection navigation scenarios covered in the manuscript have been handled using the topology shown in Figure 1.10.

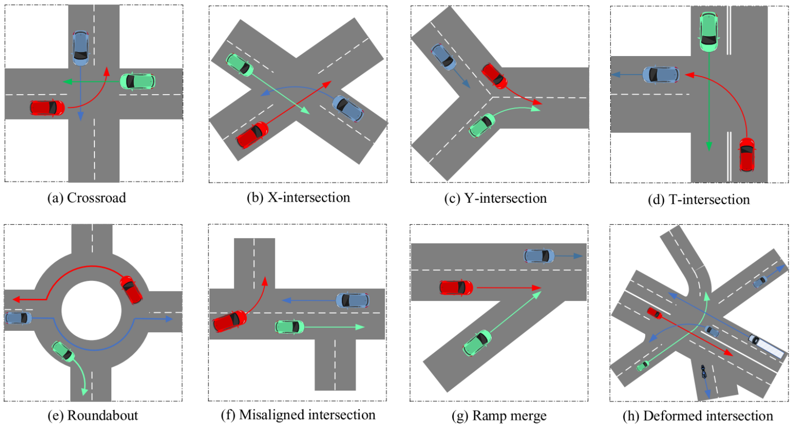


Figure 1.11: The intersection structure with different topologies [485].

According to previous research, intelligent intersection management tactics may be categorized into two categories: a) traffic management at the high level; b) MVS driving behaviors at the low level [485, 536]. In fact, there is currently no complete intersection management system capable of integrating autonomous vehicles' safety driving with these two levels at isolated intersections. Significant progress has been made in the first study topic (i.e., traffic management level) through optimizing traffic light control algorithms. Due to the fact that traffic lights are more realistic solutions for today's traffic conditions, they are considered one of the most effective method of ensuring regular traffic flows at intersections [13, 396]. Particularly, in [117], a multi-agent strategy was used to offer a novel Autonomous Intersection Management (AIM) policy termed First Come First Serve (FCFS) Light. To manage mixed traffic, it employs a reservation-based scheme for autonomous vehicles and traffic signals for human-driven vehicles. By expanding the model described in [117], the authors introduced a novel protocol named Hybrid Autonomous Intersection Management (H-AIM) in order to enhance intersection performance under mixed traffic situations in [414]. The authors in [290] suggested two adaptive signal control algorithms that are successful in alleviating traffic congestion and achieving adaptive signal control goals using real-time traffic data. Another adaptive traffic signal controller based on reinforcement learning was presented in [412]. Additionally, mathematics model [34, 129, 295], fuzzy logic [355, 388, 440], Petri Net-based control [76, 148, 300], queuing theory and agent-based learning approaches [42, 335, 547] are all critical areas of traffic light study. Several reviews and surveys on signalized intersection control may be found for further summary [85, 396]. However, it has been shown earlier that standard traffic signals are inefficient at large traffic volumes [415]. Meanwhile, as predicted by IEEE, traffic signals may be obsolete by 2040 [219]. Thus, as MVS take over the major roads, the need for traffic signals at intersections reduces. As a result, more efforts have been made for unsignalized intersection management with MVS motion planning (i.e., low-level link to autonomous vehicle's behaviors). Due of the uncertainty in human-driven vehicles' capacity to communicate and collaborate with other road users [345], mixed traffic at unsignalized intersections will not be addressed in the context of this PhD dissertation.

The works cited above give a brief overview of intersection management systems. The following section discusses the primary techniques for non-signalized intersections with MVS. Given that we will use the terms *Autonomous Intersection Management (AIM)/Decision-making and trajectory planning/Multi-agent system (MAS)*, etc. to define the proposals and deal with key scenarios in this PhD thesis, we provide a brief description to help clarify the concepts.

- **Autonomous Intersection Management (AIM):** the notion of AIM was first introduced by Dresner and Stone [117] as an alternative intersection manager (compared to current traffic signals and stop signs). AIM is expected to increase the efficiency of the present intersection by using vehicular communication to regulate traffic [499]. In [117], an early effort is made to specify the requirements of AIM. It may be considered a subset of Intelligent Transportation Systems (ITS), which strive to enhance the system by suggesting that individuals about traffic conditions and making mobility coordination safer and more intelligent [419].
- **Decision-making and trajectory planning:** MVS are commonly assumed to be primarily concerned with perception, planning and control activities. The planning layer firstly calculates the optimal global route using data from the global map and world information [124]. The planning layer then determines a local ideal trajectory through Decision-making and trajectory planning based on the vehicle's present perception messages [170]. Trajectory planning is frequently employed in vehicle collision avoidance [447] and robotic motion planning [268] to avoid conflicting paths.
- **Multi-agent system (MAS):** MAS (also referred as self-organized system or MRS addressed in Section 1.1.1) in which agents communicate and coordinate their behaviors to solve problems difficult for an individual agent [206, 393]. Transportation is an ideal environment for applying an Agent-based model (ABM) since transportation systems are very dynamic and all associated stakeholders, such as road users and infrastructure, must cooperate with one another, either actively via negotiation or passively by simply obeying rules [85].
- **Cooperative driving:** in compared to the conventional urban transportation system, the driving plans of vehicles were also supposed to be adjustable in order to further increase driving efficiency [284]. A common strategy in this region is referred to as "cooperative driving". Cooperative driving as a concept was originally presented in the early 1990s [196], mostly as automated platooning. The phrase "cooperative driving" was also used in [283] to refer to establishing collision-free vehicle travel through unsignalized intersections with the use of inter-vehicle communications.

1.2.2/ Driving strategies at an intersection

Despite surveys on intersection management and driving strategies have been substantially examined in the literature, they have not been evaluated concurrently (from manage-layer to control-layer) [485]: for example, [416, 468] reports on intersection monitoring and scheduling studies from the perspective of a component-based system. Additionally, [207, 536] contains some assessments of the decision-making process from the perspective of intelligent vehicles. In fact, the driving strategy may also be influenced by the existing traffic context's assumptions. To simplify the driving issue, for example, the related work (summarized in [396]) assumes that vehicles approaching the intersection are serviced First In First Out (FIFO), that only one vehicle is permitted in the intersection zone at a time, that no turns are permitted, and that vehicles pass the intersection at constant velocity, etc. Thus, the suggested strategies for the AIM system that incorporates MVS are classified into several main categories, including rule-based, optimization, hybrid and machine learning [345]. The authors in [85] provide an overview of significant strategies and solutions for cooperative intersection. Further, cooperative approaches are classified as time slots and space reservations, trajectory planning, and virtual traffic signals in [85]. It is proposed in [485] to categorize autonomous driving approaches into two categories: cooperative driving strategies and individual driving strategies. However, as stated in [396], numerous methods to intersection driving strategies are heavily weighted toward centralized and decentralized cooperation. In particular, AIM driving method may also adopt a hybrid approach. Thus, we divide intersection driving techniques into reactive strategies and cognitive strategies for a compromise scheme in this PhD thesis.

The concepts of reactive and cognitive control were created first for mobile robot navigation, and they are frequently utilized in the literature [8, 28, 65, 123]. The term *reactive architecture* refers to the practice of determining the robot's actions only based on current sensor data (e.g., stimuli-response robot behavior). On the other hand, *cognitive architecture* makes considerably more extensive use of data about the robot's surroundings and internal state to determine its behaviors. A summary and translation diagram provided in [8] serve to understand these two control principles, which are shown in Figure 1.12. As previously mentioned, the driving strategy used in intersection management can be similarly characterized in terms of reactive and cognitive, which is applied for MVS decision-making and trajectory planning. Clearly, no significant distinction exists between these two notions in Figure 1.12. It is worth mentioning that although the reactive method employed in AIM does not need the vehicle to be totally devoid of sophisticated perception or decision-making to respond online, it would be a pity to not utilize them in the traffic context. Its primary distinction from the cognitive strategy is that the intelligent vehicle does not make use of all available environmental information to select its trajectory across an intersection. A well-known fact is that a preset traffic coordinator may provide more real-time traffic information to individual cars, allowing for partial cooperative maneuvering by reactive strategy. A supervised intersection, on the other hand, may deploy a local supervisor to monitor or train MAS cooperative movements with all essential environmental information. The next two sections will discuss these two methods with more thorough methodologies and examples.

1.2.2.1/ Reactive strategies

This strategy has been used to determine MVS cooperative maneuvers mostly in decentralized architecture. Furthermore, reactive driving tries to respond in real time to local environmental information while maintaining the essential stability and dependability. We highlight the typical approaches as follows.

- **Priority-based resolution:** using two decision algorithms, the authors in [16] argued that an autonomous vehicle might make a decision regarding the most acceptable crossing schedule in order to avoid colliding with other humanly operated cars on the road. It is feasible to coordinate the vehicles crossing an intersection with information acquired from local sensors. In [497], the authors proposed a novel intersection crossing strategy based on V2V or V2I communications in which vehicles compete for the right to pass through the intersection.
- **Decentralized Model Predict Control (MPC):** the authors offer a decentralized

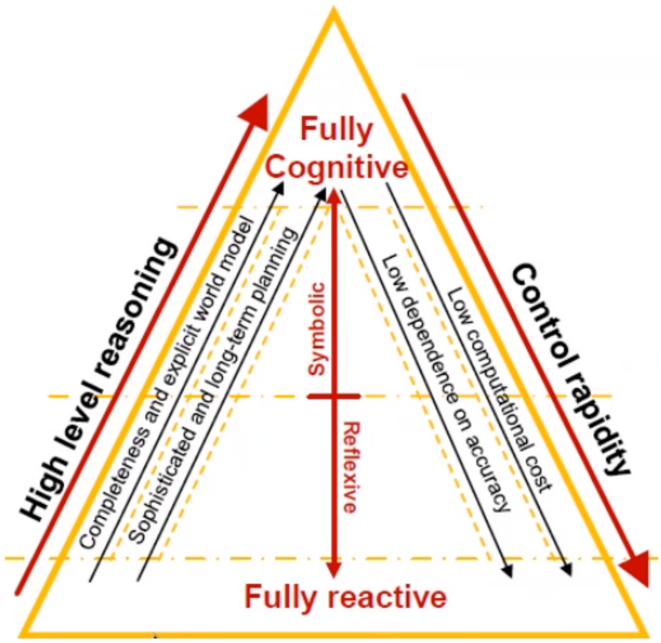


Figure 1.12: Relationship between reactive and cognitive control [8].

MPC solution for autonomous vehicle coordination at intersections in [316]. Each vehicle with a preset path is given a linear quadratic optimal controller in order to save energy while passing through an intersection smoothly. By using local information from other cars within the communication range, each vehicle can define its own constraints. Similarly, [251] details an MPC-based method.

- **Cooperative resource reservation:** cooperative resource reservation has been studied in the form of decentralized intersection management, which does not need infrastructure assistance. Previously in [347, 348], a distributed reservation strategy based on collision areas was presented, in which only one vehicle is permitted to remain in a conflict zone. A distributed reservation protocol was suggested in [464], and comparable works are also available in [32, 33].

- **Cooperative game theory:** a suggested interaction modeling based on game theory including multiple leaders and followers is created in [285]. It also takes into account common traffic regulations at uncontrolled intersections. In [517], the authors propose a driving model based on cooperative game theory. This model's characteristic functions are based mostly on the purpose of each vehicle's safety, speed and comfort. A cooperative decision-making framework for MVS is proposed utilizing a coalitional game theory to solve vehicle safety and efficiency challenges at multi-lane merging zones [190].

- **Ant Colony System (ACS):** the work given in [495] presents a system for evacuating automobiles as quickly as possible for each series of vehicle arrivals. Further, the research offers an AIM strategy based on an ACS and a discrete optimization technique to solve the control issue for a large number of cars and lanes in real-time. To investigate the viability of AIM, a prototype based on NXT robots is created.

- **Parallelizable algorithm:** a distributed and parallelizable algorithm is given in study [233] for solving the coordination issue at intersection using a method called

Augmented Lagrangian-based Alternating Direction Inexact Newton technique (ALADIN). In this case, each vehicle solves its own optimum control problem and shares information about arrival and departure timings at the intersection with its neighbors in order to prevent accidents.

1.2.2.2/ Cognitive strategies

Cognitive strategies make use of all available information about the environment in order to maximize global efficiency, and it is feasible to show the optimality of the selected decision or action using such a strategy. The most commonly used methodologies are given below.

- **Reservation-based system:** the reservation-based approach was initially presented in [116], in which automobiles request and get time slots from the intersection during which they may pass. The reservation-based multi-agent control strategy outperforms the traffic light policy in simulation and approaches the theoretical optimum. This technique was then expanded to significantly enhance some limitations [117], such as enabling turning maneuvers and ensuring the appropriate acceleration profile inside the intersection zone. Additionally, two enhancements are described that enable the system to regulate human-driven cars and prioritize emergency vehicles. Next, the authors in [210] continue developing a new reservation-based intelligent intersection method. Along with receiving and validating car reservation requests, the new algorithms prescribe a speed profile for vehicles to follow until they cross the intersection. Additionally, the new reservation algorithms use a dynamic hierarchical reservation protocol that enables distinct reservation requests to be assigned varying priority. The reserve mechanism has also been examined by [31, 107, 278, 532].

- **Platoon-based MAS:** the authors in [235] suggest a platoon-based MAS in which vehicle agents may tactically organize platoons via communication technologies. Only the platoon's Leader Vehicle Agent (LVA) interacts with the Intersection Management Agent (IMA) by transmitting the platoon's predicted Earliest Arrival Time (EAT) and Earliest Clearance Time (ECT) and getting reservation confirmation (either approval or rejection). All follower vehicle agents (FVAs) just communicate with LVA and follow its trajectory. In [299], the authors provide an evaluation of the possible mobility advantages of a platooning-based strategy at intersections.

- **Centralized optimization:** this approach is primarily concerned with the formulation of an optimization problem whose objectives are, for instance, the travel time [234, 548, 551] and/or the overlap of vehicles in the core area [271, 273]. In [81], the optimal speed profiles of two vehicles approaching an intersection under a specified safety restriction have been deduced using closed-form solutions. The study reported in [552] created a novel algorithm for optimizing vehicle movement at intersections inside a CACC framework. The proposed framework uses game theory to guarantee that no collisions occur while minimizing intersection delays.

- **Receding Horizon Control (RHC):** RHC, also known as MPC, is a general-purpose control approach that entails repeatedly solving a restricted optimization problem and choosing the control action based on forecasts of future costs, disturbances, and restrictions over a changing time horizon [321]. Just like centralized optimization, RHC is more particularly employed for multi-objective optimization, in which the objective function is minimized across a sequence of equal-length time horizons. The RHC/MPC paradigm is commonly utilized in AIM, as well as several related studies [103, 106, 238, 239]. The authors in [238, 239] proposed a coordination strategy for autonomous vehicles' safe and speedy crossing of an unsignalized intersection by considering their states collectively in an MPC framework. The optimal vehicle trajectories are determined by avoiding cross-collision risks in the vicinity of the intersection.

- **Centralized machine scheduling:** in this strategy, a control center is allocated to minimize the evacuation time of incoming cars. The authors in [496] propose a novel scheduling model that allows vehicles to negotiate their arrival time using an intelligent embedded device at the intersection. Control's objective is to evacuate all cars as quickly as possible while taking into account the possibility of the appearance of emergency vehicles. Similarly, in [509], the control center is intended to optimize vehicle passing sequence. To address this issue, a Dynamic Programming (DP) method has been developed.

- **Coordination space approach:** [177] provided a mathematical paradigm based on path-velocity decomposition. The authors provided a coordination space method for coordinating intersection vehicles. The paths of each vehicle are first determined and fixed, and then the velocity is adjusted to allow for safe and efficient intersection passage. The authors claim that it is a constructive locally optimal algorithm. Additionally, the authors explored priority-based strategies in the suggested coordination space approach [178] and the presence of legacy vehicles [382].

1.2.3/ MAIN CHALLENGES UNDER URBAN CONDITIONS

Much work has been published in the literature about MVS driving strategy at intersections in urban environments. Although the suggested cooperative intersection motion planning for MVS has been shown to be efficient in several simulations and field testing, the high computing burden or deadlock issue still restrict real-time implementation. Additionally, given the uncertainty, how much can we enhance traffic efficiency using the suggested intersection management model? How we may maximize cooperative MVS navigation at a broader scale using optimization approaches with extra information outside the ego-vehicle. A potential solution to this problem would be to expand the AIM system to incorporate connected and interdependent transportation segments like intersection and merging lanes, as well as to allow for further network-level traffic monitoring and improvement. The following are the main challenges associated with uncertainty and scalability, especially in urban settings.

1.2.3.1/ FLEXIBLE AND RELIABLE NAVIGATION UNDER UNCERTAINTY

Uncertainty should be treated as an inherent aspect of AIM in order to provide flexible and reliable MVS cooperative navigation. It may arise from a variety of sources, including control, mechanical, perception and communication systems. Vehicles (e.g., traditional vehicles with human drivers in the loop) may not obey orders, as the reservation-based system does. Generally, control and human uncertainties are not taken into account unless the task is expressly designed to cope with uncertainties (such as works presented in [178, 382]). Additionally, some research attempts to develop methods for coping with imperfect data from control systems. For instance, [66] examined a Maximal Controlled Invariant Set that allows for any admissible disturbance. Similarly, the authors addressed the collision avoidance issue in [186]. The model and the state estimation technique explicitly account for sensor uncertainty and transmission delays. These countermeasures are utilized to create a more robust controller, which makes the system more practical. In other researchers' works [280, 281], probabilistic trajectory prediction is also used to account for road users' uncertainties for autonomous vehicles, however, they either emphasize individual driving strategies or continue to rely on interacting systems. A viable option for dealing with uncertainty is to use a fusion-based approach [485]. For instance, the centralized and the distributed driving technique may be coupled to provide a complementary set of capabilities.

1.2.3.2/ Parallel implementation (scalability)

The majority of existing MVS driving strategy is concentrated on isolated intersections. A natural question is how to apply the suggested strategy simultaneously in an urban road network with multiple intersections, i.e., parallel implementation. The rule-based approaches (e.g., priority-based resolution in [16, 497]) were developed to enable real-time AIM with either autonomous or mixed traffic. Numerous rule-based approaches have been verified in the actual world due to their computational simplicity and explainable models [308]. However, the complexity of the rule-based technique rises dramatically as the model's objectives and constrains expand, and its performance may vary according to traffic circumstances [345]. In comparison, centralized optimization or machine scheduling using intersection controllers has been developed to handle single- or multi-objective problems under a variety of circumstances, ensuring optimal performance (with varying constrains). Due to the computational cost of centralized optimization techniques, only a few of the publicly known optimization-based methods can be used in real-time in parallel [19, 245, 336, 397]. Indeed, when the number of cars and roadways rises, ensuring the algorithm's real-time and reliability becomes a significant difficulty. Even in the situation of full autonomous diving. Intelligent cars may sometimes deadlock or collision in complex situations/locations. The former is often the result of an algorithm that is too conservative, while the latter is frequently the result of an algorithm that is too aggressive [485]. To avoid deadlock and save computational cost, some researchers use a hierarchical design for cooperative intersection management [372] (cf. Section 1.1.2.3). Thus, hierarchical architecture might be seen as a potential option for managing many intersections at the level of traffic management.

1.3/ Conclusion

This chapter discusses single-vehicle intelligence systems in comparison to multi-vehicle cooperation systems. The prevalent MVS control architecture is classified primarily into centralized and decentralized designs. Moreover, the circumstances in which MVS may be used in complicated environments and situations are discussed. The relevant works for both high-way entrance/exit ramps and intersections/roundabouts are summarized.

The mechanisms used by the intelligent vehicle's decision-making and trajectory planning at isolated intersections are discussed in depth. The reactive techniques for MVS that have been presented attempt to respond in real-time and need just local environmental information. In contrast, cognitive techniques use all available knowledge about the environment to choose the optimal maneuvers. The advantages and disadvantages of introduced systems for MVS navigation are examined in further detail with an emphasis on actual implementation. Finally, the major issues confronting cooperative motion planning in urban conditions for MVS are outlined, with an emphasis on uncertainty and scalability.

2

DECISION-MAKING FOR MULTI-VEHICLE NAVIGATION IN A TRANSPORTATION NETWORK

As summarized in the preceding chapter, the implementation of MVS coordination is highly dependent on the planning algorithm's response to traffic conditions. Additional research is necessary in this PhD thesis to concentrate on more challenging circumstances, such as transportation networks with multiple intersections and roundabouts. However, there is currently a lack of safe and effective MVS control systems capable of parallel application (i.e., scalability) of AIM, given the uncertainty associated with traffic (cf. section 1.2.3). Based on the previous chapter's concepts and ideas, an introduction of multiple vehicle navigation in an urban context (e.g., in intersection network structure) is provided in this chapter 2. Additionally, we address the MVS system/tasks in such a complicated intersecting network. On the basis of the anticipated road network, many research paradigms and decision-making models are explored. Due to the uncertainty inherent in real-time traffic management, we emphasize the need of using a probabilistic approach and risk management while making MVS decisions on a transportation network. Finally, the conclusion addresses the present multiple intersection management system constraints as well as the fundamental restraints on the system's operation.

2.1/ INTRODUCTION

Many research works have been devoted to coordinate MVS on highways/arterial roads, as described in the preceding chapter (cf. section 1.1.3). Urban roads with intersections, on the other hand, are more complex landscapes. It has been discovered that 50% of urban crashes and 30% of rural crashes occur near intersections [118]. Additionally, traffic congestion is a typical problem in metropolitan areas, resulting in significant economic and environmental costs, as documented by various countries. For example, drivers contribute an additional $\$121$ billion loss and 56 billion pounds of CO2 in the U.S. [408] owing to urban traffic congestion. Intersections have been identified as the primary source of urban congestion. Advanced vehicular communication and coordination technologies are expected to result in a more intelligent traffic system. Thus, coordinating strategy is frequently discussed to improve many aspects of the transportation system (e.g., travel time reduction and CO2 emission reduction) within an urban network.

Coordination of groups of vehicles of varied sizes is one of the challenges in MVS trajectory planning and decision-making. In this respect, these applications blur the line between traffic management and MVS cooperation. Essentially, it addresses comparable issues at the road network level rather than at the vehicle level. Further, Urban Traffic Control (UTC) systems have also been created to accommodate the growing demand for traffic. MVS, being one of the most developed approaches, are regarded to offer significant promise for upgrading the present ITS [314], as indicated in the preceding chapter. For concerned readers, [141, 284, 362] provides an overview of traffic control, and [41, 183, 284] discusses the link between traffic control and vehicle connectivity. Indeed, the technology for UTC, ITS, MVS and IVs often overlap. Whereas the majority of published research in recent decades has focused exclusively on ITS for transportation or IVs for vehicle control, individual vehicle characteristics are nearly never addressed, particularly in traditional traffic signal management systems [183]. The integration of MVS with traffic management systems in the urban context introduces new issues that should be properly studied. Here, we primarily offer two questions to guide the PhD thesis through two challenges:

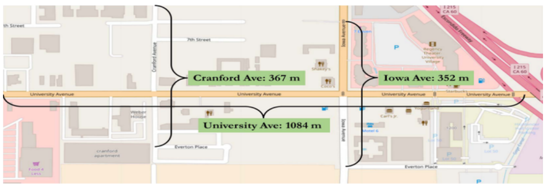
- How can the traffic system be defined and modeled based on knowledge about individual vehicle movements?
- What alternative to passive feedback may be used to regulate the traffic system by MVS-based traffic control?

Before addressing these issues in further details, we shall outline the scenarios, requirements, and associated systems, tasks, for multi-vehicle road-network navigation. This is done in the following section.

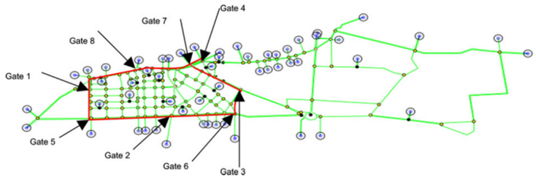
2.1.1/ Overview of a road network: scenarios and requirements

A road network can be visualized as a directed, weighted graph in which each node has a transport demand [441]. Urban road networks have a significant impact on a country's economic growth and are frequently congested, resulting in increased travel times, inconvenience for drivers/passengers, and increased air pollution [439]. It is critical to propose a systematic and sustained extension of urban networks, as well as proper maintenance, in order to ensure high-quality connections between the various areas of a geographical territory [341]. The addition of road infrastructure (e.g., I2V devices) and MVS enhances the UTC system's effectiveness and efficiency. Three forms of MVS-based navigation scenarios exist in this thesis: single intersection control, coordinated multi-intersection control of a traffic corridor and network traffic control. Section 1.2 discusses isolated intersection control. Thus, this section provides an overview of MVS navigation in traffic corridors and networks.

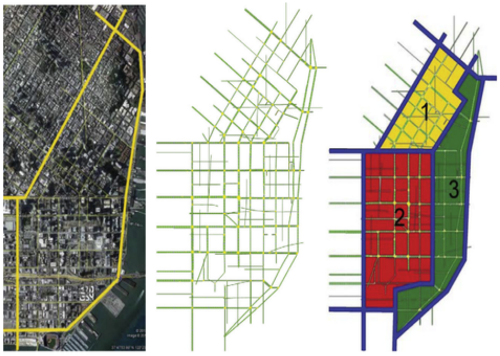
Numerous two-dimensional arterial corridors and urban road networks may be established in the literature using real-world data. To investigate the Cooperative Eco-Driving (CED) system based on MVS, researchers in [483] assume the presence of V2V/V2I-enabled cars traveling in a corridor with two traditional four-way intersections. The simulation is based on real-world flow data for the six-mile (9.66-kilometer) University Avenue corridor in Riverside, California (CA), USA. As seen in Figure 2.1a, two signalized intersections (i.e., University & Cranford, University & Iowa in Figure 2.1a) with defined lengths



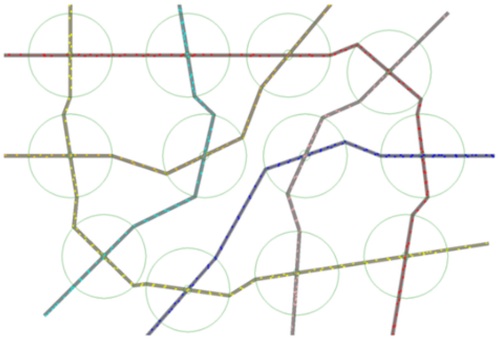
(a) Road segments in Riverside, CA, USA: a corridor with two crossroads [483].



(b) Modeled urban road networks [247].



(c) Heterogeneous large-scale networks [6].



(d) Intersection network for simulation [446].

Figure 2.1: Urban arterial corridors and road networks in the literature.

are created in the simulation scenario. Additionally, the simulation network's inputs (e.g., signal timing and traffic count data for a certain period) can be calibrated. Thus, the traffic mobility of the proposed CED system can be tested in a partially MVS environment by using microscopic traffic simulation software. Moreover, the research [247] depicts the Chania urban road network's Central Business District (CBD) in simulation scenarios, as seen in Figure 2.1b. Within the red boundary of Figure 2.1b, a protected network (PN) is established. The eight intersections shown by a black arrow are classified as gates that enable vehicles to enter. Additionally, numerous origins and destinations (O-D denotes in/out traffic flows) are inserted at network borders or positioned inside the internal network encapsulated by a circle. Thus, by altering the O-D flow rate, one may imitate real-world traffic flow in such a 2D road network. The key traffic control challenges also include tackling the management of heterogeneous large-scale networks [6, 213, 306]. A general way to solve this issue is to divide a heterogeneous network into homogeneous sections, assuming distinct control strategies for the network's unevenly distributed vehicles. In [6], the authors analyze a case of heterogeneous urban transportation networks. As seen in Figure 2.1c, a 6.47-square-kilometer region of Downtown San Francisco has 100 intersections and 400 links $(120 - 390$ meters) with multiple lanes. To implement the suggested perimeter and boundary control [6], the test site is partitioned into three homogeneous reservoirs (highlighted in yellow, red, and green), clustered by small variances in link densities [229] shown by blue lines (see Figure 2.1c). Additionally, specific road networks are developed in the literature, particularly with the need to validate intelligent transportation technology. The authors in [446] present a method for optimizing the flow of a traffic network that avoids having vehicles stop at intersections, which was developed as part of the InTraDE European project [122]. Figure 2.1d illustrates the general road that operates in [446] with several intersections. 6 roads and 12 intersections comprise the traffic network. The intersection range is around 125 meters in radius, while the distance between two neighboring intersections is approximately 450 meters. The synchronized traffic lights may be utilized in such a network to generate “green waves”.

Next, it is vital to evaluate the coordination requirements for the future generation of intelligent transportation network management systems that enable each traffic participant to perform better. In fact, the current urban traffic system is a complex multi-agent system governed by elaborate traffic laws and protocols that ensure the behaviors of many conventional road users. Traffic lights and stop signs used in such a system are actually meant to promote safe driving for human-driven cars, leaving a small margin for more accurate management by IVs or MVS [381]. To guarantee the implementation of MVS-based traffic control, one of the most significant challenges is establishing feasible agreements or explicit requirements for a variety of on-board equipment and road presetting devices. The following summarizes the safety, efficiency, and information security requirements discussed in the literature [117, 183, 455] for MVS navigation in urban corridors or road networks.

- **Reliable communication (traffic safety):** the regularly updated traffic situation is crucial for MVS to ensure a safe trajectory. For road safety applications, there are rigorous requirements for both bounded delay and high reliability [455]. Current standards permit a reliability of $90\% - 99\%$ and a latency of up to 100ms, but autonomous driving needs an ultra-high reliability of 99.999% and a ultra-low latency of up to 3ms [529]. Indeed, delayed and/or missing vehicle status (e.g., position mistakes) may result in an inability to forecast or warning of an appropriate action (for lane changes, emergency vehicles approaching, stationary vehicles and road conditions, etc.) [329, 455]. The navigation of MVS built on a centralized architecture is much more dependent on advanced communication technologies for the acquisition of new traffic status messages. Low communication complexity, on the other hand, might increase the system's scalability. Thus, apart from reliable measurement devices, robust planning [521] and stochastic programming [448] reported in the publication may contribute to the relaxation of the strict communication constraints. Additionally, recent research indicates that MVS may be better served by long-distance communication technologies [183].

- **Protocol standardization (traffic efficiency):** wireless communication applications are utilized to improve traffic efficiency (e.g., regulating road flow and minimizing emissions). An AIM protocol mechanism is early discussed in [117], which emphasizes that each agent needs a simple, standardized protocol for communication. IVs using standardized protocols are not required to comprehend the internal workings of the others. Additionally, new agents may simply be added to the system. Further, there are significant research and standardization initiatives underway as a result of the development of MVS-based technologies in the past two decades [455]. The communication protocol standardization began in 1999 when the U.S. Federal Communications Commission (FCC) authorized a 75-MHz band at 5.9 GHz especially for ITS [30]. In November 2004, the IEEE task group p was formed, which extended protocol stack to Wireless Access in Vehicular Environments (WAVE) including multiple layers. In 2010, the 802.11p vehicular “profile” (also denoted as Dedicated Short-Range Communication, DSRC) was certified [455]. Other protocol standardization efforts, such as ISO's CALM/CALM-non-IP and the European Commission's Mandata M/453, are also being developed prior to the 2010s [140]. Furthermore, Cellular Vehicle-to-Everything (C-V2X or LTE-V), which enables direct communication between connected vehicles using the PC5 interface, is considered an alternative to IEEE 802.11p [171]. Since 2017, 3GPP has included LTE support for V2X services in Release 14 [529]. A special communication mode (Mode 3 and Mode 4) are dedicated to V2V communication. Indeed, IEEE 802.11p and C-V2X have been claimed to be included in automakers unveiled cars. Further development of new standards may allow the commercialization of fully developed MVS.

- **Vehicle cybersecurity (information security):** as the on-board information technology of the vehicle becomes more integrated into our daily lives, the resulting information systems evolve into automotive Human Machine Interface (HMI) devices that enable passengers, drivers, and even other road users to interact with the targeted vehicle in a far more natural manner. As a result, ego-vehicles develop increased vulnerabilities and possible attacks, which can be mitigated by the vehicle's anti-cybercrime system. As an autonomous agent, each vehicle may have privacy concerns that must be respected. For MVS cooperative navigation, cybersecurity is especially more critical in defending car systems and components from malicious attacks, illegal access, and damage while on the road [352]. The authors in [133] examine the vulnerability of traffic control systems in a connected environment, with a particular emphasis on transmitting erroneous data to cause maximum system delay. According to trial data, cybersecurity threats have a significant influence on critical intersections in transportation network. Additionally, [87] examined the vulnerability of Connected Vehicles (CVs) in the transportation system with a simulated attacks targeted at causing traffic congestion. The authors caution that the existing CVs signal management system is very vulnerable to data spoofing attacks conducted even by a single attack vehicle. Clearly, vehicle cybersecurity will be in high demand in the near future.

One might add other desired properties or requirements to a specific UTC system, such as deadlock or starvation avoidance; for example, vehicles at intersections could reserve a scheme to handle the stuck situation or stop low-priority vehicles from waiting too long [117]. Additionally, the suggested traffic management system should possess the capability of continuous deployment in chosen circumstances (e.g., add more intersections in a transportation network). Finally, while both safety and efficiency have been extensively studied in the past for advanced urban traffic systems, it is believed that they can be balanced using a variety of criteria (e.g., robust versus efficient, deliberative versus reactive, centralized versus distributed [381], etc.) in specific situations. This issue cannot be fully explored in this PhD thesis. In the following sections, we will further explore these criteria by combining them with other decision-making models (cf. section 2.2.2).

2.1.2/ Multi-vehicle navigation management systems/behaviors

Traditional UTC in terms of traffic flow management is implemented by direct control measures (e.g., ramp metering in Figure 2.2a, traffic lights, dynamic route information panels in Figure 2.2b, and speed limits) and indirect road sensor-based operations (e.g., traffic control centers in Figure 2.2c, variable message signs, and highway advisory radio) to help maintain the congestion-free network [41, 374]. Indeed, traffic flow is now dependent on traffic signal-based management systems in large-scale metropolitan networks [247]. The critical issue remaining in conventional traffic management for multi-vehicle navigation is how to optimize network flow. This entails optimizing the phases (offsets) of the various intersections using a possibly high-dimensional variable space (for instance, as many

(a) An application of ramp metering [425].

(b) Dynamic route information [337].

(c) Traffic operations center [125].

Figure 2.2: Traditional traffic direct/indirect control.

as the network's nodes/intersections) [446]. This problem has also been investigated in the fields of operations research and queuing theory, concerning the human driver. With the emergence of IVs, studies are currently concentrating on techniques of autonomous and real-time management. Additionally, the term "Intelligent Transportation Systems (ITS)" or "Intelligent Vehicle Highway Systems (IVHS)" has been used to refer to the new generation of traffic management system [135, 433]. As previously stated, IVs/MVS are critical components of ITS/IVHS since they are capable of sensing the surroundings using on-board sensors (e.g., radar, lidar scanner, and computer vision devices) and controlling the vehicle autonomously or semi-autonomously supported by V2V/V2X communication [41]. Therefore, the term "MVS-based traffic control" will be used throughout this thesis to refer to an intelligent traffic system that utilizes connected vehicle technologies and is distinguished from conventional UTC by its signal-based direct/indirect approaches.

Similarly to ITS/IVHS, this chapter discusses MVS-based traffic control systems in road networks (see Figure 2.3). These systems incorporate traffic management, driver information and vehicle control. Naturally, the addressed system transfers the driver's tasks (steering, braking, and decision-making) from manual operation to MVS cooperation. Consequently, MVS enable real-time control decisions through the use of an appropri-

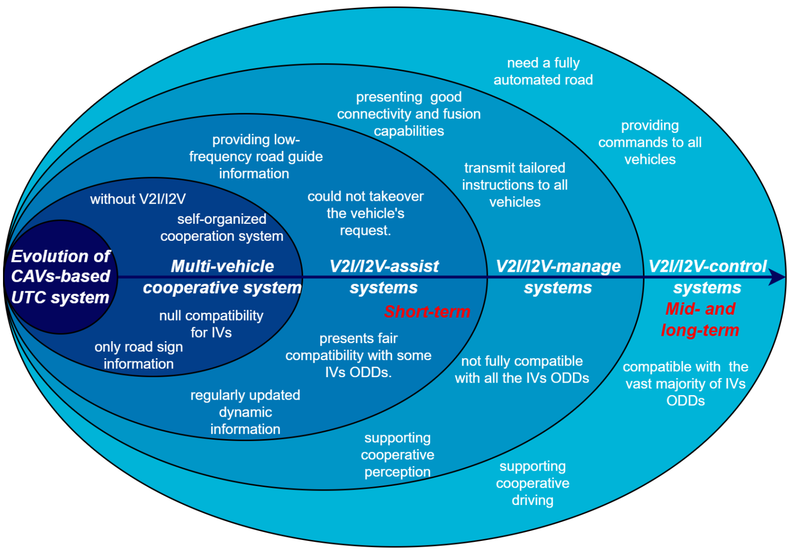


Figure 2.3: An evolution of MVS-based UTC systems (motivated by [266]).

ate computer algorithm, thereby overcoming or mitigating the negative effects of human driver limitations (e.g., slow reaction time, limited information processing capability), heterogeneity (e.g., different reactions among human drivers), and selfishness (e.g., non-cooperativeness) [383]. An example related to MVS-based traffic management issues is achieving a global optimum in traffic flow (i.e., homogeneous flow, maximum throughput, jam avoidance) during a certain traffic peak period [394]. In other words, traffic flow management may be transformed from a reactive and non-cooperative paradigm to a proactive and cooperative one based on MVS [183, 284, 383]. We provide more clarification on the V2I/I2V forms of MVS-based UTC systems by referencing the Automated Highway Systems (AHS) discussed in [41] and *Smart Roads Classification* Proposed by PIARC [150] (as seen in Figure 2.3):

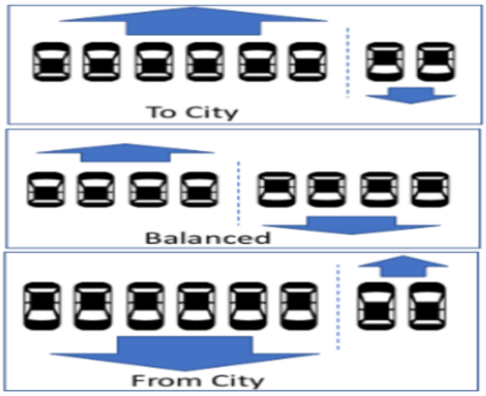
- **Multi-vehicle cooperative systems:** without requiring V2I/I2V assistance, MVS coordinate their maneuvers with other vehicles using sensors and wireless communication mechanisms. Some conventional infrastructure may provide static digital data that is accessible to MVS, but it is not updated in real time.

- **V2I/I2V-assist systems:** MVS interact with one another, and roadside infrastructure provides guidelines for the vehicle's decision-making. There is digital information accessible regarding the road segment (such as HD maps). Dynamic information (such as traffic signs, weather, etc.) is updated regularly.

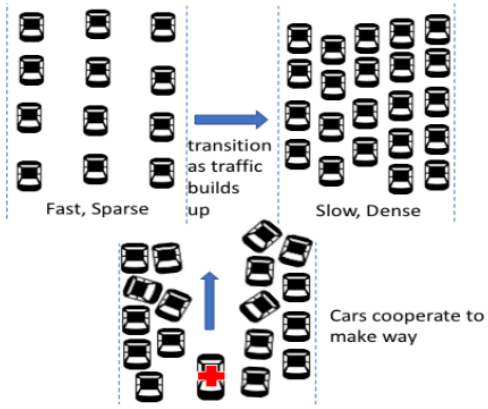
- **V2I/I2V-manage systems:** Vehicles indicate intended actions like as lane changes, exits, and entries intersections. Following that, the roadside system sends instructions/rules for inter-vehicle coordination of these maneuvers. Additionally, the road section enables cooperative perception: vehicles may communicate infrastructure about microscopic traffic and road conditions through V2I.

- **V2I/I2V-control system:** the roadside infrastructure takes complete management of vehicle operations, analyzes traffic, and optimizes vehicle operations, etc. In particular, the road section allows cooperative driving by perception information and providing commands to vehicles, hence improving safety and traffic operation.

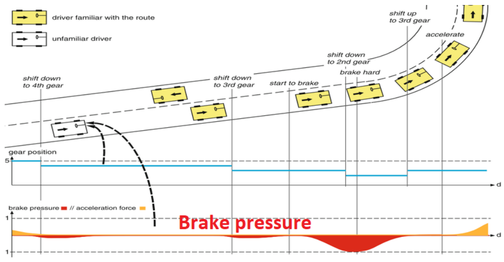
In fact, there is a need for IVs to behave cooperatively as a form of social-AI [304] or social benefit [480] in urban environments. Although conventional research has provided car-following models, intelligent driver models, and cellular automata models for developing the vehicular cooperation mechanism from a physical perspective, these models mostly focus on straight line movement [444]. Thus, numerous cooperative behaviors for more complex urban scenarios have been seen in studies [304, 394] using the MVS-based UTC system described above. For example, the dynamic traffic flow is discussed in [304]. As seen in Figure 2.4a, traffic might be heavier in one direction than the other on a highway with equal lane width. When traffic is heavy in one direction, MVS system might alert other vehicles that there are now more lanes in one direction and fewer in the other. Consequentially, the MVS-based UTC could re-balance the traffic lane. Figure 2.4b shows more flexible collective vehicle behavior. The concept of a "Danger map" is also described in [394]. MVS might communicate braking data in a specific region. The risky driving road portion is highlighted in red in the published brake pressure diagram (see Figure 2.4c). Furthermore, multiple lanes merging is a common occurrence in urban areas. It is natural to predict that the negotiation/adaptation system between a group of vehicles could adopt optimum cooperative behaviors in order to maximize throughput



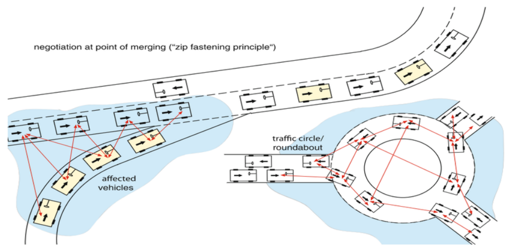
(a) Lane adaption with dynamic traffic flow [304].



(b) Flexible collective vehicle behaviors [304].



(c) "Danger map" made by collective information [394].



(d) Multiple lane merging zones [136, 394].

Figure 2.4: Numerous cooperative behaviors by MVS-based UTC system.

or traffic flow (see Figure 2.4d). Thus, the PhD thesis mainly focuses on the collective behaviors in this situation, which we'll discuss more below.

The existing MVS-based control algorithm is mainly concerned with single intersection (cf. section 1.2). Cooperative driving at neighbored intersections has also been studied by researchers [483, 510, 535]. However, multi-vehicle navigation has gotten less attention for urban traffic management with network-wide traffic control issues [183, 284]. The primary tasks or difficulties that distinguish the control technique for isolated intersections from corridors or network-level control can be divided into three major issues: *coordination of multiple intersections* using MVS, the associated *increase in traffic efficiency* in road networks, and *accurate traffic prediction/estimation* techniques.

- **Coordination of multiple intersections:** the extension of the aim from isolated to multiple intersections coordination has been studied using both centralized and distributed approaches. The optimization goals for centralized techniques may be defined by aggregating the objectives of all the intersections or by defining a common target such as throughput (equivalent to the travel time of vehicles) within a radius of a single intersection. The authors in [240] suggested a multi-objective (e.g., desired velocity, fuel economy, and safe headway) centralized model predictive control (MPC) system. A control system called the "host" processes system information (such as previous vehicles, road gradients, and traffic signals) to determine the optimal vehicle control inputs. To reduce the computational load, the distributed technique is utilized to model the optimization targets by receiving information only from neighboring intersections. The authors of [535] offer a decentralized optimum control framework based on MVS for two neighboring intersections. Individual vehicles could provide the optimal acceleration/deceleration (for minimizing fuel consumption) to pass through an intersection without crowding the connecting route between two coordinated intersections. As is the case with the MVS control architecture (see section 1.1.2), the distributed technique may be ineffective in achieving the global traffic control optimization. Additionally, the coordination (or prediction) of traffic speeds for urban corridors with multiple intersections is a prominent issue. Because drivers like to be aware of the expected speed of their route through multiple intersections when they are on the road [518]. To estimate the corridor speed between multiple intersections, the historical (and real-time) traffic information-based model [520], the extended time-series-based method [334], and the hybrid model [203] have been presented. Authors in [118] developed a consensus-based coordination technique for two unsignalized intersections in order to improve MVS navigation at the macroscopic level using the estimated corridor speed. In real-world, the work in [112] describes a field implementation based on store-and-forward modeling that includes two coordinated intersections in Chania, Greece.

- **Increase in traffic efficiency:** one of the most critical aspects of increasing traffic efficiency is dealing with traffic oscillations. Traffic oscillation is a term that refers to the stop-and-go driving situations that occur in heavy traffic and often result in bottlenecks in transportation networks [545]. For instance, the trajectory data from NGSIM (traffic microscopic dataset [461]) is studied in [545] using distance-time diagrams: vehicles traveling between 4h00pm and 4h15pm suffer minor oscillations (Figure 2.5b), while vehicles moving between 5h00pm and 5h15pm experience significant traffic oscillations (Figure 2.5a). To dampen/eliminate traffic oscillations, it has been suggested to build a sufficient time buffer [429], minimize the reaction time [100], or use a trajectory planning model [310]. Roughly, these model-based approaches aim to optimize the movement of MVS through the use of communication technology by acquiring accurate vehicle status. Further, the aggregate status of vehicles may be synthesized into traffic criteria to represent the current situation,

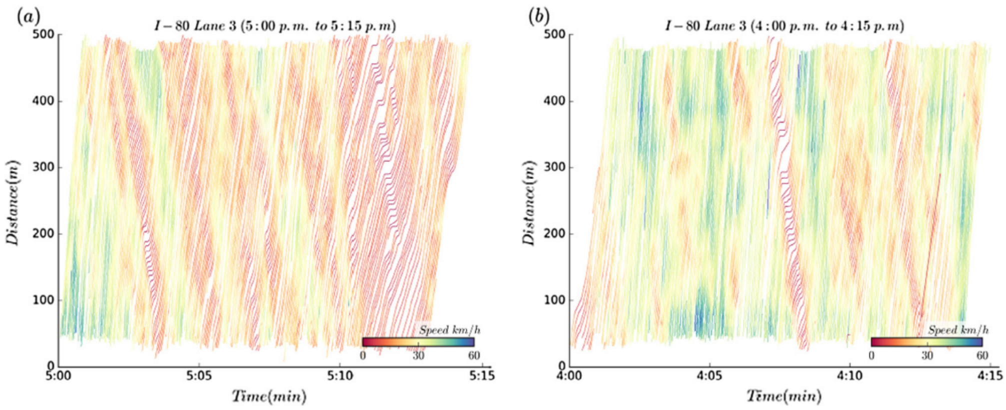
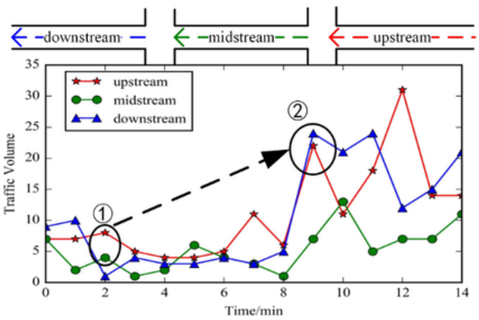


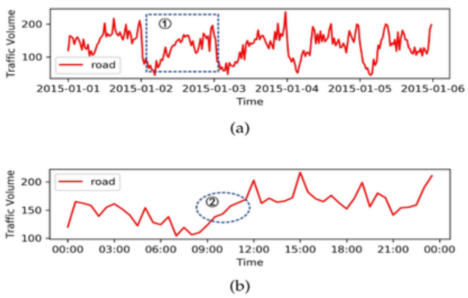
Figure 2.5: An illustration of traffic oscillations [545]: between 5:00 and 5:15 p.m. (left image), vehicles experience greater oscillations than between 4:00 and 4:15 p.m. (right image).

hence assisting macroscopic traffic management. In this understanding, traffic flow and density, vehicle travel time, and aggregated speed are the primary indicators that can be measured to evaluate the effectiveness of UTC. Additionally, queue length is also a frequently used metric for assessing traffic efficiency. MVS-based traffic control systems are capable of calculating the development of queues exactly in real time [39]. However, since the majority of research has focused on off-line traffic disturbances [383], modeling MVS to increase travel efficiency is expected to be conducted within more real-world settings in the future.

- **Accurate traffic prediction and estimation:** Estimating the traffic state is a critical component of a traffic control system. Traffic estimation or forecasting is the process of assessing the flow, speed, and density of urban traffic in order to deduce feasible traffic patterns [538]. Additionally, using this predicted data, traffic trends on the road can be forecasted. It's worth mentioning that traffic forecasting is intrinsically spatial and temporal dependent in nature [538]. Changes in traffic volume will have mutual effects (i.e., the transfer effect and feedback effect [114]) on traffic upstream and downstream roadways in different geographical network structures (see Figure 2.6a). From the view of temporal dependence, the traffic volume changes periodically over a day or a week as shown in Figure 2.6b. In particular, key traffic information can even have a direct impact on the entire control approach's performance. Without reliable vehicle position information, neither isolated intersections nor network-scale urban traffic management can implement the suggested method. For instance, the queue length approach [501] or intelligent signalized intersections [91] used to establish a congestion-free road network need previous knowledge of traffic flow in order to infer or forecast the requisite flow parameters (e.g., flow rate, densities, aggregated speed, etc.). Rather than relying heavily on parsimonious control rules to develop a traffic feedback control system [284], the traffic estimating approach must be well-designed for a feedforward (or hybrid feedback/feedforward) traffic control system. Existing traffic estimation/forecasting strategies may be categorized into two types: model-driven and data-driven approaches. Readers interested in a model-driven approach may consult [486, 507], while those interested in a data-driven approach could reference [413, 463]. Cooperative prediction using MVS is a potential method for traffic prediction, hence increasing ego-planning utility [124]. For real world application, Telecom Italia has launched a real-time monitoring



(a) Spatial dependence.



(b) Temporal dependence.

Figure 2.6: The spatial and temporal dependence in traffic forecasting: a strong influence between adjacent roads in (a); the traffic volume changes periodically within one week or one day in (b) [538].

system for Rome that enables traffic estimation [74].

To summarize, as the number of connected vehicles is growing, it is vital to consider adapting the road service level in order to ensure autonomous driving properly. A road segment in the urban transportation network may be more or less ready for vehicles to deploy automation. Thus, it is assumed that the roads of the intersecting network mentioned in this PhD thesis are able to support the V2I/I2V-assistant or V2I/I2V-mange systems that are expected to arise in the short- or mid-term. Also, it is expected to result in the development of a safer, more comfortable, and more efficient multiple vehicle navigation system in this thesis. In the next section, we will go into further details about the research on MVS network-wide navigation with multiple intersections.

2.2/ Dynamic multi-vehicle navigation in intersection networks

This section discusses dynamic multi-vehicle navigation and how it may be used to control traffic flow in intersection networks. Although traffic management and control on highways/principle arterial are not the primary focus of this thesis. Certain critical applications and control systems, including the CACC, may continue to function inside the planned intersection networks (e.g., automated platoon in urban arterial roads). It is worth noting that the following MVS-based UTC are mainly referred to as intersections management in traffic networks. The main research paradigms and implementation on this subject will be explored in more detail, both with and without a transitional traffic signal system (cf. section 2.2.1). Section 2.2.2 focuses on the decision-making models, including various traffic management layers. Finally, we provide a vision for MVN with a probabilistic method (cf. section 2.2.3) and risk management (cf. section 2.2.4).

2.2.1/ Main research paradigms and implementation

Traffic lights have been used to regulate vehicle movement for more than a century[1]. In an early review given in [364], road traffic management systems with traffic lights were classified into two general categories: fixed-time strategies and traffic-responsive strategies. The fixed-time strategies are generated off-line using historical data. While traffic-responsive strategies take into account current traffic circumstances. Coordinated strategies (including fixed-time or traffic-responsive control) are particularly effective when applied across a whole urban network. The most applicable work within these categories includes: MAXBAND (fixed-time) [301], TRANSYT (fixed-time) [399], SCOOT (traffic-responsive) [213], and OPAC (traffic-responsive) [152], etc. With the development of IVs, several surveys [183, 284] have addressed MVS-based urban traffic signal management systems in traffic networks. These papers discussed the situation for signal control systems optimizing Signal Phase and Time (SPaT) using Connected Vehicles (CVs) data and the Signal-Vehicle Coupled Control (SVCC) system. More specifically, using mathematical optimization paradigms, the authors in [183] classify three signal-based manage scheme as follows: *actuated traffic signal control, platoon-based traffic signal control* and

[1]On August 5, 1914, in Cleveland, America, the world's first electric traffic signal was deployed [488].

planning-based traffic signal control. Additionally, *reinforcement learning (RL)-based traffic signal control* is also a promising technique for controlling traffic lights in complicated metropolitan traffic networks [94]. The following are some notable works in these categories:

- **Actuated/adaptive traffic signal control:** actuated traffic signal control, as well as adaptive traffic signal control[2], have the ability to adjust the SPaT depending on historical traffic patterns [530]. The authors in [174] propose an adaptive traffic light system based on wireless communication between vehicles and fixed controller nodes placed at intersections. Despite the effectiveness of traffic signal timing optimization programs, most current research seldom considers coordinated actuation signal management based on V2X communication. A stochastic-optimization approach for coordinated actuated traffic signal systems is described in [525], however its data was gathered from real-world collected by government and fixed test locations.

- **Platoon-based traffic signal control:** the platoon-based signal control tries to schedule signal timing plans such that platoons may pass through crossings without being interrupted. Following the launch of V2X communication, it has become a popular issue [194, 232, 291]. A platoon-based self-scheduling strategy was presented in [501] to addressing the traffic signal management issue in a road network. Each intersection, in particular, is managed by a self-interested agent with a defined horizon of incoming vehicles into clusters. Indeed, platoon-based signal control is capable of aggregating vehicles in a queue, which is equivalent to handling mid-level traffic flows. The calculation burden is reduced, making it feasible to implement. However, it is difficult to quickly, efficiently, and robustly identify the approaching platoon [155]. Further, aggregated patterns (i.e., anticipated queues and platoons) of traffic flow may have an impact on overall traffic flow management performance.

- **Planning-based traffic signal control:** planning-based methods take into account the information about each individual vehicle, which allows for more detailed traffic flow management. This technique has been extensively investigated in the literature [172, 272]. Planning-based approaches evaluate the optimal trajectory for an individual vehicle with a predicted horizon. By addressing a two-level optimization problem using CVs data, the suggested approach in [132] optimizes the phase sequence and duration. Nonetheless, when dealing with large-scale networks with the prediction horizon, the computing demands of the planning-based solution becomes very high. A system for optimizing intersections and corridors that consists of two layers of optimization is described in [43]. At the intersection level, Dynamic Programming (DP) is used to change the optimum green time in consideration of coordination requirements. At the corridor level, a Mixed-Integer Linear Program (MILP) is designed to optimize offset along the corridor. The simulation indicates the model has the potential to reduce average delay and stop for coordinated routes as well as the entire network.

- **Reinforcement Learning (RL)-based traffic signal control:** the Markov Decision Process (MDP) framework is used to formulate RL, which is an alternative method

[2]Actuated/adaptive traffic signal control uses inductive loop detectors that are installed tens of meters upstream of the stop lines for retrieving vehicle information [302, 364].

for adaptive traffic signal management [434]. Unlike model-based techniques, RL fits its parametric model directly in order to learn the optimal control based on its historical interacting data. The most frequently utilized approach for training a centralized RL agent is Deep Neural Networks (DNNs) [338], which can improve the scalability of RL. Numerous RL algorithms (e.g., the deep Q-learning approach) are offered to control traffic lights in various network configurations [149, 462]. In [514], a modified Proximal Policy Optimization (PPO) algorithm is proposed to be applied in a traffic scheme including multiple intersections and dozens of vehicles. However, in reality, centralized state processing will result in excessive latency, a high failure probability, and an exponentially increasing joint action space. Therefore, adaptive traffic signal management is formulated in [94] as a cooperative Multi-agent RL (MARL) issue, in which each intersection is managed by a local RL agent with restricted communication. Its objective is to develop a completely scalable and decentralized MARL algorithm. Nevertheless, the difficulty in MARL has evolved into a trade-off between optimality and scalability [182]. Thus, researchers establish Independent Q-Learning (IQL) [438] and the Independent Advantage Actor Critic (IA2C) [94] as local agent-based solutions to the partially observed dilemma. In the simulated traffic environments, these MARL algorithms proved their scalable and robust performance in intelligent signalized control systems.

Although traffic lights are still widely used in the real world and are thought to improve overall traffic efficiency in MVS-based urban traffic signal management systems, “signal-free" control systems are preferred to reduce stop-and-go events (which can result in increased fuel emissions [142]) by allowing vehicles to pass through the intersection without fully stopping. In fact, more proactive behavior may be incorporated in the scheme of intersection management. For example, acceleration behavior is effective in coordinating certain traffic flows but cannot be governed by a traffic signal system. Additionally, it should be highlighted that the majority of developed signal-free navigation methods (cf. section 1.2) are limited to isolated intersection [183]. The following explores the unsignalized MVS-based UTC at multiple intersections. Early in 2006, a greedy search strategy was proposed in [165] for network-wide scheduling problem without a traffic signal. Later in 2015, authors in [548] attempted to establish a connection between autonomous intersection management and dynamic network assignment by using a network-level linear programming control. Further, numerous significant studies on the management of unsignalized intersecting networks include the following:

- **AIM-based traffic control:** the previously described tile-based reservation intersection control (cf. section 1.2.2), which reserves conflict-free trajectory for an AIM system, is expanded to control a network of linked intersections in [191, 277]. Indeed, AIM-based traffic control is naturally implemented with multiple intersections by using the typical multi-agent system (driver agent, intersection manager) like [116, 117]. The traffic light is actually replaced by an infrastructure (i.e., an intersection manager), who then has the authority to approve or deny a vehicle’s traversal request. By taking into account the interactions of intersection managers through a network, AIM-based traffic control aims to offer new, fine-grained, and dynamic regulation for individual vehicles, even allowing for minute-by-minute reaction to traffic circumstances [191]. Additional study conducted in [191, 277] is aimed to investigate the potential of incorporating dynamic traffic assignment (macroscopic level) into the proposed AIM-based intersection control system (microscopic level). Further, [210] developed a simulation test bed (with a network simulator) for evaluating

AIM-based traffic management. The primary distinctions between different AIM-based traffic control methods are the controlling mechanism or navigation policies [498]. Another study in [466] conducts an empirical evaluation of several policies for managing a reservation-based intersection. The majority of AIM-based research work can provide successful simulation results. However, the coordination of multiple intersection managers has not been thoroughly investigated.

- **Vehicle negotiation system:** in the field of single-intersection navigation, [347, 348] presented a decentralized solution which can be categorized as vehicle negotiation systems. In the system, the intersection manager is removed. The agents of the vehicles interact with one another to decide the order of passage and departure from the intersection. Specifically, vehicles in the collective negotiating system are intended to solve an optimization problem using sensed vehicle data (location, speed, and inter-distance, etc.). The negotiated results may include information on when and how fast to merge [394]. However, the technique is limited by the number of vehicles attempting to negotiate. Thus, in a negotiation-based approach (sometimes called auction-based approach [405]), just a few vehicles near the intersection are considered to make decisions within a certain time interval. Negotiation-based control often performs less well than AIM-based control, but the vehicle negotiation system in the valuation-aware mechanism [405] has a lower overhead for making decisions and generating agile responses to any unexpected changes [284]. Similar to the negotiating system, [273] proposes a cooperative vehicle intersection control (CVIC) algorithm that operates without the need of typical traffic signals and is expanded to cover a corridor with several intersections. Another study [467] proposes a distributed market-inspired approach for managing an urban road network. In particular, the strategy derives from the reservation-based intersection control (same as AIM-based traffic control). However, the adaptive management system enables MVS to bid on an intersection crossing in accordance with the auction-based traffic control strategy. Additionally, the competitive traffic assignment approach is intended to ensure a free-flowing movement for the desired MVS. Because of unresolved liability concerns and inter-vehicle communication challenges, evaluating negotiation-based techniques in actual traffic conditions is difficult.

- **Other work:** [293] investigates the MVS routing issue using an iterative A^* algorithm in a 9×9 grid of intersections. A novel routing algorithm is described that minimizes average delay and optimizes vehicle throughput in a network of linked intersections. The technique is capable of forecasting future traffic flows. The authors in [480] have proposed a cooperative autonomous traffic organization strategy for MVS operating on multi-intersection road networks. Notably, a three-tier decision-making framework is provided, which includes an autonomous crossing strategy at intersections, improved road segment optimization, and a composite routing strategy. In general, the traffic management system based on MVS acquire fine-grained information in this work. In comparison to traditional flow management policies, autonomous intersection control may benefit more from a combination of status information (position, velocity, route, etc.) and flow information (from the macroscopic level). However, a large computation demand may be necessary, which must be considered in the envisioned system.

To the best of our knowledge, real-world validation of MVS-based UTC approaches has just recently begun (see Figure 2.7). Although certain Advanced Driver Assistance Sys-

(a) Multiple intelligent traffic lights are deployed at the intersections of Jinan, China [209].

(b) Mcity at the University of Michigan, United States of America [454].

(c) Intelligent vehicle testing base in Changshu, China [457].

Figure 2.7: A realistic environment for deploying MVS urban navigation technology.

tems (ADAS) include a variety of real-world applications [18, 270], research on MVS-based traffic management systems has been restricted. The authors in [542] provided a comprehensive platform for forecasting traffic demand and optimizing traffic signals in Jinan, China, using vehicle trajectory data from a commercial company (Figure 2.7a), therefore enhancing traffic signal performance and lowering delay by up to 20%. Meanwhile, reports of MVS-based test track have been made in Mcity-University of Michigan, United States of America [454] (cf. Figure 2.7b) and Changshu, China [282] (cf. Figure 2.7c). With the abovementioned research paradigms and implementation for MVS-based UTC, this latter will concentrate on the decision-making model in the context of various traffic management layers.

2.2.2/ Decision-making modeling

As indicated before, traditional attempts have been made to adopt adaptive, proactive control mechanisms to enhance traffic management using real-time communication technology. However, the decision-making method, which involves building a system of rules and deducing the most suitable maneuver, cannot be accomplished by merely connecting individual intersection controllers without regard to their relationships [191]. Agent-based traffic management, in particular, has gained popularity over the past two decades as a multi-layer problem solving pattern [94, 116, 117, 168, 234, 353]. Like the majority of the hierarchical research community, in the context of our research it is adopted a bottom-up approach to describe an agent-based traffic management system in three layers, as seen in Figure 2.8. A more precise definition of the three-level agent-based traffic management architecture is as follows:

- *Macro-level:* a global supervisor (or network management agent) is in charge of the whole transportation network and is capable of recognizing real-time traffic demands.
- *Management-level:* a local supervisor (or Intersection Manager agent) is in charge of the particular intersection and is responsible for regulating local traffic changes.
- *Micro-level:* an intelligent vehicle (or driving agent) may adjust its behavior on an individual level via microscopic control or by contacting a local supervisor for navigation regulations.

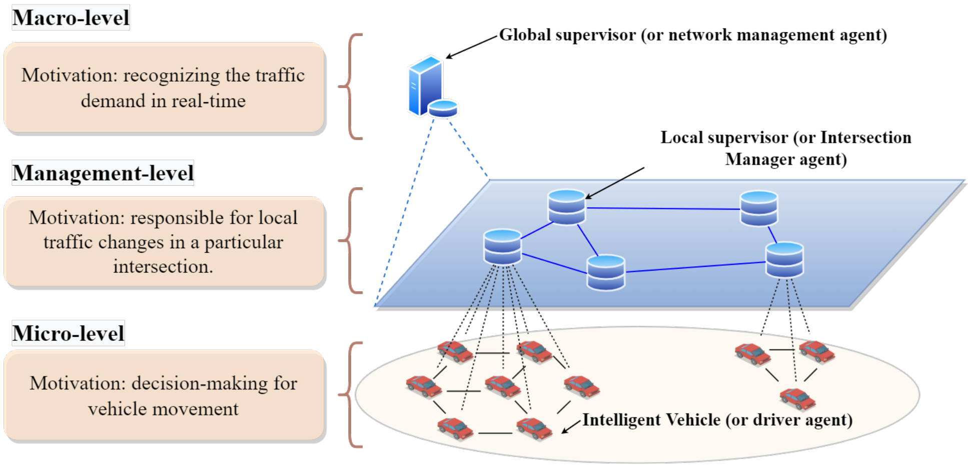


Figure 2.8: A bird's view of the proposed agent-based traffic management scheme in a bottom-up and hierarchical system.

As illustrated in Figure 2.8, each level provides a platform distinguished by different communications paradigms. At the micro-level, the IVs are expected to ensure sustainable, low-latency cooperative movements under the supervision of a local intersection manager, which performs flexible mechanism for managing traffic resources according to macro-level policies. The majority of proposed hierarchical agent-based management systems in the literature aim to achieve a balance of local (intersection) and global (network) optimums [118, 391]. As summarized in [226]:

> *"These layers are expected to make IoAV (Internet of Autonomous Vehicles) the admixture of both durability and interoperability, diversity and profundity, and most importantly, reliability and flexibility."*

Particularly, the purpose of this PhD thesis is to investigate decision-making and trajectory planning (or short for "decision-making" cf. section 1.2.1) for MVS. In other words, we focus on the intelligent vehicle (or driving agent)-based decision-making system for the micro-level, where the control objective is accomplished by independently altering the behavior of each vehicle to satisfy the demands of the macro-level or management-level. Though a fully automated transportation network is unlikely in the near future, it is worthwhile to investigate the microscopic decision-making technology embedded in the promising hierarchical architecture in order to enable novel efficient vehicle navigation that benefits the entire road network. In the following, we will discuss the decision-making problem in further detail at different levels.

2.2.2.1/ Decision-making: microscopic modeling and control

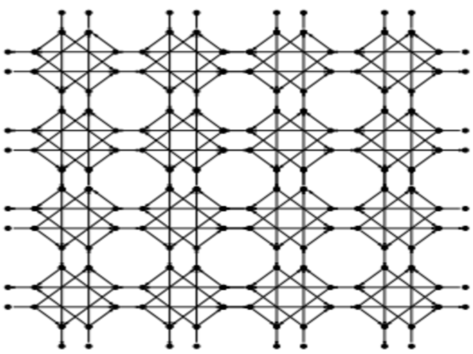
The majority of the techniques to intersection navigation presented in section 1.2 are microscopic control strategy in nature. These models, on the other hand, are regarded isolated inside their immediate surroundings. In contrast, the microscopic decision-making model of MVS mentioned in this section is designed to be adaptive to the different types of traffic networks. More precisely, *microscopic modeling* techniques (such as cellular automaton models) can provide fundamental principles for individual vehicles and their network activity. One can distinguish these main approaches as follows:

- **Cellular automaton model:** a one-dimensional array L or a directed graph $\mathcal{G}$ is used to define this computational model [165, 246, 344]. A site in L or a vertex $v \in \mathcal{V}$ can be used to represent every cell. Each cell may be filled (by a single-vehicle) or unoccupied in the setup, implying the assignment of time slots. As a result, the cellular automaton model is built into a Discrete-Time and Discrete-Space system. Additionally, researchers in the literature create cellular automaton rules for system updates, which are carried out in parallel for all cars. The authors in [344] make the assumption that each vehicle travels at an integer velocity along a boundary. Four rules are used to update the proposed cellular system: vehicle-free acceleration in safe situations, slowing down for ahead vehicles on site, speed randomization to account for natural velocity fluctuation, and motion planning based on current speed. An interesting "start-stop-waves" was observed by the integer-valued probabilistic cellular automation rules. Additionally, the authors in [165] consider the vehicle's length and the minimum safe distance as the cell length, which is related to time slots. Notably, the intersection conflict points are not regarded as cell points, whereas the cell are directly linked between the neighboring two lanes at the border, as seen in Figure 2.9a. In such a road network, the system state with n vehicles is donated by $X(t) = [x_1(t), x_2(t), \ldots, x_n(t)]$ where vertex $x_i(t) \in \mathcal{V}$ representing vehicle i at time t. Thus, the essential proposition is to calculate the new state $X(t+1)$ using the present state $X(t)$, and the feasible shift subset is defined as one that satisfies all constraint conditions. In the later part of the study, a feasible system clearing schedule solution is presented in the model, emphasizing the existence of such schedules. The feasible scheduling issue, on the other hand, remains NP-hard. In the cellular automaton model, the heuristic algorithm is commonly used.

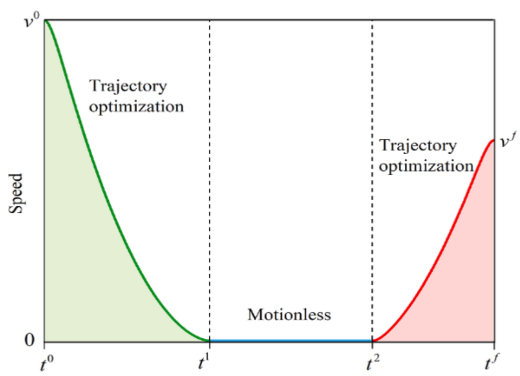
- **Trajectory optimization model:** another method for model microscopic trajectory planning is to construct an optimization control system based on the kinematic function. Taking [480] as a reference, the kinematic model is as follows:

$$\dot{\boldsymbol{x}} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ v \\ a \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} u \tag{2.1}$$

where $\boldsymbol{x} = \{x, v, a\}$ are respectively the displacement, speed, and acceleration, u is input jerk. Additionally, an objective function J is defined with regard to journey



(a) The road networks graph in cellular automaton model [165].



(b) A pieced motion process [480].

Figure 2.9: An illustration of microscopic models.

time, energy consumption, and other comfortable characteristics during the planning phase, which is subject to kinematic constraints:

$$\begin{gathered} min \;\; J = f(u) \\ \textit{Subject to: } \dot{\boldsymbol{x}} = A\boldsymbol{x} + B\boldsymbol{u} \end{gathered} \tag{2.2}$$

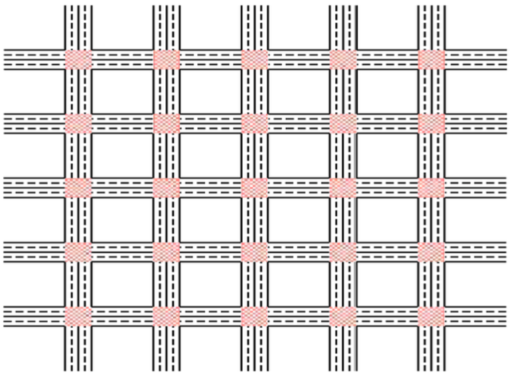
One can find the similar research in [480, 535]. Additionally, [480] employs the optimization control model to optimize the road segment's trajectory between two intersections. As seen in Figure 2.9b, a pieced motion process with three phases is introduced: deceleration, stop, and acceleration. Thus, when a vehicle departs the former intersection (at t^0) and enters the latter (at t^f), a smooth trajectory with minimal jerks and acceleration may be ensured. Another work [522] provides a Mixed-integer Linear Programming (MILP) model for cooperatively optimizing vehicular trajectories over a traffic corridor with unsignalized intersections in a completely MVS environment. In the micro-level, the vehicle model is simplified to a first-order dynamic model while maintaining the linear and convex properties of the proposed optimization model. The vehicles' trajectories in the corridor are coordinated in a unified framework to achieve system-optimal in terms of overall vehicle delay. The centralized planning framework, in particular, has the potential to deliver safe and effective car following and lane change behaviors for each vehicle driving through unsignalized intersections. However, a significant computational problem exists.

2.2.2.2/ Decision-making: macroscopic strategy

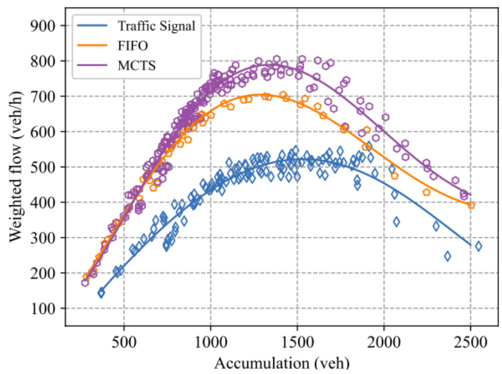
Once the microscopic modeling is assigned, the aggregated vehicle's performance can be measured to value the overall traffic efficiency. On the other hand, decision-making strategies based on *macroscopic strategy* have resulted in the development of traffic flow models with input characteristics such as throughput, velocity, and density [351, 426]. Indeed, early decision-making strategies for traffic flow such as SCOOT® (centralized) [213], SCATS (centralized) [306] and Utopia (decentralized) [322] in the UTC system remain applicable to large-scale networks. They are, however, inefficient in light of rising traffic demands, resulting in a frequently crowded traffic situation [247]. On the other hand, an optimization-based method (e.g., RHODES [152]) proposes certain sophisticated traffic responsive techniques, albeit at the cost of a variety of computing resources. Thus, interdisciplinary solutions are provided in these publications, such as genetic algorithms [77], fuzzy logic [168] and artificial immune networks [104]. This section will outline many of the most important decision-making processes from a macro view perspective, like the following.

- **Fundamental diagram (FD)-based strategy:** a fundamental diagram (FD) in the shape of a flow-density curve is employed in highways and two-dimensional urban road networks [247]. The concept of FD has been presented since 1969 [167]. It may be thought of as one of the Aggregated Traffic Relationships (ATR) between average traffic variables (e.g., speed, density, or flow) for a particular network [160]. The form of FD has been established by researchers via simulation-based tests [153], theoretical analysis (using a utilization-based approach) [198], and systematic empirical research [158]. A coordinated signal-based application described in [112] for real urban network has also been reported to have a fundamental diagram-like traffic flow. In addition, the notion of a fundamental diagram is also called a Macroscopic Fundamental Diagram (MFD) or a Network Fundamental Diagram (NFD) [247]. In fact, MFD/NFD is determined by origin-destination demand, which is very stable when traffic loads are distributed uniformly across networks [160]. Generally, the paradigm for an MFD is based on the assumption that congestion is distributed evenly [158, 160]. Nonetheless, heterogeneity in road density contributes significantly to the shape (i.e., unimodal curve) and scatter level (i.e., low scatter relationship) of MFD/NFD. The influence of heterogeneity on MFD/NFD has been investigated experimentally using real-world data from a medium-sized French city [69]. The authors in [391] offer a two-level aggregated model for the purpose of examining the dynamics of heterogeneity and its effect on the MFD/NFD model. To the best of our knowledge, microscopic decision-making based on MFD/NFD is very rare in research within the intersection networks. A recent publication [531] examined unsignalized intersection passing orders using various driving strategies (i.e., FIFO-based cooperative driving, Monte Carlo tree search based cooperative driving, and a fixed-time traffic signal strategy). The studies demonstrate that passing order (from microscopic decision-making) has a substantial effect on the efficiency of network traffic (Figure 2.10a), and that a better order may greatly increase the curve of the MFD/NFD. As seen in Figure 2.10b, the suggested Monte Carlo tree search (MCTS)-based cooperative driving method [506] outperforms the traditional traffic signal approach or the FIFO-based strategy as measured by the MFD/NFD curve. It implies that the MFD/NFD results might be more effectively used to validate and design the microscopic decision-making techniques.

- **Route planning-based strategy:** route planning is studied in particular in the context of dynamic traffic assignment, which may be accomplished via the use of simulation-based methodologies [432] or through optimization-based approaches [188]. The emerging MVS technology enables vehicles to plan their routes cooperatively in order to take the most efficient trajectory over road networks. More specifically, the authors of [480] suggest a composite strategy for route planning that incorporates cooperative decision-making of MVS: vehicles can select the route to reduce the average delay time by cooperative decision-making before they get into the road networks. To address all MVS requests, an information center (similar to global supervisor) is deployed. Additionally, a greedy algorithm is utilized to op-



(a) A typical urban traffic network with twenty-five intersections [531].



(b) MFD/NFD under different cooperative strategies [531].

Figure 2.10: A comparison of various decision-making strategies in relation to the MFD/NFD curves.

timize the sequence for route planning, taking the expected maximum delay into account. From a macro perspective, vehicles that have a high probability of causing a traffic delay are given priority when routing. Another publication in [293] describes a routing mechanism based on an iterative A^* algorithm. Each iteration consists of three stages: batch processing to store all vehicle data, routing to execute time-based A^* searches consecutively, and congestion checking to encourage vehicles traveling through congested regions to take a detour. By forecasting future traffic flows, the suggested route planning strategy aims to decrease average delay and maximize vehicle throughput. The efficiency of iterative A^* is shown by comparison to time-based and distance-based A^* using the SUMO simulator. Route planning-based strategies, on the other hand, need centralized knowledge for coordination and V2I/I2V data exchange, when in practice, information biases are inevitable.

2.2.2.3/ Decision-making: hierarchical control

Clearly, the overall traffic conditions may have an effect on the behavior of individual vehicles. Low-level vehicle control, such as speed changes, gear changes, steering, and so on, could be translated from high-level reasoning to cooperative behavior [304]. In addition, it is worth mentioning that, as previously said, there is a choice between AIM-based and vehicle negotiation-based decision-making strategies (cf. section 2.2.1). It is still seen as an open issue between centralized and decentralized control. Additionally, a *hierarchical control* system based on management-level and micro-level decision-making techniques is feasible (e.g., synchronization-based intersection control). Consequently, the *hierarchical control* often contains both an intersection manager and a driving agent (see Figure 2.8). To demonstrate how the hierarchical decision-making model regulates the vehicle's behaviors, some common instances are as follows.

- **Synchronization-based control:** to allow vehicles from different directions passing through intersections without stopping. The authors in [445, 446] proposed a two-level decentralized multi-agent system to improve traffic mobility via a stop-free strategy. The intersections network is illustrated by Figure 2.1d. The network is then modeled as a graph (v, ε) (i.e., it is made up of a collection of labeled vertices v and edges ε) with lane segments $i \to j$ where i and j are neighboring intersections (see Figure 2.11). The authors in [445] have proposed a local synchronization strategy for passing through the vehicle alternatively without stopping. Thus, each intersection is managed by a control agent (identical to the intersection manager), which communicates with the vehicle agent in order to manage their passing. However, the vehicle agent should limit their speed to ensure that they arrive at the crossing zone within the period T specified by the intersection control agent. T is derived as the minimal period required to pass two vehicles (one from each flow), which can be shared in the road network. Further, in the management-level, an intersection i directly interacts with its neighbors with its phase ϕ_i of periodic signal for synchronization-based control. On the other hand, at the microscopic level, an adaptation phase is used to achieve the desired crossing speed $V_{crossing}$. As seen in Figure 2.11, vehicles in such a decentralized system depart at a constant speed V_{MAX} from some intersection i. It will continue through the following intersection j at the velocity $V_{Crossing}$ specified by the intersection control agent j. Self adaptation phase (equivalent to motion planning) occurs in the ego-vehicle. As a result, the

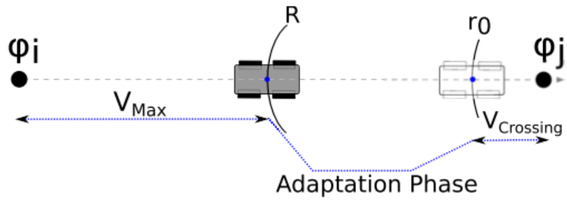


Figure 2.11: In the synchronization-based control model, any vehicle from i to j will pass through (1) the uncontrolled zone between i and j, (2) the adaption phase control zone inside j's radius of R, and (3) the crossing zone of radius r_0 [446].

desired performance (to create "green waves") can be obtained by such a stop-free strategy.

- **Consensus coordination:** consensus coordination is used to balance traffic density throughout a transportation network. Numerous consensus algorithms are explored in the literature [118, 498, 499]. The concept of coordinated multiple intersections is based on a completely AIM system and the Greenshield's traffic model [189]. Consensus coordination is specifically applied in two or three layers via a hierarchical control technique [118, 499]. The infrastructure (AIM) network is the top layer. However, each AIM-like agent is expected to coordinate only local traffic information within its neighborhood. Thus, the paradigm of decentralized control is achieved. Additionally, a single autonomous intersection can be modeled in the lower layer. To handle a vehicle crossing an intersection, the centralized control approach is used. As a result, traffic information is considered between connected neighbourhoods. The main difference is the strategy of consensus coordinating for traffic flow. To ensure uncongested traffic flow, the traffic estimation technology is addressed in [499]. Additionally, it is critical that the network topology model and I2I/I2V communication protocol are well-designed. Simulation results demonstrate that consensus coordination is capable of coping with rising mobility while still requiring a sophisticated communication technology.

Table 2.1 provides the associated research on MVS decision-making in road networks that was highlighted before.

To summarize, with vehicular communication technology, there is a trend from passive feedback control to mixed feedforward/response control in urban traffic management [183, 284]. For example, when the MVS' current states are known or partially known, the future state of traffic flow with desired control actions may be anticipated by recursively solving their dynamical differential equations [284]. Generally, distributed and hierarchical strategies may be attractive network control methods for decomposing large-scale optimization issues into manageable sub-optimization problems. In fact, the sub-problem may be handled more effectively by collective information sharing [14]. Remarkably, the majority of strategies for decomposing centralized network-level management into distributed control are mathematical programming or heuristics [14, 161, 324, 328, 495, 495]. Thus, ensuring the global optimum remains a difficulty for distributed control, so does the decomposition process's stability. Following that, hierarchical techniques make decisions at both the macro (higher) and micro (lower) levels. The main barrier is defining precise macroscopic and microscopic models. At a higher level, traffic flow models are often described as MFD/NFD including concise traffic data that encapsulate the es-

Table 2.1: Summary of decision-making model for MVS navigation in road networks

Approach	Main techniques	Objectives	References
Cellular automaton	stochastic discrete automaton	simulate traffic flow	[246, 344]
	heuristic	traffic scheduling	[165]
Trajectory optimization	optimal control	safety, fuel consumption, comfort	[480, 535]
	Mixed-integer Linear Program (MILP)	delay	[522]
FD-based strategy	theoretical research	form verification	[153, 167, 198]
	empirical research	FD existence	[69, 112, 158, 160]
	aggregated model	heterogeneity	[69, 391]
	gating control	protected network	[247]
	Monte Carlo Tree Ssearch (MCTS)	passing order	[531]
Routing based strategy	greedy algorithm	routing sequence	[480]
	iterative A^*	delay and vehicle throughput	[293]
Synchronization-based control	Hill-Climbing iteration	green waves	[445, 446]
Consensus coordination	Greenshield model	traffic density and delay	[498, 499]
	Fast Model Predictive Control (F-MPC)	traffic velocity	[118]

sential feature of network-wide vehicle flow and densities (i.e., the collective behaviors of MVS) [101, 102, 158, 159, 516]. MFD-based network control [159, 184] may outline the complete upper-level network issue and direct the lower-level (for particular regions/intersections) to generate optimization targets. However, the topic of how to merge MFD-based network control with precise intersection/corridor management for MVS remains unanswered. Another approach to resolving challenges associated with heavy traffic management is to implement a cooperative driving strategy that involves the formulation of short-term driving plans via bilateral or multilateral negotiations (i.e., Vehicle negotiation system) [16, 35, 273, 518]. Noting that this technique considers just a few vehicles passing through the intersection within a certain time period. It is seen as a lower layer of control than planning-based control in certain publication [284]. In the meantime, the inherent trade off between the control scheme quality and its computational demands is therefore a crucial issue that should be explored thoughtfully.

2.2.3/ Probabilistic approach for decision-making

Clearly, distributed/decentralized control architecture is favored in the suggested intersecting networks with moderate computation requirement. Further, probabilistic technique is widely employed for a robust decision-making strategy. For instance, the Probability Collectives (PC) algorithm is an efficient optimization searching framework for distributed systems, which was first proposed by Wolpert and Bieniawski in [58, 494]. It is a COllective INtelligence (COIN) framework that emerged from game theory, statistical physics, and optimization theory [262, 513]. A comparative study has shown that the PC-based approach is superior to traditional Genetic Algorithm (GA) in both rate of decent and avoiding local minima [208]. Kulkarni et al. in [262] designed a shrink-sampling interval method to improve the algorithm performances via benchmark functions. After that, a PC-based approach successfully solved various discrete optimization problem like Multiple Traveling Salesmen Problem (MTSP) and Vehicle Routing Problems (VRP) [261, 262]. To handle MVS/MVS intersection navigation, the PC algorithm in [373] (presented by our team) has two important qualities, namely probabilistic nature and decentralized nature: its probabilistic nature allows a probability distribution over a vehicle behavior set, guaranteeing a risk averse decision strategy. Additionally, the probabilistic method enables the management of uncertainty without causing the shared decision process to deadlock. Further, its decentralized nature allows it to be used without a specific road infrastructure. Besides, vehicles can significantly benefit from an acceptable computing time (around $0.2s \sim 0.8s$ in the full optimization cycle). Thus, it is an interesting and promising method to process the aforementioned Multi-Vehicle Navigation (MVN) problem in restricted areas. Although the formulation of PC in [373] is intended for an isolated intersection, it offers a compelling potential to adapt the probabilistic method (for microscopic-level management) to more complex traffic situations/environments.

2.2.4/ Risk management for multi-vehicle navigation

As indicated in section 2.2.2.2, route planning is explored in particular in the context of dynamic traffic assignment. However, when it comes to dynamic route assignment, safety is seldom addressed at the traffic management level. In addition, the majority of MVS-based traffic management techniques are optimized for throughput, travel duration and fuel consumption (see Table 2.1), etc. Clearly, risk management is critical in traffic control, and it can be expressed as a group of goals that increase overall control performance [504, 540]. The primary problem for risk management in the road network is determining the appropriate quantitative and qualitative methods for assessing driving risk, as well as how to establish constrains for various purposes. It is worth noting that one of the PhD thesis aims is to route and schedule vehicles on the road network (macro-level) in a manner that strikes a balance between speed and risk. In micro-/management level control, safe and smooth autonomous navigation technology have been widely considered in the intelligent Advanced Driver Assistance Systems (ADASs) [346]. Lane Keeping Assistance (LKA) and Adaptive Cruise Control (ACC), for instance, are effective tools for obstacle avoidance driving in single vehicle control [346]. However, in the view of multi-vehicle cooperative navigation, the road accidents are more likely to be regarded as the failures of the multi-agent system rather than failures of any single vehicle [333]. The historical data approach is used to identify particular traffic accidents and apply safety countermeasures [305]. Due to the sparse nature of traffic accidents, the use of such an approach is limited to perform safety analyses based on proper accident database records [27]. A more qualified form of risk management method is proximal safety indicator, which occurs more frequently for safety assessment and requires a short time for data collection [27]. Furthermore, the generally used proximal safety indicators are time measured metrics with a form of Time-To-X (e.g., Time-To-Accident, Time-To-Collision, Time-To-Break, etc.) [202, 205, 484]. Indeed, safety indicators provide an active approach assessing traffic conflicts to road users with reliable results. But these safe concerns lack of consistent definition or a robust theoretical foundation [92]. Among those methods, Time-To-Collision (TTC) is usually viewed as a more objective tool for predicting traffic accidents [27], [45]. A TTC-based traffic event can be always recorded during the entire interactive process. Controllers can decide whether to adopt evasive maneuver in advance (with regard to the intention and purpose) rather than emergency braking at the last resort [215]. The threshold for TTC is generally a definition that implies the risk-margin for drivers to react in a possible accident [92]. Arguably, TTC-concept is widely used as an important part of traffic conflict technique. However, detecting critical traffic events with TTC in varied spatial structures is more challenging. As a result, continued development of a TTC-like indicator as a risk-sensitive road proximate safety indicator is required.

2.3/ Conclusion

This chapter examines Multi-Vehicle Navigation (MVN) on road networks and the associated decision-making models. Numerous vehicle network navigation scenarios and requirements are presented in an urban setting (e.g., in the intersection network layout). Furthermore, we discussed the MVS systems/behaviors in such a complex intersecting network. Multiple research methodologies and decision-making models are examined in further depth using the anticipated road network, both with and without a traffic light system. We extend our investigation of the primary decision-making model/strategy and control mechanism in the context of several traffic management layers. Additionally, this chapter emphasizes the current limits on the operation of the multiple intersection management system, as well as the basic constraints on the system's operation. Finally, due to the inherent uncertainty in real-time traffic management, we highlight the need of using a probabilistic approach and managing risk while using MVS in a transportation network.

II

Cooperative navigation scheme in complex environment/situations

3

SAFE AND FLEXIBLE COOPERATIVE NAVIGATION WITH RISK ASSESSMENT

Cooperative Navigation (CN) is a widespread technique to ensure the efficient navigation of intelligent vehicles in complex/cluttered environments. As discussed in section 1.1.3, coordination issues that arise in rural and urban locations include motorway/highway speed coordination, merging at on-ramps, and coordination at signalized/autonomous intersection. Nevertheless, the main challenge exists in estimating and managing in-road risks while applying flexible CN strategies (cf. section 1.2.3). Thus, this PhD thesis is concerned with designing the navigation strategies used by MVS in signal-free intersections that provide reasonable communication conditions. Remarkably, the decentralized architecture has been chosen for determining the cooperative maneuvers of vehicles. It is intended to address a manner of bilateral or multilateral negotiation in our formulated system. Meanwhile, the suggested method takes into account the inherent trade-off between the quality of the control system and its computational requirements.

More precisely, this chapter firstly outlines a flexible CN scheme for MVS system to deal with a cooperative system (cf. section 3.1). With its relative low execution time (as indicated in section 2.2.3), the Probability Collectives (PC) algorithm has succeeded at generating fast and feasible solutions to cross intersections and roundabouts [373]. Moreover, IVs can run PC in a decentralized manner. However, the PC is still sensitive to uncertainty in the navigation process, which highlights the need to adopt several safety margins. This chapter focuses on balancing between the high-quality cooperative optimization and acceptable computational speed. Thus, a reliable risk management strategy is proposed by introducing a novel ε-constraint PC method (cf. section 3.2). A real-time communication mechanism is suggested for a distributed system to avoid invalid behavior due to inconsistency. The novel ε-PC based navigation strategy allows the vehicles to adapt their dynamics and react to unexpected events while respecting real-time constraints. The typical common-yet-difficult circumstances in a single unsignalized intersection appear to verify our findings: the ε-PC method can ensure collision-free behaviors and reserve reasonable reaction time for vehicles' safety insurance.

Furthermore, this chapter explores risk management issues beyond local cooperation and try to formulate an Shortest Path under Risk constraint (SPR) problem from the perspective of a global supervisor (cf. section 3.3). The idea here is to limit risk while allowing the vehicle to move as quickly as feasible. In contrast to the local CN approach, A discrete decision model is proposed that incorporates a heuristic local search algorithm for rapid run in routing strategies. Finally, the statistical instance analysis provides a thorough understanding of our algorithm.

3.1/ Problem statement

Similar to urban transportation systems, specific territories like large hospitals, university campus, commercial and industrial sites have taken steps to improve their navigation services in their shipment/transit areas [216]. MVS system in such restricted areas may help to provide more efficient transport services for passengers [8, 99, 216]. In the meantime, numerous simultaneous requests from multiple delivery locations may invoke cross-linked planning routes for MVS system. However, the inherent trade off between the control scheme quality and its computational demands is therefore a crucial issue that should be explored for this kind of cooperative navigation at intersection points.

In this chapter, a typical graph of two connected IVs cooperative navigation at an intersection is illustrated in Figure. 3.1. Similar to Multi-Robot Systems (MRS) (cf. section 1.1.1), multiple levels of coordination between the different agents take place depending on the overall navigation system feed-backs.

Main assumptions: MVS are provided with an enhanced autonomy. They may manage the assignment of the navigation tasks by themselves through embedded decisional devices and inter-vehicle communication tools. Details about other important autonomous vehicle navigation technical issues, such as cooperative perception and localization, planning and re-planning, control architectures may be found in [8]. Here in Figure. 3.1, two connected IVs are which exchanging their predicted future motion trajectories. Because IVs can better understand the behavior of each other, we consider IVs more likely to have prosocial (or altruistic) behaviors rather than too conservative (or egoistic) behaviors [410]. Thus, the two IVs may perform a collaborative search of coordinated actions based on a utility-maximizing decision model. In presence of a non-collaborative agent (but this agent broadcast its estimated behaviors at first), then the IVs can only achieve a sub-goal of the navigation system by optimizing its own behavior. Let suppose that a pri-

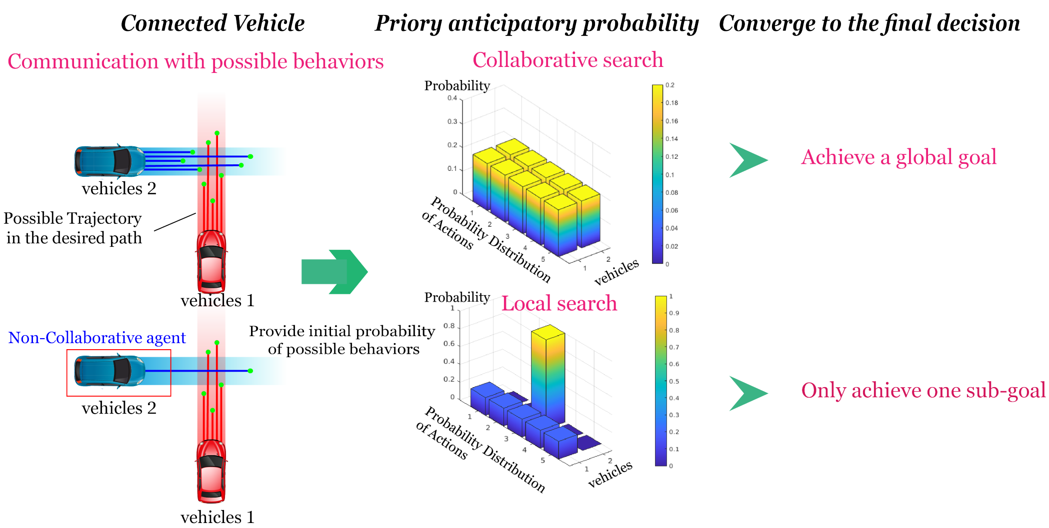


Figure 3.1: IVs system with action probability distribution to predict their behaviors.

ory anticipatory probability set is already specified to predict a potential action of the other vehicle. Nonetheless, the probability distribution of actions need to be updated while the IVs perform their collaborative searching or local optimization process. In that respect, the data processed is stored and shared as files in a distributed system. Accordingly, a distributed approach is applied in a natural way to find out coordinated actions of the MVS. Therefore, this chapter aims to validate a decentralized approach to handle this distributed multi-agent optimization problem.

3.1.1/ Related work and main challenges

In the field of intersection coordination, the direct vehicle control approach has been applied to change the traffic lights pattern [319, 435]. Slots assignment to vehicles [212] is also a popular technique which is used in the same context. However, traditional traffic signal control methods in urban city usually cannot be applied directly in above mentioned areas, because traffic light is subjected to redundant cost in such an inappropriate formed crossing-road and in certain situations increase the level of traffic jam [183]. Automation and communication have turned the cooperative intersection management into a more active research field [85]. Roughly, distributed and decentralized control are becoming a promising way to deal efficiently with this multi-scale navigation problem in complex traffic scenarios. Studies reported in [85, 179] provide more details about such cases. Additionally, a non-signal management of vehicles from a shared space is studied in [373]. A distributed and decentralized optimization algorithm, based on Probability Collectives (PC) [262] (cf. section 2.2.3), is applied to solve vehicle cooperation problem.

For a group of homogeneous MVS, researchers have tended to focus on efficient and effective controls to cut off with customer waiting time or energy consumption [54]. The existing MVS dispatch study rarely discussed how to simultaneously maintain the optimal performance and also avoid risks at intersections. As a matter of fact, risk minimization has been shown to be considered as a priority in such a case [85]. Since sudden changes in the dynamics of ground vehicles in a short time are not realistic [83], [217]. There is still considerable ambiguity with regard to a risk assessment approach for safe and flexible navigation of MVS.

To summarize, vehicles' collaboration with risk management capabilities is a promising way to solve above mentioned problem. Additionally, the consideration of the real-time concerns and the management of several simultaneous actions are of utmost importance for such a distributed navigation system. Thereby, distributed real-time cooperative systems with a safety constraint (collision avoidance) can be generated in our case. Based on the PC theory, the previous research in [260] has investigated several off-line PC optimizations with soft constraints (e.g., tension/compression spring design problem). Thus, next section focuses on the analysis of real-time MVS intersection coordination by integrating the PC theory.

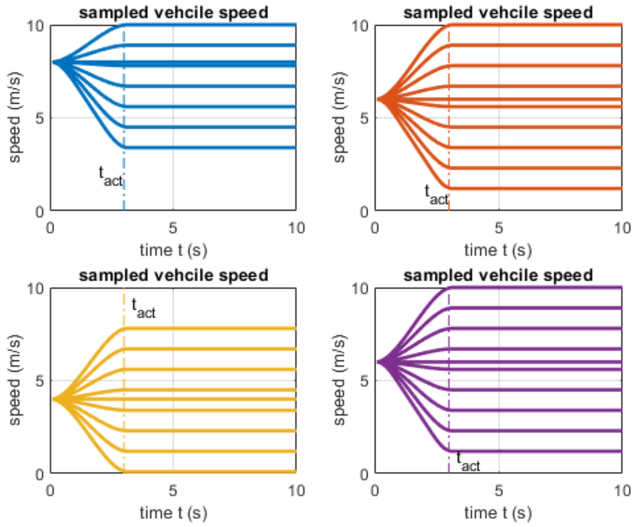
3.1.2/ Probability Collectives (PC) algorithm

In order that the proposed method can be simply read, let us sum-up in what follows the already proposed PC formulation to deal with the coordination of MVS in intersections and roundabouts [373].

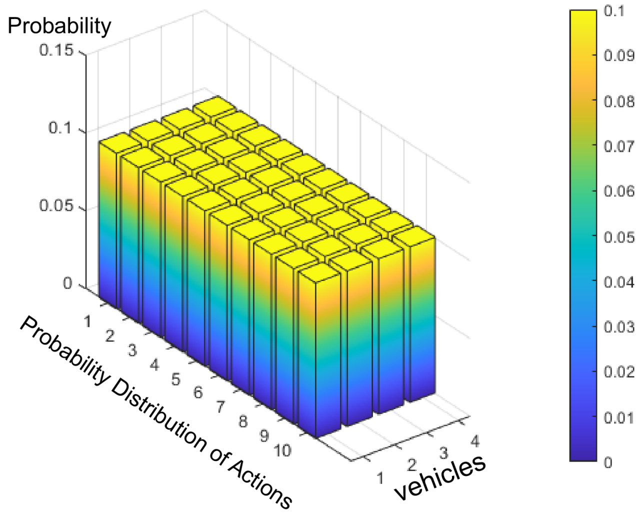
3.1.2.1/ FORMULATION OF SEARCHING SPACE

Several vehicles are considered crossing through the intersection with fixed known path. Then, the only control degree of freedom of the MVS are the speed of navigation. PC treats the vehicles in a coordination problem as individual self-interested players iteratively [494]. Thus, these agents, in our case of study several vehicles (as shown in Figure. 3.2), should select their actions (velocities in our problem) over a particular predefined interval time to coordinate their navigation motions. An illustration of the possible actions in fixed time windows ($T = 10s$) which is long enough leaving an intersection as depicted in Figure. 3.2a.

Apparently, in Figure. 3.2a, there are considerable options N_i for each vehicle i depend-



(a) Possible speeds.



(b) Uniform distribution of all the agents' behaviors.

Figure 3.2: Example of strategies hypotheses for vehicle actions.

ing on the initial speed $v_i(0)$. By both considering the safety and comfortable requests, intersection has a speed limit below $10m/s$ and vehicles tend to restrict acceleration in $[-2m/s^2, 2m/s^2]$ according to a restrained speed profile as illustrated in Figure. 3.2a. A further taken hypothesis is that all the vehicles will get a fixed speed $v_i(T)$ after a predefined action time t_{act} (such as $t_{act} = 3s$ in Figure. 3.2a). At last, the searching space for vehicle i can be summarized as a tuple $\mathbf{\Pi}^i$ i.e., $\mathbf{\Pi}^i \sim \{v_i(T), t_{act}, N_i\}, t \in [0, T]$. Then, the admissible member of actions set for the ego-vehicle can be presented as $\Pi^i \in \mathbf{\Pi}^i = \{\Pi^i_1, \ldots, \Pi^i_{N_i}\}$. Here, Π^i can be visualized as the velocity profile in Figure. 3.2a.

As mentioned before, in the PC theory the expected utility of a given action can be calculated by each vehicle. But to do so, it must get (or estimate) the possible actions of the other vehicles. It has been used probability distribution to model relative actions like $q(\Pi^i_k) \in q(\mathbf{\Pi}^i) = \{q(\Pi^i_1), \ldots, q(\Pi^i_{N_i})\}$. Obviously, the preferred actions (or strategy) have a high probability of being cost-effective. The driver model used to improve the precision of the predictive control with probability distribution is a hot topic, but not the main research topic in this section. Indeed, it is considered in the proposed work that this probability distribution is given by dedicated algorithm and according to that it is proposed an appropriate strategy to take the most appropriate decision making under this initial probability distribution. Readers are recommended to read [410] to get clearer idea about the estimation of the probability distribution of other ground vehicles. The hypotheses of prosocial (or altruistic) IVs in this section make us formulating a uniform distribution (as shown in Figure. 3.2b) of all the agents' behaviors when $q(\mathbf{\Pi}^i)$ is initially loaded for computation.

3.1.2.2/ Two steps for re-acceleration

For various collaborative navigation behaviors, vehicles choose a speed profile that allows them to safely cross an intersection based on an utility function (see section 3.1.2.3). However, for the vehicles which have to choose the arbitrary low speed (or a complete stop), the proposed algorithm allows them to re-accelerate. The re-acceleration permits the vehicles to clear the intersection as fast as possible while ensuring free collisions. An important point that needs to be addressed is that re-acceleration should ensure continuity constraints of the speed. An algorithm that enables a continuous speed profile after the action time have been designed in the previous work [373].

3.1.2.3/ Objective function

In its initial shape, the original PC approach considers only an unconstrained minimization problem. Such a research case generally involves n vehicles, and each vehicle $i \in n$ possesses a strategies/actions set of $\mathbf{\Pi}^i = \{\Pi^i_1, \ldots, \Pi^i_N\}(i = 1, \ldots, n)$ including an equal amount of N options (cf. section 3.1.2.1). After performing a local motion planning through their on-board embedded devices, each vehicle applies a strategy $\Pi^i_k \in \mathbf{\Pi}^i(k = 1, \ldots, N)$ during time interval $[0, T]$. Here, T refers to the prediction time horizon. During the period $[0, T]$, a particular set of combined strategies $\boldsymbol{Y} = [\Pi^1_k, \Pi^2_k, \ldots, \Pi^n_k]$ is selected (randomly fixed to initialize the process) to reach at least a minimum system utility level $J([\Pi^1_k, \Pi^2_k, \ldots, \Pi^n_k])$. The proposed objective function [373] can be formulated as given in equation (3.1):

$$J(\boldsymbol{Y}) = W_{sep} \sum_{i_v \neq i_{self}} \sum_{t_k=1}^{max} \frac{1}{d_k(i_v, i_{self})^2} + W_{cross}(v_{max} - v_{avg})^2 \tag{3.1}$$

where $d_k(i_v, i_{self})$ is the distance between the ego vehicle i_{self} and the vehicle i_v (i.e., all collaborative vehicles) at time step t_k (a discretization of $t \in [0, T]$). v_{max} refers to the maximum speed legally allowed on the road. In addition, v_{avg} is the average recorded speed of all the vehicles during $t \in [0, T]$. W_{sep} and W_{cross} are the weights to balance between the different criterion characterizing (3.1): low separation and slow average speed. It should be noted that the proposed $J(Y)$ value is updated iteratively during the PC algorithm execution by the agents taking part in the coordination process. Thus, the delicate designed searching space approach must ensure a sampling of "good" quality during the first action time. Readers are encouraged to read [262] and [373] for further information.

3.1.2.4/ A summary of PC model

As mentioned before, equation (3.1) is utilized without absolute safety constraints. For several cases, a very high weight W_{sep} may be admitted to penalize low separation distance to ensure more safe navigation. This can lead vehicles to preferably choose arbitrary low speeds (or a complete stop). Such behaviors may be regarded as very conservative. In real-time traffic navigation, IVs must have appropriate control architecture with reliable and real-time Risk Assessment and Management Strategies (RAMS). These targeted RAMS must reduce drastically the navigation risk in order to face sudden road hazards and risky situations. Unfortunately, the proposed previous work does not provide a fully nil risk of collision [373] and explicit risk-sensitive strategy. Further, PC running time is inconsistent depending on the number of collaborative involved entities. Theoretically, MVS should have a certain time interval to start executing self-satisfied strategy targeting lower navigation risk. Thus, this chapter main aims correspond to fill this gap and provide cycle-accurate description of these mechanisms in a systemic way. More flexible multi-criteria decision-aids techniques and time consistency in distributed systems will be further discussed in the following sections. More precisely, a method of limiting the time spent for optimizing is suggested at a common-yet-difficult scenario (cf. section 3.2.1), which can calculate the consistent action execution time before entering a conflict zone. Furthermore, in the latter case, a constrained PC algorithm is proposed (cf. section 3.2.2) to compute the corresponding multi-criteria risk management strategy to guarantee 100% collision-free navigation in an appropriate prediction horizon.

3.2/ The ε-PC for safe and flexible CN

3.2.1/ MVS formulation

Our specific objective is to explore PC theory enabling flexible and safe coordination to improve service performance of MVS in restrained and complex areas. Therefore, we can cast our case in a customer pickup-and-delivery scenario. After routes are scheduled, MVS have to decide the actions at an intersection with an on-board autonomous control system as shown in Figure. 3.3. While considering the real life application, the PC method consists in planning motions. These motions (referenced as speed profiles) can be used to control a vehicle or to warn/assist the driver to avoid dangerous situations. Accordingly, a study of motion planning that satisfies real application of MVS will be formulated within optimal control in section 3.2.1.1. However, these planning is restricted by system intrinsic dynamic limitations and surrounding communication environments. As it will be clarified later, the Time-Slot-Based (TSB) communication approach is considered for better predicting how the vehicles will interact and collaborate with each others (cf. section 3.2.1.2). More precisely, based only on every vehicle own-observations, the "single mode" addresses each vehicle individual motion planning without any further cooperation with other road participants. Contrarily, the "full mode" manages the reactions between all existing vehicles while ensuring the motion planning task as seen in section 3.2.1.3.

3.2.1.1/ An overview of MVS framework

Let suppose that our experimental scenario is as the following: vehicles track a desired path $\vec{P}$, while searching the most appropriate velocity. If the chassis of an actual car is defined in an $x - y$ reference frame, we can denote the vehicle's position as (x, y). The driving routes are identified by a series of way-points $(x_i, y_i) \in \vec{P}_i$ as illustrated in Figure. 3.3. Here, $(x_0, y_0)_i$ correspond to the the initial position at the time when the computation time is launched for vehicle i, where $(x_f, y_f)_i$ is its final position. It comes that what we want to compute is the correspondence between time $t \in [0$(initial registered time)$, T$(vehicle reaches its final position)$]$. In Figure. 3.3, three positions of vehicles are indicated (at time $t = 0$) and the control is related to the speed $v_i(t)$ (that remains in an interval $[0, v_{max}]$). At any time t, the distance between any vehicle $i, j \in \{1, 2, 3\}$ cannot be less than a $2r$ threshold (in order to avoid the collision of the vehicles), where r is a safe radius for vehicle i, j as shown in Figure. 3.3.

Furthermore, in Figure. 3.3, the communication area is specified for Inter-Vehicle Communication (IVC). After loading the computing at t_0, vehicles in communication area can exchange the state information and priory anticipatory probability of possible actions before entering the intersection. Due to real-time computing environment, it has been given a deadline for MVS returns the strategies/actions for critical applications at the intersec-

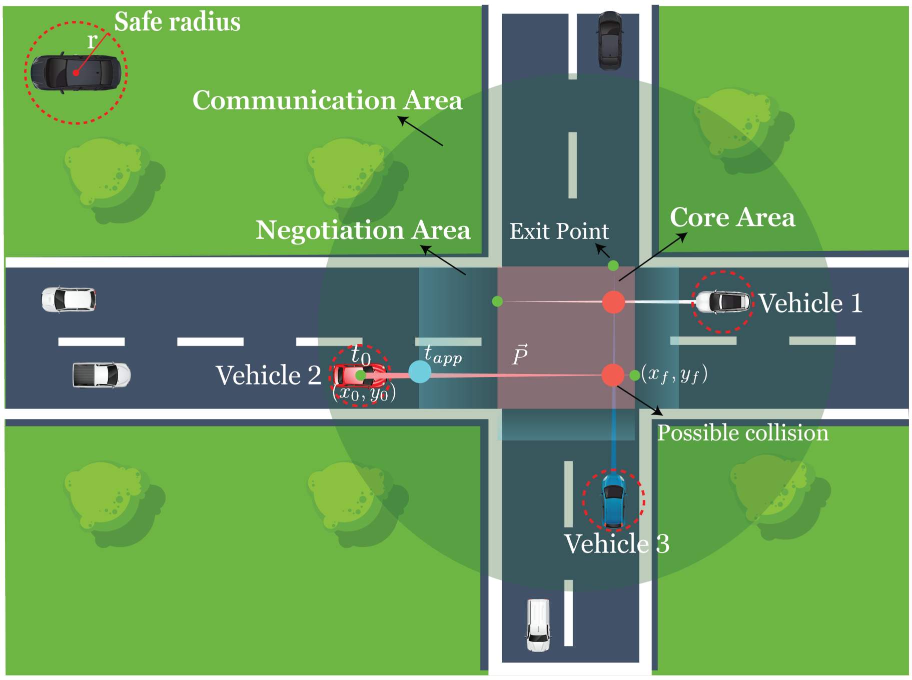


Figure 3.3: Application scenario and main zones characterizing the addressed MVS.

tion. Here, a negotiation area is defined w.r.t. action time t_{app} (data processing deadline) for synchronous cooperative navigation. Because vehicle's initial speed is different, the position of the vehicle begins to collaborate in negotiation area will be different w.r.t. t_{app}. The core area (red block in Figure. 3.3) is more critical zone which contains the possible collision.

It is important to notice that all the vehicles are provided in this setup with the same kind of control devices (or control protocol). Henceforth, vehicles will follow the same algorithm logic and share current states when loading computation at t_0. As indicated before, we recommend setting a time limit for the solver, which ensures that the PC program will terminate in a reasonable period of time Δt_{sol} (cf. section 3.2.1.2). This motion planning can be applied at time $t_{app} = t_0 + \Delta t_{sol}$. Because vehicles in our system is rolling without slipping (i.e., Pfaffian constraints), we can accurately predict vehicle's states (i.e., position and speed) at t_{app} when loading the algorithm at t_0. So, it is better to plan motions having the predicted horizon time that starts at $t = t_{app}$ for MVS ($[t_{app}, t_{app} + T]$), where T is the prediction horizon. To do this, we can always pursue an optimal solution that guarantee well-coordinated motions in time. It is worth noting that the vehicle will precisely execute its final desirable actions/strategies (as $\Pi_k^i \rightarrow v_i(t)$) during time interval $[t_{app}, t_{app} + T]$. Some additional constraints are highlighted below for applying motion planning Π_k^i at t_{app}:

- The vehicle that has already entered the intersection is not concerned by the optimization process.
- Vehicle i keeps constant speed $v_i(0)$ (and less than v_{max}) before executing Π_k^i.
- If vehicle i will enter the intersection immediately after t_{app} with current speed $v_i(0)$, then treat it as a "non-collaborative agent" with maximizing self-utility strategy.

Dynamic constraints (e.g., inertial delay in powertrain) and trajectory deviation are not considered in this model. As mentioned above, we designed the PC to run in an iterative way. When the on-board algorithm is launched, it produces a possible action plan based on states of the current agents in communication area with a prior knowledge of each other (cf. Fig 3.3).

The best combined strategies should be saved and updated if new feasible optimal solution is obtained by the MVS. To address the dynamic nature of the transportation system, users are permitted to change the action after adding any other agent in the MVS. This means that the previous plan will be executed with the possibility of few changes occurrence when new cooperative actions become available.

3.2.1.2/ Time-Slot-Based (TSB) mechanism

In the above real life application of MVS, the critical issue is the computing of each plan "fast enough" during Δt_{sol} by PC, in order so that the system can react to the changing environment without exceeding its motion capability (defined as maneuverability [57]). In our proposed PC implementation, the data exchange is aimed to be minimal and a solving time of $\Delta t_{sol} = 0.2s$ is targeted ($\Delta t_{sol} = 0.8s$ have been achieved so far for 4 vehicles [373]). Moreover, a reasonable Δt_{sol} leaves the system a maneuverability margin that can be used to move it into a safe configuration or state. To address this concern, we use Time-Slot-Based (TSB) approach to further explain the vehicle's sequential optimization and communication mechanism in PC (see Figure. 3.4).

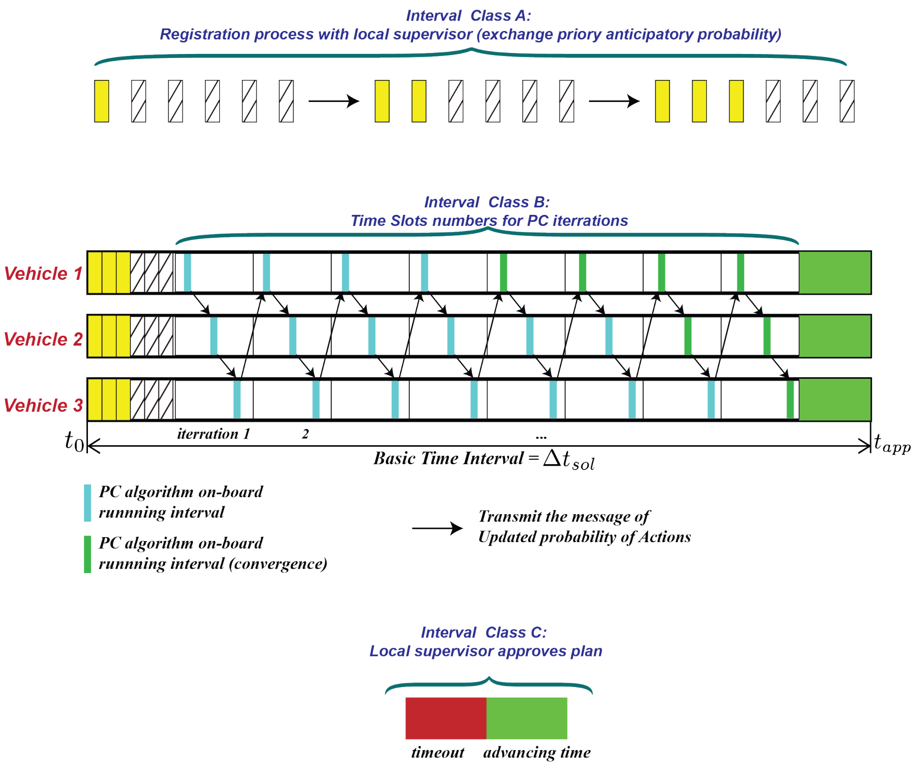


Figure 3.4: Time-Slot-Based (TSB) communication mechanism for applying PC.

In TSB vehicle communication system, the basic time interval Δt_{sol} is divided into multiple duration. Here, "class regions" are highlighted for different message classes. We can use different wireless bandwidth for these regions. In class A, vehicles transmit the status information to other connected agents and exchange possible actions for entering an intersection. After vehicles get priory anticipatory probability of other vehicles' behaviors, the navigation problem can be formulated as an optimization model and the PC will be run in its default iterations. All the vehicles successively participate in the optimization with on-board PC algorithm at each iteration. They broadcast the updated probability distribution over the set of possible strategies for repeated computing reference. The successive iterations continue until all the updated probability distributions converge to stable distributions. However, long-running can be time-consuming and difficult to optimize. The timeout mechanism in class C helps to limit that time while supplying a satisfactory motion planning. Our optimizer triggers timeout when:

- All vehicles converge to stable probability distributions.
- The algorithm's running time exceeds timeout limits.

The conduct of timeout setup may lead to complete or to incomplete search. We are aware of the fact that vehicles do not guarantee convergence to the global optimum in our standard solving time Δt_{sol}. But the PC algorithm always retains the current best results at each iteration. These strategies tend to produce high quality solutions in short time. The precise timeout limit value is changed depending on the running machines and experiment configuration but very close to the motion planning applied time t_{app}. It is interesting to note that the majority of our proposed PC models are either completed very quickly or they converge very slowly. Therefore, changing the timeout value (not too much) will not dramatically influence the computing results.

3.2.1.3/ Motion planning for continuous vehicles crossing

To the best knowledge of the authors, the PC algorithm has not been used yet to perform repeated optimizations to deal with a continuous flow of vehicles. The closest application was [423] for air traffic management, but the algorithm was demonstrated on fixed initial situations. Since a repeated full optimization of MVS is time consuming, we already defined two real-time motion planning modes of PC for searching feasible solutions in practical application:

- Single vehicle optimization (denoted “single” mode).
- Full optimization (“full” mode).

As above explained, in the single mode, a vehicle runs the PC optimization as soon as it enters the communication area as shown in Figure. 3.3. All the other vehicles are considered to be connected but non-collaborative agents. In this mode, the coordination is sequential more for the collaborative case, since the vehicles decide what to do one by one. This is an important option to reduce calculation time, because ego vehicle only needs to pick up the best actions with respect to fixed strategies of others. Also, the intersection crossing performance with the single mode may be sub-optimal as not all the vehicles coordinate with each other.

In the full optimization mode, the PC algorithm will run in its default iterative mode where all the vehicles participate in an optimization process as shown in Figure. 3.4. We recommend to perform the “full” mode long enough ($10s$ for instance) to ensure vehicle exiting the intersection, and it should be triggered by a predefined event (such as a threshold number of vehicles at intersection). New vehicles entering in the restricted communication area are not allowed to rerun the full optimization mode until the previous optimization is completed.

Later in this section, authors focus in section 3.2.4.4 to prove that the real-time solution of two modes can handle continue vehicles waves in practical real-time applications.

3.2.2/ Risk measurement by 2D TTC

Due to the probabilistic nature of the decision-making problem between vehicles, it is hard and not straightforward to directly convert the constraints to probability space. Therefore, several heuristic repair approaches are applied to narrow the optimal solution [261, 262]. The elevated computational load limits thus the use of the PC approach in hard real-time vehicle. Kulkarni and Tai et al., then handle the constraints by a penalty function method [263] while knowing that the appropriate weights parameters (between sub-criteria) are not easy to be obtained precisely. In the proposed approach, the existing ε-constraint method [323] is used in addition to the PC algorithm to solve the real time multi-criteria safety assignment MVS coordination problem. The navigation characteristics of MVS and main constraints are highlighted in section. 3.2.1.1. Then, in the following paragraph, we introduce Time-To-Collision (TTC) as a constraint indicator.

The purpose of MVS is to compute a feasible solution, which serves all the customer in a flexible and risk-sensitive manner. The system objective function in equation (3.1) can offer a combined solution that penalizes low separation and slow average speed. However, as mentioned before, the previous work needs a risk assessment approach to succeed in the road hazard prediction. Thus, the TTC is used as a predictive safety measure of vehicle's trajectory.

TTC is a risk indicator that describes the remaining time for a probable collision (i.e., traffic crash) between two vehicles. It was originally defined by [193] in car following scenarios. Generally, TTC can measure a road-user's time to react (for a critical collision event). The TTC at time instant $t \in [0, T]$ can be calculated according to the first order case (in co-linear navigation case between vehicles) [46]:

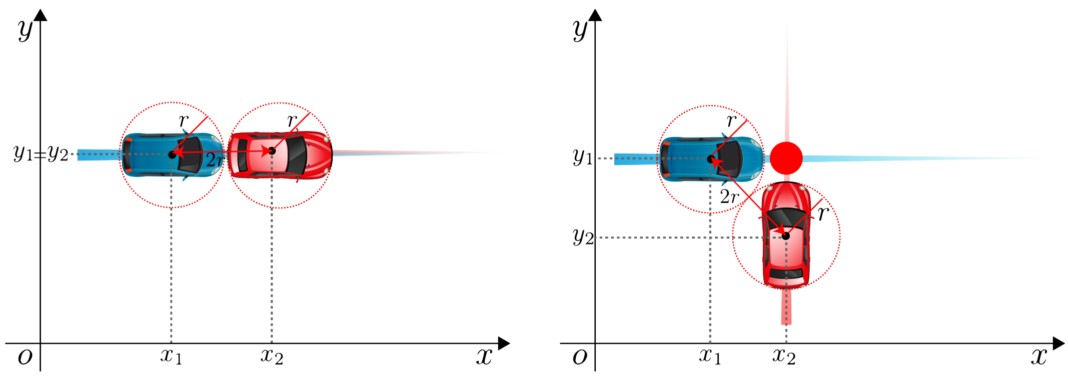
$$TTC = \frac{x_{lead}(t) - x_i(t) - 2r}{\dot{x}_i(t) - \dot{x}_{lead}(t)} \tag{3.2}$$

where $(x_{lead}, y_{lead}), (x_i, y_i) \in \vec{P}, y_{lead} = y_i$, and $2r$ is the vehicle real length as shown in Figure. 3.5a. In equation (3.2), x_{lead}, if exist, can be measured as the position of leading vehicle for vehicle i at x_i with speed $\dot{x}_i(t) > \dot{x}_{lead}(t)$. To calculate TTC in two dimensions, we simply consider a collision of two circles as shown in Figure. 3.5b.

As one may notice that it is a "collision" of two circles (not a real crash of two vehicles). We use these circles to anticipate real accident. Here, $2r$ can be seen as vehicle length l as in equation (3.2). In spite of sacrificing some accuracy, the TTC between vehicles i, j can be more easily formulated in two dimensions as:

$$\begin{aligned} &[(x_i(t) + \dot{x}_i(t) \cdot TTC_{ij}) - (x_j(t) + \dot{x}_j(t) \cdot TTC_{ij})]^2 \\ &+ [(y_i(t) + \dot{y}_i(t) \cdot TTC_{ij}) - (y_j(t) + \dot{y}_j(t) \cdot TTC_{ij})]^2 = (2r)^2 \end{aligned} \tag{3.3}$$

In equation (3.3), setting $(x_i, y_i) \in \vec{P}_i, (x_j, y_j) \in \vec{P}_j$ is the position of vehicle i, j at time instant $t \in [0, T]$. $\dot{x}_i(t), \dot{x}_j(t), \dot{y}_i(t), \dot{y}_j(t)$ denote the relative speeds measured in x, y directions.



(a) 2D TTC in co-linear navigation case. (b) 2D TTC in two dimensions navigation case.

Figure 3.5: A collision of two-vehicles based on circle area.

Accordingly, we can get a quadratic function of TTC_{ij} like:

$$\begin{aligned}&[(\dot{x}_i(t)-\dot{x}_j(t))^2+(\dot{y}_i(t)-\dot{y}_j(t))^2]\cdot TTC_{ij}^2\\&+2[(x_i(t)-x_j(t))(\dot{x}_i(t)-\dot{x}_j(t))+(y_i(t)-y_j(t))(\dot{y}_i(t)-\dot{y}_j(t))]\cdot TTC_{ij}\\&+[(x_i(t)-x_j(t))^2+(y_i(t)-y_j(t))^2-(2r)^2]=0\end{aligned} \tag{3.4}$$

Equation (3.4) can be solved by quadratic discriminant. If there are real roots in (3.4), we can take the positive lower value as the nearest TTC in the prediction horizon. For cases equation (3.4) has no real roots, it presents the collision that will never happen with this dynamic. To avoid any confusion, we defined the solutions in equation (3.4) as "2D TTC" in the following of this section. The objective of MVS is to maximize the final agents' 2D TTC to improve the navigation safety. Thus, the corresponding objective function is defined as:

$$\begin{aligned}max\quad & J_{TTC}(\boldsymbol{Y})=\min_{i,j\in\{1,2,...,n\}(i\neq j)}\{TTC_{ij}(\boldsymbol{Y})\}\\subject\ to\quad & \boldsymbol{Y}=[\Pi_k^1,\Pi_k^2,\dots,\Pi_k^n](k=1,\dots,N)\\ & \Pi_k^i\in\boldsymbol{\Pi}^i=\{\Pi_1^i,\dots,\Pi_N^i\}(i=1,\dots,n)\end{aligned} \tag{3.5}$$

Where $\min\{TTC_{ij}(\boldsymbol{Y})\}$ represents the minimum 2D TTC value of the most critical situation between n agents in the prediction horizon $t\in[0,T]$ within vehicles' combined actions/strategies $\boldsymbol{Y}$. J_{TTC} aims to maximize the critical 2D TTC value for more safety response to the concerned situation. Above all, an optimization problem can be formulated by considering equation (3.1) and (3.5). To handle the TTC constraint, ε-PC algorithm is addressed in next section (cf. section 3.2.3).

3.2.3/ RISK MANAGEMENT BASED ON ε-PC FRAMEWORK

The original PC algorithm focuses on a straightforward task with only one objective function as shown in equation (3.1). Nevertheless, the MVS needs to deal with RAMS as suggested by the discussion given in section 3.1.2.4. The ε-constraint method, which was firstly proposed in [187], can be introduced to handle this trade-off problem. Only one objective function is optimized in the method, while others are converted into constraints with a permitted value ε by a limited range. In our case, the objective function J_{TTC} in equation (3.5) can be adopted as a constraint during optimizing the main objective function J in equation (3.1). Hence, the transformed optimization problem is formulated as below:

$$\begin{aligned}min\quad & J(\boldsymbol{Y})\\subject\ to\quad & \boldsymbol{Y}=[\Pi_k^1,\Pi_k^2,\dots,\Pi_k^n](k=1,\dots,N)\\ & \Pi_k^i\in\boldsymbol{\Pi}^i=\{\Pi_1^i,\dots,\Pi_N^i\}(i=1,\dots,n)\\ & J_{TTC}(\boldsymbol{Y})\geq\varepsilon\end{aligned} \tag{3.6}$$

According to the model, the optimal results could be given by the following theorems. The interested readers may consult [330] for more details:

- *Theorem 1*: If objective J and vector $\varepsilon=(\varepsilon_1,\dots,\varepsilon_m)$ exist, such that $\boldsymbol{Y}^*$ is an optimal solution to the problem (3.6), then $\boldsymbol{Y}^*$ is a weakly Pareto optimal solution.

- *Theorem 2*: $\boldsymbol{Y}^*$ is a strict Pareto optimal solution if and only if, for objective J, there exists a vector $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_m)$, such that $\boldsymbol{Y}^*$ is the unique objective vector corresponding to the optimal solution of the problem given in equation (3.6).

3.2.3.1/ A SELECTION OF ε VALUE

An advantage of the ε-constraint method, presented in equation (3.6), is that we do not need to scale different objective functions by adding weights. The obtained solution, if it exists in equation (3.6) with a given parameter $\varepsilon = (\varepsilon_1, \ldots, \varepsilon_m)$, is proved to a weakly Pareto optimal solution as Theorem 1 and 2. Actually, the Pareto front can be obtained by varying the vector ε. To find an efficient solution (that means close to a strict Pareto optimal solution) in problem (3.6), selecting an appropriate ε is the key. Accordingly, for calculating a more efficient solution, we must have at least the range of constraint objective function J_{TTC}. Unfortunately, the calculation of the J_{TTC} range in searching space is not a trivial task. The worst value is hard to compute, while we can get the best value in an individual optimization. Hence, a general selection of ε_m can be provided by equation (3.7):

$$J_{TTC}(\boldsymbol{Y}^*_{inf}) \leq \varepsilon_m \leq J_{TTC}(\boldsymbol{Y}^*_{sup}) \tag{3.7}$$

Where $\boldsymbol{Y}^*_{inf}$ is the optimal solution of single optimal problem (3.1) for minimum objective function J without any constraint, and $\boldsymbol{Y}^*_{sup}$ is the optimal solution for single optimal problem that maximize J_{TTC} in equation (3.5) in a predefined searching space. After that, for the bounded value in equation (3.7), we define the range of normal J_{TTC} values as $J_{TTC}(\boldsymbol{Y}^*_{sup}) - J_{TTC}(\boldsymbol{Y}^*_{inf})$ in problem (3.6). Note that, with the ε-constraint, we can get different efficient solutions close to a strict Pareto optimal solution. Therefore, a more rich and flexible solutions are favorable in the applied traffic scenario. Thus, we can divide the ε range into p equal intervals by $p+1$ "grids points" [323] like the following:

$$\varepsilon_m = J_{TTC}(\boldsymbol{Y}^*_{inf}) + (J_{TTC}(\boldsymbol{Y}^*_{sup}) - J_{TTC}(\boldsymbol{Y}^*_{inf})) \cdot (\frac{m}{p}), (m = 0, 1, \ldots, p) \tag{3.8}$$

Let consider equation (3.8), we can also get efficient solutions by properly adjusting the the number of "grid points" gradually increasing ε_m by referential signs and linear logic. An indicator $\sigma(\varepsilon_m)$ to interpret the linear relationship between J and J_{TTC} with different ε_m is calculated as:

$$\sigma(\varepsilon_m) = \begin{cases} 1 & \text{if } \varepsilon_m = \varepsilon_p \\ \frac{\varepsilon_m - J_{TTC}(\boldsymbol{Y}^*_{inf})}{J_{TTC}(\boldsymbol{Y}^*_{sup}) - J_{TTC}(\boldsymbol{Y}^*_{inf})} & others \\ 0 & \text{if } \varepsilon_m = \varepsilon_0 \end{cases} \tag{3.9}$$

For the bounded value in equation (3.7), we define the range of normal ε_m by two bound values J_{TTC} with respect to the individual optimal problems. As a matter of fact, the proposed "ε-Constraint" in the bounds is to correctly estimate the trade off between crossing time and risk which we aimed to achieve a good trajectory schedule. To guarantee the feasible solution in the bounds, we divide ε_m into several equal intervals as a constraint in original PC algorithm. Only the feasible solutions afford the constraints will be reserved in the PC searching procedure as depicted in Figure. 3.6. It is also essential to note that too small bound intervals will lead to ineffective 2D TTC constraint for a safety-sensitive solution. A simple remedy in order to bypass the difficulty of estimating lower bound is to define reservation values as shown in [323]. We capture minimum 2D TTC threshold as

$1.5s$ for a reference in this section [96]. Because the strategy hypotheses include full stop actions to avoid the extreme situation (i.e., conflict immediately), thus ε-PC can filter the decision states while remains optimal feasible solutions.

To sum up, the advantages of ε-constraint method in MVS are:

- ε-constraint method in PC algorithm avoids scaling multi-objective function in a complex target function by adding too much weights, which are never so simple to fix.
- we can control the number of efficient vehicle's actions by properly adjusting ε_m with predefined grid points p. A membership function σ can indicates the degree of optimization in different objective functions.
- the feasible solutions obtained after the optimization are indeed Pareto optimal solutions.

A simply remedy in order to bypass the difficulty of estimating the worst values of the searching results (e.g., $J_{TTC}(\boldsymbol{Y}^*_{inf})$ with optimal $\boldsymbol{Y}^*_{inf}$ in (3.1) for minimum J is to define reservation values for the objective functions [323]. Thus, we only need to calculate the maximum $J_{TTC}(\boldsymbol{Y}^*_{sup})$ in conventional PC algorithm. In the context of the proposed MVS, several approximate block solvers are recommended as initialization fast algorithms. For example, adopting max-min resource method in [228] to calculate $J_{TTC}(\boldsymbol{Y}^*_{sup})$. It is also essential to note that too small equal intervals will lead ineffective 2D TTC constraint for safety sensitive solution. Therefore, setting 2D TTC constraint indicators are expected to regard real-life situations. Furthermore, the ε-PC algorithm can be explained with detailed flow diagram as shown in Figure. 3.6.

3.2.3.2/ ε-PC FRAMEWORK

In Figure. 3.6, as the original PC method, vehicle i assigns uniform probabilities $q(\Pi^i_k)$ to its strategies/actions set $\boldsymbol{\Pi}^i$ (for example, $q(\Pi^i_k) = 1/N$ is a distribution over $\boldsymbol{\Pi}^i$) at $t = 0$. From a vantage point of associate a probability for the strategy Π^i_k, vehicle i can further compute the N corresponding expected system objective function values w.r.t. its strategies set $\boldsymbol{\Pi}^i$. Thus, when vehicle i in turn to run its PC algorithm, it can help to optimize the distribution $q(\boldsymbol{\Pi}^i)$ (for ego-vehicle) in an Expectation function like equation (3.10).

$$
\begin{aligned}
\mathit{min} \quad & E(q(\boldsymbol{\Pi}^i)) = \sum_{k=1}^{N} J(\boldsymbol{Y}^i_k) q(\Pi^i_k) \prod_{(i)} q(\Pi^{(i)}_?) \\
\mathit{subject\ to} \quad & (\boldsymbol{Y}^i_k = [\Pi^1_?, \Pi^2_?, \ldots, \Pi^i_k \ldots, \Pi^n_?]) \\
& q(\Pi^i_k) \in q(\boldsymbol{\Pi}^i) = \{q(\Pi^i_1), \ldots, q(\Pi^i_N)\} \\
& \sum_{k=1}^{N} q(\Pi^i_k) = 1, \quad q(\Pi^i_k) \geq 0
\end{aligned}
\tag{3.10}
$$

Where (i) represents every vehicle other than i, and $\Pi^{(i)}_?$ is the other vehicle's strategies selected randomly (with question marks "?") depending on its probability $q(\Pi^{(i)}_?)$. It is important to underline that $q(\Pi^{(i)}_?)$ is a priory anticipatory probability of the actions/strategies of all the other agents. For vehicle i in turn to minimize expectation function $E(q(\boldsymbol{\Pi}^i))$,

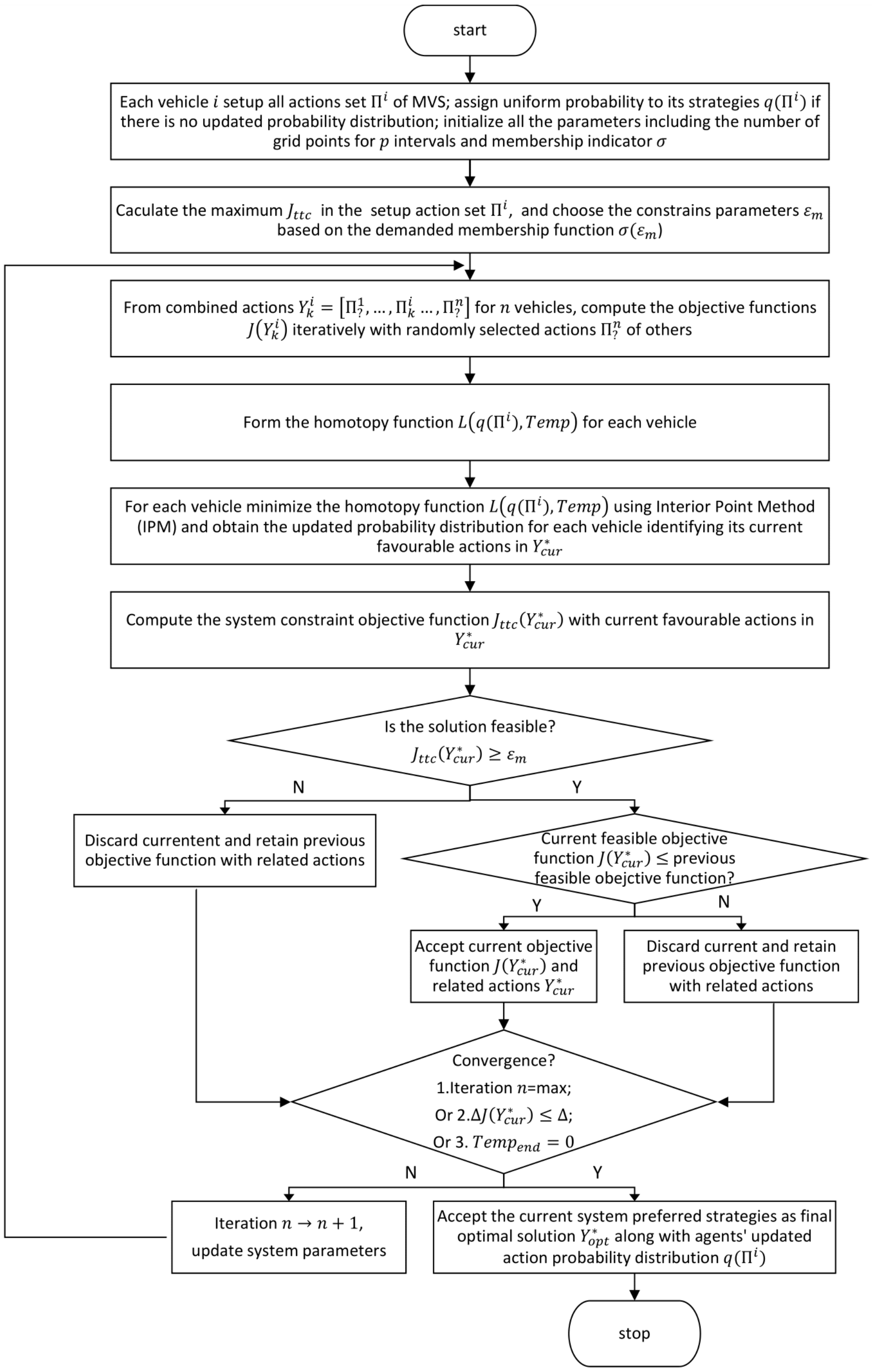


Figure 3.6: Flowchart of the proposed ε-PC algorithm: at the initial state, for vehicle i in turn to run the ε-PC algorithm; a combined strategy $\boldsymbol{Y}_k^i$ including its own strategy Π_k^i and other selected strategies is given after each vehicle's iteration. Additionally, MVS keeps track of current favorable actions $\boldsymbol{Y}_{cur}^*$ and compares them to earlier ones. Finally, as the solution converges, the final optimal solution $\boldsymbol{Y}_{opt}^*$ is chosen.

a combined strategy $\boldsymbol{Y}_k^i$ include its own strategy Π_k^i and other randomly selected strategy $\Pi_?^{(i)}$ (i.e., $\boldsymbol{Y}_k^i = [\Pi_?^1, \Pi_?^2, \ldots, \Pi_k^i \ldots, \Pi_?^n]$). Thus, we can underline these the combined probabilities distribution of in $\boldsymbol{Y}_k^i$ w.r.t. each Π_k^i as the following:

$$\begin{aligned}
q(\boldsymbol{Y}_1^i) &= [q(\Pi_?^1), q(\Pi_?^2), \ldots, q(\Pi_1^i), \ldots, q(\Pi_?^n)] \\
&\vdots \\
q(\boldsymbol{Y}_k^i) &= [q(\Pi_?^1), q(\Pi_?^2), \ldots, q(\Pi_k^i), \ldots, q(\Pi_?^n)] \\
&\vdots \\
q(\boldsymbol{Y}_N^i) &= [q(\Pi_?^1), q(\Pi_?^2), \ldots, q(\Pi_N^i), \ldots, q(\Pi_?^n)]
\end{aligned} \tag{3.11}$$

Thanks to the cost function in equation (3.10), it is easier to optimize probability than the original problem in (3.6). Such a method is referred as the homotopy approach that converts the primal problem into the probability space. Next, a key attraction, and most important Maximum-Entropy (MaxEnt) principle in PC algorithm is applied, so that we formulate $E(q(\boldsymbol{\Pi}^i))$ into equation (3.12):

$$\begin{aligned}
L(q(\boldsymbol{\Pi}^i), Temp) &= E(q(\boldsymbol{\Pi}^i)) - Temp \times E_{free} \\
&= \sum_{k=1}^{N} J(\boldsymbol{Y}_k^i) q(\Pi_k^i) \prod_{(i)} q(\Pi_?^{(i)}) - Temp \times (-\sum_{k=1}^{N} q(\Pi_k^i) \log_2 q(\Pi_k^i))
\end{aligned} \tag{3.12}$$

The objective function (3.12) is called MaxEnt Lagrangian and is widely used in statistical physics considering free energy as E_{free} [511]: a parameter $Temp$ called temperature is specific for the Simulated Annealing (SA) process. At the beginning of the ε-PC algorithm, the parameter $Temp \in [0, \inf)$ is huge, which weights more the entropy term. Then we can always get uniform probabilities. Since function E_{free} can stand for the largest uncertainty (highest entropy) at the beginning (this means each vehicle's actions has probability $1/N$ of being most favorable). Shannon entropy is a general choice for function $E_{free} = -\sum_{k=1}^{N} q(\Pi_k^i) \log_2 q(\Pi_k^i)$, where it can be proved mathematically that: $argmax(E_{free}) \to q(\Pi_k^i) = 1/N$.

The formulation of the Maxent Lagrangian $L_i(q(\boldsymbol{\Pi}^i), Temp)$ is very appropriate in the original PC theory, since the probability nature may handle the rest of work to solve in a convex space of probability distribution. To obtain the updated probability, the Broyden–Fletcher–Goldfarb–Shannon (BFGS) method is used in PC algorithm for the reformulated optimization problem in equation (3.13):

$$\begin{aligned}
min \quad & L(q(\boldsymbol{\Pi}^i), Temp) \\
subject\ to \quad & \\
& \sum_{k=1}^{N} q(\Pi_k^i) = 1 \\
& q(\Pi_k^i) \geq 0
\end{aligned} \tag{3.13}$$

In equation (3.13), the expected global utility $L(q(\boldsymbol{\Pi}^i), Temp)$ based on the combined strategy is calculated under a specific temperature $Temp$. Vehicle i updates the probabilities $q(\boldsymbol{\Pi}^i)$ of all the actions after each iteration. However, the adoption of BFGS method cannot keep the probability value within $[0, 1]$. Even though standardization may be used to handle such case, the interior point method [511] is recommended in the proposed ε-PC algorithm. Because it can be guaranteed that the probability keep within $[0, 1]$ during each iteration. Interior point method have been proven to efficiently solve linear (or-nonlinear) constraints with less iterations.

After that every vehicle runs the ε-PC algorithm, the probability distribution of its actions will be updated. Combined strategies $J(\boldsymbol{Y}^*_{cur})$ with the minimum value $J(\boldsymbol{Y}^*)$ will be saved as current preferred solution. It must be mentioned that, the accepted combined strategies $\boldsymbol{Y}^*_{cur}$ as current preferred solution at an iteration afford $J_{TTC}(\boldsymbol{Y}^*_{cur}) \geq \varepsilon_m$. Otherwise, discard $J(\boldsymbol{Y}^*_{cur})$ and retain previous objective function value with related actions. At last, if any of the three criteria listed below is valid, then, accept the current system best solution $\boldsymbol{Y}^*_{cur}$ as the final optimal strategy $\boldsymbol{Y}^*_{opt}$ of all the vehicle.

- if temperature $Temp = Temp_{end} \rightarrow 0$
- if maximum number of iterations exceeded
- if the difference of objective function $J(Y^*_{cur})$ between two iterations reaches the prescribed threshold of Δ

Above all, the main difference between ε-PC algorithm and the original PC framework can be highlighted as following:

- The process which confirms available constraints to the feasible solutions is considered in the PC framework in a randomly improved way with additional calculation steps. The proposed method uses accessible individual optimization process to define the ranges of constraints in advance. The grid points is inserted in the algorithm, therefore, a feasible solution can always be calculated in due time.
- The interior point method is used in the improved PC algorithm to guarantee the probability value within $[0, 1]$. It is essential to apply the Monte-Carlo sampling principle based these probability distribution rather than standardization.
- The process of narrowing/updating sampling interval is excluded in the proposed ε-PC algorithm. Because the searching space is well-designed before (see section 3.1.2.1). This fact leads us to the obvious advantage of reducing computational time.

The main interest of the proposed ε-PC algorithm is a proper balance between the high-quality solution and acceptable computational speed. The method is flexible and produces approximation algorithm solution rather than global optimal results. It is supposed to be a good decision support system for transportation service and risk assessment. The typical MVS coordination will be tested in section 3.2.4.4.

3.2.4/ SIMULATION RESULTS

3.2.4.1/ COMMUNICATION CHARACTERIZATION FOR THE EXPECTED DATA EXCHANGE BETWEEN VEHICLES

In ε-PC algorithm, we designed a distributed approach in the hypothesis that there are n processors with the ith processor (vehicle i) assigned the responsibility of updating the

ith probabilities $q(\Pi_k^i)$ of actions/strategies set $\mathbf{\Pi}^i$ according to equation (3.13). Processor i inform processor j (e.g., vehicle j) to calculate its preferred actions/strategies relying information of preceded probabilities $q(\Pi_k^i)$. All the processors repeat the process until the convergence the aforementioned iterative sequence (cf. Figure. 3.4).

Due to the limitations in the measurement and control units, it is often impossible to acquire measurements at an arbitrarily fast speed and to execute the control inputs instantaneously. Thus, the MVS in this section is described in a continuous-time setting while measurements and control inputs are described in a precise constant sampled data $T_{sample} = 0.2s$. It is assumed also that the messages are received correctly within a finite time (but still leave an open way to consider synchronous or asynchronous implementations). In our predefined scenario, for example three connected vehicles in Figure. 3.3, each action/strategy is a float vector of size 50 ($10s$ horizon and $0.2s$ sampling time) and the set of possible velocity profile has 10 strategies as shown in Figure. 3.2a. That is a total of 1500 floats-$5.86kB$ (kilo Bytes)-for three vehicles. It is done again at the beginning of the re-acceleration phase (cf. section 3.1.2.2). Consequently total $11.72kB$ is prior data volume needs to be broadcasted in the considered case. Then, for each iteration the vehicle broadcasts its updated probability vector $q(\Pi_k^i)$ of 500 floats ($10s$ horizon and $0.2s$ sampling time with 10 strategies). The number of iterations is various in different mode according to experimental statistics. So the total broadcast per vehicle is depend on the iterations. Accordingly, the communication demand in “single” (only one vehicle) and “full” modes (for three vehicles) are compared in Table 3.1 as an instance.

Table 3.1: Data exchange in “single” mode and “full” mode for three vehicles

Single mode	Value	Full mode	Value
Prior data	$11.72kB$	Prior data	$11.72kB$
Strategy	10	Strategy	10^3
Iterations	10	Iterations	$20 \sim 50$
Probability data	$500 floats(1.95kB)$	Probability data	$1500 floats(5.86kB)$
Data volume	$19.53kB$	Data volume	$117.19kB \sim 292.97kB$
Total volume	$31.25kB$	Total volume	$128.91kB \sim 304.69kB$
Solver time	0.2s	Solver time	0.8s
Network request	$0.4MB/s$	Network request	$0.4MB/s$
Physically possible	$4MB/s$	Physically possible	$4MB/s$

We suppose that the required network throughput for all modes will not exceed a magnitude of $0.4MB/s$ as shown in Table 3.1. Then, the optimization can be achieved in about $0.2s \sim 0.8s$. A faster network throughput (e.g., $4MB/s$) is physically possible. Therefore, our ε-PC method may be executed with on-board processors that have a better C++ implemented code for a faster running. But it is important to note that the experiments in this section were all run by a program developed in MATLAB with a computer of Core i5-6300HQ, 2.30GHz and 8GB RAM.

3.2.4.2/ Parameter setting and results evaluation

Indeed, the single and full modes are both processed by ε-PC. The main difference between the two strategies is that the single mode only considers its best options w.r.t. the fixed strategies of others. It is a special case of full optimization that vehicles have several actions that may be chosen for self-interested behavior. Therefore, it is discussed in what follows only full optimization of MVS. To explain better the performance of the proposed intersection navigation scheme for the MVS based on ε-PC, let us decompose the experiments into several parts to evaluate the characteristics of the algorithm. The main parameters in our proposed algorithm are presented in Table 3.2:

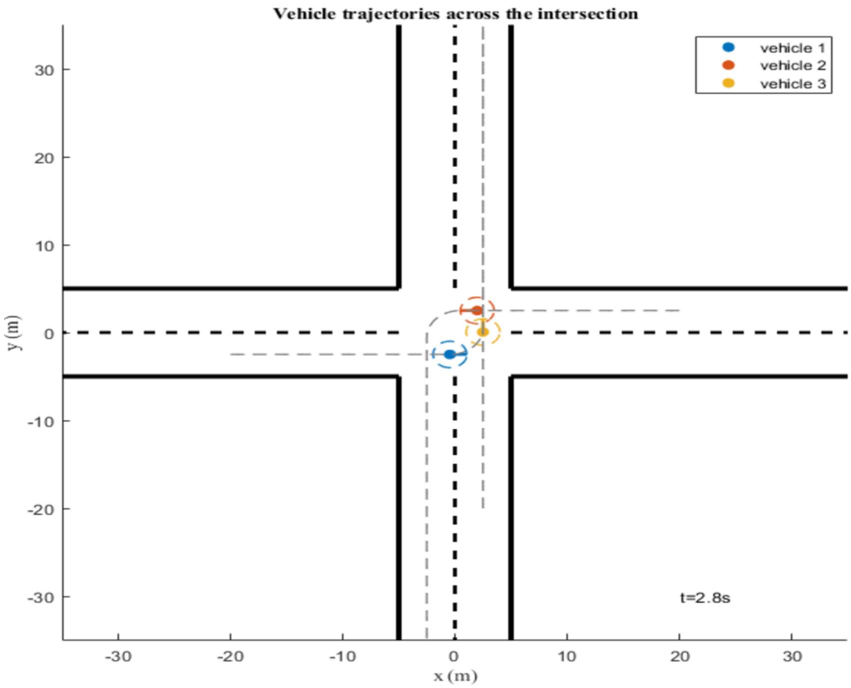
Table 3.2: Parameters and initial states

Parameter	Value	Parameter	Value
(x_1, y_1)	$[-20, -2.5]$ [m]	v_{min}	0 [m/s]
(x_2, y_2)	$[20, 2.5]$ [m]	v_{max}	10 [m/s]
(x_3, y_3)	$[2.5, -20]$[m]	r	1.5[m]
$v_1(0)$	6.0[m/s]	T_{sample}	0.2[s]
$v_2(0)$	5.0 [m/s]	T	10
$v_3(0)$	5.5 [m/s]	t_{act}	3
W_{sep}	1	$N_{samples}$	10
W_{cross}	10	$N_{vehicles}$	3
Δ	0.01	TTC_{min}	1.5[s]
ε_1	1.5	$\sigma(\varepsilon_0)$	0%
ε_2	1.97	$\sigma(\varepsilon_1)$	33.33%
ε_3	2.43	$\sigma(\varepsilon_2)$	66.66%

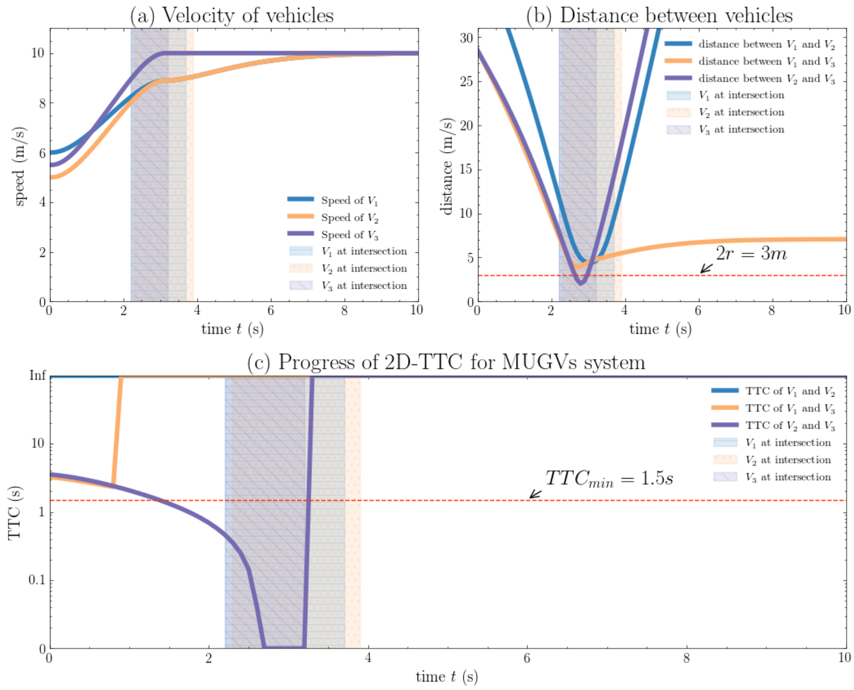
To evaluate the proposed method, contract experiments between original PC and ε-PC are given in a simulation. Three vehicles cooperative navigation at an intersection with predefined trajectories which include left-turn maneuvers for vehicle 1 and vehicle 2 (as shown in Figure. 3.7a and Figure. 3.8a). One of the important property highlighted in the simulation is the safety of the proposed navigation strategy and the ability to avoid collisions. In original PC, the cost function considered by MVS includes the average crossing time (altruistic objective) and the separation distance as shown in equation (3.1). The simulation results are illustrated in Figure. 3.7b. Because the control effort has been focused on the crossing time ($W_{cross} > W_{sep}$), the original PC method attempted to maintain a fast crossing speed. Thus, there is a low probability but high impact to choose extreme strategy which allows all vehicles to accelerate as shown in Figure. 3.7b (a). Such speed growth had led to a collision as the distance indicator exhibited in Figure. 3.7b (b): the distance between vehicle 2 and 3 (purple line) violated the safety limit of $2r = 3m$. The 2D TTC profile of this two-vehicle also collapsed to zero during the collision as Figure. 3.7b (c).

In comparison, ε-PC made vehicle 1 to maintain current speed at the beginning two seconds in order to increase the distance between adjacent vehicles as indicated in Figure. 3.8b (a). Due to the threshold constraint of $\varepsilon \geq TTC = 1.5s$ with respect to equation (3.6), a 100% free collision navigation can be guaranteed in the whole time horizon $[0s, 10s]$ as the indicator of distance and 2D TTC underlined in Figure. 3.8b (b) and Figure. 3.8b (c).

Several ε-constraint values are carried out to highlight the performance of the proposed method in the previous scenario (cf. Figure. 3.8a). The approximated maximum $J_{TTC}(\boldsymbol{Y}^*_{sup}) = 2.8975$ is fixed in predefined MVS by initially heuristic searching (cf.



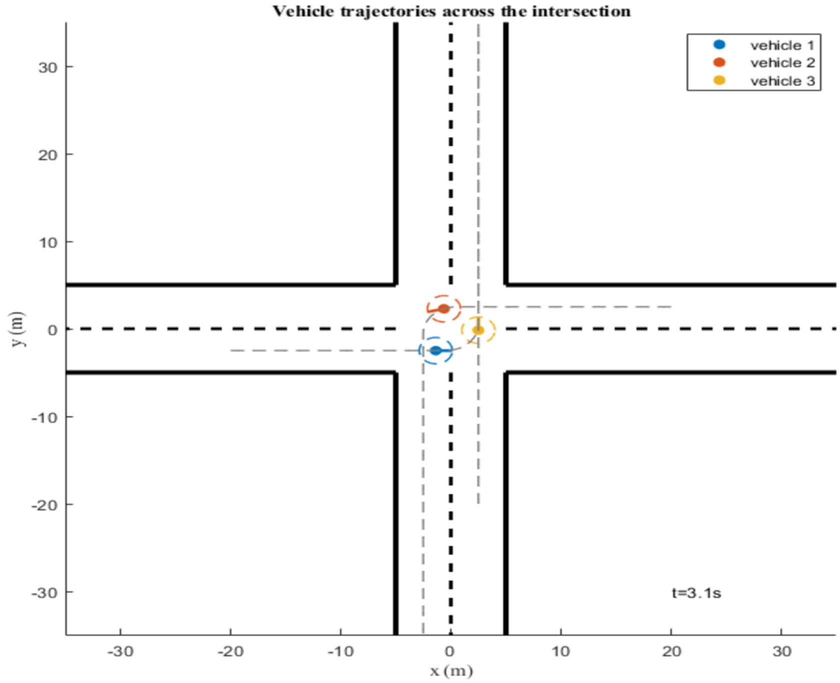
(a) Critical situation with the original PC.



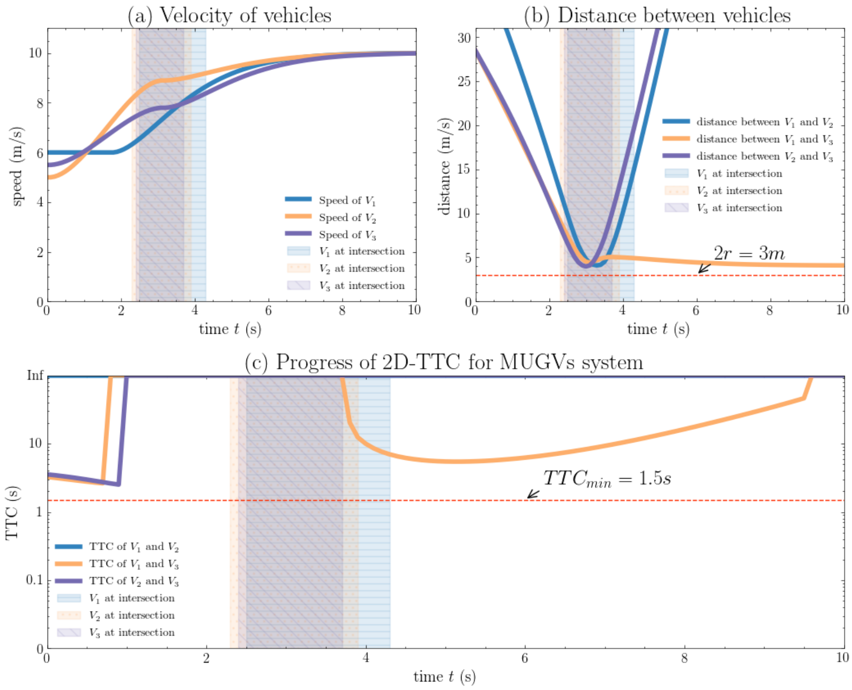
(b) Performance indicators: distance, velocity and 2D TTC in MVS by original PC.

Figure 3.7: Three vehicles navigation by original PC (simulation video https://bit.ly/3kkRJ9v).

Sec 3.2.3.1). Here, the reservation value $J_{TTC}(\boldsymbol{Y}^*_{inf}) = 1.5$ for a minimum 2D TTC in whole time horizon $[0s, 10s]$. After that, it is used several grids point (cf. equation (3.8)) in the range of $1.5 \leq \varepsilon_m \leq 2.8975$ to get a constraint set ε_i and membership function $\sigma(\varepsilon_i)$ (cf.



(a) Critical situation with the ε-PC.



(b) Performance indicators: distance, velocity and 2D TTC in MVS by ε-PC.

Figure 3.8: Three vehicles navigation by ε-PC (simulation video https://bit.ly/3KmRgxZ).

equation (3.9)) as presented in Table 3.3.

A comparison of average intersection crossing time (in presence of three vehicles) during four trails is shown in Table 3.3. It is instructive to note that the original PC algorithm, which does not use any 2D TTC constraint (i.e., $\varepsilon = 0$), shows a fastest crossing time with as expected a lowest performances of 2D TTC. Increasing ε_i with weighting more on the membership function $\sigma(\varepsilon_i)$ can generally provide more better temporal margins of 2D TTC while increasing vehicles average crossing time. However, ϵ-PC can still avoid conservative actions/strategies with low crossing time in dangerous situation as in trial 4 (about $1.33s$ late than trial 1). Moreover, the increasing iteration numbers implies that the convergence of the model needs more execution time. Therefore, MVS has potential applications in different navigation environments when a proper selective ε-constraint model is designed.

Table 3.3: Performance comparison of different ε_i

	ε_i	$\sigma(\varepsilon_i)$	**Average crossing time**	**Iterations**	J_{TTC}
Trial 1	0	-	3.60 [s]	20	0.04 [s]
Trial 2	1.5	0%	4.70 [s]	21	2.07 [s]
Trial 3	1.97	33.33%	4.70 [s]	21	2.07 [s]
Trial 4	2.43	66.66%	4.93 [s]	26	2.51 [s]

3.2.4.3/ Scalability properties

To enable the qualified strategy to fulfill certain specific situations in MVS navigation (the long tail challenge), it is important to reserve enough strategies in searching space. In order to have a clear picture of the computational demanding under such applications, the execution time of varied number of strategies for MVS is compared in the Figure. 3.9.

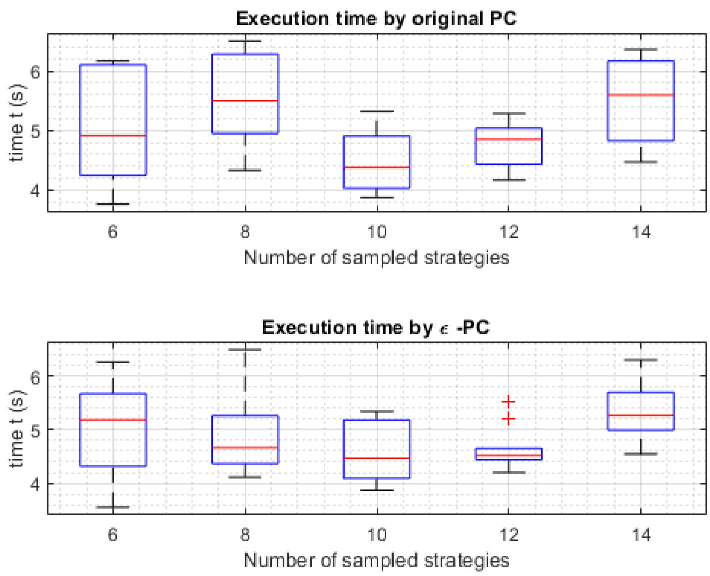
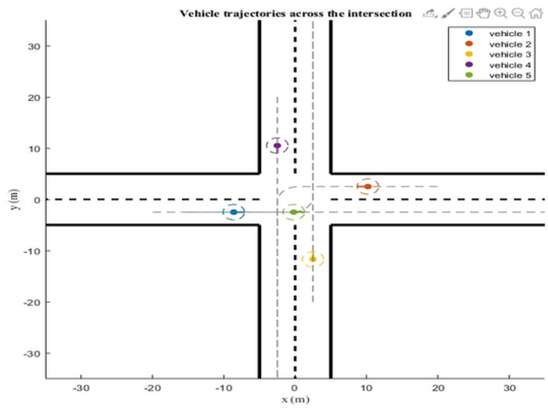


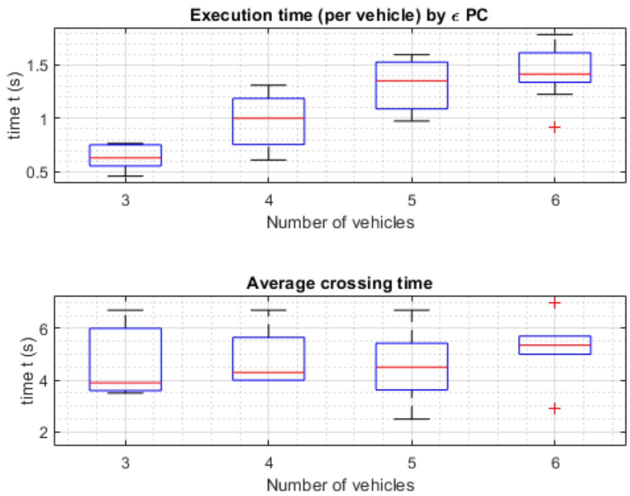
Figure 3.9: Effect of strategy number on the execution time.

The results given in Figure. 3.9 show a slight difference in terms of the execution time between the original PC and ε-PC. More importantly and within this small decrease in the execution time, the ε-PC outperforms the original method by its capacity in avoiding the potential collision. Based on the results shown in Figure. 3.9, it can be admitted that the ε-PC method guarantees the no collision between vehicles without any additional computational burden to satisfy the minimum safety navigation requests. As a reminder, minimum 2D $TTC = 1.5s$ is specifically considered in all these simulations of ε-PC. Furthermore, it appears that setting $N_{samples} = 10$ improves the satisfaction of the computationally demanding. To conclude, over-or under-estimated static sampling strategy may lead to more execution time to find optimal results that can meet the requirements.

The complexity of the ε-PC algorithm is strongly correlated to the scalability properties of the proposed method. So that we attempt to run ε-PC algorithm with an increasing number of vehicles. The randomized initial parameters (position and speed) are within the same range. Vehicles are generated with different distance to the intersection. The result has further explored the limiting number of vehicles for the application of ε-PC in more exhaustive navigation states (see Figure. 3.10).



(a) Critical situation with ε-PC (simulation video https://bit.ly/3krlcOV).



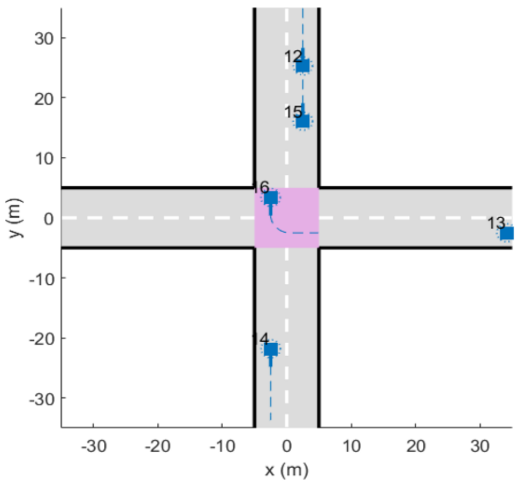
(b) Effect of vehicle number on the performance of ϵ-PC.

Figure 3.10: Effect of vehicle number on the performance of ϵ-PC.

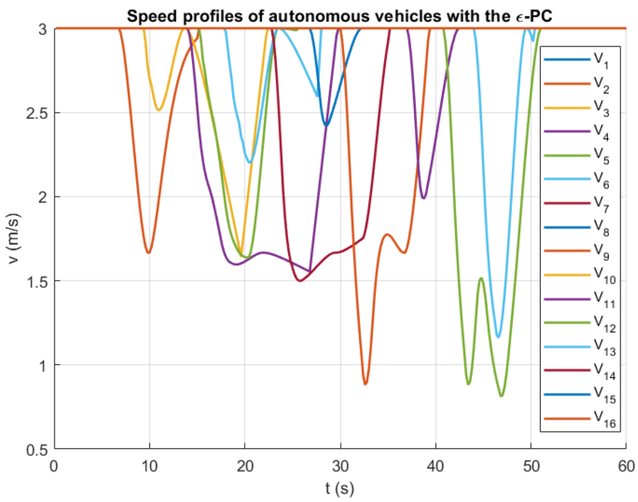
Figure. 3.10 shows results for $N_{vehicles} = 3$ to $N_{vehicles} = 6$. The execution time of per vehicle show a steady increase for both the number of vehicle and the average crossing time. The $\varepsilon = 1.5s$ is fixed in each simulation. This indicates that ε-PC can guarantee a safe navigation with increasing number in MVS. A further analysis of complexity will be carried out in further works, and more realistic execution time will be measured after an optimization of the produced code and its parallelization.

3.2.4.4/ Experiments using continuous vehicle flow

In the case of the "single mode", all the vehicles are non-collaborative. This mode is useful to demonstrate the capabilities of the algorithm to deal with a high number of non-collaborative connected vehicles. Figure. 3.11 illustrates the continuous traffic situation during the simulation.



(a) Real time scenario for MVS.



(b) Real time speed with the ε-PC.

Figure 3.11: MVS navigation in real-time (simulation video https://bit.ly/3KojvfO).

It is demonstrated also that the use of the algorithm in the special case of single vehicle optimizes the navigation performances. On the other hand, the “full” mode shows the exact opposite as it forces all the vehicles to run the optimization when triggered by a predefined event. This mode has been used in the previous section when an optimization is done on a fixed initial situation with all the vehicles. It should be noted that “single mode” has been preferred for a fast decision making. While “full mode” is more preferred for collaboration in complex environment. In the tackled simulation (see Figure. 3.11), no conflicts did happen between any of the present vehicles, even though they did the optimization one by one.

3.3/ BEYOND LOCAL COOPERATION: SPEED VERSUS RISK FROM A GLOBAL PERSPECTIVE

This section discusses MVS navigation in a protected region that includes multiple intersections. It is expected, in particular, that all vehicles are trained to accomplish internal transportation tasks. As indicated in section 2.2.4, the suggested approach in this PhD thesis is intended to route and schedule vehicles in a manner that strikes an optimal balance between speed and risk. Thus, a MVS is supposed to be regulated by a hierarchical supervision architecture that distributes and schedules pick-up and delivery tasks at the highest level while ensuring intersection safety and trajectory control at the lowest level. Unlike the previous parts (i.e., section 3.1 and section 3.2), which concentrated on cooperation at a single intersection, this section will analyze the top level from a global perspective while also providing a time-dependent estimation of the risk generated by traversing any path at a given time. Furthermore, a local search algorithm involving dynamic programming, which implements the Reinforcement learning (RL) principle, is analyzed with experimental results. More specifically, section 3.3.1 explains the general context and relative definitions. In section 3.3.2, we formally describe global risk management model and state some structural results. In section 3.3.3, we describe the Local Search (LS) heuristic algorithm for Shortest Path under Risk constraint (SPR) problem (short for “LS-SPR”) that incorporates the RL principle. Section 3.3.4 is devoted to numerical experiments.

3.3.1/ DEFINITIONS AND GENERAL CONTEXT

As mentioned in section 2.2.2 (Figure 2.8), the hierarchical supervision architecture is proposed to manage a MVS system relying on the 2nd and 3rd level. Recalling that the first level, or micro-level, is defined by the monitoring and sensing devices that are embedded inside the vehicles, they compute the trajectories in real time and adapt them to the possible presence of obstacles. The majority of the robotics community’s effort is still focused on this micro-level, which primarily involves optimal control and artificial perception techniques [67, 288, 398]. The second one, or management-level, is in charge of the supervision of small tricky areas, like for instance intersections or loading/unloading spots (see Figure 3.3). Working as a mediator agent, it sends signals and instructions to the vehicles in order to regulate their transit and to avoid them to collide when they get through those areas. This level has been motivating a rise in interest for the last years [118, 391, 550], and sometimes a confusion with the first level: in many cases, hypothesis is set that all vehicles involved are run by the same embedded software and exchange perfect information; this become equivalent to supposing the existence of a local external mediator. The third one, or macro-level, consists in tactical dynamic planning and routing of the MVS, in order to make vehicles achieve some internal logistics requests [137, 477]. Depending on the complexity and the size of MVS, the management-level[1] may merge with either the micro-level or the macro-level. In any case, a true challenge is the synchronization of those monitoring levels to correspond to different time scales and goals, as well as creating communication protocols that will allow them to interact.

The goal in this section is to deal with the macro-level. A global supervisor is supposed to be deployed at the top level. By some aspects, related problems may be viewed as cases of well-known Pick up and Delivery Problem (PDP, see [53]), since in most cases a task will consist of moving a vehicle in a protected area, performing some loading or unloading transaction. But two specific features are going to bring its specificity to this PDP variant:

- The time horizon of autonomous or semi-autonomous vehicles is usually somewhat short: decisions have to be taken fast, in a dynamic context, and decisional processes must take into account the communication infrastructure [430] and the way the global supervisor can be provided, at any time, with a representation of the current state of the system and its short-term evolution;

- As soon as autonomous or semi-autonomous vehicles are involved, safety is at stake: the global supervisor must compute and schedule routes in such a way that not only are tasks going to be performed fast (standard industrial efficiency) but also that local manager will perform their tasks more easily. In other words, risk minimization should be a criterion for a good schedule (see [19, 46, 362, 454]).

A consequence is that performing the top-level supervision of MVS requires disposing at any time of an accurate representation of the current state of the system and its short-term evolution. This representation should enable us to quantify the risk induced by an additional vehicle that enters the transit network and is asked to follow a given trajectory. Addressing this risk quantification problem requires converting real-time acquired data about current traffic into risk estimators using statistical data analysis (see [401, 493]). We are not going to directly address this issue. Instead, we will concentrate on how the resulting estimators may be utilized to make routing and scheduling decisions that avoid tricky situations as much as possible and so simplify management of the vehicles at the management and embedded levels. More precisely, we are going to suppose that, at the time when we are trying to schedule this vehicle, supposed to perform a move (or a sequence of moves) from some origin o to some destination d, we are provided with a procedure that, for any arc $e = (x, y)$ of the transit network and any time value t, computes an estimation of the risk resulting from the presence of our vehicle on arc e at time t. Then our goal becomes to compute and schedule the route Γ of our vehicle in such a way that its riding time is minimized and that its induced risk estimation which does not exceed some threshold $Risk_{Max}$. For the sake of simplicity, we shall limit ourselves to a single task tour, which means that Γ will be constrained by its starting point o and its destination point d. Described this way, our problem might be viewed as the search for the *constrained shortest path* [137]. But the fact that both risk and arc traversal times are time-dependent makes the problem significantly more difficult (see [137]). Similarly,

[1] This PhD thesis will be expanded on the discussion of the management-level in Chapter 4.

the on-line capability of a MVS system prevents us from relying on heavy mathematical programming, and forces us to develop highly reactive decision-making tools

We propose three steps for achieving the above-mentioned purpose here:

- The first step is devoted to configuring our SPR: Shortest Path Under Risk (SPR) problem, as well as a discussion of its complexity and some structural aspects. The SPR problem is associated with time versus risk routing issues that can be involved within for instance a warehouse environment.
- The second step is devoted to the design of static-context algorithm LS-SPR: Local Search (LS) heuristic algorithm for SPR problem (i.e., LS-SPR), whose structure can be compared to the structure of Split algorithms, which implement *Route First-Cluster Second* approaches [44] for Vehicle Routing Problem (VRP) and estimate the quality of a given route using a filtered dynamic programming procedure.
- The final step is to implement the RL principle in our searching algorithm: the goal is to convert the above-mentioned static algorithms LS-SPR into reactive algorithms for on-line contexts. According to this hypothesis, we use statistical learning and auto-adaptive RL techniques to correlate ad hoc arc traversal decisions with any present traffic patterns.

3.3.2/ Global transit network and SPR model

Transit Network and Risk Function: it is supposed that, MVS moves inside a simple planar transit network $G = (N, A)$, N denoting the nodes of G, and A corresponds to the set of arcs, likely to represent, for instance, a constrained area (e.g., a warehouse see Figure 3.12 below).

Every arc $e = (x, y)$ is provided with a maximal speed of V_{Max_e} and a length of L_e. At the time $t = 0$, when the global supervisor of MVS needs to make a decision about the

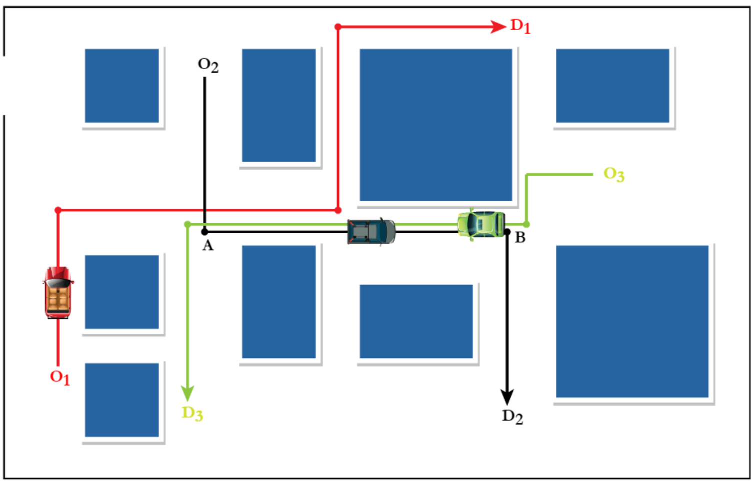


Figure 3.12: A warehouse like transit network: at time t, both green and black vehicles are scheduled in a risky area within an arc $e(A, B)$ (inspired from [38]).

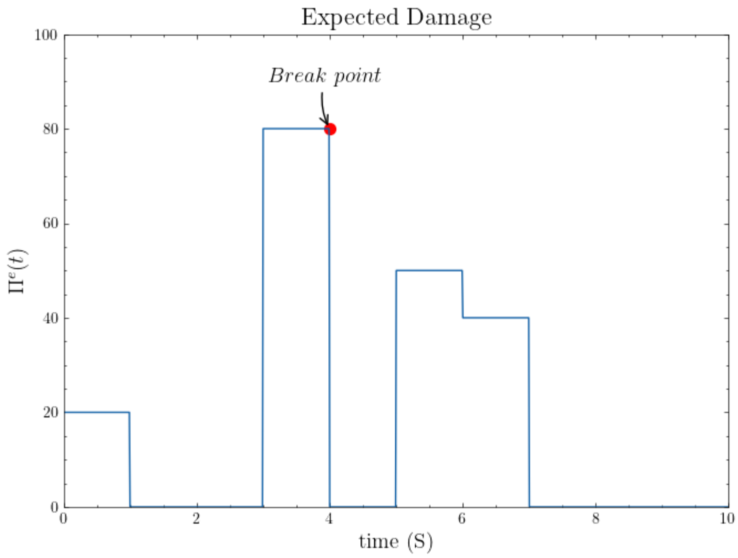


Figure 3.13: A piecewise function $\Pi^e(t)$.

target vehicle VEH (short for $VEHICLE$), it knows about the routes followed by the other vehicles and the tasks they are going to perform. This knowledge enables the vehicle to be provided with a rough representation: for any arc $e = (x, y)$ and any future instant $t > 0$, with an estimation of the number of vehicles and obstacles which are going to be located in e at time t. For instance in Figure 3.12, both green and black vehicles will travel through an arc $e(A, B)$ at time t, $e(A, B)$ can be considered a risky area along the scheduled path. This allows global supervisor to derive a risk estimation $\Pi^e(t)$, the meaning of which is:

- For any small value dt, $\Pi^e(t)dt$ is the *Expected Damage* between time t and time $t + dt$ in case VEH moves at maximal speed V_{Max_e} along e during this period.

Obtaining function $\Pi^e(t)$ is not included in this study: the *Expected Damage* is going to be assessed by experimental data and statistical analysis (e.g., observing risk behaviors such as hazardous breaking and steering in real-world driving [401]). In fact, these risky behaviors depend on spatial and temporal factors (e.g., time of day, road type and properties, etc.). When a high frequency of unexpected and dangerous maneuvers is detected, autonomous driving becomes difficult or impossible in a crowded e. Intuitively, it will involve number of vehicles related to the arcs. Because the global supervisor must be able to retain such risk estimate functions $\Pi^e(t)$ throughout the supervisory process, we must do so in a structure that makes them easy to calculate and update. Thus, it is supposed that any function of $\Pi^e(t)$, which translates those configurations into risk, is a piecewise linear function (see Figure 3.13) with a not too large number of break points. Particularly, we call the break points of $\Pi^e(t)$ when the values t make the value of $\Pi^e(t)$ changes. Thus, if VEH traverses arc e during some interval $[t, t + dt]$ at a speed of $v \leq V_{Max_e}$, then related *Expected Damage* is given by (3.14):

$$Risk^e(v, t) = \Phi(v/V_{Max_e}) \times \Pi^e(t)dt \tag{3.14}$$

Where Φ is an increasing convex function with values in $[0, 1]$ and such that for any value $u = v/V_{Max_e}$ where $u \in [0, 1]$, $\Phi(u)$ is significantly smaller than u. Those conditions are imposed in order to confirm the intuition which tells that the slower the vehicle moves, the smaller the resulting risk. Particularly, we define $\Phi(u) = u^2$ in this PhD thesis. As a result, if vehicle VEH moves across arc e between time T and time $T + \sigma$, according to speed function $v(t)$, then the related *Expected Damage* can be developed as:

$$Risk^e(v,t) = \int_T^{T+\sigma} \Phi(v(t)/V_{Max_e}) \times \Pi^e(t)dt = \int_T^{T+\sigma} (u(t))^2 \times \Pi^e(t)dt \tag{3.15}$$

Routing strategies: it is supposed now that origin o and destination d are given as nodes of the transit network $G = (N, A)$ (see Figure 3.12). A routing strategy for a vehicle is going to be a pair (Γ, v), where Γ is a path from o to d in the network G, and v is a speed function, which, to any time value $t \geq 0$, $v(t)$ is the corresponding speed of the vehicle. Clearly, if at time t, VEH in located on arc $e \in \Gamma$, then $v(t)$ must not exceed V_{Max_e}. Specifically, a speed normalization is assumed to have $V_{Max_e} = 1$. Thus, all that matters here is that the speed value $u \in [0,1]$ in the model. Path Γ may be viewed in a standard way as a sequence $\Gamma = \{e_1, \ldots, e_n\}$ of arcs of G. If we set $T(0) = 0$ and denote by $T(i)$ the time when VEH arrives to the end-node of e_i, then values $T(i)$ are completely determined by speed function $u(t)$. Then the global duration and risk of the routing strategy (Γ, u) can be denoted as follows:

$$\begin{aligned} G_{Time}(\Gamma, u) &= T(n) \\ G_{Risk}(\Gamma, u) &= \sum_{i=1}^{n} \int_{T(i-1)}^{T(i)} \Phi(u(t)) \times \Pi^{e_i}(t)dt \end{aligned} \tag{3.16}$$

Shortest Path under Risk (SPR) Model: then the purpose becomes in a natural way to make vehicle VEH move from o to d while achieving minimal values of G_{Time} and G_{Risk} values. In fact, risk and time play very different roles inside a real industrial system, and so the risk is usually managed as a constraint rather than through a weighted method. Thus, some threshold $Risk_{Max}$ is given and the trajectory (Γ, u) of vehicle VEH is required to be such that resulting risk G_{Risk} does not exceed threshold $Risk_{Max}$. It comes that our SPR comes in a natural way as follows:

- *SPR model:* given origin o and destination d, together with some threshold $Risk_{Max}$, compute a routing strategy (Γ, u) such that $G_{Risk} \leq Risk_{Max}$ and G_{Time} is the smallest possible.

Indeed, the SPR model is a multi-objective optimization. A challenge that arises is how to convert risk to time in a way that allows us to solve a mono-objective problem. This leads us to establish the *Risk versus Distance* coefficient λ, which indicates that the anticipated risk in per unit distance dR/dL. One may check the quantity $u(t)\Pi^{e_i}(t)$ means the instantaneous risk per distance at the time t when VEH move along e_i. Thus, we have:

$$\lambda = \frac{dR}{dL} = u(t)\Pi^{e_i}(t) \tag{3.17}$$

Reconstructing routing strategies: the above results can significantly simplify the SPR model by replacing the search for speed $t \to u(t)$ (in a strategy (Γ, u)) with a search for risk per distance $e \to \lambda$. Further, seeing that $\frac{1}{2}\Phi'(u)\Pi^{e_i}(t) = u(t)\Pi^{e_i}(t)$ in case $\Phi(u) = u^2$. We define a risk versus distance strategy as a pair $(\Gamma, \lambda_{e_i}^{RD})$ where:

- Γ is a path, that includes a sequence $\{e_i, \ldots, e_n\}$ of arcs, which connects origin node o to destinations node d;

- $\lambda^{RD}_{e_i}$ is Risk versus Distance coefficient associating with any arc e_i in Γ, which is defined by $\lambda^{RD} = \frac{1}{2}\Phi'(u)\Pi^{e_i}(t)$.

In the PhD thesis, it is supposed that both $u(t)$ and λ^{RD}_e are piecewise constant on e, we see that the knowledge of (Γ, λ^{RD}_e) allows us to reconstruct standard routing strategy $(\Gamma, u(t))$. Therefore, the SPR model may be rewritten as follows (we extend previous notations $G_{Time}(\Gamma, u)$ and $G_{Risk}(\Gamma, u)$ by denoting by $G_{Time}(\Gamma, \lambda^{RD})$ and $G_{Risk}(\Gamma, \lambda^{RD})$ respectively as the time value and risk value of a risk driven routing strategy (Γ, λ^{RD}):

- *Risk versus Distance SPR Reformulation:* compute risk versus distance strategy (Γ, λ^{RD}) such that $G_{Risk}(\Gamma, \lambda^{RD}) \leq Risk_{Max}$ and $G_{Time}(\Gamma, \lambda^{RD})$ is the smallest possible.

3.3.3/ Local search algorithm for SPR

The method for the SPR issue is based mostly on a notion of *state* and a notion of *decision*. A state is 3-tuple (i, T, R) in which:

- i is a node of G where vehicle VEH is currently located;
- T is the times spent in order to reach i, and R is the amount of risk induced by this process of moving from origin o to node i.

The *state* denotes the amount of time and risk required to travel an arc e. As a result, a transition function for updating the *state* may be created. Notably, as noted above, such a transition is dependent on the risk versus distance coefficient λ. Therefore, our *decision* process is as follows:

- Choosing the arc e along which the vehicle is going to move;
- Choosing some parameter λ which is going to determine the speed function u along the arc e.

For the sake of simplicity, we still restrict $\Phi(u) = u^2$. Further, the *Algorithm 1* is given containing the method for the proposed transition function, which is based on the assumptions and equations in section 3.3.2. A heuristic method for local search LS-SPR is designed for the suggested SPR model's decision process, which consists of two steps (as seen in *Algorithm 2*):

The *Update* step is designed in order to modify Γ and improve its quality. More precisely, the arrival time of the vehicle VEH at any node i along the route Γ is specified in *Evaluate* step. Considering that, the consumed time and/or risk in local pairs of nodes along the entire path Γ may remain high. Thus, the *Update* step will test a change to Γ (which involves some proximity threshold) and implement it only if it improves the performance of Γ. Following is a more detailed overview of these two steps.

Update step: it supposes that some proximity threshold S_{Prox} has been fixed, and that for any two nodes i, j of the transit network G such that length $L_{ij} \leq S_{Prox}$, MVS are provided with a collection $Path(i, j)$ of elementary route from i to j. This allows us to introduce a local transformation operator $Detour(\Gamma, i, j, \gamma)$, which acts on any path Γ through parameters i, j and γ: i and j are two nodes of Γ, such that $L_{ij} \leq S_{Prox}$ and i is located before j

Algorithm 1: Transition function for SPR

Input: $(i, T, R), \lambda, \{e, \Pi^e(t)\}$
Output: (i, T, R)
/* $\Pi^e(t)$ is the piecewise risk function of arc e and λ denotes the decision value obtained in algorithm 2. The output (i, T, R) represents a state transition between two nodes with associated time and risk. */

Initialization: $i = 0, T = 0, R = 0, L = 0$, and $NotStop = true$;
while $\underline{NotStop == true}$ **do**
  $\pi = \Pi^e(t),\ u = Inf(1, \lambda/\pi)$; // Refer to equation (3.17)
  $t = Inf((length(e) - L)/u, t_q)$; // $t_q \in [t_1, \ldots, t_Q]$ denotes the breakpoints
  $L = L + ut,\ T = T + t, R = R + u^2\pi t$; // Refer to equation (3.16)
  $i = getUpdateNode(e, L)$; // update the node i by current position
  if $\underline{R > Risk_{max}}$ **then**
    $break$
  if $\underline{L > length(e)}$ **then**
    $NotStop == False$
return (i, T, R)

Algorithm 2: $LS - SPR$: A local search algorithm for SPR

Input: $G = (N, A), (o, d)$
Output: Γ^*
/* Input the graph $G = (N, A)$ with the vehicle's desired origin and destination (o, d) and output the best scheduled path Γ^* */

Initialization Γ from o to d and $NotStop = true$;
while $\underline{NotStop == true}$ **do**
  $\Gamma_1 \leftarrow Evaluate\ \ \Gamma$; // Running Dynamic Programming (DP) procedures
  $\Gamma_2 \leftarrow Update\ \ \Gamma_1$; // Running Update algorithm to improve Γ_1
  if Improve failed **then**
    $NotStop = False$;
  $\Gamma^* = \Gamma_2$; // keep the best solution Γ ever obtained
return Γ^*

Algorithm 3: Update algorithm

Input: Γ
Output: Γ^{ipv}

while $\underline{NotStop == true}$ **do**
  $Generate\ \ (i, j, \gamma)$; // Generate a 3-tuple
  $Schedule\ \ Detour(\Gamma, i, j, \gamma)$; // Using a Detour operator
  if $\underline{TIME(Detour) \leq TIME(\Gamma)}$ **then**
    $NotStop = False$;
    $\Gamma^{ipv} = Detour(\Gamma, i, j, \gamma)$; // Replace Γ by Detour
return Γ^{ipv}

on Γ. Noting that, the $Detour$ replace $\Gamma_{ij} \in \Gamma$ from i to j by path $\gamma \in Path(i, j)$. The Update algorithm is given in *Algorithm 3*.

Due to the possibility that $Detour$ may include a significant number of parameter values (Γ, i, j, γ), we must describe how those values will be created prior to applying $Detour$. Intuitively, we find pairs of nodes (i, j) in path that have a significant crowd coefficient $(R_j - R_i)/(T_j - T_i)$ and then choose one of these pairs (i, j). Then, we select a route in Path γ that is not too crowded between times T_i and T_j (it means ratio $(R_j - R_i)/(T_j - T_i)$ is not large with respect to the mean risk $\Pi^e(t)$ between time T_i and T_j).

Evaluate step: as illustrated before, *Evaluate* step means the key point inside the *decision* process given in *Algorithm 2*. Basically, it consists in a dynamic programming (DP) procedure DP_{eval} whose main features come as follows:

- the arcs of current path Γ is denoted by $\{e_1, \ldots, e_n\}$, and by $\{i_0, \ldots, i_n\}$ related nodes. The time space of DP_{eval} comes in a natural way as the set $\{0, 1, \ldots n\}$ and a state (or label) at i is a pair (T, R), where T and R are defined as before in *state*. For any i, we shall denote as $State(i)$ the set of *state* computed in relation with i. Those states will be used in order to move along arc e_i. Clearly, initial state is $(0, 0)$ and final state should be any pair (T, R) such that $R \leq Risk_{Max}$.

- a decision at time becomes a value λ (equal to λ^{RD} referring to section 3.3.2) and such a decision induces a state transition (cf. *Algorithm 1*): $(i, R, T) \to (i + 1, T^\circ, R^\circ)$ with a cost $R^\circ - R$ (or $T^\circ - T$). This decision is feasible if it does not induce $R > Risk_{max}$ (*Algorithm 1*, line 7).

- the Bellman principle is performed in the DP procedure DP_{eval}: applying Bellman principle means eliminating state $(T1, R1)$ that not in Pareto optimal set from $State(i+1)$. For instance, state $(T1, R1)$ are not in Pareto optimal set if there does not exists (T^1, R^1) in $State(i + 1)$, such that $T1 \leq T^\circ$ and $R1 \leq R^\circ$. One at least of those inequalities is being strict. In other words only non-dominated solution set $R1 \leq R^\circ$ are reserved into $State(i + 1)$.

Generate λ-decision set Λ: the above DP procedure DP_{eval} rely on an instruction to generate any decision λ^{RD} which is the part of an optimal solution. However, λ^{RD} values are continuous ones and if we want to implement both above algorithms, we must proceed in a heuristic way and decide about the way to generate the λ-decision set Λ. In this PhD thesis, a mean value for λ^{RD} is defined as:

$$\lambda^{RD}_{Mean} = \frac{Risk_{Max}}{L^*_{o,d}} \tag{3.18}$$

Where, $L^*_{o,d}$ is the whole length from o to d. Then a way to generate λ-decision set Λ is to choose an odd number $2K + 1$ of λ^{RD} values as the decision number. Next, we set a geometric step value $\delta > 0$, and sampled the decision sets $\Lambda = \Lambda_1 \cup \Lambda_2 \cup \Lambda_3$ by equation (3.19). According to this, Λ can be determined by the parameters K and δ.

$$\begin{aligned}
\Lambda_1 &= \{\lambda^{RD}_{Mean}\} \\
\Lambda_2 &= \{(1 + \delta)^k \lambda^{RD}_{Mean}, k = 1, \ldots, K\} \\
\Lambda_3 &= \{(1 + \delta)^{-k} \lambda^{RD}_{Mean}, k = 1, \ldots, K\}
\end{aligned} \tag{3.19}$$

Bounding state through learning: as mentioned in section 3.3.2, SPR puts computing costs are at stake. Above DP_{eval} procedures should be very fast, and so $State(i)$ should be constrained, or it may expand in size as the number of arcs in the route transit network increases. To address this problem, we are going to rank pairs (T, R) in $State(i)$ according to growing values $\omega T + R$ and maintain the top S ones while eliminating the others. Particularly, ω is a risk rate per unit of time, and S is the limited number of states. In addition, ω can be denoted by equation (3.20) with an optimal SPR value (T^*, R^*):

$$\omega = \frac{Risk_{Max}}{T^*} \tag{3.20}$$

However, the objective in this case is to learn ω value from the SPR model's pre-defined values. Thus, supposing that the mean value of $\Pi^e(t), e \in A$ is Δ. The following functions may be deduced from equation (3.15):

$$\begin{aligned} u^2 \Delta T &= Risk_{max} \\ uT &= L^* \end{aligned} \tag{3.21}$$

Then, we can deduce the expected $T = \frac{\Delta L^{*2}}{Risk_{max}}$ from equation (3.21). Referring to equation (3.20), this will allow us to initialize ω as:

$$\omega = \frac{Risk^2_{Max}}{\Delta L^{*2}} \tag{3.22}$$

Nonetheless, under such a chosen mechanism, a ω value that is not fully well-fit may be obtained, resulting in an unbalanced $State(i)$. Thus, using RL techniques, we may consider to learn ω value in an auto-adaptive way. More precisely:

- We fix the number $2K + 1$ in λ-decision set Λ, and impose a threshold S on the size of state with initialed ω value (w.r.t. equation (3.22)). Those values K, S and ω become parameters of the LS-SPR algorithm. During some process to compute $State(i+1)$ through transition function (cf. *Algorithm 1*), the current state $State(i)$ may provide a subset $State(i + 1)$ whose size is like to exceed S by applying decisions in Λ. Then we rank state (T, R) of $State(i + 1)$ according to $\omega T + R$. Ideally, states (T, R) ordered this way should make S best states (T, R) be balanced in the sense that risky states should get along within a reasonable level.
- According to this, the ranked state (T, R) in $State(i + 1)$ should have a ratio $R/Risk_{Max}$ centered around the ratio $TIME(o, i + 1)/TIME(o, d)$. If, for instance, those values are centered significantly above this ratio, then we deduce that we are moving in a too risky way and must make ω decrease. Conversely, if those best values are centered above this ratio, then we are too careful and must make ω increase. Then we drive ω values in an auto-adaptive way by implementing some RL principles.

We implement this principle by performing a kind of statistical analysis of those best values in $State(i + 1)$. In order to derive, from those S best states (T, R), an indicator $Risk_{Balance}$, which takes symbolic values $\{Risky, Normal, Careful\}$ depending on the way the mean $R/Risk_{Max}$ is located with respect to $TIME(o, x_{i+1})/TIME(o, d)$. The filtering and learning Procedure can be addressed as given in *Algorithm 4*.

Algorithm 4: Filtering learning Procedure

Input: $State(i)$
Output: $(T,R)^*$ for $State(i+1)$
/* Input the current state $State(i)$ and output the S best states $(T,R)^*$ in $State(i+1)$. */
$State(i+1) \leftarrow State(i)$; // Compute $State(i+1)$ by Algorithm 1
Rank (T,R) of $State(i+1)$; // Rank states according to $\omega T + R$
$(T,R) \leftarrow State(i+1)$; // Select S best (T,R) according to *Rank*
compute $Risk_{Balance}$;
if $\underline{Risk_{Balance} == Normal()}$ **then**
  $(T,R)^* = (T,R)$; // keep only the S best states in $State(i+1)$
else
  if $\underline{Risk_{Balance} == Risky()\ or\ Risk_{Balance} == Careful()}$ **then**
    $S_1, S_2 \leftarrow Split\quad State(i+1)$; // Split $State(i+1)$ into two subsets with same size
    if $\underline{Risk_{Balance} == Risky}$ **then**
      Keep only the $S/2$ best states in S_1, S_2 in $State(i+1)$ and decrease ω ;
    else
      Keep only the $S/2$ best states in S_1, S_2 in $State(i+1)$ and increase ω ;
return $(T,R)^*$

3.3.4/ Comparison experiments

We performed several numerical experiments with the purpose of getting information about the following points:

- The ability of the different algorithms to get good solutions under small computational costs, and the dependence of their behavior to the size of the transit network.
- The sensitivity of those algorithms to the parameter S and K, which bounds, for every algorithm, the numbers of possible states and decisions.
- The sensitivity of our algorithms to the structure of the piecewise functions Π^e, and on the intensity of current traffic inside the transit network at the time when the algorithms are applied.

In order to do so, we used the A^* like algorithm, run with large S and K values as an almost exact algorithm, which provided us with reference results. Additionally, a greedy approach that removes the *update* step in the LS-SPR method (cf. *Algorithm 2*) is used for comparison.

Instances: We generated networks $G = (N, A)$ as connected symmetric partial grids, which means grids $n \times m$, modified through removal of a percentage $\rho = 30\%$ of nodes and arcs. The arc connecting two points is a one-way direction. Finally, those partial grids are summarized through their number $|N|$ of nodes and their number $|A|$ of arcs. Additionally, each arc's length is randomly ranged from 0.5 to 2, with a normalized maximum speed of specified $V_{Max_e} = 1$. Function Φ is taken as function $u \rightarrow \Phi(u) = u^2$. Next, function Π^e are generated by fixing a time horizon T_{Max}, fixing a mean number B of *break points*

t_i^e in $[0, T_{Max}]$, and an average value Δ for value $\Phi(u)$. More precisely, $\Pi^e(t_i^e)$ values are generated within a finite set $\{2\Delta, 3\Delta/2, \Delta, \Delta/2, 0\}$. As for threshold $Risk_{Max}$, we follow a pair (o, d) related path Γ with length L_{Man}, where L_{Man} is the corresponding Manhattan length between o and d. Then it comes that $Risk_{Max} = L_{Man}\Delta$. Additionally, we calculate the *Mean Risk*, which is the average of all the risk functions in the graph $G = (N, A)$. The related presetting parameters in instances can be found in Table 3.4:

Table 3.4: Characteristics of the instances

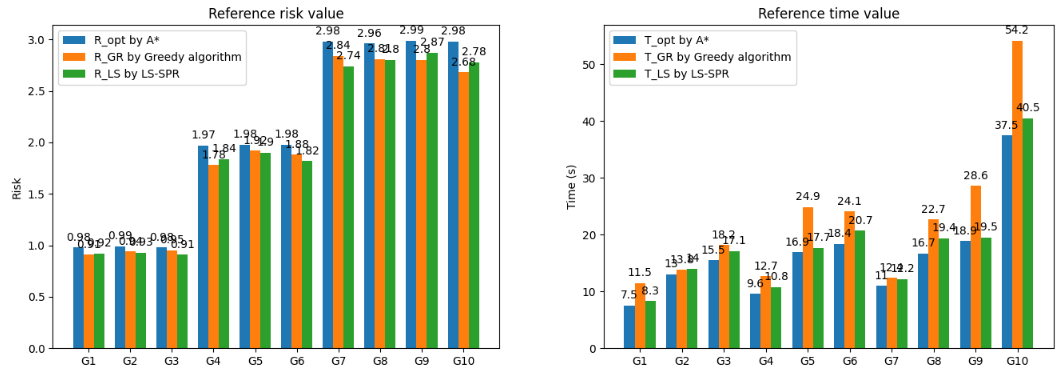
Instance	$\|N\|$	$\|A\|$	B	Δ	L_{Man}	**Mean Risk**
1	20	65	1	2	44.54	5.73
2	18	65	2	1.5	59.03	2.85
3	19	65	1	3	47.15	5.64
4	54	160	1	4	42.3	11.12
5	52	160	2	2.5	71.66	5.75
6	51	160	1	3.5	64.23	4.56
7	82	250	2	3	77.57	5.73
8	83	250	3	3	139.39	5.67
9	88	285	2	4.5	87.27	5.71
10	92	285	3	5	82.68	8.51

For each instance, the following comparative studies were conducted, involving three algorithms:

- **LS-SPR algorithm:** computing the Risk value R_{LS}, the Time value T_{LS} in *Algorithm 2*, the number of iterations $ITER$ of its main loop (modification of Γ) and related CPU time CPU_{LS}.
- **Greedy algorithm:** the Risk value R_{GR}, the Time value T_{GR} computed by the greedy algorithm GR_{SPR}, together with related CPU time CPU_{GR}.
- A^* **like algorithm:** almost exact Risk value and Time value R_{Opt}, T_{Opt} computed by the A^* like algorithm, performed with large S and K values, together with related CPU time CPU_{A^*}.

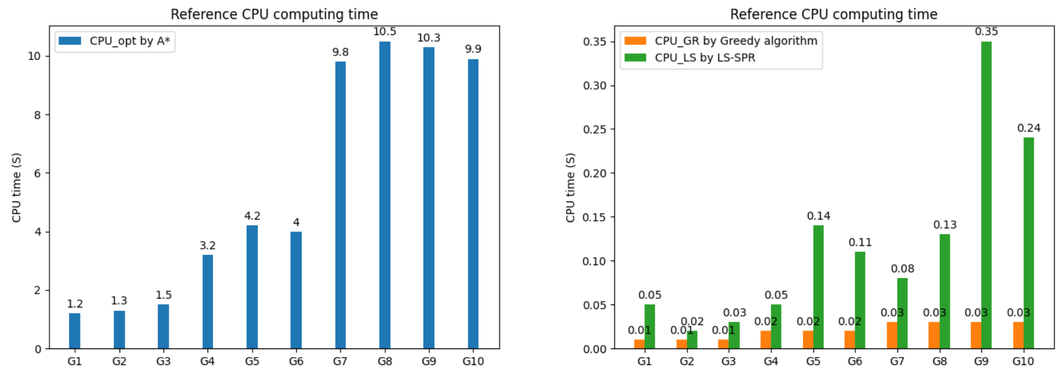
Obtained results are summarized in the following Figure 3.14 and Figure 3.15:

The A^* like algorithm provided nearly accurate Risk and Time values R_{Opt}, T_{Opt} in each case. Thus, as seen in Figure 3.14, the proposed LS-SPR method's results are near to the optimal risk and time values and outperforms the Greedy algorithm in terms of path Γ's time consumption. Results obtained through GR_{SPR} are rather erratic, because this algorithm relies on the current state of shortest path Γ from o to d, which can be bad at the travel time when we did not launch the *update* step. A^* tends performs better than LS-SPR as for the accuracy, but is more time consuming for algorithm running (see Figure 3.15). Depending on the cases, results of A^* may be also significantly impacted by parameters values S and K. Finally, we also notice that obtaining almost exact optimal values is rather time costly, even on small instances. In order to improve it, we should find a way to provide a criterion which could identify, at any times, whether a decision λ_e^{RD} has to be tried or not.



(a) Risk value for every instance. (b) Time value for every instance.

Figure 3.14: Risk versus time for every instance.



(a) Related CPU time by A^* like algorithm. (b) Related CPU time by LS-SPR and Greedy algorithm.

Figure 3.15: Reference CPU computing time.

The simulations reveal that our proposed LS-SPR may give a pretty good solution within an ideal time-risk trade-off. The computing time is rather quick, and the method appears to be suitable for use in a real-time scenario. However, it is necessary to emphasize that the risk function must still be demonstrated empirically and statistically, which are not included in this PhD thesis. We simplified the instance by using a fixed break point and maximum risk value. Maintaining the same assumptions in complicated urban navigation contexts is challenging. Section 3.3 may be viewed as an exploratory approach to high-level modeling and decision making, which is also a goal of this PhD thesis. Nonetheless, due to the model core difficulty (uncertain urban environments), the following chapter's focus will be on management-level, which will not use the suggested LS-SPR method.

3.4/ Conclusion

This chapter proposed a distributed optimal approach for dynamic MVS CN with risk-sensitive management strategy. A distributed architecture of MVS system has been formulated. The proposed formulation employs the PC theory, which enables a competitive solving time $(0.2s \sim 0.8s)$ by approximating the optimal solution in real-time applications.The TSB communication mechanism was adopted for bilateral or multilateral negotiation. Furthermore, a key safety indicator 2D TTC was adopted as a risk assessment measure to impact vehicle's decision. We model the 2D TTC in two dimensions and assume that the minimum 2D TTC value in MVS is the corresponding objective function. Such an application with the proposed ε-PC lead to promising results. Particularly, the proposed ε-PC can be applied in trajectories tracking, maneuvers warning/assisting or directly as feedback control law in Model Predictive Control (MPC). The experiments shown in this chapter prove the efficiency of the proposed ε-PC framework for real-time intersection management. Additionally, this chapter develops a local heuristic search algorithm called LS-SPR for obtaining an approximate optimal solution to the SPR problem involving a trade-off between time and risk. A learning process for LS-SPR with a limited number of decisions and states is discussed, and experiments demonstrate that it is possible to get a solution that is close to the optimal value while saving computational time. However, given the more difficult settings associated with urban traffic management, our assumptions regarding a constrained transit network (a warehouse area) may not be valid. As a result, it will not be applied in the subsequent chapter. Generally, the issues discussed in this chapter include MVS cooperation at the micro-control level and routing strategy from the perspective of a global supervisor. Both approaches for motion planning can be extended to the transportation network. However, when things get more complicated, a hierarchical design needs to be dealt with a reliable and practical way. In the following chapter, we will go through these issues in further details.

4

MIMAFC-BASED HIERARCHICAL TRAFFIC MANAGEMENT ARCHITECTURE IN TRANSPORTATION NETWORKS

This chapter considers vehicle decision-making in a transportation network with multiple intersections. In fact, advanced intersection control systems have been created to alleviate traffic congestion (cf. Chapter 2 for a literature review). Regular MVS using Cooperative Navigation (CN) principles make it easier to accomplish a shared purpose than traditional traffic. Nonetheless, due to whole uncertainty in transportation network, conventional motion planning for local areas may lead to undesirable effects in long run. Previous work in Chapter 3 developed a safe and flexible CN strategy for resolving local conflicts at an unsignalized intersection. This chapter will design a Micro-Macro Flow Control (MiMaFC) technique for investigating MVS' navigation at unsignalized intersection networks. More precisely, it is intended to get a better understanding of micro control and how it might be used to influence the behavior of traffic flows based on the proposed CN strategy.

As mentioned before, our work will employ hierarchical architecture (cf. section 4.2) to investigate the global navigation performance of MVS in complex environments/situations. Next, a macroscopic flow model for interpreting the real-time status of a dynamic transportation network is provided in section 4.3. Correspondingly, CN protocol used in the addressed architecture is specifically developed for MVS that continually cross intersections (cf. section 4.4). Further, spatio-temporal velocity adaptation is presented in this work. Depending on the vehicles' location and speed, MVS might use either the MiMaFC-based or self-interested speed approach. Simulation results (cf. section 4.5), which include a congested traffic network, are shown to demonstrate the suggested method's potential. It finds that the suggested motion planning framework may increase urban network mobility over a pure, distributed, non-supervised MVS system.

4.1/ BACKGROUND AND CHALLENGES

Urban transport systems are expected to be enormously improved thanks to the connected Intelligent Vehicles [8, 275]. The efforts made by the academic institutions, car manufacturers and Big Tech companies permit to avoid the in-road hazards through MVS [166], improve fuel economy and reduce emissions [175] by more efficient CN technologies. Under this circumstance, a review research work presented in [331] investigated the "ripple effect" of the vehicle automation. This work has built a ripple model to classify the implications of vehicle automation (the core of the ripple) on three levels. In the first level, the travel cost/choice and traffic capacity are emphasized for the near future. It will directly impact the vehicle ownership and sharing, residential location choices, land use and transport infrastructures as the sequential effects in the second level. Finally, the third level is related to broader social challenges such as energy use and pollution and public health, etc. As a result, it's critical to create modern traffic management systems that can adapt to the process of autonomous driving and pay attention to its sequential effects. Obviously, MVS may contribute in a better manner to boost the public transportation in urban areas and regulate their navigation in an arranged way [124, 275, 363]. From this perspective, an important question arises: how can MVS help to fulfill the increasing mobility demands and better adapt intelligent transportation development in the future? Therefore, developing novel mobility platforms, which are focusing on improving the arterial traffic performance, is attracting a considerable interest in the transportation systems community.

As illustrated in section 1.1.1, the majority of studies indicates that MVS will become a reality in the near future (although at very modest market penetration rates) and will have the capacity to significantly decrease traffic congestion, road accidents, and car emissions [127, 363, 377]. Additionally, research on autonomous highways has proven significant promise in a variety of traffic scenarios, facilitating the deployment of MVS [428]. In high-ways/instrumented intersections, a number of detecting technologies are used, including in-road sensors (loop detectors, magnetic detectors, and magnetometers) and over-roadway sensors (cameras, radars, ultrasonic, infrared, and acoustic sensors) [82, 163, 299]. Intersections may be instrumented to broadcast messages to neighboring cars through DSRC (SAE standard J2735-Dedicated Short Range Communications message set dictionary), which contains information about the signal phase, time and geometry of the intersection [181]. Due to advancements in both the on-board system and sophisticated sensors in surrounding environments, research under the premise of all MVS on the road has also attracted the traffic control community's attention. Most urban road users feel that implementing MVS technologies (such as cooperative trajectory prediction and motion planning) will considerably increase urban road capacity at a corridor or a road network level in a fully automated setting [24, 241, 244, 519]. In this sense, these MVS applications address comparable traffic-control issues. In [552], researchers used game theory to an unsignalized intersection, suggesting that an intersection controller collect data from automated vehicles on the road network and minimize overall trip delay. A decentralized Model Predictive Control (MPC) approach provided by [316] is used to determine the time necessary to arrive at an intersection for each vehicle in the network. A survey related to a review of traffic control and its links to vehicle connectivity can be found in [41] and [284]. In particular, many decentralized approaches for MVS CN still requires a local manage agent in charge of synchronizing the vehicle to cross the intersection [445]. It is important to note that the dynamics and distributed controller are qualities of the individual MVS, but the information flow network and macro traffic control are aspects of the entire MVS system. Consequently, most of the research on on-ramp/intersection coordination in road networks use a multi-layer/multi-level control framework [406, 446, 498].

In summary, there are two main challenges that need to be addressed in the context of MVS CN in a complex intersection network (non-highway scenarios). First, how to create a specialized large-scale optimization framework for addressing the issue of large-scale vehicle operation. Due to the fact that unexpected driver behaviors often contribute to traffic uncertainty, cars are prone to unnecessary delay and, as a result, slow traffic [195]. Additionally, increased traffic data must be analyzed inside a MVS system. There is no established concept, standard or platform for resolving this problem at the moment. Rather than that, a framework that unifies the protocol for CN. Second, we are concerned not only with the safe movement of a single agent inside MVS, but also with the coordinated and safe movement of the whole system. Nonetheless, in the expanded macro traffic flow model, the cooperative motion planning methods remain inexact and suboptimal. Additionally, the trajectory chosen to resolve conflicts in a local region may result in an increase in travel time and fuel consumption over time. As a result, speed guidance (at a targeted vehicle speed or a constrained speed) is required to account for macro-traffic circumstances.

4.2/ MiMaFC-based Hierarchical architecture

The overview of the addressed circumstances is explained in Fig. 4.1. This chapter assumes that all navigation vehicles can interact with one another and with the infrastructure via communication. The designated paths of MVS have been computed based on the state information from global supervisor. A module named local supervisor (S_{Loc_A}) is located at each intersection region. Additionally, assume that downstream traffic information are provided by roadside sensors implanted along the mid-blocks between two intersections. For the sake of simplicity, a S_{Loc_A} is assumed to receive updated approaching traffic flow data without considering measurement errors (and/or delays) induced from the Infrastructure-to-infrastructure (I2I) communication. In the micro control level, it is thought

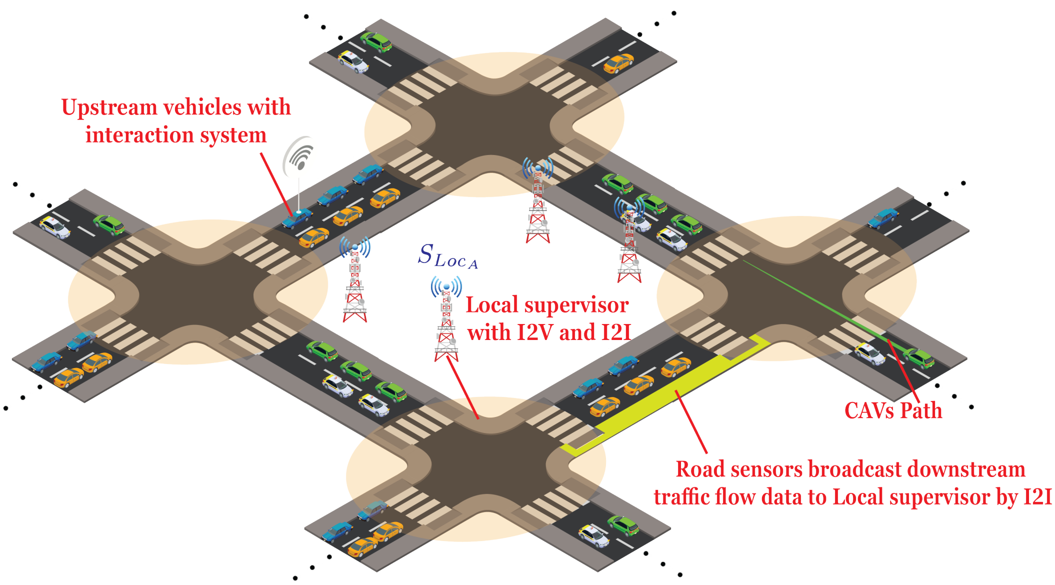


Figure 4.1: Urban road network for autonomous vehicle CN with local supervisor S_{LocA} at each intersection region.

that all interactive vehicles might make decisions after communication with neighboring vehicles. (see Fig. 4.1). Vehicles originating from various points of entry into the urban network are assigned to predetermined destinations. Further, S_{Loc_A} is assumed to obtain the updated approaching traffic flow messages without considering measurement errors and delays.

4.2.1/ SUPERVISED TRAFFIC MANAGEMENT SCHEME.

As mentioned in section 2.2.2. The current tendency is toward the establishment of a hierarchical supervisory architecture with two or three levels for managing such a system. The following summarizes the roles of the newly established global/local supervisor and MVS in this Chapter.

- **Global supervisor:** at the macro level, the global supervisor is responsible for tactical dynamic planning and routing of the vehicle, as well as task allocation among the vehicles (e.g., pick-up and delivery). In section 3.3, we developed a transit network model and demonstrated how to balance speed and risk on the road using the Local Search (LS) heuristic algorithm for Shortest Path under Risk constraint (SPR) problem (i.e., LS-SPR algorithm). In contrast, this chapter focuses mostly on a management-level agent that is located at traffic intersections. To simplify the scheme, the global supervisor might still get all information while assigning just the vehicle's path.
- **Local supervisor:** local supervisors S_{Loc_A}, at the management level, are responsible for supervising minor difficult locations, including as intersections (or loading/unloading zones in warehouse-like areas). As a mediator, it communicates with the vehicles, regulating their transit and avoiding collisions as they pass through specific zones. This level has sparked renewed interest in recent years (see [118, 391]), and occasionally caused confusion with the micro control level: in many cases, the hypothesis is made that all involved vehicles are run by the same embedded software and exchange perfect information; this becomes equivalent to supposing the existence of a local external mediator. Clearly, in an urban environment, the goal of S_{Loc_A} is to prevent congestion and car collisions. However, it can only be provided partial information about the traffic status.
- **Multi-Vehicle System (MVS):** the MVS or CAVs is defined at the micro-level, by the monitoring and sensing devices installed inside the vehicles; these devices calculate real-time paths and modify them to the presence of potential obstacles. The majority of the robotics community's attention is still directed at the micro-level, where optimum control and artificial perception approaches are predominantly utilized [67, 288, 398]. As a component of the transportation system, the MVS prefers the adaptable and safe CN. Additionally, proactive motion planning is foreseen in our planned system, which facilitates traffic flow fluency.

4.2.2/ HIERARCHICAL AND HYBRID DECISION-MAKING ARCHITECTURE

The proposed Multi-layer Hybrid Control Policy and Motion Planning (MHCP-MP) framework is shown in Fig. 4.2. The MHCP-MP architecture is divided into two primary layers for each intersection: a macroscopic flow model and a trajectory-based optimization

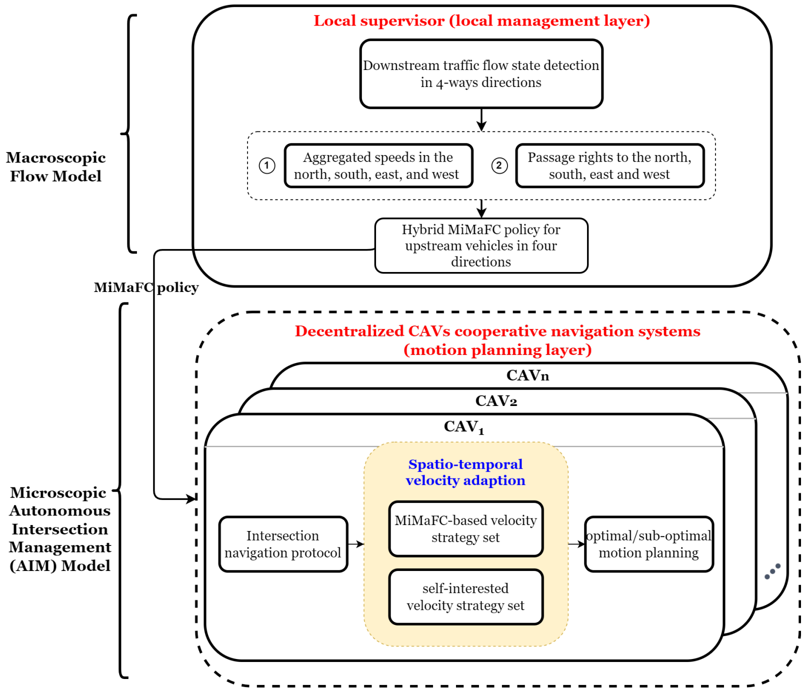


Figure 4.2: Basic schematic of the proposed Multi-layer Hybrid Control Policy and Motion Planning (MHCP-MP) framework.

model for AIM. Local supervisors S_{Loc_A} observe the 4-way downstream traffic flow status. Thus, the traffic aggregated speeds and the rights of passage are then disseminated for upstream vehicles[1] in different directions. MVS are therefore considered to have onboard system to retrieve a hybrid control policy from S_{Loc_A}. It is important to note that all the approaching MVS in the 4-way upstream are investigated as a distributed cooperative system based on their network topology structure. Additionally, the microscopic strategies and optimization solver are addressed by a previously introduced ε-Probability Collective (PC) algorithm [1, 2]. In so doing, the MVS system will guarantee an optimal (or suboptimal) trajectories-based planning for lower control layer. Finally, the CN for multiple MVS systems is conducted regarding the traffic flow fluctuation while ensuring locally efficient and safe navigation. The main idea standing behind the proposed architecture is to construct a feasible link between the developed macroscopic flow strategy and the microscopic motion control as seen in the prior work [4]. A more detailed explanations of the macroscopic flow model regarding urban network (cf. section 4.3) and MVS CN method based on MiMaFC policy (cf. section 4.4) will be provided in the following sections.

4.3/ MiMaFC strategy in Traffic flow model

The macroscopic flow model interprets the real-time state of the dynamic transportation network including multiple intersections. Firstly, a primitive car-following model is illustrated by ordinary difference equations in section 4.3.1. Next, the urban road network is explained in section 4.3.2.

[1]Vehicles that will cross imminently the intersection (cf. Fig. 4.1).

4.3.1/ Formulation of vehicle driving model

The vehicle mobility is developed referring Krauss model [259] where each vehicle can perform two motion states (i.e., free motion and interacting motion). Firstly, the proposed car-following model is illustrated by Ordinary Difference Equations (ODE) like follows:

$$\begin{cases} a_i(t) = u_i(t) + \varepsilon_i(t) \\ v_i(t+\Delta t) = v_i(t) + a_i(t) \times \Delta t \\ x_i(t+\Delta t) = x_i(t) + v_i(t) \times \Delta t + \frac{1}{2} a_i(t) \times \Delta t^2 \end{cases} \tag{4.1}$$

Where $x_i(t)$ and $v_i(t)$ denote respectively the displacement and velocity of the vehicle i at time instant t. $a_i(t)$ is the corresponding acceleration for a time interval Δt . Besides, $a_i(t)$ in (4.1) is addressed by the control input $u_i(t)$ and an uncertain disturbance factor $\varepsilon_i(t)$ which is related to the perception and sensing errors. It is supposed that $u_i(t)$ corresponds to a movement of a particle with constant acceleration between two instants, which has been defined by Δt. Thus, considering the relative distance $\Delta x_{i,i-1}(t) = x_{i-1}(t) - x_i(t)$ and relative speed $\Delta v_{i,i-1}(t)$ between two successive vehicles (i.e., ego vehicle i and vehicle $i-1$ ahead). It assumes that MVS either perform Cruise Control (for free motion) to maintain a preset speed v_{ref} or Adaptive Cruise Control (for interacting motion) when a vehicle ahead is detected within a distance $\Delta x_{i,i-1}(t) \leq R_w$. R_w is assumed to be a fixed sensing range. Thus, a reference distance d_{ref} is defined for Adaptive Cruise Control:

$$d_{ref} = d_{safe} + \Delta x^*_{i,i-1} \tag{4.2}$$

In (4.2), d_{safe} is the preset standstill safe distance. $\Delta x^*_{i,i-1}$ is the desired distance at current speed. Thus, the control law $u_i(t)$ for vehicle i can be addressed in (4.3):

$$u_i(t) = \begin{cases} -k_0 \cdot (v_i(t) - v_{ref}) \quad if\ \Delta x_{i,i-1}(t) > R_w \\ k_1 \cdot (\Delta x_{i,i-1}(t) - d_{ref}(t)) + k_2 \cdot \Delta v_{i,i-1}(t) \quad if\ \Delta x_{i,i-1}(t) \leq R_w \end{cases} \tag{4.3}$$

Where $\{k_0, k_1, k_2\}$ are positive control gains. It is important to remark that $\Delta x^*_{i,i-1}$ represents the preferred distance for each vehicle in (4.2). MVS can be assigned with stochastic space policy like human driver applying invasive or conservative following strategy on road. In this chapter, the desired distance $\Delta x^*_{i,i-1}$ is defined by the stochastic time headway th_i: $\Delta x^*_{i,i-1} = th_i \cdot v_i(t)$. Further, it is assumed that th_i is sampled based on a shifted log-normal distribution as introduced in the literature [287]. Therefore, the i^{th} vehicle is supposed to generate an independent and identically distributed (i.i.d.) $\hat{th}_i$ as self-preferred time gap (i.e., $th_i = \hat{th}_i$). Consequently, $\hat{th}_i$ is specified by (4.4):

$$\hat{th}_i \sim \text{Log-}N(\mu_v, \sigma_v) \tag{4.4}$$

Where μ_v and σ_v are the predefined velocity dependent parameters in log-normal distribution (cf. appendix B). These parameters can be estimated using statistical inference by empirical datasets like the Next Generation Simulation (NGSIM) [461] described in section 4.5.

4.3.2/ Formulation of traffic flow fundamentals

In this section, in order to have enough representative example, we will consider an area of 9 neighborhood intersections which are combined together as an urban road network

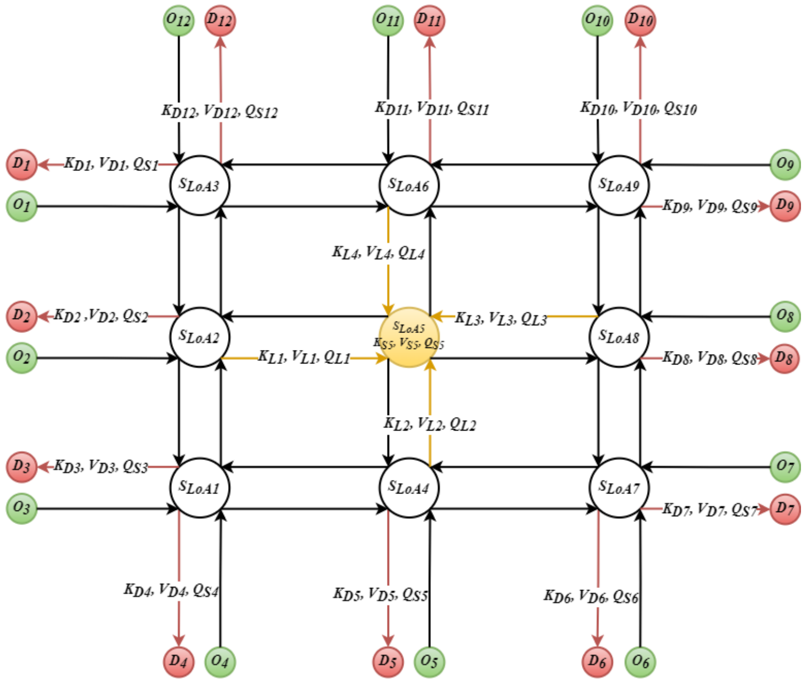


Figure 4.3: CAVs navigation in transportation network with Multiple unsignalized intersections: the origins (destinations) are noted by $O_i(D_i)$. Each 4-way intersection is in charged by a local supervisor S_{LoAi}. The 3-tuple of traffic density, velocity and flow rate are defined for each link $\{K_{L_i}, V_{L_i}, Q_{L_i}\}$, destination lane $\{K_{D_i}, V_{D_i}, Q_{D_i}\}$ and intersection area $\{K_{S_i}, V_{S_i}, Q_{S_i}\}$.

like in Fig. 4.1. The whole transportation network contains 48 links and as mentioned above 9 junctions. The Origins and Destinations (O-D) are set to manage the flows input/output at the borders of the traffic network (see Fig. 4.3). Clearly, destinations points are located in 12 links (thus, define the destination links number: $n_D = 12$) which are not belong to any of the internal intersection areas (red lines in Fig. 4.3). In such neighborhood-sized sections of urban area, it is assumed that the traffic load is homogeneously distributed at the initial state. Further, the external conditions especially for the time-dependent traffic flow are supposed to change slowly. In addition, the traffic flow characteristics linking flow, speed and density can be uniformly defined and revealed by what is called Macroscopic Fundamental Diagram (MFD) (cf. Fig. 4.4 developed in our prior work [3]). For exploiting the MFD, interested reader may refer to [158, 247, 315].

There are many ways to interpret the value of fundamental traffic flow characteristics (flow, speed and density). Here, the measured space mean speed V, traffic density K and calculated travel flow Q are addressed in this section (see Fig. 4.3 for example). Generally, we consider in the proposed modeling that the infrastructure has the possibility to cyclically collect instantaneous vehicle speed v_i and vehicle number N_i for each lane. Thus, the lane density at every instant can be defined as follows:

$$K_{L_i} = K_{D_i} = \frac{N_i}{LGTH_i} \tag{4.5}$$

Where $LGTH_i$ is the length of a link, K_{L_i} represents the lane's density towards the intersection (black arrows in Fig. 4.3) and K_{D_i} is the destination lane's density (red arrows in Fig. 4.3). Accordingly, the density of intersection K_{S_i} (combined by n_{L_i} links, for instance, a group of $n_{L_i} = 4$ yellow arrows in Fig. 4.3) is defined as:

$$K_{S_i} = (\sum_{L_i=1}^{n_{L_i}} K_{L_i})/n_{L_i} \tag{4.6}$$

Moreover, the overall intersections density K_S and exits lane density K_D are developed as follows (n_S and n_D are respectively the overall number of intersections and the number of destinations):

$$\begin{cases} K_S = (\sum_{S_i=1}^{n_S} K_{S_i})/n_S \\ K_D = (\sum_{D_i=1}^{n_D} K_{D_i})/n_D \end{cases} \tag{4.7}$$

The space-mean speed[1] has been more commonly adopted to reveal current traffic state than time-mean speed[2] (which overestimates the influence of faster vehicles [255, 453]). Hence, the space-mean speed, which is also calculated as a harmonic mean of collected vehicle speeds, is used in this section as the traffic velocity associated with a specified length of roadway. Thus, the traffic velocity for flow input lane, exit lane and intersection area are respectively defined as $\{V_{L_i}, V_{D_i}, V_{S_i}\}$, see (4.8):

$$\begin{cases} V_{L_i} = N_i/\sum_{i=1}^{N_i}(1/v_i) \\ V_{D_i} = N_{D_i}/\sum_{i=1}^{N_{D_i}}(1/v_i) \\ V_{S_i} = N_{S_i}/\sum_{i=1}^{N_{S_i}}(1/v_i) \end{cases} \tag{4.8}$$

Where $\{N_i, N_{D_i}, N_{S_i}\}$ are the vehicle quantity in the corresponding areas. Similarly, the traffic velocity for overall intersections (contain N_S vehicles) and destination lanes (for N_D vehicles) are written as:

$$\begin{cases} V_D = N_D/\sum_{i=1}^{N_D}(1/v_i) \\ V_S = N_S/\sum_{i=1}^{N_S}(1/v_i) \end{cases} \tag{4.9}$$

In such a manner, the calculated flow rate can be also addressed as $Q_{L_i} = K_{L_i} \times V_{L_i}$ (for flow input lane), $Q_{D_i} = K_{D_i} \times V_{D_i}$ (for destination lane) and $Q_{S_i} = K_{S_i} \times V_{S_i}$ (for each intersection area) at every instant (see also in Fig. 4.3). In so doing, we avoid to hourly measure flow rate which reflect the equal traffic knowledge as calculated flow rate in the experimental intersection network.

The current proposed work aims to develop proactive vehicle motion planning regarding the dynamic changes in urban environments between controlled intersections. Therefore, the study develops a global supervisor to broadcast the aforementioned traffic characteristics to the preassigned S_{Loc_A} on a regular basis. A global supervisor observes the status of traffic and encourages intelligent vehicles to take specific routes, as shown in the urban setting in Fig. 4.1. It is also compatible with a GPS device, which can suggest the best route (consuming shortest travel time) to get to the targeted destination [38]. Next, the obtained traffic key factors are formulated to the macroscopic fundamental diagram (see

[1] The space-mean speed is the average speed of vehicles traveling a given segment of roadway during a specified period of time and is calculated using the average travel time and length for the roadway segment (i.e., $SpaceMeanSpeed = \frac{\text{distance traveled}}{\text{avg. travel time}}$ as seen in [453], Chapter 1).

[2] The time-mean speed is defined by the arithmetic average speed of all vehicles for a certain duration of time.

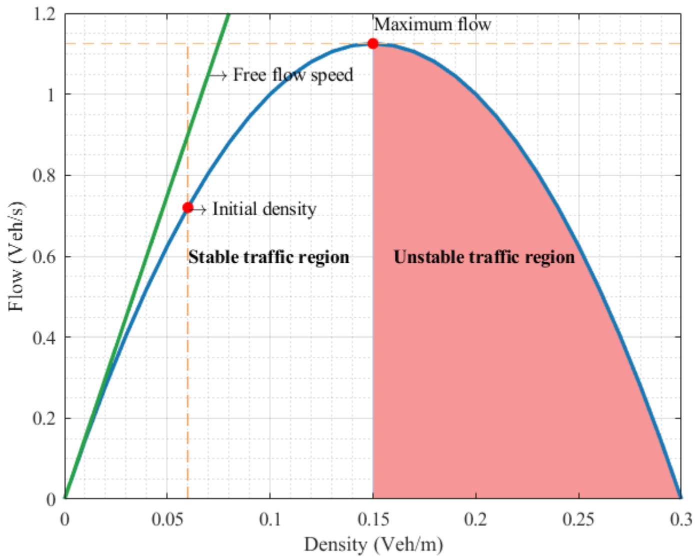


Figure 4.4: The Macroscopic Fundamental Diagram (MFD) of theoretical correlation between traffic density and traffic flow.

Fig. 4.4) by the notable Greenshields model [176] for every single lane as follows:

$$\begin{cases} \mathbb{V}_{L_i} = V_f(1 - \frac{K_{L_i}}{K_{jam}}) \\ \mathbb{Q}_{L_i} = V_f(K_{L_i} - \frac{K_{L_i}^2}{K_{jam}}) \end{cases} \tag{4.10}$$

where V_f and K_{jam} are respectively the free-flow speed (maximum desired speed) and jam density (where automobiles are unable to move) regarding the current road conditions. $[\mathbb{V}_{L_i}, \mathbb{Q}_{L_i}]$ are the dependents on the measured lane density K_{L_i} in the proposed traffic fundamental diagram (cf. Fig. 4.4). It is worth acknowledge that the maximum road flow $\mathbb{Q}_{L_i}^{max}$ is theoretically defined at the vertex of the parabola in Fig. 4.4 where $\partial\mathbb{Q}_i/\partial K_{L_i} = 0$ in (4.10). If the vehicle number increasing consistently (while $\partial\mathbb{Q}_i/\partial K_{L_i} \leq 0$) till to the maximum road capacity, the flow rate will decrease and even collapse to zero at the jam density K_{jam}.

4.3.3/ Formulation of MiMaFC strategy

Ultimately, MVS are supposed to adopt appropriated actions to ensure a proper spatio-temporal strategy at intersection areas w.r.t. the policy info from the local supervisor S_{Loc_A} as depicted in Fig. 4.2. When a car driving at the decision-making points (bounds of a local area), the crossing policy is assigned for each one including the downstream lane's aggregated speed (flow speed) $\mathbb{V}_{L_i}$ referring to (4.10) and the corresponding "road-weights" W_{r_i} referring to upstream density. The road-weights W_{r_i} for each upstream approaching car from the lane i can be defined as (4.11):

$$W_{r_i} = (\frac{K_{L_i}}{K_{S_i}})^{\sigma_{S_i}} \times \varphi_{r_i} \tag{4.11}$$

Where:

$$\varphi_{r_i} = \begin{cases} \Pi^{e1}(t), & \text{if } \partial Q_i/\partial K_{L_i} > 0 \\ \Pi^{e2}(t), & \text{if } \partial Q_i/\partial K_{L_i} \leq 0 \end{cases} \tag{4.12}$$

Note that $[\sigma_{S_i}, \Pi^{e1}, \Pi^{e2}]$ are independent model parameters. σ_{S_i} is designed to amplify the W_{r_i} impacts in the corresponding intersection. The piecewise-defined function φ_{r_i} indicates the free or congested traffic flow state w.r.t. the calculated flow-density ratio $\partial Q_i/\partial K_{L_i}$. Every function $t \to \Pi^e$ is constant whereas Π^{e2} is greater than Π^{e1} to significantly increase the congested road-weights W_{r_i} among others. To summarize, the macroscopic flow model (implemented by an intersection supervisor S_{Loc_A}) was created primarily to monitor traffic conditions and transmit relevant intersection crossing policy. In fact, the suggested crossing policy, which is based on the aggregated speed and road-weights of lanes (i.e., $\{\mathbb{V}_{L_i}, W_{r_i}\}$), will be used for CN strategy at the microscopic motion planning level (cf. section 4.4.2).

4.4/ MIMAFC STRATEGY FOR CN

A systemic approach is implemented in this section to deal with consecutive vehicles' CN at every single intersection (see Fig. 4.5). Indeed, our research focuses on both macro-traffic management and micro-vehicle decision-making, a complicated system in which it is hard to focus on every element. In order to better comprehend such a system without splitting it into much more independent sub-systems (for a more analytical program), the systemic approach is used to analyze all attributes of the full cooperative system under the supervisory scheme. Thus, this latter (for a clearer picture of the microscopic layer in the MHCP-MP framework) is divided into two succeeding parts to highlight the proposed standardized navigation protocol (cf. section 4.4.1 as seen in Fig. 4.6) and local conflicts processing model (cf. Section 4.4.2).

4.4.1/ PROPOSED INTERSECTION NAVIGATION PROTOCOL

As seen in Fig. 4.5, before reaching the Initial Decision-Making Point (IDMP) P_0, a car approaching the intersection will decelerate at a specific distance S_1 (e.g., $S_1 = 50m$ which corresponds to the bounds of local interactive area). When a vehicle arrives at IDMP P_0, a local supervisor S_{Loc_A} (cf. Fig. 4.5) immediately sends the local policy, which instructs the vehicle's cooperative motion planning. It's also worth noting that cars arriving at the IDMP P_0 are supposed to have all of the information they need to make decisions (including other vehicles' predicted paths). As a result, if two or more cars join IDMP P_0 (from different directions) at the same time, a local supervisor S_{Loc_A} will appoint the vehicle that makes the decision first at random. The interactive area is divided into three parts labelled by different colors in Fig. 4.5. If a vehicle is identified as a cooperative agent, it will firstly run the MiMaFC-based speed strategy (cf. section 4.4.2.1) which creates the most chance to satisfy the S_{LocA} policy relating the traffic aggregated speed (i.e., the proposed traffic flow velocity). Unfortunately, the crossing strategy is sensitive to the initial speed and it may be re-planned in the proposed cooperation protocol as mentioned in the following paragraph. Thus, MiMaFC-based Decision-Making Area (MiMaFC-DMA,

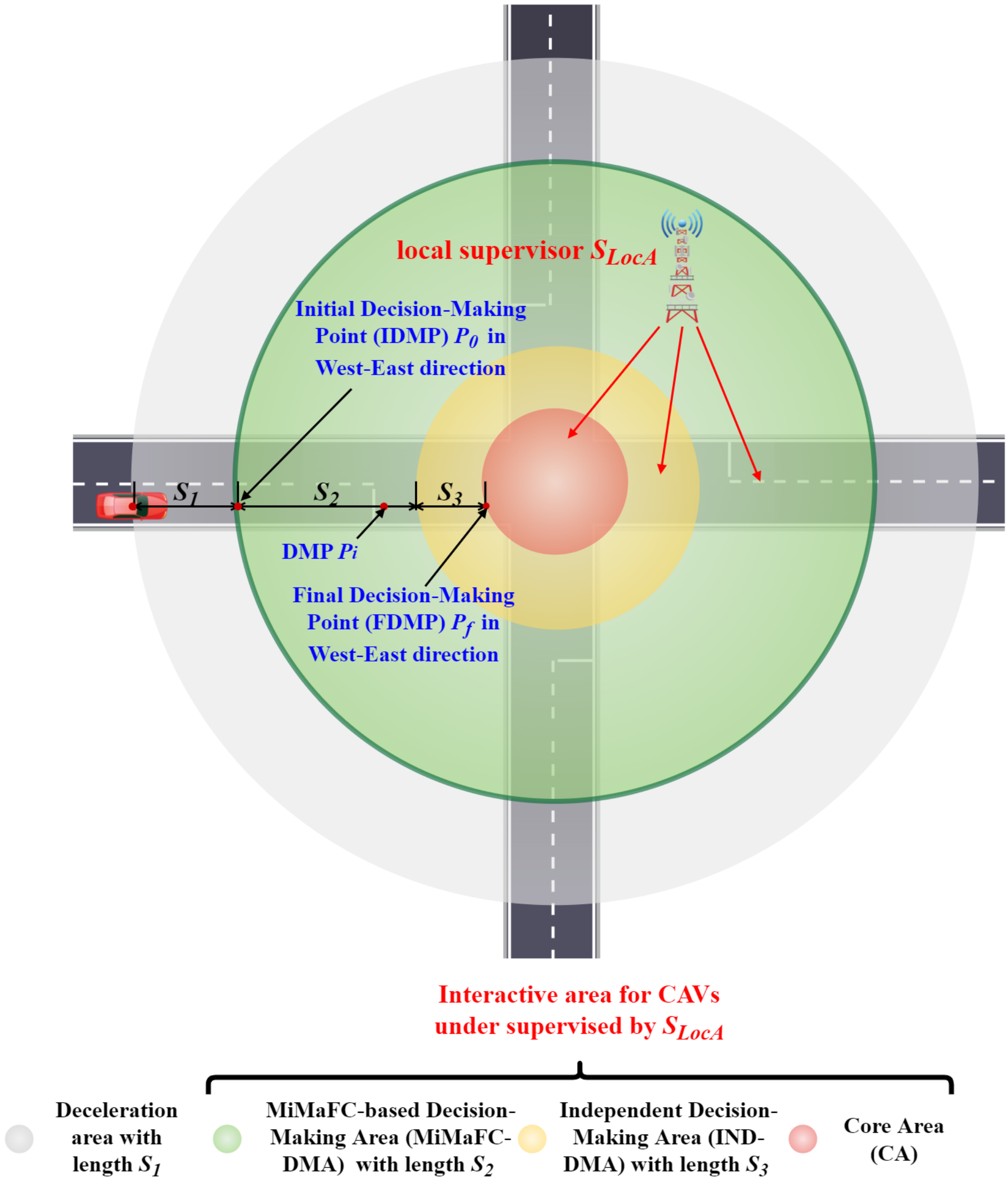


Figure 4.5: Individual vehicles approach the intersection and make decision from IDMP P_0 to participate in CN. The interactive area supervised by S_{LoA} is divided into three parts (i.e., MiMaFC-DMA, IND-DMA and CA identified by different colors), each of which implements different corresponding navigation protocol for cooperative strategy.

the green area in Fig. 4.5) is reserved with a length S_2 for vehicles to find the best-sampled strategy to compose a feasible cooperative trajectory at other DMP P_i (as seen in Fig. 4.5). Secondly, when a vehicle still can not find a feasible solution to satisfy the local policy (or have to recompute a solution for CN) after MiMaFC-DMA, it will adopt the self-interested strategy (cf. section 4.4.2.1) in the INDependent Decision-Making Area (IND-DMA, the yellow area in Fig. 4.5). In so doing, safety solution can be lastly guaranteed when a vehicle closing to the intersection Core Area (CA) with red color in Fig. 4.5. In such a case, the S_{LocA} policy can not be fully satisfied. But the vehicle's priority (road weights) are still considered in the optimized trajectory. Thirdly, after the Final Decision-

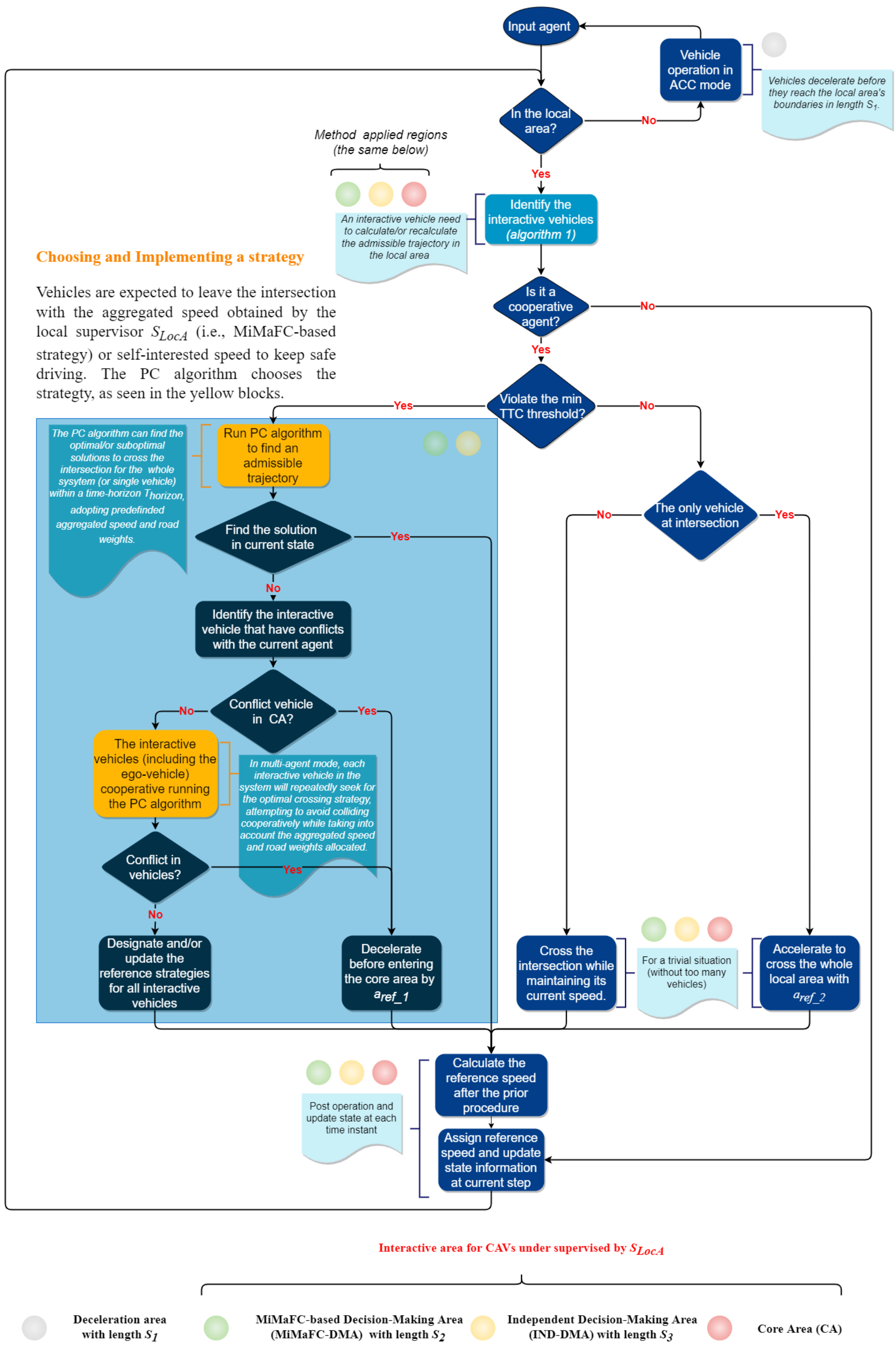


Figure 4.6: Flow-chart showing the proposed cooperative strategy for traffic network navigation diagram.

Making Point (FDMP) P_f (see Fig. 4.5), vehicles in CA are not permitted to modify the targeted speed profile. Namely, vehicles in CA that have already calculated a sufficiently safe trajectory will be excluded from any optimization.

A basic CN protocol in the local supervised area (see Fig. 4.5, for example) has been addressed in our previous work [4] for unidirectional traffic flow or in a single arterial road. The main contribution in this work is to develop reliable and adaptable measures to counter more complicated traffic flows (e.g., left and right turning is possible) in multiple intersection networks. The overall traffic network intersection navigation diagram is provided in Fig. 4.6 for more clearly understanding. Through this framework the augmented cooperative protocol which integrally considers both vehicle's conflicts and multi-intersection management at the level of large area in urban environment is proposed in this section. The suggested protocol, in particular, are customized for various regions (i.e., highlight by different colors in Fig. 4.6) within the supervised interactive area. In the following sections, we will further describe the primary contents and underline adapted zones of the augmented protocol.

4.4.1.1/ Preparation area: vehicle sorting

Firstly, a new car added in the MVS system executes sorting algorithm (cf. *Algorithm 5*) to identify the interactive vehicles. The cooperative vehicles need to further choose their intersection strategies (either to search a feasible optimal trajectory or help other vehicle to avoid conflicts). Notably, the preceding entering vehicle that owns the assigned crossing strategy usually does not cooperate with a new arriving vehicle until there is a conflict that cannot be avoided by the succeeding cars' own efforts. Particularly, vehicle sorting occurs regularly (at a short interval, for instance $0.1s$) in all interactive areas for MVS supervised by S_{LoA}.

A sorting algorithm (as shown in *Algorithm 5*) is firstly performed to identify the interactive vehicles at IDMP P_0 (see Fig. 4.5). Let us assume that the embedded motion planner of each vehicle in the distributed MVS system SYS can update the coordination state at every instant. Then, the Boolean's values are correctly assigned for the labeled states such as: collaboration flag V_{Col}, optimization flag V_{opt}, conflict flag $V_{conflict}$ and remain in intersections flag V_{rem}, etc. When a vehicle equipped with an embedded system enters a local monitored area, it will initialize all of these default flags (at IDMP P_0). The detailed steps to distinguish between the collaborative and non-collaborative vehicles are given in *Algorithm 5*.

4.4.1.2/ Decision area: selecting strategy

Secondly, the collaborative vehicle calculates its minimum Time-To-Collision which is a risk indicator to describe the remaining time for a probable collision between any two vehicles. The developed *2D TTC* in our prior work [2] (this article focuses on developing risk-sensitive intersection cooperation strategies) is revisited to identify the cars that have potential conflicts with other vehicles. Noting that, a threshold of TTC_{min} is used to select the violated *2D TTC*. A vehicle that does not hit the minimum threshold TTC_{min} will execute a constant accelerating strategy by predefined a_{ref} (if it is the only vehicle) or maintain current speed (if there are other vehicles). Notably, the risk valuing mechanism that is first implemented at IDMP P_0 is capable of handling a trivial situation (e.g., not too

Algorithm 5: Sorting algorithm for collaboration

/* Sorting algorithm is executed periodically in supervised areas */
Input: SYS, V_{opt}, $V_{conflict}$ and V_{rem}
Output: V_{Col}
/* Initial $V_{opt}, V_{conflict}, V_{rem}, V_{Col}$ are set to the default value 0 */
if vehicle in local area **then**
  for all $i \in SYS$ **do**
    if $V_{opt} == 0$ **then**
      $V_{Col} = true$; // The vehicle without optimal strategy should participate in collaboration
    else
      $V_{Col} = false$;
      if $V_{conflict}$==1 **then**
        $V_{Col} = true$; // The vehicle participates in collaboration when an inefficient strategy induced conflict
      if V_{rem}==1 **then**
        $V_{Col} = true$; // The vehicle participates in collaboration when it stays at the local area after predicted time
else
  $V_{Col} = false$
return V_{Col};

many automobiles in an interaction) without requiring additional optimization. Additionally, it is conducted on a frequent basis to monitor the collision risk in all local regions. Next, the labelled cooperative agent (i.e., $V_{Col} = true$ after *Algorithm 5*) will run ε-PC algorithm which is impacted by the aforementioned MiMaFC-based speed strategy from S_{LocA} in MiMaFC-DMA with length S_2 (green part in Fig. 4.5). The aggregated speed and lane priority are both considered among a utility maximizing model (cf. Section 4.4.2.3). The feasible solution within a time horizon $T_{horizon}$ will be adopted for the vehicle's control system. Particularly, if a vehicle does not find any solution in former step, it will identify the conflict vehicle in the current state.

4.4.1.3/ Implementation area: conflicts processing

As mentioned before, vehicle in CA (see Fig. 4.5) is not allowed to re-plan their trajectory. In such a context, a vehicle will perform decelerate strategy (i.e., with a constant deceleration) in order to find a better-sampled strategy in the next time instant during it is driving in S_2. It's worth noting that the car following model continues to operate even when subsequent cars decelerate in MiMaFC-DMA. In addition, the detected conflict vehicles are permitted to do multi-agent PC algorithm immediately, if they are both out of the CA. The MiMaFC strategy from S_{LocA} is still adopted in the cooperation. However, if cooperative vehicles are placed in IND-DMA with length S_3 (which is typically characterized as being shorter than S_2 and closer to CA; see the yellow region in Fig. 4.5), they will solely follow their own self-interest regardless of the local aggregated speed policy. In such an IND-

DMA of length S_2, it is assumed to prioritize a safe intersection crossing strategy before FDMP P_f (as seen also in Fig. 4.5). Finally, vehicles will either discover an admissible solution to avoid any conflicts corresponding the desired strategy policy (before FDMP P_f) or decelerate to wait a chance to find better sampled-strategy at next DMP P_i belong to MiMaFC-DMA or IND-DMA (as seen in Fig. 4.5).

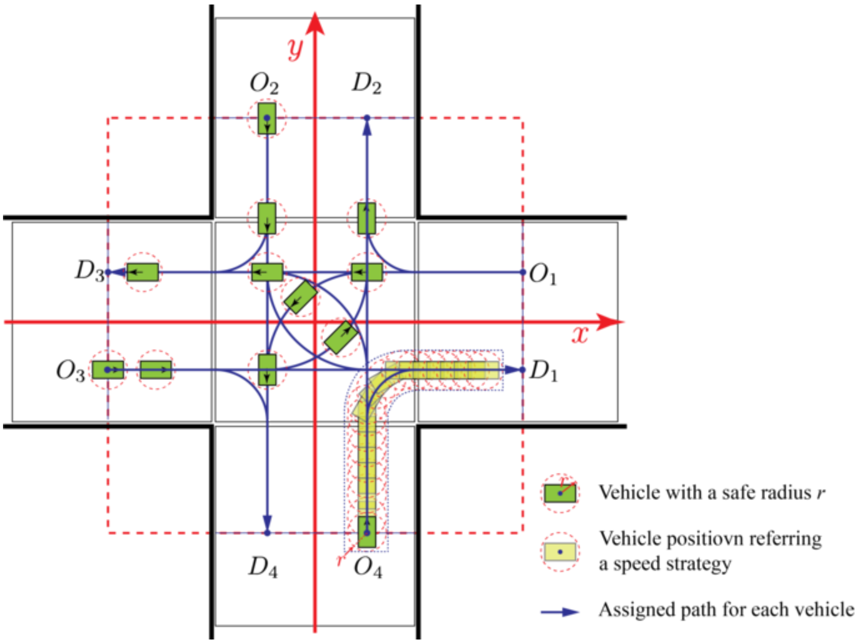
In summary, the augmented protocol described in this section ensures the safe (non-conflict scene) and/or optimal (conflict scene) operation of subsequent vehicles by allowing them to make decisions using the MiMaFC strategy (from S_{Loc_A} in MiMaFC-DMA with length S_2) or a self-interested strategy (in IND-DMA with length S_3). With regard to the above mentioned protocol for strategy selecting (cf. section 4.4.1.2), the MVS system is required a deliberate effort on approximate optimal solutions integrating the S_{Loc_A} policy and the CN utility. As a result, the following section proposes the spatio-temporal velocity adaptation approach (cf. section 4.4.2.1) for MVS along with an local optimization objective (cf. section 4.4.2.3) to select the proposed strategy.

4.4.2/ Developing and executing CN strategy

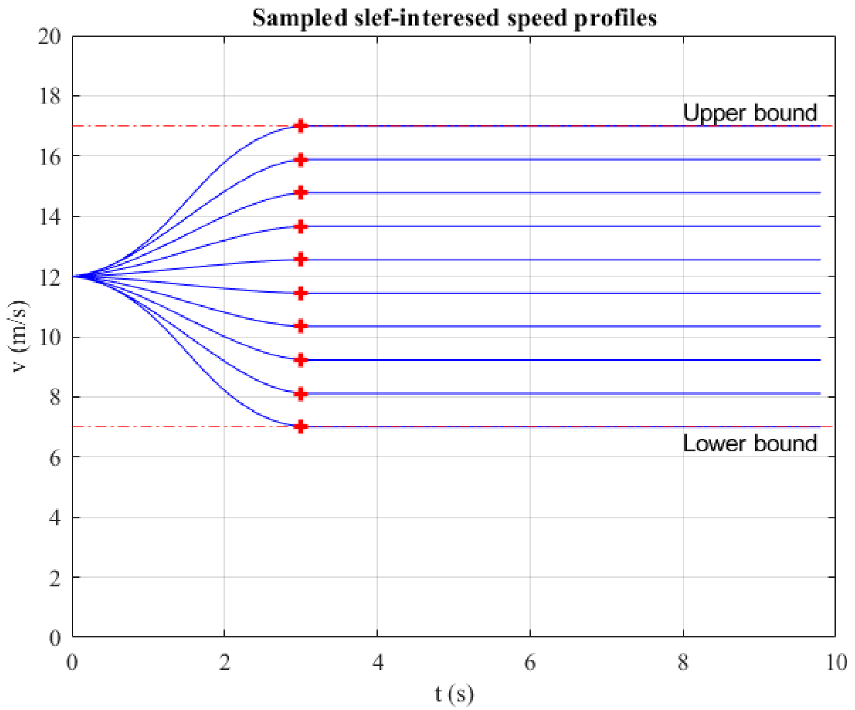
The introduced traffic navigation diagram (see Fig. 4.6) is primarily intended to facilitate vehicle cooperation during intersection conflicts. Other trivial cases (non-violation occurred at intersection) are excluded from the cooperative strategy execution. Further, the detected conflict (by risk valuating, cf. section 4.4.1.2) between any two vehicles will be optimized immediately referring to current system states. An intersection with multiple conflicted vehicles is depicted in Fig. 4.7(a). In this section, the aforementioned MiMaFC-based speed strategy and self-interested strategy will be further developed inside the spatio-temporal velocity adaptation approach (cf. section 4.4.2.1). Additionally, an objective function in PC framework (cf. section 4.4.2.3) is discussed in relation to searching the optimal strategy.

4.4.2.1/ Velocity-planning-based strategy

The conflict resolutions were developed with the aim of producing a low-complexity and rapid optimization strategy for the intersecting network. In fact, the vehicle's path is supposed to be fixed during the movement in the local area. Therefore, the only degree of freedom to re-plan a conflict-free trajectory is the speed for each of the collaborative agents. As seen in Fig. 4.7(a), the vehicles (e.g., the green rectangles) are assigned paths (e.g., the blue arrow) with origins O_i and destination D_i before crossing the intersection. For simplify, a red circle of radius r is defined to surround the car during movement. Any two circles in the 2D graph can not violate a center distance less than $2r$ when a vehicle follows its path. Therefore, a velocity planning-based optimization problem for MVS is formulated in this section. Particularly, the formulated model only uses the information of the displacements in the path without concerning the path geometry. In so doing, the algorithm is also independent of the topology of the intersection as long as the possible paths are defined. Our previous work in [1, 2] have applied a version of PC algorithm to search feasible solutions with self-interested speed strategy (see Fig. 4.7(b)) in such a single (or adjacent) intersection(s). Readers interested in the creation of self-interested speed strategy are encouraged to consult earlier works [373]. However, the bounded conditions (e.g., the initial speed) are sensitive for MVS system navigation in the pro-



(a) CAVs cooperative navigation at an intersection.



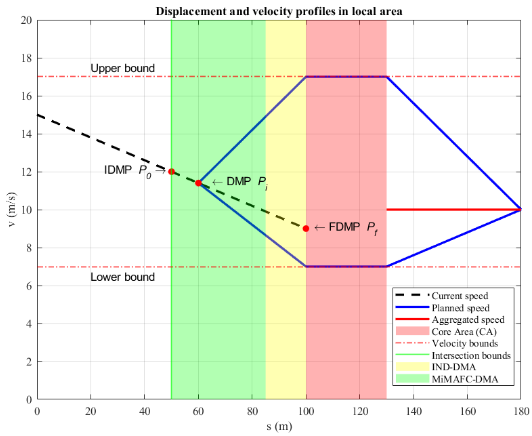
(b) Sampled self-interested speed-time profiles.

Figure 4.7: An illustration of the possible CAVs trajectories with sampled self-interested speed profiles.

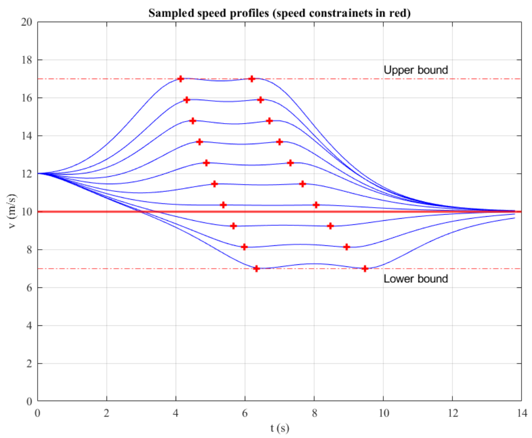
posed road network. As a result, the strategy of sampled speed profiles is refined by a spatio-temporal velocity adaption approach in this section.

As mentioned in previous section, a car will decelerate in S_1 until reaching IDMP P_0 (see Fig. 4.5) to identify whether the considered vehicles will participate in the optimization.

See Fig 4.8(a), in the proposed spatio-temporal velocity adaption approach, the collaborative vehicle can firstly choose the actions at IDMP P_0. If it can not find any feasible solution at IDMP P_0, the vehicle will go on decelerating regarding previous speed during a specified interval (e.g., after an interval of $0.1s$). Thus, the vehicle rerun the optimization after arbitrary time steps at DCM P_i (belong to MiMaFC-DMA) and generate a set of possible speed profiles with lower initial speed. Generally, as seen in Fig 4.8(a), the speed profiles (blue line) have a constraint (red dotted line) of the acceptable range and final target speed (red line). The addressed MiMaFC-based speed strategy $\mathbb{V}_{L_i}$ are defined as the reference speed v_{ref} for each direction. Additionally, the sampled speed must keep constants when entering CA (see Fig. 4.5) to ease the system complexity associated with developing more practical vehicle crossing solutions. Thus, the sampled speed interval can be addressed regarding different constant speeds in CA within the upper/lower bound.



(a) Displacement-velocity profiles in a local area.



(b) Sampled speed-time profiles.

Figure 4.8: A spatio-temporal velocity adaptation approach for CAVs' developing speed strategy at the supervised intersection.

4.4.2.2/ SPATIO-TEMPORAL VELOCITY ADAPTATION APPROACH

The generation of predefined speed profiles from the spatio-temporal velocity adaption approach are inspired by [212, 264]. Indeed, the speed profile set is calculated based on predictive time horizon, as defined by Model Predictive Control (MPC). Thus, a cost function f with initial state $\boldsymbol{x_k} = (v_k - v_{ref}, a_k)^T$ (recall that v_k, a_k is the ego vehicle speed/acceleration, v_{ref} is the reference speed for exiting an intersection) is created in this section. Moreover, jerk (links which influence the physiological aspects of the passenger) is denoted as the input signal $\boldsymbol{u}_k \in [\boldsymbol{u_{min}}, \boldsymbol{u_{max}}]$ in f. Thus, the running-cost (integral-cost) is modeled as follows:

$$f = \sum_{i=1}^{N_{opt}} \boldsymbol{x}_{k+i}^T Q \boldsymbol{x}_{k+i} + \boldsymbol{u}_{k+i-1}^T \boldsymbol{R} \boldsymbol{u}_{k+i-1} \tag{4.13}$$

Where, Q and R are the positive-definite matrix weights to penalize the state error and system input respectively. N_{opt} is the maximum optimization step number after the discretization of the predicted horizon. Assuming that, the step size is defined by Δt. Then, the dynamics model of the proposed system can be explicitly defined as follows:

$$\begin{gathered} \boldsymbol{x}_{k+1} = A\boldsymbol{x}_k + B\boldsymbol{u}_k \\ A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, B = \begin{bmatrix} 0 \\ \Delta t \end{bmatrix}, \boldsymbol{x}_k = \begin{bmatrix} v_k - v_{ref} \\ a_k \end{bmatrix} \end{gathered} \tag{4.14}$$

Hence, it is possible to recast the quadratic optimization problem into the whole prediction time horizon with any initial state $\boldsymbol{x}_k$ by introducing the vectors $\overline{\boldsymbol{x}}_{k+1}$, $\overline{\boldsymbol{u}}_k$, $\overline{\boldsymbol{Q}}$, and $\overline{\boldsymbol{R}}$ in the form:

$$\overline{\boldsymbol{x}}_{k+1} = \begin{bmatrix} \boldsymbol{x}_{k+1} \\ \boldsymbol{x}_{k+2} \\ \vdots \\ \boldsymbol{x}_{k+N_{opt}} \end{bmatrix}, \overline{\boldsymbol{u}}_k = \begin{bmatrix} \boldsymbol{u}_k \\ \boldsymbol{u}_{k+1} \\ \vdots \\ \boldsymbol{u}_{k+N_{opt}-1} \end{bmatrix}, \overline{\boldsymbol{Q}} = \begin{bmatrix} Q & & \\ & \ddots & \\ & & Q \end{bmatrix}, \overline{\boldsymbol{R}} = \begin{bmatrix} R & & \\ & \ddots & \\ & & R \end{bmatrix} \tag{4.15}$$

The running-cost function f in (4.13) can be rewritten as:

$$f = \overline{\boldsymbol{x}}_{k+1}^T \overline{\boldsymbol{Q}} \overline{\boldsymbol{x}}_{k+1} + \overline{\boldsymbol{u}}_k^T \overline{\boldsymbol{R}} \overline{\boldsymbol{u}}_k \tag{4.16}$$

Further, the state space model in (4.14) is correspondingly formulated as:

$$\begin{gathered} \overline{\boldsymbol{x}}_{k+1} = \overline{A}\boldsymbol{x}_k + \overline{B}\overline{\boldsymbol{u}}_k \\ \overline{A} = \begin{bmatrix} A \\ A^2 \\ \vdots \\ A^{N_{opt}} \end{bmatrix}, \overline{B} = \begin{bmatrix} B & 0 & \cdots & 0 \\ AB & B & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A^{N_{opt}}B & A^{N_{opt}-1}B & \cdots & B \end{bmatrix} \end{gathered} \tag{4.17}$$

Finally, we substitute (4.17) into (4.16) to reserve only the input matrix $\overline{\boldsymbol{u}}$ by a standard quadratic form:

$$\begin{aligned} f(\overline{\boldsymbol{u}}_k) &= \frac{1}{2}\overline{\boldsymbol{u}}_k^T \boldsymbol{H} \overline{\boldsymbol{u}}_k + \boldsymbol{f}\overline{\boldsymbol{u}}_k + \boldsymbol{d}_k \\ \boldsymbol{H} &= 2(\overline{\boldsymbol{B}}^T \overline{\boldsymbol{Q}\boldsymbol{B}} + \overline{\boldsymbol{R}}_k) \\ \boldsymbol{f} &= 2(\overline{\boldsymbol{A}}\boldsymbol{x}_k)^T \overline{\boldsymbol{Q}\boldsymbol{B}} \\ \boldsymbol{d}_k &= (\overline{\boldsymbol{A}}\boldsymbol{x}_k)^T \overline{\boldsymbol{Q}\boldsymbol{A}}\boldsymbol{x}_k \end{aligned} \tag{4.18}$$

Where the quadratic part described by $\boldsymbol{H}$ and linear part described by $\boldsymbol{f}$ will influence the input $\overline{\boldsymbol{u}}_k$. Therefore, the independent part $\boldsymbol{d}_k$ (constant related to the initial state $\boldsymbol{x}_k$) in (4.18) can be eliminated to make the objective function f running more compactly. Thus, the proposed quadratic optimization problem can be defined as:

$$\begin{aligned} \min_{\overline{\boldsymbol{u}}_k} \quad & f^*(\overline{\boldsymbol{u}}_k) = \frac{1}{2}\overline{\boldsymbol{u}}_k^T \boldsymbol{H}\overline{\boldsymbol{u}}_k + \boldsymbol{f}\overline{\boldsymbol{u}}_k \\ \text{subject to} \quad & A_{ineq}\overline{\boldsymbol{u}}_k \leq b_{ineq} \\ & A_{eq}\overline{\boldsymbol{u}}_k = b_{ineq} \end{aligned} \tag{4.19}$$

Where $\overline{\boldsymbol{u}}_k$ belongs to the bounds of $[\overline{\boldsymbol{u}}_{lower}, \overline{\boldsymbol{u}}_{upper}]$ regarding the inequality constrains. The equality constrains are used to enforce the speed to keep constant at CA (see Fig. 4.5). If a car enter the conflict area at i_1 and exit at i_2 where $i_1, i_2 \in [1, \cdots, N_{opt}]$, the constraints can be addressed as:

$$A_{ineq} = \begin{bmatrix} \boldsymbol{I} \\ -\boldsymbol{I} \end{bmatrix}, b_{ineq} = \begin{bmatrix} \overline{\boldsymbol{u}}_{upper} \\ -\overline{\boldsymbol{u}}_{lower} \end{bmatrix}, A_{eq} = \begin{bmatrix} [\overline{CB}]_{i_1,*} \\ [\overline{CB}]_{i_2,*} \end{bmatrix}, b_{eq} = \begin{bmatrix} [-\overline{CA}\boldsymbol{x}_k]_{i_1,*} + \overline{v}_{ref} \\ [-\overline{CA}\boldsymbol{x}_k]_{i_2,*} + \overline{v}_{ref} \end{bmatrix} \tag{4.20}$$

Where:

$$\begin{aligned} \overline{C} &= \begin{bmatrix} C & & \\ & \ddots & \\ & & C \end{bmatrix}, C = [1, 0] \\ \overline{v}_{ref} &= v_s - v_{ref} \\ v_{ref} &= min\{\mathbb{V}_L, v_{upper}\}, \quad \mathbb{V}_L \in [\mathbb{V}_{L_1}, \mathbb{V}_{L_2}, \mathbb{V}_{L_3}, \mathbb{V}_{L_4}] \end{aligned} \tag{4.21}$$

In (4.20), $[\overline{CB}]_{i,*}$ and $[-\overline{CA}\boldsymbol{x}_k]_{i,*}$ stand for the row i in matrix $\overline{CB}$ and $-\overline{CA}\boldsymbol{x}_k$. The sampled speed v_s (between the bounds of $[v_{lower}, v_{upper}]$) are defined as the constant speed in CA. The reference speed v_{ref} is defined according to the aggregated speed $\mathbb{V}_L$ in the targeted direction or local speed limit. More precisely, the final speed of the vehicle either tends toward the maximum allowed speed v_{upper} in the intersection or reach the traffic aggregated speed (if $\mathbb{V}_L < v_{upper}$). Therefore, the different solution (i.e., the possible speed profiles) for the quadratic problem are given by various sampled v_s. As seen in Fig 4.8(b), the red plus signs present the time vehicle entering the conflict area by 10 sampled speeds $v_s \in [7m/s, 17m/s]$. All proposed speed profiles are converged to the lane aggregated speed $\mathbb{V}_L = 10m/s$ (red line.) at the end of the time horizon. The next section will further explore the optimal sampled velocity profiles.

4.4.2.3/ MiMAFC-based CN strategy

Considering the search space for MVS (a distributed system), the suggested objective function for selecting the optimal sampled speed profile is as follows:

$$\begin{aligned} J = & W_{sep} \sum_{i_v \neq i_{self}} \sum_{k=1}^{max} \frac{1}{d_k(i_v, i_{self})^2} \\ & + W_{speed} \sum_{k=1}^{max} (v_k - v_{end,i_v})^2 + \sum_{i_v} W_{cross,i_v} T_{i_v} \end{aligned} \tag{4.22}$$

In (4.22), W_{sep}, W_{speed} and W_{cross,i_v} are respectively characterized as weights for the vehicle's separation d_k, deviation for reference exit speed v_{end,i_v} and intersection crossing time T_{i_v}. k is the interval indicator computed by the discretization step regarding a predefined time horizon. v_k is the ego vehicle's speed at every k instant. Moreover, the S_{Loc_A} policy is considered by the second term (v_{end,i_v}) and the third term (W_{cross,i_v}) in relation with downstream aggregated speed $[\mathbb{V}_1, \mathbb{V}_2, \mathbb{V}_3, \mathbb{V}_4]$ and "road-weight" W_{r_i} (cf. Section 4.3) for each vehicle like:

$$\begin{cases} v_{end,i_v} = v_{ref}^{i_v} \\ W_{cross,i_v} = W_{r_i}^{i_v} \end{cases} \tag{4.23}$$

Where, $W_{r_i}^{i_v}$ is defined through (4.11) in the lane of vehicle i_v and v_{end,i_v} is defined corresponding to the reference speed $v_{ref}^{i_v}$ in (4.21). It is worth noting that the first term in (4.22) is devoted to guarantee a safe spacing between vehicles in an isolated intersection. Besides, the second and third terms are linked to the intersection policy from S_{Loc_A} to achieve the proposed MiMaFC strategy. To do that, the upstream vehicle can acquire a consensus speed at the beginning of the entrance of the downstream traffic flow. Furthermore, the third term in (4.22) is specified to alleviate the congestion upstream. $W_r^{i_v}$ will be significant increased value if the upstream (the corresponding downstream of the previous adjacent intersection) traffic flow fall in the congestion state. Under such situation, the vehicles i_v in higher density road will ensure more efforts to have a short crossing time. Therefore, the collaborative vehicles in MVS will reserve the preferred trajectory making vehicles i_v own priority to cross the intersection. Finally, such a technique may be used to alter the density of traffic on crowded roads. In particular, our prior work [1, 2] emphasized the benefits of employing the ε-PC optimization framework for modeling and managing distributed systems. The purpose of this research is to demonstrate how the proposed MiMaFC method can be used to improve the performance of the MVS system navigation in intersection networks by modifying both candidate speed profiles and the objective function in the ε-PC framework. The next section's simulation results will provide further information on the aforementioned strategy.

4.5/ Simulation Results

To illustrate the performance of the proposed two-layer MHCP-MP framework, the Next Generation Simulation (NGSIM) data sets [461] are explored to characterize the stochastic headway distribution in (4.4). Further, the simulations in Matlab considering multiple unsignalized intersections are executed within a computer of Core i7-10750H, $2.60GHz$ and $16GB$ RAM. The main parameters adopted in the tackled scenario are summarized in Table 4.1.

The verified scenario can be seen in Fig. 4.9. The overall MHCP-MP framework was run in 3×3 urban road networks. The unidirectional flows arrive from outside of the network according to a Poisson distribution with the default parameter $\lambda = 1.5veh/s$. All the vehicles were set up with the initial speed $10m/s$ in the velocity bounds $[0, 20]$[m/s] (as given in Table 4.1). Vehicles on the road were provided with in-vehicle embedded system for running CN algorithm considering hybrid control policy from S_{Loc_A}. An Adaptive Cruise Control (ACC) system is adopted for maintaining a desired reference speed $v_{ref} = 20m/s$ or time headway linking the log normal distribution $\{\mu_v, \sigma_v\}$ (see Table 4.1). To highlight the advantages of the proposed method, this section performs a baseline model

Table 4.1: Parameters adopted in the tackled scenario

Parameters	Notation	Value	Units
Simulation time	T_{end}	200	s
Sampled time interval	T_{sample}	0.2	s
Vehicle safe radius	r	3	m
Lane length	L	410	m
Lane speed limit	$[v_{min}, v_{max}]$	$[0, 20]$	m/s
Bounds on acceleration	$[a_{min}, a_{max}]$	$[-3, 3]$	m/s^2
Bounds on jerk	$[j_{min}, j_{max}]$	$[-2, 2]$	m/s^3
Initial speed for all the vehicle	$v_{initial}$	10	m/s
Decision-Making area	$\{S_1, S_2, S_3\}$	$\{50\ 35\ 10\}$	m
Minimum 2D TTC	TTC_{min}	10	s
The radius of S_{Loc_A}	R	65	m
Road weight parameters	$\left\{\sigma_s, \Pi^{e1}, \Pi^{e2}\right\}$	$\{1, 1, 10\}$	-
CC reference speed	v_{ref}	20	m/s
Control gains	$\{k_0, k_1, k_2\}$	$\{1, 1, 3\}$	-
Log-normal distribution parameters for ACC	$\{\mu_v, \sigma_v\}$	$\{0.73, 0.52\}$	-
Standstill safe distance	d_{safe}	6	m
Sensing range	R_w	30	m
Strategy number	N_s	10	-
Matrix weight for strategy	$\{Q, R\}$	$\left\{\begin{bmatrix}1 & 0\\0 & 1\end{bmatrix}, \begin{bmatrix}0 & 0\\0 & 1\end{bmatrix}\right\}$	-
Prediction horizon	$T_{horizon}$	15	s
Weight on exit speed	W_{speed}	1	-
Weight on separation	W_{sep}	10	-
Weight on crossing time	W_{cross}	0.5	-
Max number of iterations	$N_{iteration}$	100	-

which did not include S_{Loc_A} and navigation protocol (cf. section 4.4.1). The baseline model reserve the same kinematic characters as the proposed car-following model on the road. Nevertheless, vehicles without S_{LocA} simply choose the fixed time strategy to reach the target speeds (spanned the sampled velocity range) at the covered area of the intersection.

As seen in Fig. 4.10, the up-left and up-right velocity diagram give a global view of baseline model without S_{Loc_A} and the proposed method with S_{Loc_A}. The desired exit speed in the baseline model is equal to the maximum speed in their strategy set. Although vehicles expect to leave the intersection as fast as possible, MVS have to wait for their turn to participate in the decision-making. In such an approach, the maximum allowed agents can participate the optimization is five. Therefore, the remained MVS in the local area have to slow down until permit to participate in cooperative optimization. Moreover, the initial speed is very sensitive to vehicle's decision-making. A decelerate policy was widely adopted before entering the intersection in the unsupervised MVS system. Simulations show that vehicle decelerate to around $5m/s$ in order to have the ability to find the maximum admissible crossing strategy in predefined conditions. Nevertheless, due to the speed fluctuation, the desired velocity causally collapsed to $0m/s$ when the vehicles increase during the second half simulation time.

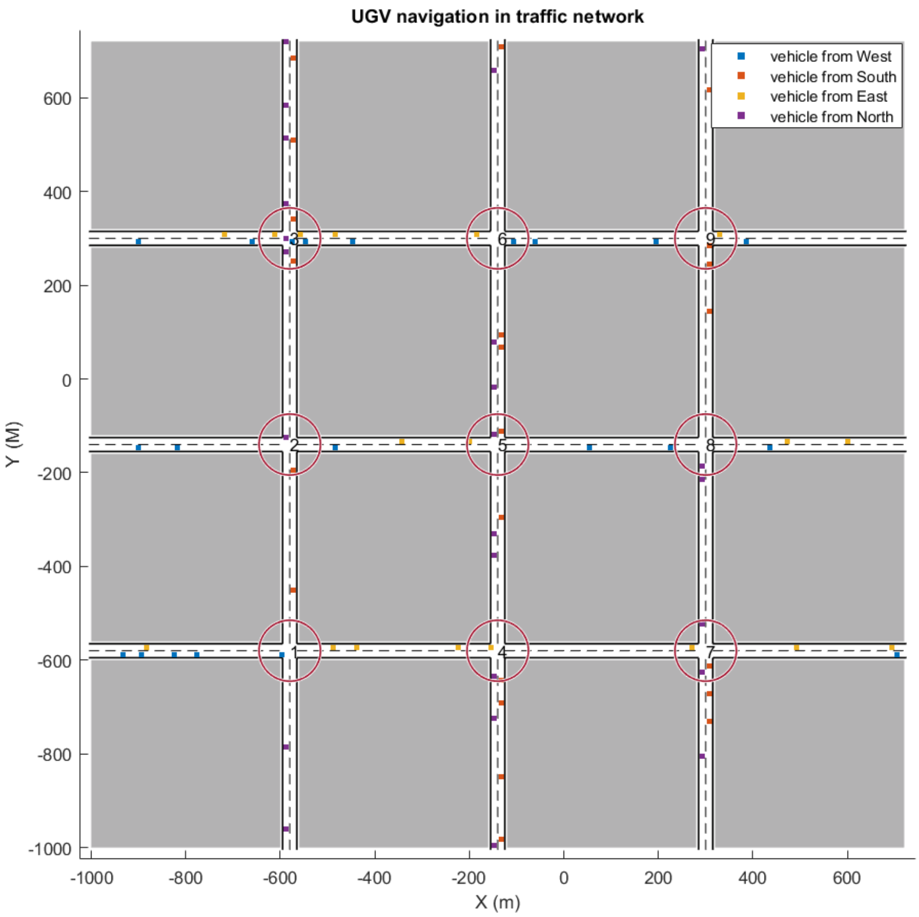


Figure 4.9: Unidirectional flow of CAVs navigation in traffic network for both supervised and unsupervised system. The red circles stand for the coved range of a local supervisor S_{LoA} noted from 1 to 9 (simulation videos can be found at https://bit.ly/3zcDwAu).

In contrast, MVS adopting the I2V technology can obtain the real time traffic policy by S_{Loc_A}. The vehicle exit speed was expected to be close to the aggregated speed, which can help to harmonize the flow fluctuation. The augmented navigation protocol also wins the chance to find optimal (or suboptimal) crossing strategy at relative high speed. The up-right velocity diagram in Fig. 4.10 shows most vehicles can deal with the CN task when a self speed greater than $10m/s$. As a consequence, the proposed MHCP-MP framework including S_{Loc_A} can improve the average velocity (blue line in bottom-right graph in Fig. 4.10) comparing with the whole distribute MVS system's average speed (red line in bottom-left graph in Fig. 4.10). In addition, all the adjacent vehicles keep a safe distance $d_{safe} = 6m$ in the addressed approach. On the contrary, twice violations of inter-vehicle distance are observed in the baseline model as seen in Fig. 4.11. In brief, the overall cooperative MVS system can benefit from the augmented navigation protocol and assigned real-time traffic policy of S_{Loc_A} to guarantee reliable, smooth, and safe running.

The corresponding traffic fundamental diagram for each intersection and the exits of the whole urban network can be seen in Fig. 4.12. The color bar stands for the time in the

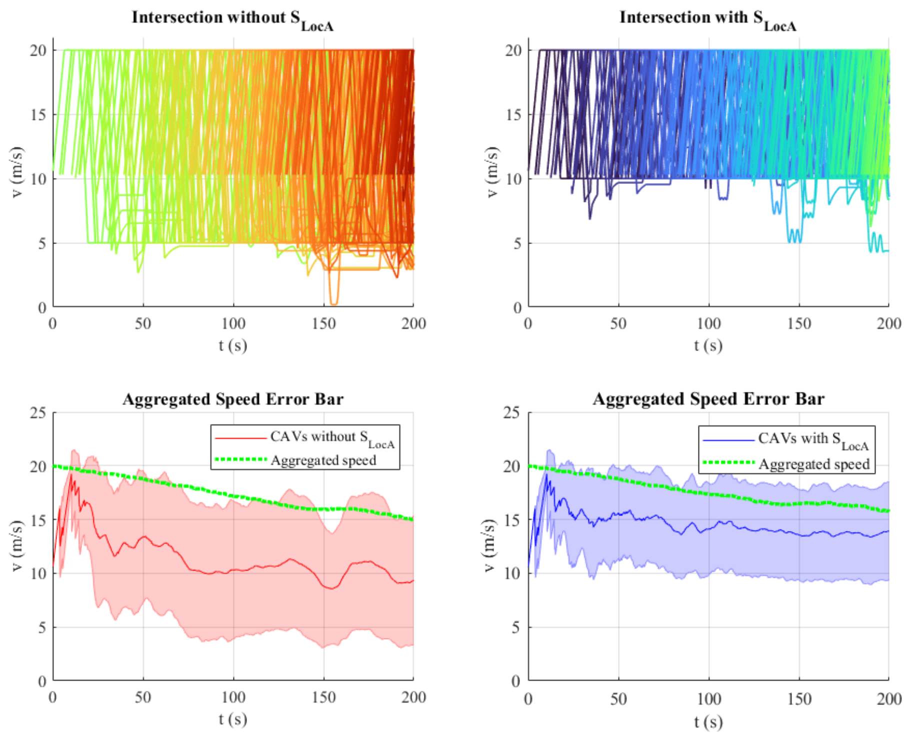


Figure 4.10: A Comparison of CAVs velocities between MHCP-MP framework with S_{LocA} and baseline method without S_{LocA}. An augmented navigation protocol was also implemented in the MHCP-MP framework.

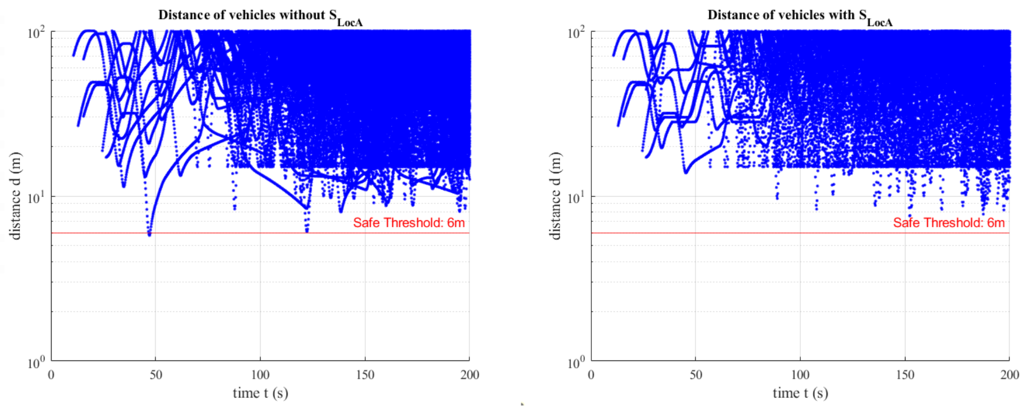


Figure 4.11: A comparison of inter-vehicle distance in traffic network.

depicted flow-density diagram. One can find that the vehicle density in the unsupervised MVS system was unevenly distributed at various intersections. The flow decreases with the system running (e.g., intersection 1). Correspondingly, the output flow of the intersection network was showed at the bottom-left of Fig. 4.12. The approximate maximum output flow is $300 Vehs/hr$. After that, it dropped to a lower value. Nevertheless, the proposed method maintains a promising traffic flow-density performance within the same input flow rate. The S_{LocA} can regulate the traffic flow by considering the “road weights” linking to the road density. Therefore, a proportional increase in the flow-density dia-

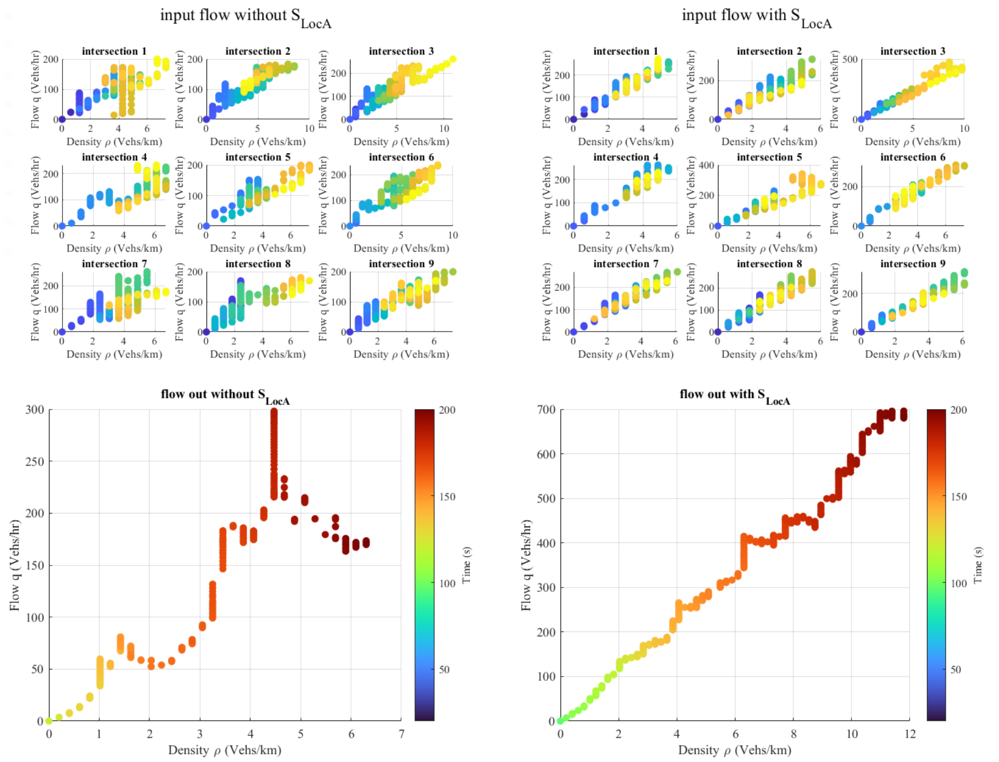


Figure 4.12: Traffic flow-density diagrams for intersections and output flow in whole exits.

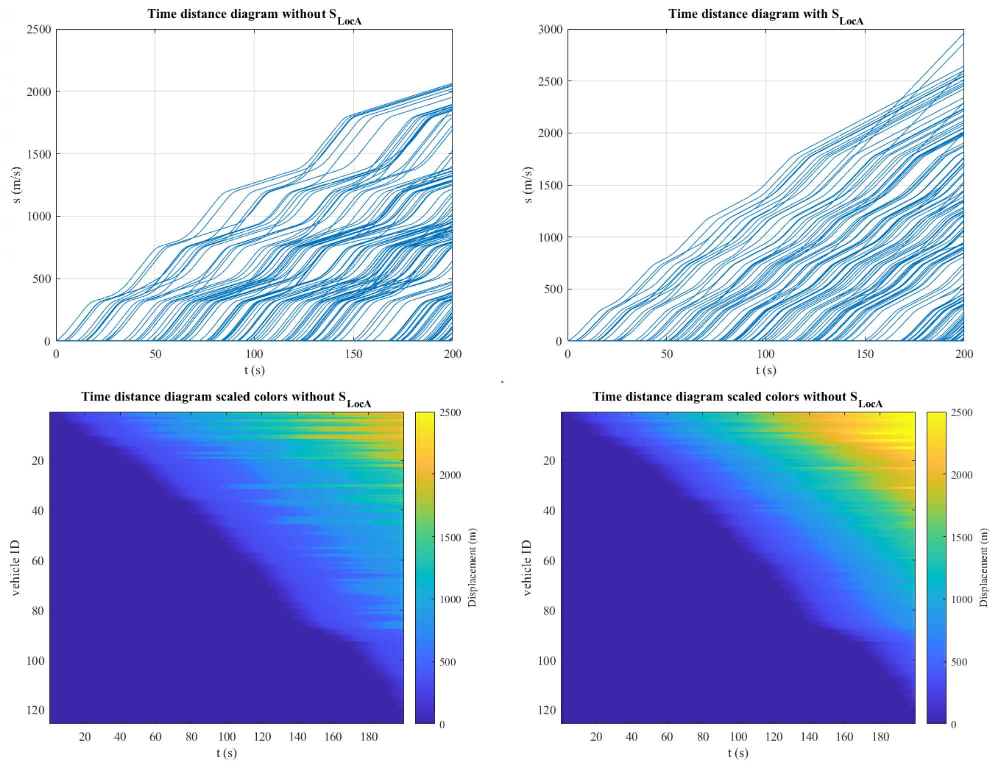


Figure 4.13: The traffic displacement diagram for the whole vehicles

gram has been observed during the whole simulation time. Additionally, the output flow with S_{LocA} remarkably increase to $700Vehs/hr$ at the end (see the bottom-right graph of Fig. 4.12). Similarly, the accessibility of the MVS system can be explained by Fig. 4.13. The displacement-time graphs were exhibited in up-left (unsupervised system) and up-right (supevised system) graph. A shock wave (congestion state) was induced between vehicles in the same lane when the ahead agents change their speeds. In contrast, the traffic congestion was alleviated in the supervised system which can adjust the traffic state properly. In addition, traffic accessibility can be improved by the proposed system with S_{LocA}. See bottom graph of Fig. 4.13, the color bar represents the displace for each vehicle. Roughly, vehicles in the supervised system shows a better accessibility of transportation.

Finally, the average flow of the compared MVS systems is recorded in Table 4.2:

Table 4.2: Average flow in local area

Intersection	Average flow $[Vehs/hr]$		
	Without S_{Loc_A}	With S_{Loc_A}	
	-	Self-Interested Protocol	MiMaFC-based Protocol
1	99.9748	146.9410	148.9427
2	103.4904	130.8983	134.6613
3	101.9862	161.7955	160.3477
4	97.2312	137.6753	138.6609
5	87.7476	126.0182	126.2508
6	96.4529	127.0486	127.8843
7	106.0823	141.2156	142.5730
8	91.8322	117.2555	118.9887
9	89.1932	117.4012	118.0336
flow out	50.8298	166.4516	169.0731

Noting that, the MVS system with basic protocol [4] was also included. Vehicle can participate in the optimization whenever it was labelled as a “conflict agent” in basic protocol. In general, the proposed approach with local supervisor S_{Loc_A} can guarantee relatively high traffic flow rates comparing to the total distributed MVS system without I2V technology in the different intersection. The vehicles with proposed augmented protocol even have better transportation performance comparing to vehicles implementing basic protocol. Seeing that, the average traffic flow rate (around $166Vehs/hr$) out of the network with S_{Loc_A} is greater than the flow-out rate ($51Vehs/hr$) with non-supervised road network. While the augmented protocol can keep a higher output flow of $169Vehs/hr$. It indicates that MVS system in the signal-free intersection with S_{Loc_A} and augmented protocol has the potential to improve traffic mobility. Briefly, the designed intelligent S_{Loc_A} can be beneficial as novel urban mobility management platforms to handle arterial traffic transportation.

4.6/ Conclusion

In this chapter, we explored the MHCP-MP architecture for MVS' CN in a road network based on the prior works in Chapter 3. First, an overview of the planned MHCP-MP traffic scenario is given. We then built a macroscopic flow model to determine proposed MVS navigation references (speeds, passing rights) based on traffic flow fluctuation. Thus, the high-hierarchical MiMaFC-based policy can ensure that the reference behavior in micro motion control is applied robustly in response to traffic flow changes. Based on the developed MHCP-MP architecture, this study offered a CN protocol to efficiently decide each agent's motion planning approach. In a highly networked environment, the procedure was done by a local supervisor. Furthermore, the spatio-temporal velocity adaptation technique proposed in this chapter also improves the microscopic MVS optimization model for AIM. The local conflict resolution strategy can be easily calculated by adopting the velocity adaptation approach. The ε-PC algorithm's optimization target is redesigned to determine the recommended velocity strategy for crossing the intersection for micro motion planning. Simulation results indicate an overall improvement in traffic flow control. At an unsignalized intersection, the local supervisor S_{Loc_A} can guide the MVS' motion planning, so enhancing CN efficiency.

General conclusion and future work

General conclusion

Several contributions dealing with multi-vehicle navigation in complicated environments/situations have been proposed throughout this PhD manuscript. The real objective of using the Collective Intelligence (CI) theory-based probability method is to increase the reliability and flexibility of the navigation system and, hence, on-road safety. As a risk-sensitive method, the suggested probability approach has been established in an attempt to avoid excessively conservative or too invasive procedures for cooperative intersection navigation. Under the risk preference hypothesis, the crossing ego-vehicles could make a quick decision while negotiating with other involved agents. Correspondingly, a logic risk indicator relationship is built between the measurement circumstances and the vehicle's current state. Furthermore, a well-suited trade-off between speed and risk from a global perspective is addressed in order to improve the vehicle navigation trajectory in a transit network. To deal with multi-vehicle navigation in a transportation network, in particular, the management-level agent that acts as a mediator between the global system and local cooperative vehicles are characterized. The Macroscopic Fundamental Diagram (MFD) allows us to monitor the present traffic status and assign policy in a distributed hierarchical control framework, providing instructions to regulate all vehicle trajectories. The intelligent intersection navigation systems are established with uncertain traffic flows under different directions, which combines the hierarchical traffic management architecture and the probability cooperative method for multi-vehicle systems. Finally, the developed vehicle cooperation system contributes to affecting the overall traffic state in a decentralized system while also enabling the mobility of the overall road network.

The first part of this thesis studied a variety of vehicle navigation strategies in typical multiple-vehicle driving environments. There has been a greater emphasis on intersection navigation systems, which comprise the management architecture and associated motion planning approaches. Moreover, we specifically evaluated the literature relating to transit network trajectory optimization.

Chapter 1 details real-world examples involving cooperative driving between multiple vehicles. The ultimate objective is to identify critical characteristics that contribute to the development of safe trajectory planning systems that account for inherent on-road uncertainty. More specifically, this chapter discussed the advantages and disadvantages of existing cooperative navigation techniques as well as current developments in autonomous intersection management systems. As a primary result of the state-of-the-art investigation, the usage of hierarchical design was deemed to be a very promising option for multiple vehicle cooperation. The centralized and distributed driving techniques, in particular, may be combined to create a complementary set of capabilities.

Subsequently, Chapter 2 was devoted to digging more into the cooperative navigation system used in a transportation network. More precisely, decision-making for IVs is primarily focused on resolving local conflicts, and the impact of this micro-level control on overall traffic efficiency has not been adequately explored. The scope of the examined literature includes traffic control and cooperative operation of multiple vehicles. The research community's attempts to improve both of these targets were emphasized. It has been found that although traffic lights remain the most relevant approach, cooperative navigation technology should carefully analyze all conceivable decision-making strategies in urban traffic networks, ranging from passive feedback control to feedforward/response control. Additionally, the probabilistic approach and risk management are emphasized in order to execute a cooperative driving strategy that includes the development of short-term driving plans via bilateral or multilateral negotiations.

The successive chapters in the second part are devoted to explaining cooperative navigation methods for a group of vehicles, from a single intersection to a transit network. For a negotiated system, a probabilistic approach is taken while considering the research gaps described in the first part.

Chapter 3 firstly introduced a novel flexible and risk-sensitive cooperative navigation technique at a single intersection. The new approach enhances an existing Probability Collective (PC) algorithm based on a framework for multiple vehicle negation by explicitly accounting for the diverse risk preferences represented by ε-constraint values. ε-PC is a flexible negotiation scheme that allow vehicle to find a feasible crossing strategy between a group of vehicles in the proximity of an intersection. This chapter's main contribution is to include an on-road risk indicator as a major component of the proposed ε-PC's analysis scheme in order to assure safe autonomous navigation through a real-time communication mechanism. Simulation results prove that the decentralized negotiating system and probabilistic approach based on heuristics enable the cooperative navigation method to maintain a competitive computing time while processing uncertainties in an undetermined (but feasible) way. Secondly, the inherent issue of balancing risk and speed for IVs is examined from the viewpoint of a global supervisor in order to operate in a transit network. A heuristic local search algorithm LS-SPR is designed and appropriate learning principles is used for a speedy run in routing strategies based on the formulation of the short route under risk constraint (SPR) problem. Different instances are used to validate the simulations with bounded state and decision numbers. The findings demonstrated the efficacy of the suggested LS-SPR in obtaining a speedy solution in routing methods while taking risk and speed into account.

Finally, in chapter 4, a Micro-Macro Flow Control (MiMaFC) strategy is proposed, with a local supervisor acting as a mediator between a global traffic supervisor and local intelligent vehicles. Its application is suitable for multi-vehicle cooperative navigation in a network without signalized intersections. Further, MiMaFC policy is combined with a decentralized navigation framework called Multi-layer Hybrid Management Policy and Motion Planning (MHCP-MP) in order to provide proactive traffic flow control. This goal is what highlighted in the previous part of the state-of-the-art. Also, a macroscopic flow model was made using the elements associated with traffic fundamental diagrams. Correspondingly, a car-following model with an uncertain following strategy was used to simulate fluctuating traffic flow. Additionally, suitable speed-position-based decision-making procedures were presented to define the attributes of the autonomous navigation system in order to offer an adequate intersection navigation protocol for continuous vehicle flow. More precisely, the protocol consists of three steps: vehicle sorting, strategy selection, and conflict resolution in order to ensure the suggested MHCP-MP architecture. In particular, this chapter presented the spatio-temporal velocity adaptation method in order to improve the feasibility of cooperative solutions. Intelligent vehicles may use either the MiMaFC-based or self-interested speed strategy, depending on their location and speed. Thus, the heuristic searching procedure will not fail in a planning/re-planning process. The preceding chapter's suggested PC algorithm is implemented into the decision-making architecture. Finally, simulation results demonstrated that models developed using MiMaFC inside the MHCP-MP framework are capable of dealing with fluctuating vehicle flow in a traffic network and improving mobility compared to an unsupervised system.

PERSPECTIVES AND FUTURE WORK

The various contributions made in this thesis may result in an introduction of a heterogeneous traffic flow navigation framework. The flexible and safe cooperative navigation approach enables the management of unsignalized intersections. Indeed, this will allow us the exploration and extension of various research topics in the field of MVS cooperation, microscopic control model, and traffic flow management. The following summarizes the most prominent works that we plan to perform in near future.

Extend the approach of Cooperative Navigation (CN) to meet diverse objectives: our work is primarily concerned with the issue of intersection cooperation in motion planning decision-making. However, several optimization objectives such as constrained time to destination for MVS, fuel economy for cooperative eco-driving, cooperative maneuvering for comfort driving, and collision avoidance/mitigation remain unresolved (see Figure 4.14). Because the majority of the methods examined for MVS dynamic driving tasks have been developed under strict conditions. The suggested targets will add complexity to the CN strategy design process. How to use the bottom-up method to produce a fully available modular system remains an unanswered question. It could be interesting to use our decentralized collaboration framework to accomplish the suggested tasks.

Improve the MVS microscopic control model for mixed traffic flow: a heterogeneous MVS navigation framework can integrate various traffic participants, such as human-driven cars, emerging vehicles, and/or commercial/public vehicles, among others. The addressed risk assessment/management and cooperative navigation protocol must be reviewed in various layers of the proposed hierarchical control architecture. Nevertheless, since the suggested ε-PC technique is probabilistic in nature, it may simply be used to put the traffic participants' movements into probability space. Thus, Intelligent Vehicles (IVs) might still execute the suggested intersection navigation approach without distinguishing between an automated or human-driven vehicle. Additionally, we may use Reinforcement Learning (RL) technologies to accelerate the formulation of the navigation strategy space for conventional vehicles. Similarly, the formalization of the 2D TTC should be expanded to include more complicated situations involving uncertainty, such as overtaking maneuvers by non cooperative traffic players.

Contribute to the enhancement of macroscopic modeling: due to the several layers of assured performance, this hierarchical navigation system with partially centralized decision-making would possess significant capabilities for avoiding traffic conges-

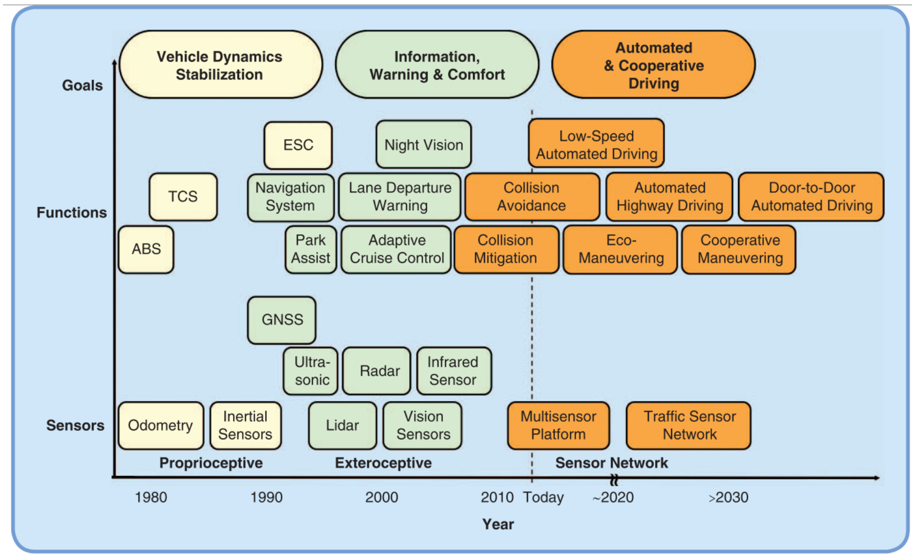


Figure 4.14: Past and potential evolution towards Cooperative Navigation (CN) [49].

tion. However, the cooperative architectures proposed in this thesis may be upgraded to a completely transportation navigation framework within which the global supervisor may operate more effectively. One may observe that the proposed MiMaFC strategy does not contain a global route strategy that incorporates the ideal trade-off between risk and speed (i.e., our proposed LS-SPR algorithm). This is because the proposed SPR issue is discrete decision-making model in nature, imposing constraints on the (piecewise) speed function (cf. Appendix A). Additionally, a cooperative navigation technique for multiple vehicles is presented in this PhD thesis based on an optimum control issue with a regular continuous speed function. Thus, integrating these two layers (macro and micro) in order to ensure overall performance remains a difficulty. Because the global supervisor represents the system's current condition and short-term development, navigation risk may be significantly reduced when following a pre-scheduled low-risk path. Thus, the local supervisor and/or on-board embedded system can execute their task more simply.

Simulation with real-world data and estimation techniques: the majority of the proposed methodologies have been proven only through extensive simulation work. As a result, the proposed PC method and MiMaFC strategy should be implemented on multiple real-world vehicles or a large-scale simulation based on real-world traffic data in the near future. This will create a number of technical challenges, including as the reliable implementation of software components and the functional safety of automobile operating systems. Furthermore, it is uncertain how to instance these hierarchical layers, which include various components that allow a collaborative function. Indeed, the test ground's multiple coordination of various signal-free intersections has been just getting started. Additional efforts are required to implement the navigation protocols while dealing with the many types of interference in vehicle communication. A more practical research may be done at the Institut Pascal laboratory, which has various Véhicule Individuel Public et Autonome (VIPALAB) and Plate-forme d'Auvergne pour Véhicules INtelligents (PAVIN) test ground. Additionally, reliable traffic status estimation remains an unresolved issue. As noted in state of the art (section 2.1.2), traffic assessments based simply on data collection would be challenging in the absence of actual measurement tools. Combining data collecting and estimation techniques for our traffic state estimation may be a potential method in a future research.

III

ANNEXES

A

STRUCTURE RESULTS FOR SHORTEST PATH UNDER RISK CONSTRAINT (SPR) PROBLEM

As it is said in section 3.3, SPR problem appears to be more of an optimal control problem than a combinatorial one, because the speed function $t \to u(t)$ can be thought of as a regular continuous function. However, as we will see shortly, we can apply constraints on this speed function, bringing the SPR model closer to a discrete choice model. These constraints will greatly simplify the formulation of SPR. The first is about the shape of the speed function $u(t)$ which can be chosen as piecewise linear with severe breakpoint constraints:

Proposition 1: Optimal solution (Γ, u) of SPR may be chosen in such a way that u is piecewise constant, with breakpoints related to the times t_i when vehicle VEH arrives at the end-nodes of arcs $t_i, i = 1, \dots, n$, and to the breakpoints of function $\Pi^{ei}, i = 1, \dots, n$.

Proof. Let us suppose that VEC is moving along some arc $e = e_i$, and that δ_1, δ_2 are 2 consecutive breakpoints in above sense of proposition 1. If function $t \to u(t)$ is not constant between δ_1 and δ_2 then we may replace $u(t)$ by the mean value u^* of function $t \to u(t)$ between δ_1 and δ_2. Time value $Time(\Gamma, u)$ remains unchanged, while risk value $Risk(\Gamma, u)$ decreases because of the convexity of function Φ. So we conclude. □

It comes that we may impose function $u(t)$ to be piecewise constant in section 3.3, with breakpoints which corresponds to the times when vehicle VEC shifts from an arc e to its successor in Γ and to the breakpoints of functions $t \to \Pi^e(t)$.

B

THE STOCHASTIC SPACE POLICY IN MACROSCOPIC FLOW MODEL

It assumes that MVS can be predefined with preferred car following strategy (e.g., invasive or conservative behaviors). Therefore, the desired distance d_{ref} can be defined by stochastic time headway (d_{safe} standstill safe distance, cf. section 4.3.1)

$$d_{ref} = d_{safe} + th_i \times v_i(t) \tag{B.1}$$

We further assume that th_i sampled based on a shifted log-normal distribution. Vehicle is supposed to generate an independent and identically distributed (i.i.d.) $t\hat{h}_i$ as self-preferred time gap (i.e., $th_i = t\hat{h}_i$)

$$th_i \sim Log - N(\mu_v, \sigma_v) \tag{B.2}$$

Where μ_v and σ_v are the predefined velocity dependent parameters in log-normal distribution as illustrated in Table B.1. Notably, we use the NGSIM [461] data set to match the log-normal distribution over four distinct speed ranges as seen in Figure B.1. Generally, as the speed of the vehicle decreases, the vehicle's time headway increases. This implies that while a vehicle's speed is low, it is more sensitive to the safe gap between it and the vehicle ahead of it. Thus, in section 4.5, we select the time headway based on the speed shown in Table B.1. A more detailed $t\hat{h}_i$ distribution based on the NGSIM data set can be found in Figures B.2.

Table B.1: A test of the log-normal distribution's parameters

No.	$t\hat{h}_i$ based on a log-normal distribution		
	Speed range	Parameters in a log-normal distribution	
	-	μ_v	σ_v
1	$[0m/s, 5m/s]$	1.3115	0.520339
2	$[5m/s, 10m/s]$	0.8800	0.419708
3	$[10m/s, 15m/s]$	0.7765	0.435128
4	$[15m/s, +\infty m/s]$	0.7337	0.521951
Confidence interval	-	$[0.7266, 1.3169]$	-

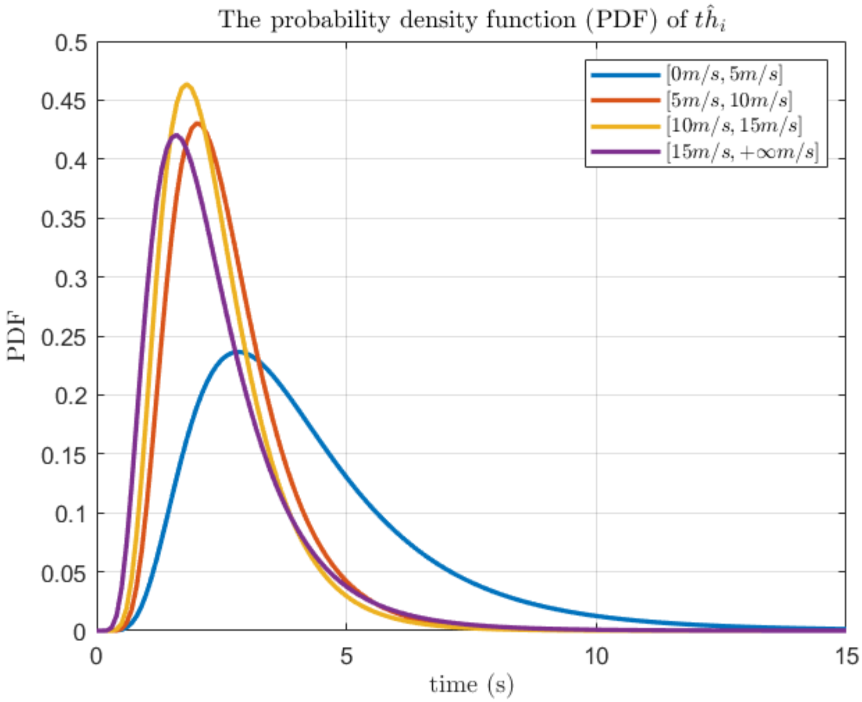


Figure B.1: A comparison of different time headway $t\hat{h}_i$ distribution.

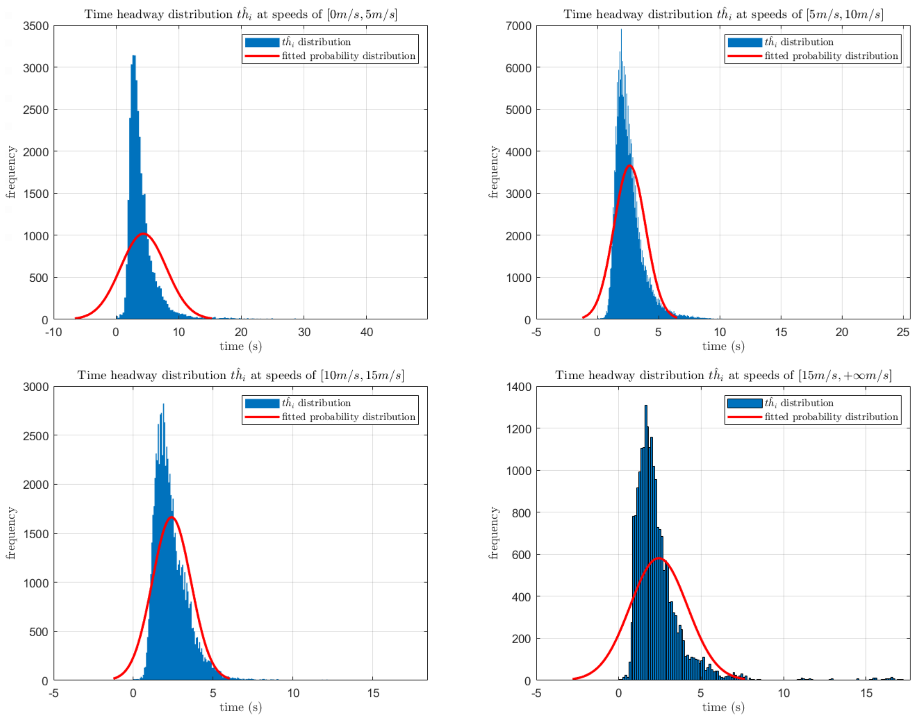


Figure B.2: The time headway distribution $t\hat{h}_i$ at speeds of $[0m/s, 5m/s]$, $[5m/s, 10m/s]$, $[10m/s, 15m/s]$ and $[15m/s, +\infty m/s]$.

LIST OF MY PUBLICATIONS

[1] ZHU, Z., ADOUANE, L., AND QUILLIOT, A. **A decentralized multi-criteria optimization algorithm for multi-unmanned ground vehicles (mugvs) navigation at signal-free intersection**. *IFAC Symposium on Control in Transportation Systems (CTS) 54*, 2 (Lile, France, June 8-10 2021), 327–334.

[2] ZHU, Z., ADOUANE, L., AND QUILLIOT, A. **Flexible multi-unmanned ground vehicles (mugvs) in intersection coordination based on ε-constraint probability collectives algorithm**. *International Journal of Intelligent Robotics and Applications 5*, 2 (2021), 156–175.

[3] ZHU, Z., ADOUANE, L., AND QUILLIOT, A. **Hierarchical control for trajectory-based intelligent navigation in urban adjacent intersections**. *2021 IEEE International Intelligent Transportation Systems Conference (ITSC)* (Indianapolis, USA, September 19-22 2021), 948–954.

[4] ZHU, Z., ADOUANE, L., AND QUILLIOT, A. **Intelligent traffic based on hybrid control policy of connected autonomous vehicles in multiple unsignalized intersections**. In *2021 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computing, Scalable Computing & Communications, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/IOP/SCI)* (Atlanta, USA, October 18-21 2021), pp. 416–424.

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Abstract:

Cooperative navigation (CN) is a frequently used technique for ensuring the effective navigation of Intelligent Vehicles (IVs). In this background, efforts to establish a Connected Autonomous Vehicles (CAVs)-based traffic control system via vehicular communications technology have accelerated in recent decades. Safe and flexible multi-vehicle coordination (MVC) technology, in particular, has attracted considerable interest for its ability to deal with complicated environments/situations. Additionally, a feasible hierarchical architecture is critical for cooperative driving with numerous control goals in autonomous vehicles. Thus, the objective of this PhD thesis is to develop reliable MVC technology (e.g., trajectory planning and decision-making for motion planning) and CAVs-based frameworks for use in complex environments/situations. To achieve this goal, this thesis first presented a safe and flexible cooperative navigation technique with risk assessment for cramped local locations (defined as single intersection/roundabout). The ε-constraint Probability Collectives (PC) algorithm, which is based on the distributed Collective Intelligence (CI) theory, is developed to offer proper solutions for cooperative driving. More precisely, IVs can compute their optimal/sub-optimal and risk-sensitive (i.e., invasive or conservative) cooperative navigation strategies base on the decentralized ε-PC framework, enabling collision-free trajectories in the decision-making level. Next, it is suggested a global supervisor responsible for scheduling and improving vehicle navigation routes while also proposing well-suited trade-offs between speed and risk to achieve the targeted tasks. To better deal with the inhere complexity of CN system in a transportation network (e.g., intersection/roundabout and the expended intersection network), the second part of the thesis addresses the potentialities of adopting Multi-layer Hybrid Control Policy and Motion Planning (MHCP-MP) framework. Given the fluctuating road traffic, it was recommended that local supervisors be in control of the urban network's intersections (tricky regions). Specifically, the local supervisor works as a mediator between the global traffic management level and the CAVs decision level, sending instructions to regulate vehicles' trajectories and improve the mobility and safety of the overall transportation system. To accomplish the aim, a Macroscopic Fundamental Diagram (MFD)-based approach in the proposed MHCP-MP framework is designed with concise urban traffic data (e.g., vehicle position, speed, etc.). Further, the Micro-Macro Flow Control (MiMaFC) strategy is proposed to demonstrate the advantages of establishing a link between the suggested local collective optimization framework and macro traffic model for improving the fluidity of the overall transportation system. Following that, the suggested intersection navigation protocols in a deep relationship with our established intelligent intersection management system are designed to permit an uncertain traffic flow. Finally, the proposed CN management architecture in this thesis has been proven in a dedicated transportation network through intensive simulation.

Keywords: Cooperative navigation, Multi-vehicle coordination, Hierarchical architecture, Risk assessment, Probability collectives, Traffic management.

Résumé :

La Navigation Coopérative (NC) est une technique fréquemment utilisée pour assurer la navigation efficace des Véhicules Intelligents (VI). Dans ce contexte, les efforts visant à établir un système de contrôle du trafic basé sur les véhicules autonomes connectés (CAVs) par le biais des technologies de communication entre véhicules se sont accélérés au cours des dernières décennies. La technologie de coordination multi-véhicules (MVC) sûre et flexible a suscité, en particulier, un intérêt considérable grâce à sa capacité à gérer des environnements/situations complexes. En outre, une architecture hiérarchique faisable est essentielle pour la conduite coopérative avec de nombreux objectifs de contrôle des véhicules autonomes. Ainsi, l'objectif de cette thèse est de développer une technologie MVC fiable (e.g., la prise de décision pour la planification) et des cadres basés sur les CAVs pour une utilisation dans des environnements/situations complexes. Pour atteindre cet objectif, cette thèse présente, tout d'abord, une technique de NC sûre et flexible avec une évaluation des risques pour les emplacements locaux encombrés (définis comme une seule intersection et/ou un rond-point). L'algorithme ε-Probabilté Collective (PC) à contrainte, qui est basé sur la théorie de l'Intelligence Collective (IC) distribuée, est développé pour offrir des solutions appropriées pour la conduite coopérative. Plus précisément, les VI peuvent calculer leurs stratégies de navigation coopérative optimales/sous-optimales et sensibles au risque (invasives ou conservatrices) en se basant sur le cadre décentralisé ε-PC, ce qui garantit des trajectoires sans collision. Ensuite, nous suggérons d'utiliser un superviseur global responsable de l'ordonnancement et de l'amélioration des trajectoires de navigation des véhicules, tout en proposant des compromis adaptés entre la vitesse et le risque de la réalisation des tâches visées. Afin de mieux gérer la complexité inhérente aux systèmes NC dans un réseau de transport (e.g., les intersections/ronds-points et le réseau étendu d'intersections), la deuxième partie de la thèse aborde le potentiel de l'adoption d'une architecture de contrôle hybride multicouches et de planification du mouvement (CHM-PM). Compte tenu de la fluctuation du trafic routier, il a été recommandé que des superviseurs locaux contrôlent les intersections du réseau urbain (régions dangereuses). Plus précisément, le superviseur local joue le rôle intermédiaire entre le niveau de gestion global du trafic et le niveau de décision des CAVs, en envoyant des instructions pour réguler les trajectoires des véhicules et améliorer la mobilité et la sécurité du système de transport globale. Pour atteindre cet objectif, une approche basée sur le Diagramme Fondamental Macroscopique (DFM) dans l'architecture CHM-PM proposée est conçue avec des données de trafic urbain concises (par exemple, la position du véhicule, la vitesse, etc.). En outre, la stratégie de contrôle des flux micro-macro (MiMaFC) est proposée pour démontrer les avantages de l'établissement d'un lien entre l'architecture d'optimisation collective locale proposée et le macro modèle de trafic pour améliorer la fluidité du système de transport global. Ensuite, les protocoles suggérés de navigation aux intersections, en forte relation avec notre système de gestion intelligente des intersections, sont conçus pour permettre un flux de trafic incertain. Enfin, l'architecture de gestion des NC proposée dans cette thèse a été évaluée dans un réseau de transport par un travail de simulation intensive.

Mots-clés : Navigation coopérative, Coordination multi-véhicules, Architecture hiérarchique, Évaluation des risques, Probabilté Collective, Gestion du trafic.