AN ABSTRACT OF THE DISSERTATION OF

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Title: Decentralized Multiagent Coordination for Connected and Autonomous Vehicle Routing in Congested Networks

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Haizhong Wang

In 2017, the cost of congestion in the United States was around 305 billion dollars, and city-dwellers, on average, lost 1400 dollars while sitting 42 hours in traffic jams[1]. Aiming for better mobility and more efficient utilization of the transportation network, emerging connected and autonomous vehicle (CAV) technologies and their communication capabilities can produce well-coordinated and more efficient routing behavior to dissipate the traffic rather uniformly throughout the network, resulting in slower travel times. Vehicle routing is among the most critical and challenging, yet unsolved, tasks in CAV research. Current routing strategies either rely on a centralized control system which can fail in scaling, or employ decentralized schemes that yield sub-optimal coordination and poor system performance. In addition, it is of great importance for the deployment of CAV technologies to

[1]INRIX Research study

understand the transportation systems behavior in a mixed environment with various levels of communication complexity, where CAVs and Non-CAVs coexist and interoperate. The routing problem in a multiagent system resembles a competitive congestion game. The decisions of one agent (in this case, a CAV) directly impacts the performance of the others. When the number of agents traversing the same transportation facility at the same time exceeds a certain threshold, bottlenecks may occur, and thus, higher travel times. Therefore, coordination between CAVs is key to avoiding such circumstances. This dissertation answers *how* and *to what extent* different routing optimization algorithms, under various levels of autonomy and communication capabilities, can increase the mobility of the transportation system. This work designs this system in a decentralized manner that scales linearly in achieving a social and system-level optimum. To realistically analyze this system, we investigated the coordination behavior of CAVs under (1) *No Communication*, (2) *Minimal Communication*, and (3) *Extensive Communication*. In the absence of connectivity between the CAVs, a learning-based approach has been implemented where each CAV optimizes its own route using a reinforcement learning technique and based on its prior experiences. This competitive game quickly overwhelms the system as the market penetration of CAVs surpasses the critical threshold range (50% to 75%), where the mobility improvements are the most significant, and beyond which the system performance degrades. Under minimal communication level, we assumed the CAVs share information regarding their location and speed with the rest of the CAVs in their communication cluster through a multi-hop network. Then, a coordination scheme was implemented where each

CAV minimizes its travel time based on the limited information it receives. Results showed that this application can reduce system travel time by up to 20%. Additionally, the emergence of mobility benefits are shown to correlate with the CAV network characteristics through the lens of percolation theory. The results revealed that, for the mobility benefits to surface, at least 70% of the CAVs are required to form a communication cluster. Under an extensive communication capability, where the CAVs not only share their location and speed but also their preferred path to their destination, a reduction of up to 40% in system travel time was achieved for high levels of CAV market penetration and communication radius. Moreover, the improvement in mobility was proved to be highly associated with the uniform dissipation of traffic onto the network. These findings provide solid support to create evidence-driven frameworks to guide future CAV development and deployment in a decentralized and coordinated manner.

# Decentralized Multiagent Coordination for Connected and Autonomous Vehicle Routing in Congested Networks

by

Alireza Mostafizi

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I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Alireza Mostafizi, Author

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Throughout this dissertation, you will find several instances of the word "we" instead of "I." Like any other scholar, I am *"standing on the shoulders of giants"*[1]

[1] Isaac Newton

and in those instances, the giants being my colleagues, co-authors, and advisors. I would like to again thank my advisor, Dr. Haizhong Wang, for his invaluable contribution in this dissertation. I would like to also acknowledge the contribution of Dr. Shangjia Dong, my former colleague and current competitor, in modeling percolation behavior and characterization of the connected and autonomous vehicular network in Chapter 5. Without Dr. Dong's fruitful collaboration and 3 AM brainstorming sessions in the office, this dissertation wouldn't have been possible. I would also like to thank Matthew L. Frantz for his contribution into the concept of the decentralized collaborative time-dependent shortest path algorithm in Chapter 6. And finally, I would also like to thank Philip R. Carleton and Mohammad Rayeedul Siam for their input in Chapters 3 and 4 respectively.

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To my Mom, Dad, and Brother

# Chapter 1: Introduction

## 1.1 Background

The problem of congestion has been in the spotlight of most transportation mobility research in the past decade. Prior studies have shown that this problem has worsened drastically over the past 40 years (Schrank et al., 2009, 2012; David Schrank, 2015), despite efforts in expanding the capacity of the transportation facilities (Chen et al., 2001). The question, "Is it possible to reduce the total travel time of transportation network with current road infrastructure?" remains unanswered. Systematics (2005) showed that about 50% of the traffic congestion is associated with the bottlenecks and work zone environments, which are not inherently different than bottlenecks from the mobility perspective. Bottlenecks occur where the demand is higher than the capacity that a transportation facility can sustain. To alleviate such circumstances and in the realm of intelligent transportation systems (ITS), rerouting vehicles more intelligently has been the center of congestion avoidance applications (Wang, 2016; Pan et al., 2012). Now, with the advent of Connected and Autonomous Vehicle (CAV) technologies, such applications have emerged as part of CAV initiatives by US Department of Transportation (USDOT), categorized under the umbrella of *Dynamic Mobility Applications (DMA)* (Chang et al., 2015; USDOT, 2019a; McGurrin et al., 2012). As an example, *EnableATIS* is one of the core application of DMA, that focuses on improving the network-wide performance of a transportation system. It aims to provide valuable route choice insights that facilitate decision making for users, either human-driven connected vehicles or autonomous vehicles (USDOT, 2019b; Burgess et al., 2012). Regardless of the specifics of the application, the cornerstone of increasing network mobility and reducing the network-wide travel time through DMAs is a sufficient multiagent routing algorithm that dissipates traffic uniformly onto the network (Rossi et al., 2018; Pan et al., 2016). Similar to any other case of Congestion Games (Helbing et al., 2005; Milchtaich, 1996; Christodoulou and Koutsoupias, 2005), where the payoff of one player is negatively associated with the number of other players who take the same action, the collective performance of vehicles travelling in the network, and thus, the performance of the selected routing algorithm, is widely dependent on coordination between vehicles (Wolpert et al., 1999; Tumer and Wolpert, 2004). In other words, to avoid vehicles from traversing the same transportation facility at the same time, which increases network travel time, a successful routing (or rerouting) algorithm and procedure necessitate higher levels of collaboration between vehicles (Rossi et al., 2018; Wedel et al., 2009). Prior studies have also shown that non-collaborative (or as some would label *"selfish"*) routing behavior can result in many vehicles choosing the same route at the same time, which was initially perceived to be the shortest path to their destination (Mostafizi et al., 2017; Lim, 2012). Only if the vehicles are able to communicate the preferred route they are taking and are able to use this information efficiently, can they effectively bypass congested (or predictably congested) routes. Now, the needed coordination between the vehicles relies on,

- A robust and resilient communication network
- Appropriate information at hand for each vehicle to optimize their route
- A collaborative algorithm that can sufficiently predict traffic patterns and compute the optimal route for each vehicle to their destination
- Efficient computing infrastructure

All of these components can be achieved by the introduction of CAVs in the transportation system. Figure 1.1 shows the possible communication links, either through Dedicated Short Range Communication (DSRC), Wifi, or LTE network, that can facilitate the creation of a vehicular network, and consequently, the available data cloud that can be used to inform navigational and routing decisions (Amadeo et al., 2016; Abboud et al., 2016).

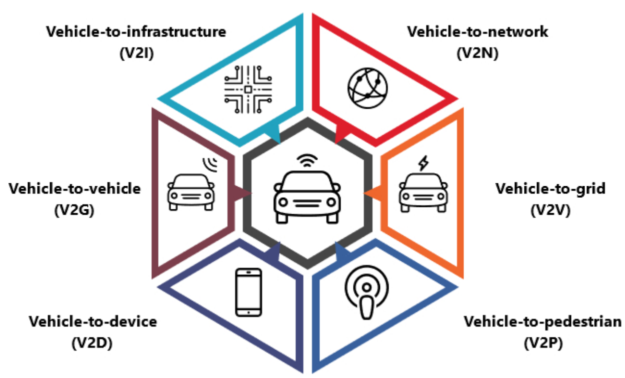


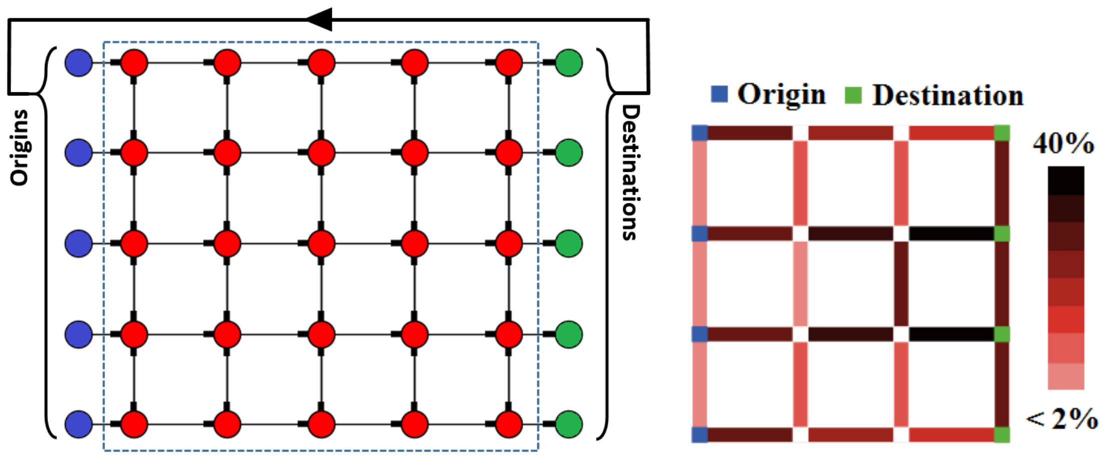

Figure 1.1: CAV Communication Capabilities (V2X) (Martin and Ivanov, 2018)

Besides, the Onboard Unit (OBU) of these vehicles can be a source of computational power (Evans et al., 2014) that processes the shared information in a decentralized manner and suggests the optimal route to the vehicle or driver (Mostafizi et al., 2017).

This dissertation focuses on addressing *how* we can leverage the emergent CAV technologies, and their communication capabilities, through Vehicle-to-Vehicle (V2V) connections, to achieve a fully utilized transportation network through a more intelligent, coordinated, and decentralized routing behavior. This work provides insights on development, implementation, and deployment of CAV technologies to increase mobility of transportation networks as they currently stand by dissipating the traffic more uniformly onto the network. We also analyze the potential mobility benefits of these technologies under various levels of infrastructure complexity, communication capability, and market penetration of equipped vehicles. Moreover, special attention has been given in designing these systems with a decentralized and distributed architecture that scales well.

## 1.2 Problem Definition

Imagine an urban transportation network at rush hour, when the demand is highly directional from residential areas to the Central Business District (CBD) or vice versa. This commonality in demand between the majority of users results in high levels of traffic on certain transportation facilities at the same time, hence congestion and higher travel times (Arnott et al., 1993; Evans et al., 2002). There have been many efforts to solve rush hour congestion through different types of incentives and rewards (Nie and Yin, 2013; Ben-Elia and Ettema, 2011; Hu et al., 2015), however, one important factor that is missing in most of the prior research is that the concept and importance of arrival time are not sufficiently considered. This motivates us to approach this issue from a different perspective that not only reduces the travel time of the network but also takes the arrival time of trips into consideration. As mentioned earlier, collaborative routing, where vehicles communicate certain information regarding their location, speed, and path with each other, can alleviate rush hour traffic patterns (Mostafizi et al., 2017; Lim and Rus, 2012; Moran and Pollack, 2016).




(a) Sample Grid Network (b) Background Traffic

Figure 1.2: Grid Transportation Network and Traffic Pattern under uniform OD pair distribution.

In this work, the transportation network and the rush hour travel demand has been simplified to a grid network (Figure 1.2a) where the origins and destinations are on opposite nodes of the grid. If the OD pairs of the vehicles are distributed uniformly, under a pre-defined routing algorithm, Figure 1.2b shows the non-uniform background traffic pattern where the edges of the grid are relatively less congested than the middle links. That is to say, the network is not uniformly and fully utilized (Mostafizi et al., 2017; Zhang et al., 2017).

As for any network, there will be numerous different routes that can take a vehicle from origin $A$ to destination $B$. However, not all of these routes have the same travel time. Noting the computational capabilities of CAVs and their ability to send and receive information from the other CAVs as well as the infrastructure (Lu et al., 2014), we assume that in the foreseeable future CAVs comprise a considerable portion of our transportation systems (Bansal and Kockelman, 2017). Therefore, the ultimate research question for this work is *how* can the CAVs choose a route and reroute more intelligently to avoid congestion, reduce their own travel time, and most importantly, to minimize network travel time in a coordinated and decentralized fashion? More specifically, *what* information needs to be shared over the CAV network with the other vehicles in the cluster? *How* this information should be used and *what* decentralized algorithms need to be in place to achieve a social optimal for the network, as opposed to local minimal travel time for each individual vehicle? We formulate these questions in the form of a multiagent coordination problem under different levels of communication similar to Bowman et al. (2016). More specifically, we consider three communication levels within CAV clusters, and accordingly, an appropriate decentralized algorithm has been implemented to study the effects of coordination on system travel time.

1. **No Communication**: At this level, it is assumed that the CAVs are not capable of any sort of communication. Therefore, they aim to optimize their path to their destination through their individual past experience. A *Re-*

*inforcement Learning* environment and algorithm is set up for this scenario (Watkins and Dayan, 1992) where the CAVs learn from their previous actions at every trip they make and aim to improve their performance after each iteration.

2. **Minimal Communication**: Under this scenario, the CAVs communicate their current location and travelling speed with the other CAVs within their cluster through multi-hop wireless communication scheme (Kosch et al., 2002). This information is utilized by each CAV to build an online abstraction of the network and the travel time of each link. Later, an *Online $A^*$ Algorithm* (Hart et al., 1968) is implemented to update the path for each CAV as they traverse in the network, and corresponding to their dynamic clustering attributes.

3. **Extensive Communication**: With this level of communication, CAVs not only communicate their current location and speed but also share their proposed path with the other CAVs in their cluster. With this information, CAVs can predict the state of the network at any point the future and plan in a way to avoid congestion. This dissertation proposes a Decentralized Collaborative Time-dependent Shortest Path (*Dec-CTDSP*) algorithm which is an extension of regular TDSP proposed by Dreyfus (1969), extending the original algorithm of Dijkstra (1959). In this algorithm, the time dependency of the link in the network comes from the location, speed, and the proposed path of other CAVs that have communicated their information with the CAV

at hand, and hence, the term *"collaborative."*

It is assumed that the information has been shared through a multi-hop wireless communication system within each CAV cluster (Kosch et al., 2002). In addition, to realistically analyze the impacts and benefits of such technologies, we also took into consideration the following key factors:

- Mixed environment at which both CAVs and Non-CAVs interoperate with a varying market penetration of CAVs from 0 to 100%,
- Varying communication radius, and
- Communication degradation in urban environments.

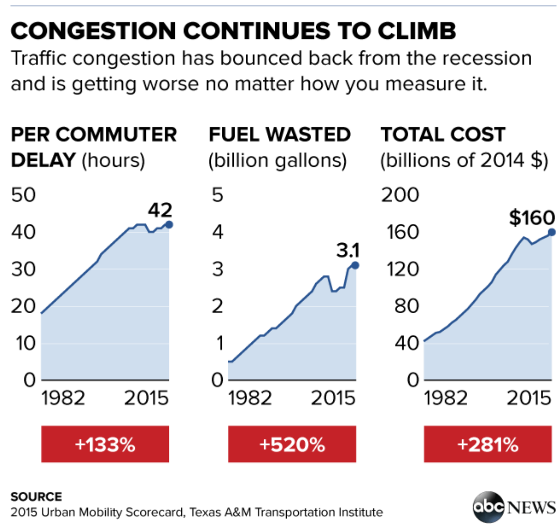
The formulation of each problem is further elaborated under each chapter and for each scenario in this dissertation.

## 1.3 Significance

Congestion is a world-wide problem that exacerbates year by year due to the ever-increasing demand (Cookson and Pishue, 2017; David Schrank, 2015). Figure 1.3 shows the extent and the cost of delays created by the congestion, as well as the inclining trend of the problem.

Studies have shown that the cost of congestion, in the US alone, was around 305 billion dollars collectively (Cookson and Pishue, 2017), making an average commuter spend 42 hours in traffic per year, equivalent to $1,400 (David Schrank,


(a) Congestion Ranking[1]




(b) Congestion is increasing[2]

Figure 1.3: Congestion Scoreboard (Cookson and Pishue, 2017; David Schrank, 2015)

2015). This is also when 72% of the cost of congestion is associated with the opportunity cost of the travellers, meaning that the only solution to reduce this cost is to facilitate the travel (Economics, 2009). As 50% of this congestion is caused by bottleneck and work zones (Systematics, 2005), our solution can address half the cost of congestion, that is associated with where demand is higher than capacity, potentially reducing the cost of congestion by up to 20% with well-coordinated routing behavior.

In addition, in the context of CAVs, not only mobility-related applications, such as *EnableATIS* (USDOT, 2019b) have been listed as the most beneficial application that has to be prioritized by DOTs for deployment and readiness (Bertini et al.,

[1]https://www.economist.com/graphic-detail/2018/02/28/the-hidden-cost-of-congestion
[2]https://abcnews.go.com/US/time-americans-waste-traffic/story?id=33313765

2017), but also they have been in the top 5 features that 69% of the users look for in future CAVs (Cookson and Pishue, 2017). Figure 1.4 shows that different applications in Traffic Network and Traveler Information fields are generally found to be the most beneficial from experts' point of view (Bertini and Wang, 2016).

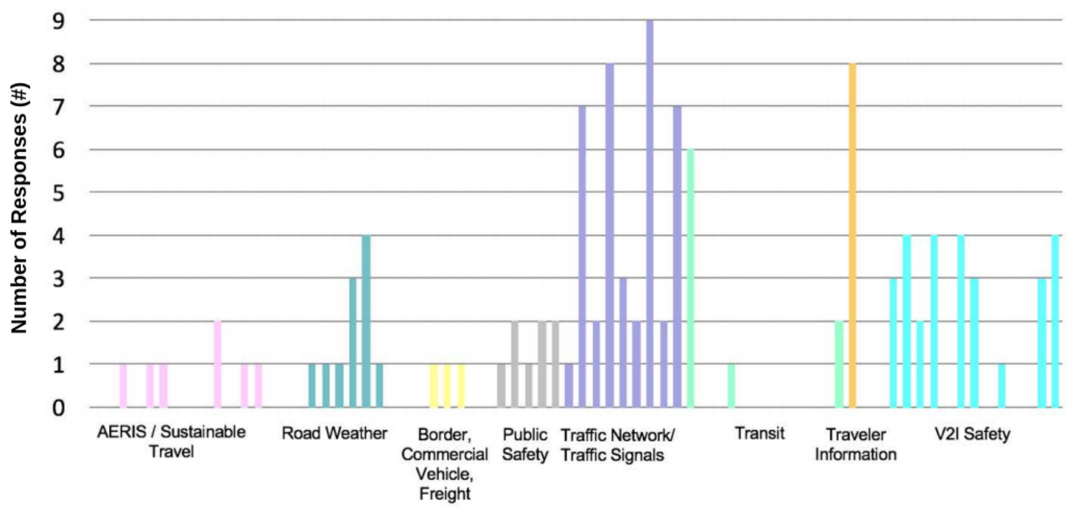



Figure 1.4: Most beneficial CAV applications, according to a survey done by Bertini and Wang (2016)

From the perspective of problem complexity, transportation networks are highly dynamic and stochastic in both space and time. Several studies have attempted to quantify these dynamics (Cascetta, 1989; Cantarella and Cascetta, 1995; Ran and Boyce, 2012). Predicting traffic congestion is an inherently complex problem, as it directly correlates to the joint decisions of all the vehicles in the network (Chiu et al., 2011). Hence, the multiagent coordination to minimize system travel time soon becomes a daunting task as the number of agents grows (Scerri et al., 2006). This makes this problem, albeit simple in definition, complex to solve in a decentralized manner, to avoid scaling issues that arise in centralized systems (Yang et al., 2008). This is where the use of communications for coordination comes into play (Roth et al., 2005) which necessitates considering different levels of communication capability as well as communication degradation, both of which are given special attention in this research. Besides, to analyze scaling, it is crucial to study such systems under different levels of CAV market penetration, that is an underlying factor in all components of this dissertation. The solution to this problem can be directly applied to CAV routing behavior, yielding network-wide optimal performance, and ultimately, can help exploit the current transportation infrastructure to its fullest.

## 1.4 Contribution and Objectives

This dissertation contributes to the existing CAV routing knowledge by developing a decentralized and coordinated routing optimization framework, algorithm, and procedure that yield a socially optimal state, beyond which the performance of the transportation network cannot be improved through routing behavior. To achieve this, the *objectives* of this dissertation are laid out and categorized as follows,

1. **Communication**: This dissertation extensively analyzes the impact of different levels of communication capabilities for the CAVs on their network-wide mobility benefits and multiagent coordination. As a result, this research sheds light on the necessity and the extent to which CAVs are required to communicate for the mobility benefits to emerge. In addition, the communi-

cation radius that OBUs can accommodate has been taken into consideration.

2. **CAV Network**: This research further connects the CAV network characteristics to expected mobility benefits. An integrated approach is formulated by combining network science, percolation theory, and communication in a multiagent system to characterize a CAV network and achieve this objective.

3. **CAV Market Penetration**: This research is motivated by the prevalent uncertainties with the benefits of deploying CAVs in a transportation network with competing goals of cost (e.g., market penetration and the required communication radius) and benefits (e.g., mobility) (Chang et al., 2015). Therefore, this work focuses on system performance in terms of the average travel time in a mixed environment where the market penetration of CAVs varies from 0% to 100%.

4. **Design, Algorithm, and Procedure**: This work provides the details and specifics with which CAV development and deployment are analyzed with the lens of multiagent coordination. That is to say, how CAVs need to communicate, what needs to be communicated, and how the information can be used to minimize system travel time are discussed. These details are provided in the form of procedures and algorithms that should be considered in the design and deployment of these technologies both from the private and public sector.

5. **Open-source contribution**: A secondary contribution of this work is to introduce an open-source and agent-based modeling platform to analyze dif-

ferent coordinated routing algorithms for connected and autonomous vehicles in a grid network.

The results of this work inform CAV network design to achieve significant mobility benefits under different CAV adoption rates. Also, this dissertation bridges the gap between network-wide CAV impact analysis and multiagent coordination and robotics concepts that need to be further analyzed for successful large-scale technology deployment.

## 1.5 Dissertation Organization

The rest of this manuscript is organized as follows. Chapter 2 reviews relevant literature discussing CAV networks and the concept of intelligent routing, specifically in the context of CAVs. Chapter 3 introduces the CAVs' car-following behavior implemented in this work, which governs the vehicle interactions in the simulations conducted throughout the dissertation. This chapter also presents the macroscopic behavior of the micro-level cross interactions of CAVs and Non-CAVs on a highway segment. Under the *"No Communication"* condition, Chapter 4 presents a reinforcement learning method that has been used to optimize the routing behavior of multiple CAVs in a mixed and competitive environment, and discusses the challenges arising from multiagent learning when there is no communication between the CAVs. Increasing the communication level to *"Minimal Communication,"* Chapter 5 introduces a routing optimization method using the information shared (i.e., speed and location) within the CAV clusters. In addition, this chapter characterizes the dynamics of the CAV network through percolation theory. Enhancing the communication capabilities to *"Extended Communication,"*, Chapter 6 introduces a novel negotiation-based routing algorithm, Decentralized Collaborative Time-dependent Shortest Path (*Dec-CTDSP*), and demonstrates its performance on system travel time, speed, and network utilization. Given this routing scheme and communication level, speed, location, and the proposed path of each CAV is shared within its own cluster. This information is further utilized in routing optimization for each CAV. Finally, Chapter 7 concludes the dissertation with major findings and discusses the expected system-level performances considering different communication levels, different market penetrations of CAVs, and different algorithms. In addition, possible future directions are listed in this chapter.

# Chapter 2: Literature Review

To identify the knowledge gaps and to establish the relevance of the existing work to this research, a comprehensive literature review is conducted. There is a spectrum of studies focusing on the benefit assessment and implementation of Connected and/or Autonomous vehicle technologies (Gay and Kniss, 2015; Olia et al., 2016; Chang et al., 2015) on (1) work zone safety (Genders and Razavi, 2015); (2) intersection operation efficiency (Guler et al., 2014); (3) mobility and mode choice (Minelli et al., 2015); (4) highway capacity (Ni et al., 2012); (5) variable speed limit control (Khondaker and Kattan, 2015); (6) roadmap for CV deployment scenarios and infrastructure readiness (Bertini et al., 2016a,b); (7) optimal speed advisory (Wan et al., 2016); (8) basic safety messages (BSM) (Liu et al., 2016); (9) platoon based cooperative driving (Jia and Ngoduy, 2016) and designing platoon trajectory (Zhou et al., 2016; Ma et al., 2016); and (10) dynamic automated lane change maneuver (Luo et al., 2016). Figure 2.1 presents a summary of relevant CV studies. This summary is not intended to be complete in any sense, but a review of the most recent and relevant efforts.

Connected Vehicles (CV) are the leading edge of disruptive forces that will upend the traditional traffic composition, usher in new operation models, change the nature of traffic flow fundamentals and management (Viereckl et al., 2015; Mahmassani, 2016), and further reshape the future of safety and mobility manage-

| Approach | Studies | Focus & Application |
|---|---|---|
| CV — Simulation | LeBrun et al. (2005) | Communication protocol |
| | Priemer and Friedrich (2009) | Adaptive traffic signal control |
| | Kafsi et al. (2009) | VANET Connectivity |
| | Guler et al. (2014) | Intersection efficiency |
| | Osman and Ishak (2015) | Network-level connectivity |
| | Minelli et al. (2015) | Mobility and mode choice |
| | Khondaker and Kattan (2015) | Variable speed limit |
| | Guériau et al. (2016) | Assessing CV benefits |
| | Goodall et al. (2016) | Freeway vehicle position |
| | Genders and Razavi (2015) | Work zone safety |
| | Dey et al. (2016) | Assessing CV benefits |
| | Bertini et al. (2016a) | CV deployment roadmap |
| | Olia et al. (2016) | Potential impacts of CVs |
| | Talebpour and Mahmassani (2016) | Traffic flow stability |
| | Talebpour et al. (2016) | Driver behavior |
| CV — Analytical | Ukkusuri and Du (2008) | VANET Geometric Connectivity |
| | Xiong et al. (2016) | Node degree distribution |
| | Zhou et al. (2016) | Platoon trajectory design |
| CV — Others | Jin et al. (2011b) | VANET connectivity |
| | Martinez et al. (2011) | VANETs |
| | Ni et al. (2012) | Highway capacity |
| | Talebpour et al. (2015) | Lane-change behavior |

Figure 2.1: A summary of relevant connected vehicle studies

ment (Newman, 2014). According to the Texas Transportation Institute mobility report (David Schrank, 2015), U.S. highway users wasted 6.9 billion hours stuck in traffic congestion in 2014. It is believed that CV technology has great potential to ease traffic congestion through the creation of a safe and interoperable connected vehicle network (Ubiergo and Jin, 2016). Within this network, vehicles can exchange information regarding speed, position, and individual route as well as their surrounding vehicles, which helps drivers navigate the roads more efficiently. It also enables the system operators to improve the operation of the transportation system, reducing congestion, travel delay, and improving the overall mobility. Multiple CV application development efforts and studies have demonstrated the potential for significant mobility benefits from the V2X (vehicle-to-x) applications (Dey et al., 2016; Luo et al., 2016; Jia and Ngoduy, 2016). Existing studies have shown combinations of V2V (vehicle-to-vehicle) and V2I (vehicle-to-infrastructure) applications can potentially reduce travel time on freeways up to the range from 27 to 42% (Chang et al., 2015). The magnitude of the CV benefits depends on the varying level of market penetration in technology deployment, as well as the characteristics of the technology itself.

The growing innovation of CV technologies accelerates the market adoption and gradual implementation of mature CV applications (Gay and Kniss, 2015). However, the market will not be occupied by CV over a night. The CV market penetration in the United States is at 9.33% in 2016 and is expected to hit 27.66% in 2020[1], and around 98% of U.S.'s vehicle-fleet is likely to have connectivity in year 2030 (Bansal and Kockelman, 2016). Although the definition of CV might vary depending on the context, the market penetration of CVs that are able to perform a reasonable range of applications is expected to increase exponentially in the foreseeable future. The increasing market adoption of connected vehicles to the conventional traffic flow adds additional complexity since the interaction mechanism between vehicles alters (Guériau et al., 2016; Abdulsattar et al., 2017).

[1]https://www.statista.com/outlook/320/109/connected-car/united-states

The CVs on the highway would use dedicated short-range communication system (DSRC) or 5G LTE network (Murry, 2015) to communicate with each other, so that every vehicle on the road is aware of where other nearby vehicles are. This information can potentially be used to perform driving maneuvers. Nonetheless, there has been a lack of research focusing on the overall network performance in the transition regime. Further, at what market penetration of CVs after deployment of the technology, and how the greatest benefits can be achieved is a significant question yet to be addressed (Guériau et al., 2016). In addition, the technology evolves rapidly over time, opening windows to new opportunities and challenges in this area. This necessitates the study of how the advancements in technology affect the outcomes of the application. This work is largely motivated by the urgent need for transportation authorities, industries, and government agencies to understand the extent to which the mobility benefits of CVs will be, and how we can possibly maximize the opportunities that they will bring in order to better manage the increasing CV networks today and in the future (Global, 2016).

## 2.1 Vehicular Network

Instead of only considering the information exchange between neighboring CVs, Vehicle Cloud Networking (VCN) (Lee et al., 2014) allows us to delve into the CV networks from a larger scale. A vehicle cloud can facilitate collaborations among the vehicles within the cloud to perform an advanced vehicular task that an individual vehicle cannot achieve in isolation. Two computing and networking models supporting the VCN are vehicular cloud computing (VCC) and information-centric networking (ICN) respectively (Lee et al., 2014). Contrary to the Internet cloud, the vehicle cloud is temporarily created by interconnecting resources in vehicles or the roadside units (RSUs). In VCN, vehicles are interconnected and they can negotiate the level of resource sharing. Once the cloud is formed, travel information such as speed, density, and signal timing can be retrieved from the connected clusters. This information would help the driver's decision-making and eventually enhance the mobility benefits of CV in terms of travel time. Also, vehicles can freely join and leave the vehicular cloud as they move, which adds to the intriguing dynamics of the network. The enormous data collected in VCN will also contribute to the development of applications such as EnableATIS (USDOT, 2012) to improve the overall transportation system mobility and safety. The integration of data would also facilitate the development of dynamic and transformative applications (Chang et al., 2015).

The benefits of VCN-related CV applications are primarily dependent on the communication range that the vehicles can accommodate and the market penetration of the technology. These two elements can be modeled by the percolation theory. This study also shows the existence of critical percolation phase transition properties that appear in the dynamic CV network with time-correlated link and node dynamics (Basu et al., 2012). The results of the analysis show that percolation phase transition phenomenon exists in (1) the impacts of both market penetration and the communication range of CVs on system-wide mobility benefits measured by mean travel time of the vehicles; (2) the impacts of market penetration and communication range on CV network characteristics, studied from giant component size perspective, as widely used in percolation theory context. Although there are existing studies adopted percolation methods in VANET network (Jin et al., 2011a,b), the applications are mainly focused on the intersection grid network connectivity. This research proposes a novel application of percolation theory to understand the dynamics of CV network as well as resultant mobility benefits, with varying market penetration and communication range.

### 2.1.1 CAV Clusters as complex Network

CAV technologies allow vehicles to communicate with each other by forming connected vehicle clusters with varying sizes (Li et al., 2011). It is a rapidly emerging paradigm designed with direct access to the Internet (Murry, 2015) or dedicated short-range communication (DSRC) (Shakshuki et al., 2014), enabling vehicle links to all other connected objects, including cars, buses, trucks, smartphones, traffic lights, and other tracking devices (Viereckl et al., 2015). Each vehicle in the connected vehicle network, known as Vehicular Ad-Hoc Network (VANET) in computer science community (Martinez et al., 2011; Kafsi et al., 2009), is a mobile node with diverse nodal dynamics; therefore, the CAV network is a mobile dynamic network (Li et al., 2011). Dynamic network analysis is one of the most intriguing branches of network science and theory (Basu et al., 2012). It is an emerging field that applies our knowledge or simulated statistics of link and node dynamics to derive and validate varying aspects of network behavior such as percolation phenomena under random Markovian dynamics (Basu et al., 2012), network pattern evolution (Zhou and Lipowsky, 2005), dynamic graph properties of mobile network (Birand et al., 2011), asymptotic properties of stochastic dynamic network (Britton et al., 2011), and tracking group formation and group mobility in connected networks (Aung et al., 2015; Backstrom et al., 2006). It has applications ranging across social networks, information networks and various strata of communication networks (Basu et al., 2012). Although significant progress has been made in understanding how vehicles communicate with each other (Kerley and Mallin, 2014; Lavrinc, 2014) and with users or infrastructure (Shakshuki et al., 2014), almost all existing work so far has focused on adoption and deployment through pilot studies and testbeds (Gay and Kniss, 2015) led by industries and government collaboration; while academics focus on the evaluation of the safety, mobility and environmental impacts of connected vehicles through scenario simulations (Chang et al., 2015; Olia et al., 2016).

### 2.1.2 CAV Network Connectivity

The inter-vehicle connectivity between CVs is dependent on a combination of several factors such as temporal and spatial dynamics of moving vehicles (vehicle speed and vehicle density), traffic speed variance, distribution of roadside units, CR, and MP (Coon et al., 2012b), which might lead to unwanted network connectivity failure (Jin et al., 2011b). The connectivity between vehicles form the links among vehicles where the link up-down dynamics is governed by a time-varying stochastic process which exhibits critical phase-transition (percolation) phenomenon as a function of the MP and CR (Basu et al., 2012). Where the phase transition happens is called a critical value denoted by a threshold $p_c$ (Coon et al., 2012b).

Jin et al. (2011b) analyzed the connectivity of VANETs through a percolation theoretical framework. In their study, each intersection was considered as a node, and the connections between the nodes were formulated into a bond percolation problem. With the given $p = 0.5$, a percolation transition is found in average cluster size and number of clusters with various CRs. Jin et al. (2011a,b) mainly focuses on the VANET properties without considering the parameters' impact on network mobility. In addition, the experiment is conducted with an emphasis on bond open probability $p = 0.5$, it should be thoroughly investigated in the later study. Based on the theory proposed by Dousse et al. (2002), the quantitative relationship among network connectivity, vehicle density, and transmission range in grid network were discovered, and a jump in the connectivity was observed when vehicle density and transmission range were large. Basu et al. (2012) studied the behavior of end-to-end message latency in stochastic time-varying networks. Each link's dynamics was governed by a stationary but arbitrary time-correlated stochastic process (Basu et al., 2012). The simulation demonstrated a critical threshold that the message cannot be delivered within the deadline, while above which the message can be delivered within a proper time frame. Talebpour et al. (2016) presented a comprehensive simulation framework to model the drivers' behavior in a connected driving environment. The FHWA Next Generation Simulation: US-101 Highway data set was used to replicate the vehicular movement in a highway environment. The paper points out that to ensure full connectivity, the minimum effective communication range decreases as the market penetration increases. Employing the giant component concept, the result suggests that at an 80% MP, the operation of a V2V communication network is similar to 100% MP.

Kafsi et al. (2009) studied the impact of characteristics such as vehicle density, the proportion of equipped vehicles, radio communication radius, roadside units, and traffic lights on the connectivity of VANETs. The results revealed that there is a critical vehicle density, above which the connectivity significantly improves. They also suggested that accumulation of vehicles at red traffic lights creates a meeting point for vehicles. On the other hand, clustering increases the distance between CVs, which leads to low giant cluster sizes. Artimy et al. (2004) used a micro traffic simulator to evaluate VANETs connectivity for both highway and simple road configurations. Vehicle density, relative velocity, and the number of lanes were found to have a significant influence on connectivity. Artimy et al. (2005) investigated the effect of vehicle density on the minimum transmission range required to maintain the connectivity in the vehicle ad-hoc network. Ubiergo and Jin (2016) studied advisory speed limit (ASL) control strategies based on vehicle to infrastructure communication to smooth vehicle trajectories in stop-and-go traffic on urban streets. Moreover, they quantified the mobility and environment improvements of the green driving strategy with respect to the market penetration rate of CV, traffic conditions, communication characteristics etc., both in isolated and non-isolated intersections. The results show a saving of 15% in travel delays and 8% in fuel consumption and greenhouse gas emission.

Message forwarding is also critical for connected vehicle connectivity. The routing protocols can be categorized into two distinct groups: topology-based protocols and position-based protocols. Greedy routing normally forwards the packet to a node closest to the destination (Pirzada and McDonald, 2007). However, greedy routing will result in unconnected V2V communication network because vehicles might not be evenly distributed in the network (Li and Wang, 2007; Talebpour et al., 2016). Liu et al. (2004) proposed anchor-based street- and traffic-aware routing to strengthen greedy algorithm's weakness. LeBrun et al. (2005) compared five different opportunistic forwarding schemes. In their designed experiment, the results suggest that the location-based routing algorithm outperforms other algorithms.

## 2.2 Percolation Phase Transition

Percolation is a phase transition phenomenon in large random networks where a critical value $p_c$ controls when the transition occurs (Coon et al., 2012b). The giant connected component (cluster) of the system experiences a sudden change from $p < p_c$ to $p > p_c$ (Coon et al., 2012b,a). Percolation model was introduced by Broadbent and Hammersley (1957), and it has been utilized ever since to analyze various phase transition phenomenon in VANET connectivity analysis (Dousse et al., 2002; Jin et al., 2011b,a) and random networks/graphs (Basu et al., 2012). Although the applications of percolation theory in transportation research is still relatively rare (Li et al., 2015b), accurate predictions of the network connectivity can be made using percolation theory, describing the behavior of connected clusters in a random graph (Kafsi et al., 2009). However, the exact relationship of network connectivity with transportation-related measurements of effectiveness (e.g. travel time or travel delay) still necessitates the significant further investigation. Extending the findings of Dousse et al. (2002) for ad-hoc and hybrid networks, Jin et al. (2011a,b) assessed the connectivity of VANET both theoretically and using simulations. Ammari and Das (2008) studied the sensing-converge and network-connectivity in wireless sensor networks using percolation theory. A probabilistic approach is created to compute the covered area fraction at the critical percolation threshold. Critical density and radius of the covered components are identified under various scenarios and the phase transitions are revealed. Similarly, Khanjary et al. (2015) conducted percolation study in the two-dimensional fixed-orientation directional sensor network. The critical density of the nodes can be analytically computed from the framework. Further, Talebpour et al. (2017) investigated the effect of information availability on the stability of traffic flow through continuum percolation theory. The percolation theory is used to determine the impact of the connected vehicles density and the communication range on the connectivity of the network. The results show that as communication range increases, the system becomes more stable. Among all the related research presented in this section, there however still remains a lack of incorporation of transportation application-oriented performance measures (e.g. mobility). Therefore, one of the main objectives of this study is to analyze the correlation of CV network characteristics to the resultant mobility benefits of the corresponding network.

## 2.3 Routing Behavior in Congested Networks

There are methods in the literature that aim to model the route choice behavior of drivers. Most of these models, under the umbrella of Dynamic Traffic Assignment (DTA) models, aim to reach Nash Equilibrium, where changes in the route of any agent degrade the system and the agent's performance (Merchant and Nemhauser, 1978; Janson, 1991; Chiu et al., 2011). The most applicable version of these models to our problem is simulation-based DTA where the controller iteratively routes and reroutes the vehicles to find the optimal states of the system (Florian et al., 2008). However, most of these approaches are entirely relying on a centralized controller. Rossi et al. (2018) looked at routing (and rebalancing) of the Autonomous Mobility on-Demand (AMoD) system by transforming the problem into a linear programming problem. Their approach leads to an optimal solution that minimizes the travel time of the system as well as the congestion and provides the optimal path for individual agents. However, it relies heavily on a centralized controller with complete travel demand information for the entire transportation network. The same applies to Wilkie et al. (2011) where the centralized controller optimizes the route for each agent in a sequential manner, taking into account the impact of previously routed agents on the current traffic conditions and the congestion evolution patterns of the system.

Towards a less centralized system, Maciejewski Michałand Nagel (2011) implemented an extension to Multiagent Transport Simulation (MATSim) (Horni et al., 2016) for Dynamic Vehicle Routing Problem (DVRP) which dynamically optimizes the fastest route to destinations for certain vehicles. However, this system still assumes full observability and predictability of traffic conditions from origin to destination. Besides, the optimality of the solution it yields has not been benchmarked. Inspired by swarm intelligence methods, Moran and Pollack (2016) implemented a communication environment where the agents broadcast their paths to another agent with the same origin-destination pair at each episode. As the frequency of the broadcast is associated with the travel time of the path, the shorter trips are broadcasted more often and thus the population moves toward these paths. The algorithm converges where all agents are taking paths with relatively same travel time, and accordingly, broadcasted roughly the same number of times. Their results have shown impressive learning behavior in a multiagent system. Mostafizi et al. (2017) implemented a communication environment for CAVs where they can utilize the travel time information from other vehicles in their connected cluster to optimize their route with $A^*$ algorithm. However, their method largely depends on proper and robust communications within each CAV cluster. Similarly, CARAVAN (Desai et al., 2013) leveraged communication between adjacent cars in *negotiating* the route preference between the cars, and accordingly, reducing the traffic. Their results showed 21-43% increase in the performance compared to a shortest-path-update algorithm for the cases where the demand is lower than the capacity. Claes et al. (2011) implemented a heterogeneous environment, in which, on top of vehicle agents, there are congestion forecast agents that can detect and communicate the congestion to the vehicle agents for them to reroute to a less congested route. Congestion-aware Traffic Routing (Lim, 2012) has also been proposed in the literature as a distributed routing algorithm that uses local information, however, it is capable of reaching social optima, minimizing the aggregated travel times.

It is of note that similar congestion problems have been addressed in robotics in the field of path planning. For instance, MAPP (Wang and Botea, 2011) offers a decentralized and scalable path planning algorithm for multiagent systems that guarantees optimality. Planning the routes of each agent can be done using a decentralized path planning algorithm based on cost negotiations. Initially, agents will share information about requested and reserved areas. To find the optimal path, agents need to know the most recent information about the state of other agents. From there, possible future states can be analyzed, and potential conflicts can be resolved based on a cost-reduction algorithm similar to that presented in (Purwin et al., 2008). Each agent, after it has chosen its next location, will generate a cost value for this action. Should the reserved area conflict with another reserved area, the lower cost agent will be allowed to overrule the higher cost agent, effectively taking control of the desired space out from under them. Decentralized algorithms such as these allow the system to scale freely, not slowing down with increased agent counts (Purwin et al., 2008). Additionally, this algorithm can be bolstered to allow agents to account for the unpredictable action of non-networked agents. This would be done by allowing agents to calculate the probability that a non-networked agent might decide to occupy the space they intend to reserve during the next time step, in a similar fashion to the algorithm presented in (Lim and Rus, 2012). CAV agents would essentially navigate around the agents that they are not communicating with as if they were moving obstacles.

### 2.3.1 CAV Routing Optimization Algorithms

Multiple traffic control approaches have been investigated around building frameworks for CAV coordination. Networks of linked traffic lights that are optimized through a central controller have been a popular approach (Zhao and Tang, 2009; Balaji and Srinivasan, 2010; El-Tantawy and Abdulhai, 2017; Wiering, 2000), but a centralized controller can quickly become overwhelmed as agent numbers increase. Furthermore, it is unrealistic to have traffic lights at every intersection as it would be cost-prohibitive. To the best of our knowledge, this problem has been minimally analyzed from the agent-level perspective with a decentralized controller (Mostafizi et al., 2017), and the literature is still lacking an efficient coordination-based routing approach for CAVs. Along the same lines, Monte Carlo Tree Search has been used for CAV planning in the past studies (Lenz et al., 2016; Kurzer et al., 2018). This approach focuses on single-vehicle interactions and relatively short planning horizons. Furthermore, those approaches focused on knowing the exact path of the CAVs. Monte Carlo Tree Search (MCTS) makes use of the random sampling techniques of Monte Carlo methods (Hammersley and Handscomb, 1964) by applying them to a tree search problem for a specific domain (Browne et al., 2012). It has proven to be a very powerful technique for Artificial Intelligence (AI), particularly in competitive deterministic games such as Go which has a large branching factor (Browne et al., 2012; Marcolino and Matsubara, 2011). One of MCTS's most useful properties is its ability to solve sequential decision problems given a finite state and action space.

Although others have used Monte Carlo Tree Search for CAV planning (Lenz et al., 2016; Kurzer et al., 2018), their approaches focused on single-vehicle interactions and relatively short planning horizons. Furthermore, those approaches focused on knowing the exact path of the CAVs. Therefore, Best et al. (2018) proposed an approach to utilize joint-action probabilities which are sampled from a combination of the CAVs possible paths and the potential path distributions of other CAVs that are in communication. The action plans are represented by a probability distribution over an action sequence.

### 2.3.2 Collaborative Routing

Collaborative routing aims to utilize communications of preferred agent paths to decrease travel time and reduce congestion by avoiding other agents routes, or by routing traffic intelligently. Communicating individual priority of a vehicle on a route, based on emergencies or task importance such as running late, was introduced by Kala (2016). This approach utilized cooperative traffic lights and inter-vehicle communication to optimize for priority vehicles. Although it may be wise to implement a priority queue for emergency service vehicles, the temptation for everyone to cheat in order to arrive quickly to their destination would be difficult to manage. Several approaches have utilized optimization techniques inside a multiagent framework. Kishimoto and Sturtevant (2008) combined classical path planning algorithm $A^*$ and Dijkstra's algorithm with auction-based methods to determine bids on shortest paths in multiagent teams. Silver (2005) created *Co-*

*operative* $A^*$ which showed impressive results even for environments of 100 agents. However these approaches do not incorporate time, are centralized, and require perfect observability of the system.

## 2.4 Reinforcement Learning in Traffic Control

Connected and Autonomous Vehicle (CAV) systems coupled with vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) information exchange may introduce far-reaching impacts on several levels on the current transportation arena such as demand and behavior side, traffic mobility, as well as environmental relevant issues, and consequently, have attracted significant attention from both academia and industry. Actual performance at the network level will echo these new changes and will be greatly affected by the specific routing and scheduling algorithms developed for both individual autonomous vehicles and vehicle fleets. To address the above notion, Du et al. (2015a) developed a coordinated routing mechanism that allows smart vehicles to talk to each other so that they can make online routing decisions in real-time; this strategy may aid in avoiding probable traffic congestion to some degree. Later, Du et al. (2015b) extended the work and developed a coordinated online in-vehicle routing mechanism that also accommodates information perturbation. This work has some attractive features such that: (1) CAV vehicles make a routing coordination group based on their route choice; each smart vehicle in each group shares traffic information including its route choice with other members; and (2) a control center that collects and processes real-time information including general traffic condition, vehicles' tentative route choice, and travel time prediction among vehicles in a connected environment. Chapter 4 introduces a reinforcement learning (RL) approach to define the quickest path for the intelligent agents traveling along the transportation network. RL is a technique for learning control strategies for autonomous agents from trial and error (Kaelbling et al., 1996; Sutton and Barto, 2018). The agents interact with the environment to obtain information and use resulting feedback (reward and the consecutive state) to reinforce behavior that results in desired conclusions. A lot of research (Boyan and Littman, 2013; Baruah et al., 2004; Peshkin and Savova, 2002) have successfully applied RL algorithm in the context of vehicle routing; however, this is the first attempt, to the best my knowledge, to implement RL algorithm in a multiagent connected and autonomous vehicle routing.

# Chapter 3: Connected and Autonomous Vehicle Traffic Flow in Mixed Environments

## 3.1 Introduction

Understanding and improving flows of material, energy, and information has been a fundamental endeavor of science throughout history, and much of the development of modern society can be attributed to improvements in these flows. The flow of vehicles along a road network, likewise, has a long history of analysis and improvement, starting from Greenshields et al. (1934) and continuing to improve to this date (Tang et al., 2019). Now, with the advent of CAV technologies and their rapid developments, some of the most interesting and least understood opportunities for improving traffic flow are forming as part of CAV applications (Talebpour and Mahmassani, 2016; Delis et al., 2015; Amoozadeh et al., 2015). Dedicated Short Range Communication (DSRC) and sensory inputs of CAVs paves the way for these vehicles to *see* their surroundings more accurately than a human driver would, and thus, make smarter decisions faster (Lefevre et al., 2015; Wen-Xing and Li-Dong, 2018). There are high hopes for improvements across the entire transportation system with the evolving CAV technologies (Harding et al., 2014). Improvements to safety, sustainability, mobility, and comfort are the main objectives to which these applications aspire, but this chapter will focus on the possible effects to efficiency and mobility enabled by the implementation of a CAV application known as Cooperative Adaptive Cruise Control (CACC) (Van Arem et al., 2006; Milanés et al., 2013; Shladover et al., 2012). The current understanding of the CACC application is that CAV technology equipped vehicles will exchange status and location information in small data packets, similar to Basic Safety Message (BSM) (Liu et al., 2016), and subsequently, each will automatically adjust its speed to allow for synchronous speeds and small headways (Milanés et al., 2013). It is thought that CACC enabled platooning can increase flow and reduce back propagation of congestion (Shladover and Gettman, 2015). However, it has to be noted that the market penetration of the equipped vehicles is expected to have great impact on overall improvements resulting from these technologies (Harding et al., 2014).

This chapter presents the CACC application of CAVs, which is the underlying and core car-following behavior throughout all the simulations conducted in the next chapters of this dissertation. Moreover, the effects of the proposed CACC application on traffic flow in a highway environment, with various CAV market penetration, were analyzed and the results are presented in forms of highway average travel time, throughput, and shockwave backpropagation time. Further, the benefits of having CAVs in the system will be compared to the baseline scenarios where all vehicles are neither connected nor automated. Alternately, a "best-case" scenario, where all vehicles are CAVs, is of interest to set a hypothetical upper bound on possible effects. Of primary interest to transportation agencies and private industry may be critical thresholds of CAV market penetration, that is, when effects may begin to be noticeable, and when impacts may begin to be of significance (Shladover and Gettman, 2015).

## 3.2 Simulation and Experiment Design

To implement and test the car-following behavior of the CAVs, a highway segment in an agent-based simulation environment (Bernhardt, 2007) was created, and were used to perform repeated monte-carlo simulations experiments. The simulated agents represented vehicles entering the highway segment, and the system behavior was observed as the vehicles interacted with each other and the simulated highway environment. The simulation was then run with repetitions for various levels of CAV technology adoption with CACC application in place. A zero percent adoption rate (i.e., no equipped vehicles) was used to represent the baseline scenario, and to check for anticipated system behavior. The open source agent-based simulation software, NetLogo (Wilensky and others, 1999), was used to run all scenarios. Figure 3.2 shows a snapshot of the simulation domain.

### 3.2.1 Highway Model

In the hopes of isolating the effect of the CACC application on traffic flow, characteristics the simulated highway environment was purposefully kept simple. To this end, a single lane of a 3.5-mile segment of straight highway was modeled. There were no on- or off-ramps included, to conserve the number of vehicles along the segment, and there was no passing allowed to preserve the order of vehicles in the flow. A one-mile bottleneck section was included in the middle of the highway segment (i.e., a speed-drop zone starting at 1.25 miles and ending at 2.25 miles) to induce acceleration and deceleration and stop-and-go situation in the flow (Yeo and Skabardonis, 2009). This bottleneck was intended to be generic in nature, but could be seen to have a practical interpretation as a highway work zone or residential areas where speeds must be lowered. Practical speed limits of 70 mph for the highway and 10 mph for the bottleneck (i.e., work zone) were assigned to the simulated highway segment. An extremely low speed limit has been chosen for the speed-drop zone to simulate the extreme case of shockwave backpropogation and analyze the benefits of CAV technologies in the worst-case scenario. Figure 3.1 shows the a schematic view of the simulated highway corridor. In addition, Figure 3.1 shows the platooning behavior CAV clusters that arises as a result of CACC application (Segata et al., 2012). This phenomenon is later discusses in the Section 3.3.

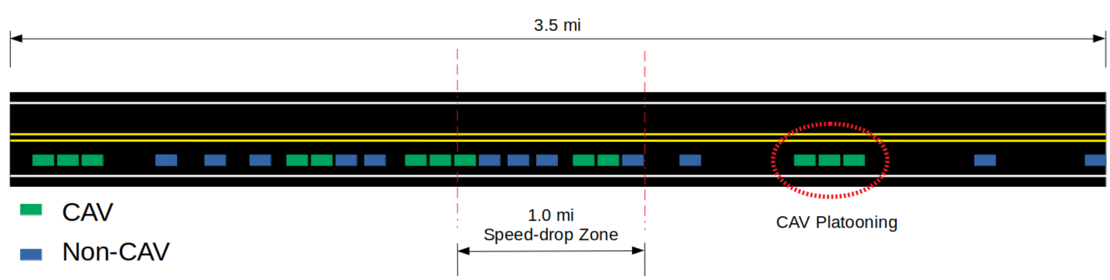



Figure 3.1: Schematic view of the simulated highway segment

### 3.2.2 Vehicle Generation

The simulation was coded to generate vehicles with inter-arrival times following an negative exponential distribution with a mean of 4 seconds, implying Poisson distributed arrivals (Vandaele et al., 2000). This mean is set in a way that highway operates at its 50% capacity ($900 veh/hr$) (Manual, 2000). This value also seemed to be the best choice for both avoiding congestion development towards the beginning of the segment before the bottleneck, and for displaying expected baseline shockwave behavior in reasonable simulation time. Additional randomness was introduced through the initial speed of each vehicle upon generation, entering the experimental highway segment (Medina and Tarko, 2005). This method was also employed to mimic expectations on a real highway. These initial speeds were designed to vary uniformly between 40 mph and 60 mph. This could be seen to represent a scenario where vehicles are entering a segment with a higher speed limit than the upstream segment and are accelerating up to match the new, higher speed limit. Some vehicles will still be traveling around the lower speed limit and other will have already begun accelerating in anticipation of approaching the higher speed limit segment. The final aspect of vehicle generation deals with the attribute of each vehicle as being modeled to be CAV technology equipped or not. The market penetrations levels of CAV technology adoption were modeled through the generation of vehicles. In each scenario, the desired market penetration was modeled by the probability of the entering car being equipped or not (Wadsworth, 1960).

### 3.2.3 Car-Following Behavior

The behavior of the vehicle agents was modeled using either traditional car-following models (Chandler et al., 1958) for non-CAVs or through a time headway maintaining rule (Zhao and Sun, 2013) for CAVs. For a leading vehicle, if there is no vehicle within 500 ft. downstream, and for all CAVs, acceleration behavior is modeled as the constant values below in Table 3.1, that are also well below comfortable rates according to Fambro et al. (1997). That is to say that these vehicles will use those constant acceleration and deceleration values in order to reach their desired speed. For leading vehicles, the desired speed is the speed limit of the roadway section they are traveling in, and for CAVs, this speed is determined by a time-headway-maintaining rule to follow.

Table 3.1: Acceleration/Deceleration parameters

| | **Rate** |
|---|---|
| *Acceleration* | $3.3 ft/s^2$ |
| *Deceleration* | $7.9 ft/s^2$ |

#### 3.2.3.1 Non-CAV Car-following

The acceleration behavior for following Non-CAVs was set using the 5th generation of General Motors car-following model (Gazis et al., 1961):

$$a_{n+1}^{t+\Delta t} = \alpha \frac{{V_{n+1}^{t}}^{m}}{[X_n^t - X_{n+1}^t]^l}[V_n^t - V_{n+1}^t] \tag{3.1}$$

Where $a_{n+1}^{t+\Delta t}$ is the acceleration of the following vehicle at $t + t$, $V_{n+1}^t$; $V_n^t$ are the speed of the following and the leading vehicle respectively; and $X_{n+1}^t$ and $X_n^t$ are the location of the following and the leading vehicle respectively. The rest of the parameters are presented in Table 3.2.

Table 3.2: GM5 Model Parameters

| **Parameter** | **Notation** | **Value** |
|---|---|---|
| *Distance Headway Exponent* | $l$ | 2 |
| *Speed Exponent* | $m$ | 0 |
| *Sensitivity Coef.* | $\alpha$ | $0.35mi^2/hr$ |
| *Reaction Time* | $\Delta t$ | 0 |

From macroscopic point of view, these sets of parameters lead to the Greenshields Model (CHUNG et al., 2005). For simplicity, it was assumed that the reaction time of drivers is minimal and can be estimated to be equal to zero. In fact, this assumption results in comparing the CAVs with the best of Non-CAVs (with reaction time 0), which in turn gives a lower-bound threshold for the improvements in mobility that are to follow the introduction of CAVs into the traffic flow. In addition, $\alpha$ can be estimated as following:

$$a_{n+1}^{t+\Delta t} = \alpha \frac{{V_{n+1}^t}^m}{[X_n^t - X_{n+1}^t]^l}[V_n^t - V_{n+1}^t]$$

$$\ddot{X}_{n+1}^t = \alpha \frac{1}{[X_n^t - X_{n+1}^t]^2}[V_n^t - V_{n+1}^t]$$

Let's say $[X_n^t - X_{n+1}^t] = h$. then we have,

$$\ddot{X}_{n+1}^{t} = \alpha \frac{1}{h^2} \frac{dh}{dt}$$

$$\frac{dV}{dt} = \alpha \frac{1}{h^2} \frac{dh}{dt}$$

$$dV = \alpha \frac{1}{h^2} dh$$

$$\int dV = \int \alpha \frac{1}{h^2} dh$$

$$V = \frac{-\alpha}{h} + c$$

Now, in jam condition we have,

$$K = K_j \text{ or } h = \frac{1}{K_j} \text{ and } V = 0$$

Therefore we can say $\alpha K_j = c$. In free flow condition we have,

$$K = 0 \text{ or } h = \infty \text{ and } V = V_f$$

Thus, we can conclude $c = V_f$. Putting these two equations together, and if we assume $V_f = 70mph$ and $K_j = 200vpm$, the $\alpha$ will be,

$$\alpha = \frac{V_f}{K_j} = \frac{70}{200} = 0.35mi^2/hr \tag{3.2}$$

The above assumptions for $V_f$ and $K_j$ are selected as reasonable under the circumstances of the simulation scenario, where speed limit is 70 mph and the length of car and the space headway between vehicles is assumed to be 26ft ($K_j \approx$ 5280/26) (Mannering et al., 2007).

#### 3.2.3.2 CAV Car-following

For CAVs, the car-following behavior has been modeled to follow a simple rule to maintain a desired time headway. The logic of this method of modeling follows the anticipated implementation of the CACC application (Zhao and Sun, 2013; Nowakowski et al., 2011). As, CACC depends on the packets of Basic Mobility Message (BMM) (Stowe et al., 2017) to be delivered to the vehicles in the platoon, it is reasoned that only adjacent vehicles in the traffic flow will be able to communicate and coordinate under the CACC application. In other words, CAVs will not communicate if a non-CAV is between them. Given two adjacent CAV, the following CAV receives location information of the leading car, and accordingly calculates its *desired speed* using the following formula to maintain a reasonable time headway:

$$DesiredSpeed = \frac{SpaceHeadway}{DesiredTimeHeadway} \tag{3.3}$$

The following car then uses a constant acceleration, presented in Table 3.1, to reach this desired speed. Interestingly, our experiments have showed that even maintaining 7 seconds time headway for CAVs, which is well above the comfortable time headway of 1 second (Ayres et al., 2001), CAVs can reduce the shockwave backpropagation, and also decrease travel time of the segment. Therefore, a realistic and yet conservative time headway of 1.5 seconds has been chosen for the rest of the simulations in this dissertation among adjacent CAVs. Actual implementation of the CACC application may use an even smaller value for this setting (Ploeg et al., 2011). Figure 3.2 shows the snapshot of the simulation platform where you can adjust acceleration and deceleration rate, vehicle intervals, desired headways for connected vehicles, and market penetration. As a result, the travel trajectories and other macroscopic traffic quality measurements (e.g., travel time and speed) are then outputted from the simulator.

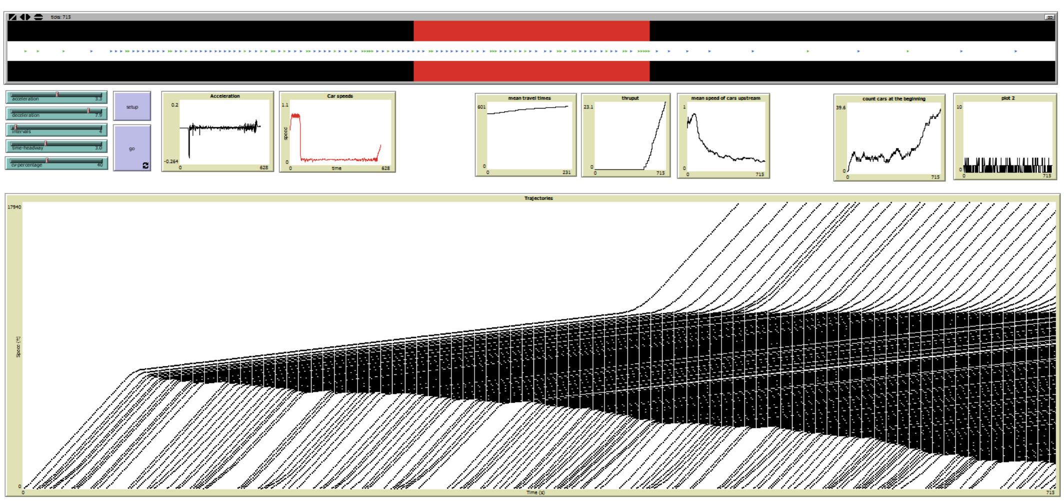


Figure 3.2: Snapshot of the simulation platform

## 3.3 Results

The results of this chapter shows a strong correlation between the macroscopic traffic characteristics of the highway segment, such as mean travel time, throughput, and backpropagation time of congestion caused by the bottleneck, with the market penetration rate of CAVs. Figure 3.3 shows the impacts of the CACC technology associated with the introduction of CAVs into the traffic flow, on the mobility of the highway, as a function of CAV Market Penetration. These impacts are translated into percentage of travel time decrease, percentage of throughput increase, and the percentage of shockwave backpropagation time increase, compared to the base scenario where there are no CAVs in the system ($MP = 0$).

### 3.3.1 Mean Travel Time

As shown in Figure 3.3a, mean travel time of the vehicles in a 2-hour time period, entering and exiting the corridor, decreases significantly for high market penetration of CAVs. It is also interesting that for market penetration levels lower than 75%, the mean travel time is relatively constant. However, with an increase in the percentage of connected vehicles over 75%, it changes rapidly to the extent that mean travel time for the fully CAV penetrated traffic flow is roughly 50% of mean travel time for 75% and lower market penetration levels.

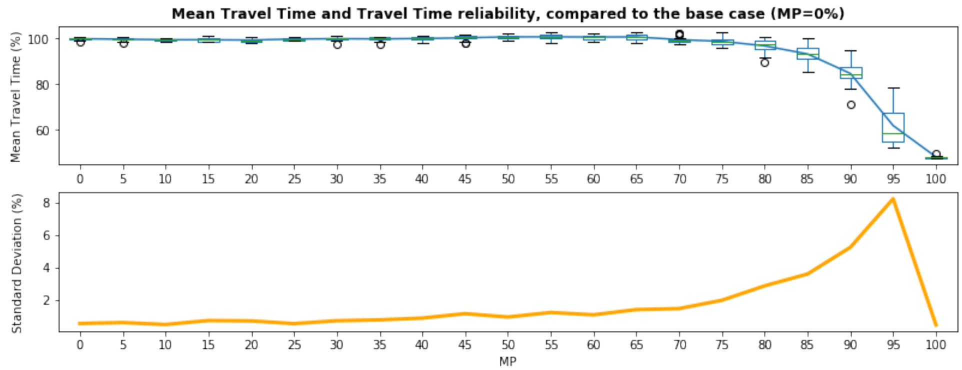
Another point to notice is that the mean travel time variability starts increasing at around 30% and reaches its maximum at 95% market penetration, beyond which it rapidly decreases to a reliable fully connected environment. This shows that for high levels of CAV market penetration, the presence of a few non-CAVs exposes the entire system to a strong uncertainty that emerges as travel time *un*reliability, which can be avoided by replacing them with CAVs.

### 3.3.2 Throughput

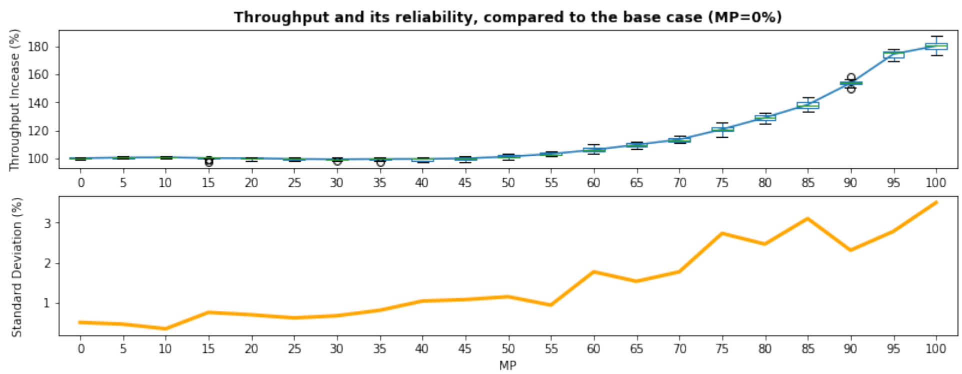
Similar to the mean travel times, the throughput of the corridor varies with changes in CAV market penetration over a critical value which is estimated to be around 50%, based on Figure 3.3b. It can also be noted that throughput increases by 80% with the change in market penetration from 50% to 100%. These results are fairly consistent with previous studies (Talebpour and Mahmassani, 2016). However, our simulations show that the uncertainty in the added throupout is much less than that of mean travel time. And interestingly, the uncertainty increases almost monotonically as the CAV market penetration increases, starting from 10% MP, even before the actual benefits in throughput emerge (at about 50%). Comparing Figures 3.3a and 3.3b, a fully CAV penetrated traffic flow, although very reliable in terms of travel time, is not as certain from the perspective of throughput.

### 3.3.3 Shockwave Backpropagation Time

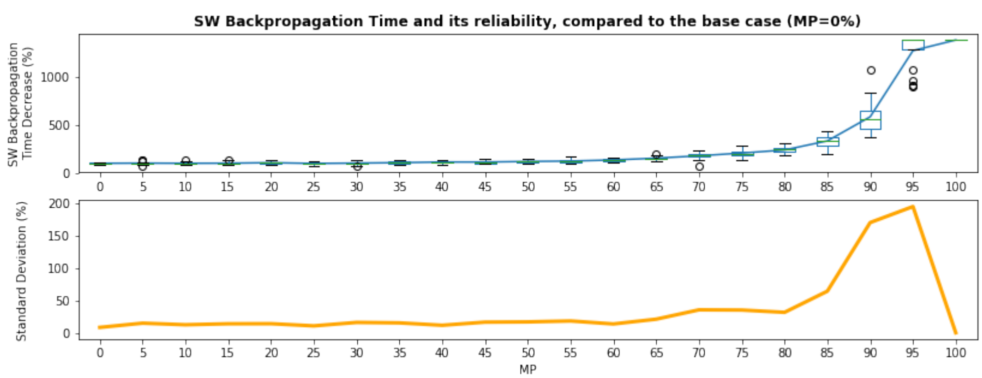
Looking at Figure 3.3c which shows the time that the shockwave propagates back to the start of the corridor, it can be stated that this backpropagation time increases, or in other words, the speed of shockwave decreases once the percentage




(a) Mean Travel Time




(b) Throughput



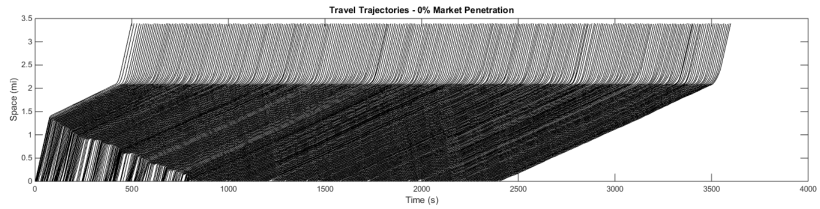

(c) Shockwave Backpropagation

Figure 3.3: Traffic Characteristics with change in the CAV Market Penetration

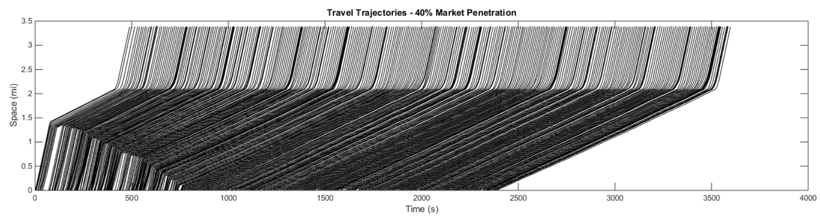
of connected vehicles hits 60%. Interestingly, with 100% market penetration, the shockwave never reaches the upstream during the simulation time window, which was set to 3 hours. This is the results of CAV platooning and CACC application that damps the chain effect of stop-and-go condition in congestion (Stern et al., 2018). The reliability in this aspect also follows a similar pattern as travel time.

### 3.3.4 Trajectory Analysis

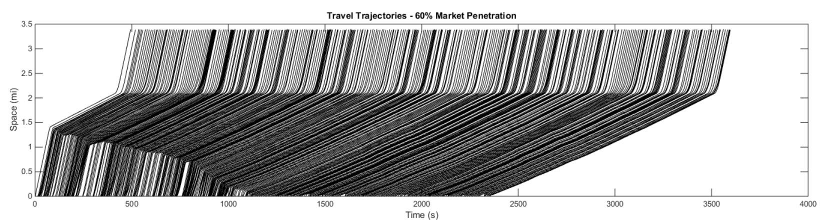
In addition to the findings above, looking at travel trajectories of the vehicles under different market penetration of CAVs unearths an emergent platooning phenomenon in CAV clusters (Liu et al., 2018). Figure 3.4 shows travel trajectories for different market penetration levels. The increase in the cluster of trajectories is easy to recognize as the CAV market penetration goes up. These platoons get larger and denser as the percentage of CAVs in the system goes up. It has to be noted that this behavior is an artifact of the simple car-following model that was implemented for the CAVs, which only works towards maintaining a constant headway between them (Uhlemann, 2016). Another point to notice is that as shown in Figure 3.3c, the shockwave backpropagation time increases with increase in CAV market penetration, to the point that the shockwave never backpropagates to the upstream under 100% market penetration.



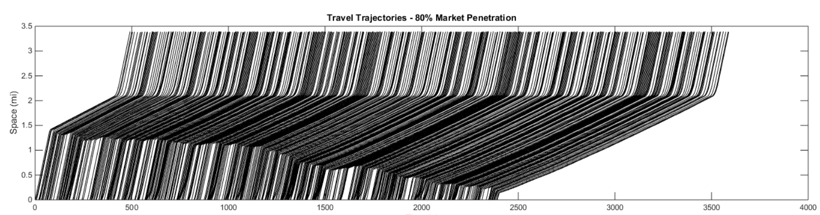

(a) 0% MP



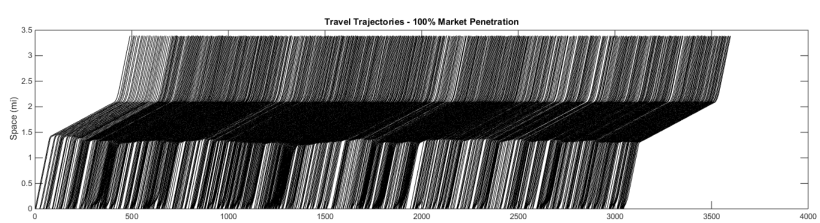

(b) 40% MP




(c) 60% MP




(d) 80% MP




(e) 100% MP

Figure 3.4: Travel Trajectories for different Market Penetrations

## 3.4 Conclusions

From the simulation experiments and the vehicle trajectories in this chapter, it can be concluded that the CACC application can have a noticeable impact on traffic flow, and that this impact increases along with increasing market penetration of this technology. The vast difference in results from the baseline scenario (0% CAV) vs. the "best case" scenario (100% connectivity) make this conclusion readily apparent. This chapter also demonstrates the ability to obtain realistic and expected results through the agent-based simulation method. An interesting finding of this study is that significant effects are not seen until the market penetration exceeds a critical threshold at around 50%. This may correspond to a real phenomenon which will be duplicated in real-world scenarios. Another interesting result of these simulations is the conclusion that at some level of market penetration the congestion caused by the bottleneck no long propagates backwards. In other words, the shockwave speed is zero. This implies that upstream congestion, far removed from the location of the cause, may be able to be completely avoided. This can be seen in comparing results from 90% and 100% market penetration rates where the ever shallowing slope of the shockwave become effectively flat at 100%.

# Chapter 4: Connected and Autonomous Vehicle Routing Optimization under No Communication: A Reinforcement Learning Application in a Competitive Environment

## 4.1 Introduction

The escalating advancement of information and communications technology, the internet of things (IoT) and vehicular data cloud (He et al., 2014), and the automation have had a significant influence on the landscape of transportation (Guerrero-Ibanez et al., 2015). These technologies have given rise to the prospect of connected and autonomous vehicle technologies which aim to improve traffic performance in terms of safety, mobility, and environmental impacts (Genders and Razavi, 2015). The idea of driverless vehicles has been in existence for decades (Nelson and Cox, 1990; Frazzoli et al., 2002); however, the exorbitant costs and the lack of proper technological advancements in the past have been stalled its large-scale production (Fagnant and Kockelman, 2015). Nevertheless, an acceleration in the research and development efforts in the last decade has brought the idea of the CAV to realization (Kato et al., 2015; Poczter and Jankovic, 2014). For example, the introduction of the Google car brought CAVs to the spotlight (Guizzo, 2011). However, the existing literature does not document the approaches by which CAVs find and determine their routes in the road networks (Bagloee et al., 2016), especially when there is no communication between the vehicles (Aoki and Fujii, 1996; Hussain and Zeadally, 2018). Current strategies heavily rely on real-time traffic information to be communicated to the drivers or vehicles in order to make an informed navigational and routing decision (Wedel et al., 2009; Pan et al., 2016, 2012). Although this real-time communication is known to be beneficial to the vehicles' directionality abilities, leading to more efficient and intelligent route-finding algorithms (Mostafizi et al., 2017), it is of great significance to study CAV systems where there is no communication capabilities (Willke et al., 2009). As a result, the future of autonomous vehicles, and routing behavior in particular, to some extent relies on a decentralized control system that scales easily in order to fully utilize the transportation network capacity, and does not fail in absence of communication capabilities.

In this chapter, to simulate routing optimization in absence of communication between CAVs, a decentralized learning environment is replicated to find the shortest path for the CAVs travelling through a grid transportation network using a Q-learning algorithm (Watkins and Dayan, 1992). The objectives of this chapter are two-folded. In the first part, I focused on replicating the behavior of the controller in terms of learning the shortest path for a single CAV in a simplified transportation grid network with a background traffic. Later, transitioning from a single-agent to a multiagent system (Wolpert et al., 1999; Tumer et al., 2002; Buşoniu et al., 2010), I studied how different percentage of CAVs impacts the learning behavior as well as total mobility of the system as a whole, measured by the average of travel times. In addition, this chapter discusses how reinforcement learning yields sub optimal policies in the case that there are a large number of CAVs trying to minimize their travel times simultaneously (Chang et al., 2004). The Q-learning algorithm with a reverse order Q Matrix is updated (Singh and Sutton, 1996) to reach the optimal path within a grid network, during which different coefficients have been evaluated and analyzed based on their impact on the algorithm's performance. The reinforcement learning algorithm is then applied to the multiagent system with different market penetration of CAVs. The results revealed that as the percentage of CAVs increases, convergence to the optimal joint policy gets more complex, as shown in previous multiagent coordination studies on loosely coupled tasks (Yu et al., 2015; Brafman and Domshlak, 2008), similar to the route planning task at hand. A physical interpretation is that when all of the agents are trying to maximize their own utility in a congestion game (Milchtaich, 1996) where the agents have conflicted interests with each other, the system does not converge to a global optima (Helbing et al., 2005). The results of this study reveals that the critical CAV market penetration where the final converged total travel time reaches its minimum lies between 50% and 75%, above which the system performance degrades with learning.

## 4.2 Learning Environment

This dissertation considers a network grid where nodes represent intersections and edges represent travel links. Nodes at the farthest left of the grid are the origins and the other side nodes are representing the destinations (See Figure 1.2a). In each origin, there are 50 vehicles whose destination is randomly assigned to one of the destination nodes. Each vehicle can either be a CAV or a Non-CAV, depending on the market penetration. Non-CAVs are assumed to have no learning ability, and therefore choose their route based on a so-called diagonal shortest path, calculated with the following pattern.

$$DiagonalShortestRoute = \begin{cases} \overbrace{R..R}^{\left\lfloor \frac{6-D_y}{2} \right\rfloor} \quad \overbrace{RDRD..RDRD}^{d_y} \quad \overbrace{R..R}^{\left\lfloor \frac{6-D_y}{2} \right\rfloor} & d_y < 0 \\ \underbrace{R..R}_{\left\lfloor \frac{6-D_y}{2} \right\rfloor} \quad \underbrace{RURU..RURU}_{d_y} \quad \underbrace{R..R}_{\left\lfloor \frac{6-D_y}{2} \right\rfloor} & d_y \geq 0 \end{cases} \tag{4.1}$$

where $d_y = Y_{destination} - Y_{origin}$, $R$ represents Right action, $D$ represents Down action, and $U$ represents Up action. This behavior is put in place to replicate the predictability in commuting route of the drivers that are not provided with any real-time information or any navigational intelligence of any sort (Evans et al., 2002; Ponieman et al., 2013). On the other hand, CAVs learn from their past action sequences and intend to optimize their routing policy (Han et al., 2016). For each agent travelling through this network, the route would be a combination of certain number of "Right" and "Up" or "Down" actions, based on the sign of $d_y$. In lines with the objectives of this chapter, two scenarios were simulated here,

- *Single CAV Learning*: How a CAV, that is characterized as a reinforcement learning agent, can learn the optimal shortest route by itself and without any external source of information? For this scenario, I assumed that the CAV travels from one corner to the opposing one in the grid.

- *Mult-CAV Learning*: How multiple CAVs learn their optimal routes, without any external source of information or any intent communication between them, and just by learning from their own experiences and state-action space, to yield minimum system travel time?

This environment with one single CAV learner has been used to tune the learner in order to be deployed in the Multiagent setting. The performance of the algorithm in this scenario is discussed and tuned in Section 4.3. The performance of the tuned learning algorithm in a multiagent setting is presented in Section 4.5 in terms of mean travel time of the system.

### 4.2.1 Learning Procedure

The general approach to optimize the route for the CAVs in this study is to exploit the Q-learning algorithm (Watkins and Dayan, 1992) with reverse updates, known as *eligibility trace* in the literature (Singh and Sutton, 1996; Precup, 2000), to speed up convergence in the goal based domains. The simulator was built in Netlogo (Wilensky and others, 1999) with the car-following model presented in Chapter 3 in place. It also has to be noted that since traffic congestions are simulated in the model and incorporated in the process of learning, the travel times were stochastic to the extent that impact the optimized route (Laporte et al., 1992). Therefore, each trajectory for a vehicle was run 10 times and the average travel time were used to calculate the reward and update the Q matrix consequently. Algorithm 1 presents the general learning work-flow of a CAV.

**Algorithm 1** Learning Algorithm

```
procedure LEARN
Input: Agent r: Origin & Destination
Output: Optimal Route (in form of a sequence of actions - Policy)
Q ← 0
for LearningHorizon iterations do
    ActionSet ← []
    Rewards ← []
    state ← origin
    while state ≠ destination do
        Action ← ϵ-greedy Action
        Add Action to ActionSet
        Collect reward
        Rewards(state) ← Rewards(state) + reward
        update state
    end
    Rerun ActionSet 10 times
    Average the Rewards for each state
    Q(s,a) ← Q(s, a) + α(R(s) + βMax_a' Q(s', a') − Q(s, a))
end
return argmax_a[Q^r(s, a)]
```

The specifics on how the state-action is defined and how time-based rewards are calculated are elaborated in the following sections.

### 4.2.2 State, Action, and Reward

In addition, to formulate this problem, three key features of reinforcement learning are defined as following,

- **States**: Each intersection is defined as a state, where CAVs take action at.
- **Actions**: For the Single CAV learning scenario, possible actions are $R$ and $D$, considering the network constraints and not moving beyond the network boundaries. For the Multi-CAV learning scenario, possible actions are $R$ and either $D$ or $U$ (based on the sign of $d_y$), and again, considering the constraint that a CAV cannot move outside the network. Also, a CAV cannot pass its destination vertically. This means that any sets of possible actions will certainly take an agent to its own destination. This constraint is put in place so the CAVs focus on learning *the* shortest path, and not just *a* path. In simple words, to learn what matters (Dayan and Balleine, 2002; Berridge, 2000).
- **Rewards**: Since the objective is to find the *quickest* path, reward of each state is based on the time to get to that state from previous states,

$$Reward(state) = (Max_{Traveltime} - Traveltime(state)) * 10^3$$

where $Max_{Traveltime}$ is calculated based on the link length and the minimum speed of the vehicles. There also is a significant reward for the destination, based on the time it takes to get to the destination from the origin, formulated as the following,

$$FinalReward = (Max_{TotalTraveltime} - TotalTraveltime) * 10^3$$

Where $Max_{TotalTraveltime}$ is calculated based on Manhattan distance between origin and destination and the minimum speed of the agents.

### 4.2.3 Single CAV Learning

For this study two different network sizes were considered, $3X3$ and $6X6$, to reduce the amount of computational needs, and to prove the concept. For a Single-CAV learning scenario, all vehicles are Non-CAVs, except one CAV at the top left intersection of the grid, heading to bottom right intersection. Based on the travel pattern proposed earlier and the diagonal shortest path algorithm defined, the expected background traffic resembles Figure 4.1.

It can be seen that as the simulation progresses beyond 50%, the middle of the network becomes heavily congested, and thus, the quickest path should avoid these links as much as possible. Therefore, the shortest path from the top left to the bottom right is not the diagonal path, and it is more likely to be inclined to the bottom left of the grid. Also, since vertical links are less congested in the beginning, it is expected that the shortest path will be more vertical in the beginning and after that, it tries to get to the destination by moving horizontally.

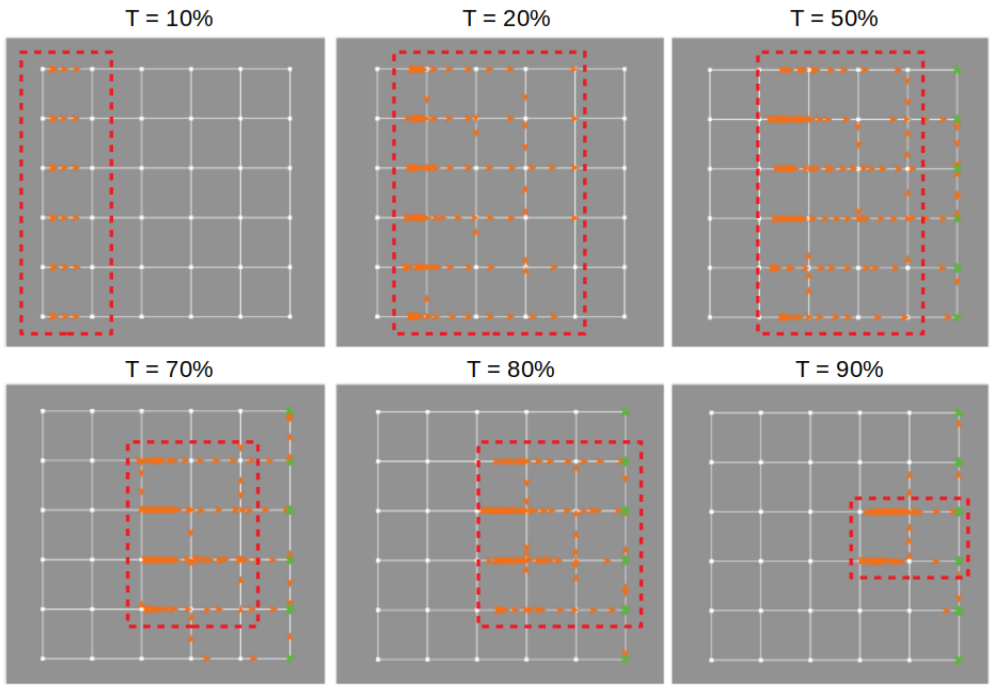



Figure 4.1: Background traffic pattern

This scenario has been mainly used to tune the learning parameters in order to deploy the algorithm in the Milti-CAV scenario.

### 4.2.4 Multi-CAV Learning

In this scenario, I the performance a system where multiple CAVs learn the shortest path at the same time is analyzed. As mentioned earlier, there are 50 vehicles in each origin, and a specific percentage of them are set as CAVs, with learning capability, based on the CAV market penetration. The destinations are assigned randomly and uniformly for each vehicle. The definition of States and rewards are exactly the same as the first scenario. However, possible actions are defined as the following,

$$PossibeActions = \begin{cases} RU & d_y > 0 \\ \text{R D} & d_y < 0 \\ \text{R} & d_y = 0 \end{cases} \tag{4.2}$$

It is assumed that a CAV cannot travel outside the network. Also, an agent cannot pass its destination vertically. Since the objective is to identify the optimal shortest path, logical constraints are applied to ensure possible actions in a way that a CAV reaches its destination for sure, and to ensure that the simulation realizes the learning potential for finding the shortest path (Mataric, 1994). The next section presents the results from both scenarios. In addition, to compare the impact of different coefficients, the learning environment is set for two different network sizes, and for deferent values for learning parameters, i.e., , $\alpha$, and $\epsilon$ for the *epsilon*-greedy exploration exploitation policy.

## 4.3 Hyperparameter Tuning

The objective of the first scenario is to fine-tune the learning algorithm to ultimately deploy it in the multiagent system with many CAVs learning simultaneously. Therefore, the following sections discuss distinctive performances of the learning algorithm, with varying coefficients, for a single CAV, travelling from top left corner to the bottom right corner of the $3X3$ grid network. Travel time increase, compared to the minimum and optimal route travel time, has been utilized as a performance measurement.

### 4.3.1 Exploration vs. Exploitation

In this study, the reinforcement learning agent (CAV) utilizes an $\epsilon$-greedy approach to balance between exploitation of the already found *good* policy (route) and the exploration of new routes (Gomes and Kowalczyk, 2009; Wunder et al., 2010). With this approach, at each state, the so-far best action will be explored by the probability of $\epsilon$, and any of other actions with the probability of $1 - \epsilon$. Figure 4.2 shows the algorithm's performance for diverse values of $\epsilon$. Note the $y$ axis of the plot that shows the increase in travel time, compared to the minimum value. Therefore, 100% means that the algorithm has converged to the optimal policy.

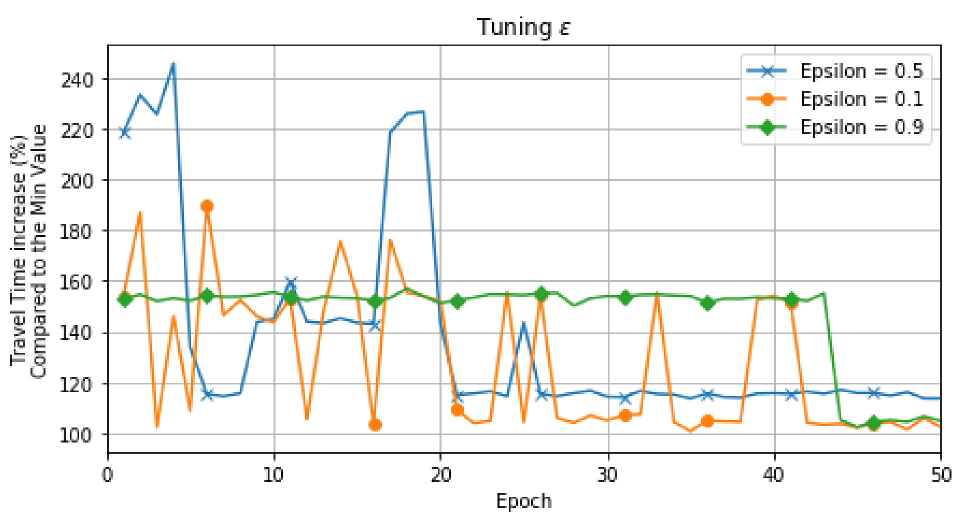



Figure 4.2: Learning curve for various $\epsilon$ ($\alpha = 0.1$ and $\beta = 0.99$).

The results show that $\epsilon = 0.9$ has a more constant behavior and it converges to the optimal route eventually. This is due to the nature of grid networks where exploring the corner states are less likely, and thus, takes longer. Remember that, keeping the background traffic shown in Figure 4.1 in mind, the optimal route would be the one that passes the bottom left intersection, and thus, less likely to be travelled. On the other hand, setting $\epsilon$ to be 0.1 makes the learning curve very noisy, and a reliable convergence to the optimal route is achieved almost at the same time as 0.9-greedy policy. In this study, as convergence to the optimal policy is more important than the way of convergence and the algorithm's performance, $\epsilon$ is set to be 0.5, to avoid the noises associated with a low $\epsilon$ (Fox et al., 2015) and the likelihood of not converging to the optimal route that minimizes the travel time with a high $\epsilon$. Also, Figure 4.2 shows that the final performance of $\epsilon = 0.5$ is not drastically different that the other cases.

### 4.3.2 Discount Factor

Figure 4.3 represents how different discount factors affect the performance of the algorithm. Since the rewards of each state are factored with the final reward, having a large $\beta$, that transports most of the final reward backwards, makes the learning curves to be noisy (Precup, 2000).

As it can be seen in Figure 4.3, all three curves show that the algorithm converged to the near-optimal route. However, $\beta = 0.99$ seems to ensure proper backpropagation in the rewards in a way for the 0.5-greedy policy to swipe the

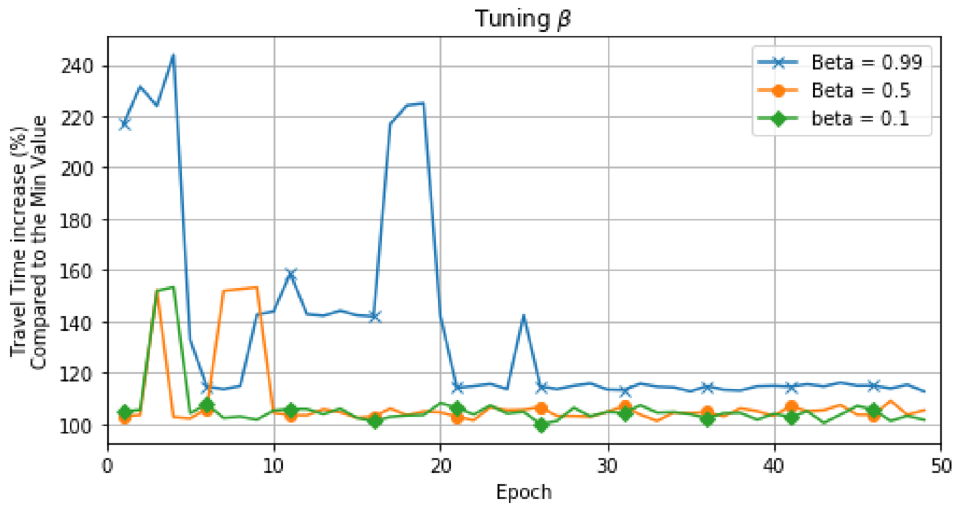



Figure 4.3: Learning curve for various $\beta$ ($\alpha = 0.1$ and $\epsilon = 0.5$)

entire network looking for the shortest path. Plus, the final converged route is comparable to the other cases in terms of the travel time. Therefore, to ensure that the algorithm converges to the shortest route, $\beta$ is set to 0.99 for the rest of simulations. Low $\beta$ of 0.1 or 0.5, although converging to the optimal route early on does not seem to be exploring other routes enough.

#### 4.3.2.1 Learning Rate

Figure 4.4 presents the impact of different values of $\alpha$ on the algorithm's performance. As expected, the smaller the $\alpha$ is, the smoother the learning process would be (Even-Dar and Mansour, 2003). However, for this special case, it appears that the learner, perhaps randomly, was locked in the optimal route at the beginning of the process, and due to low learning rate, barely explored any other policies.

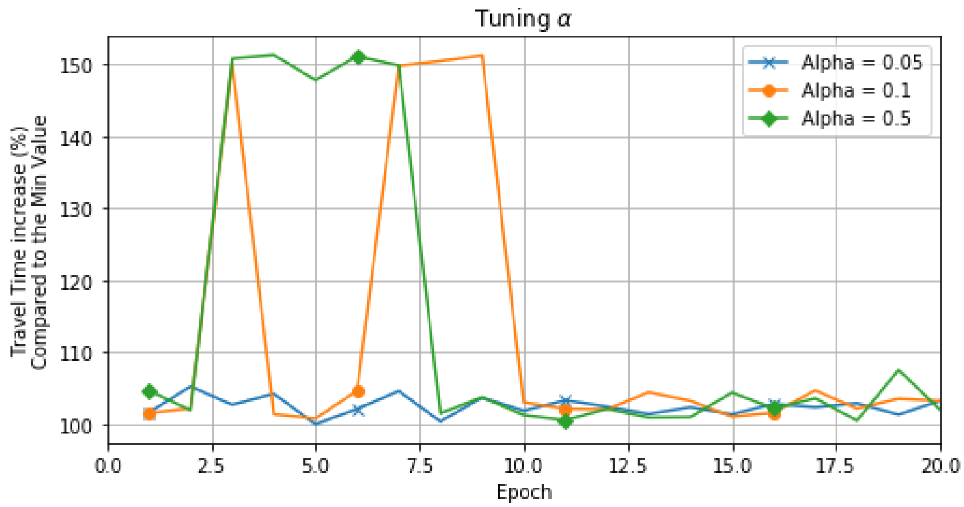



Figure 4.4: Learning curve for various $\alpha$ ($\beta = 0.5$ and $\epsilon = 0.5$)

All considered, for deployment of this algorithm to the Multi-CAV scenario, I chose the learning rate of 0.1 that is not low enough to hinder the exploration of other states and policies and is not too high that diverges from the optimal policy.

Based on the tuning analysis, the coefficients are set to the following values for Multi-CAV scenario.

Table 4.1: Q-Learning Hyperparameters

| *Parameter* | **Exploration Exploitation** $\epsilon$ | **Discount Factor** $\beta$ | **Learning Rate** $\alpha$ |
|---|---|---|---|
| *Value* | 0.5 | 0.99 | 0.1 |

## 4.4 Scaling

The algorithm was tested in a $6X6$ network to inspect how the algorithm scales for a larger state-action space. Figure 4.5 shows the experiments with different values of $\epsilon$. The results show that, similar to the smaller network, $\epsilon$ of 0.5 converges faster to the optimal route, compared to the other two cases tested. Moreover, reducing $\epsilon$ directly impacts the noisiness of the convergence. The final route that came from each algorithms, after 200 training epochs, is shown in Figure 4.6. As expected, the optimal route is inclined to the bottom left part of the network for all three cases, indicating that the learning algorithm is behaving correctly for a single reinforcement learning CAV. However, as shown in the expected travel time of the final converged route in Figure 4.5, $\epsilon = 0.9$ yields an slightly sub-optimal route, compared to the other two cases.

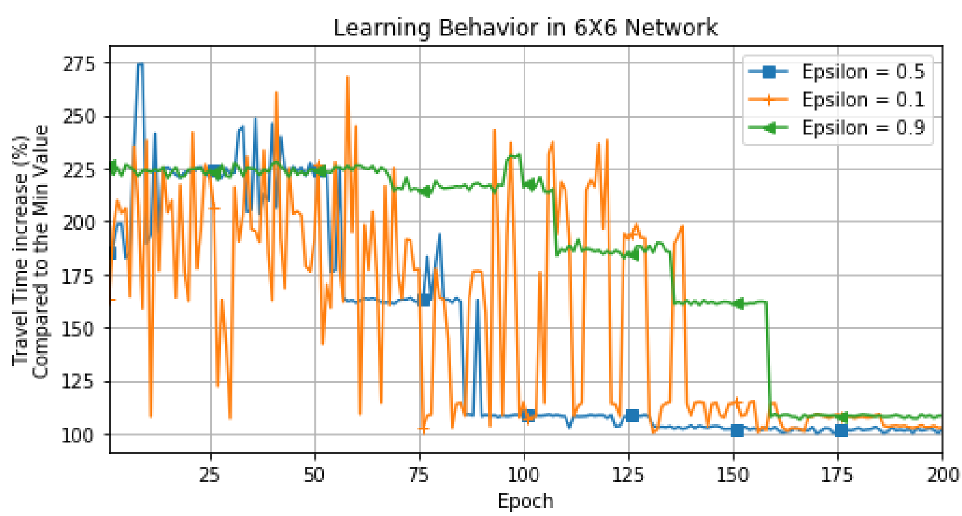
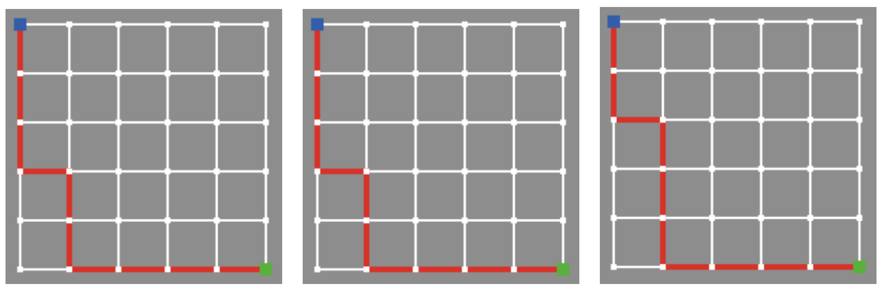



Figure 4.5: Learning curve for various $\epsilon$ ($\alpha = 0.1$ and $\beta = 0.99$).

One other point to notice is the longer convergence time. Comparing Figures 4.5 and 4.2 shows that 0.5-greedy algorithm converged almost 80% faster for the smaller network. In other words, doubling the size of the network, as it exponentially enlarges the state-action space (Santamaría et al., 1997), results in 4 times longer convergence time.



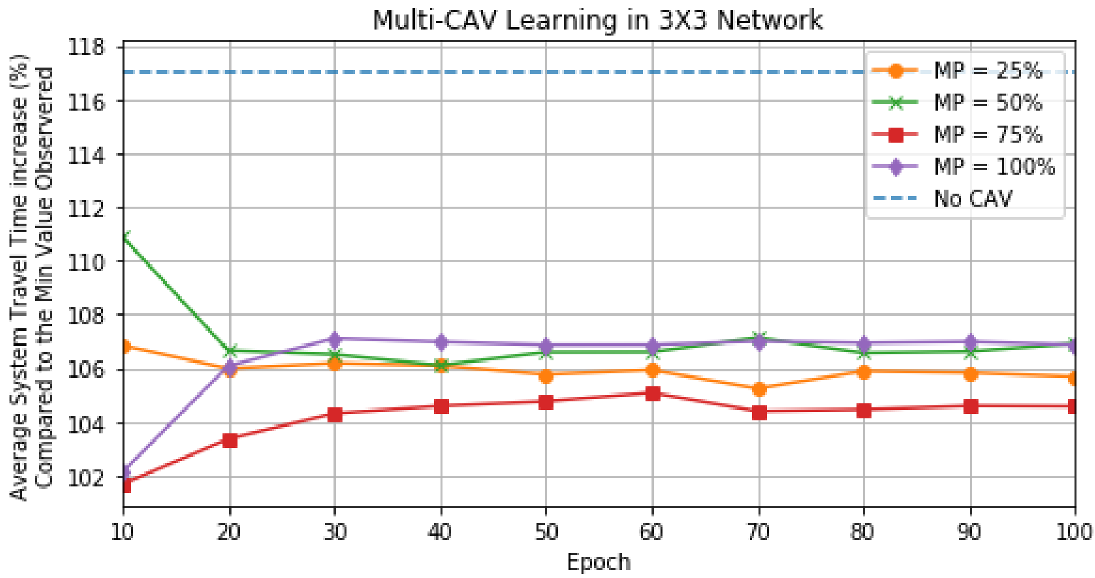
(a) 0.1-Greedy (b) 0.5-Greedy (c) 0.9-Greedy

Figure 4.6: Final optimal routes

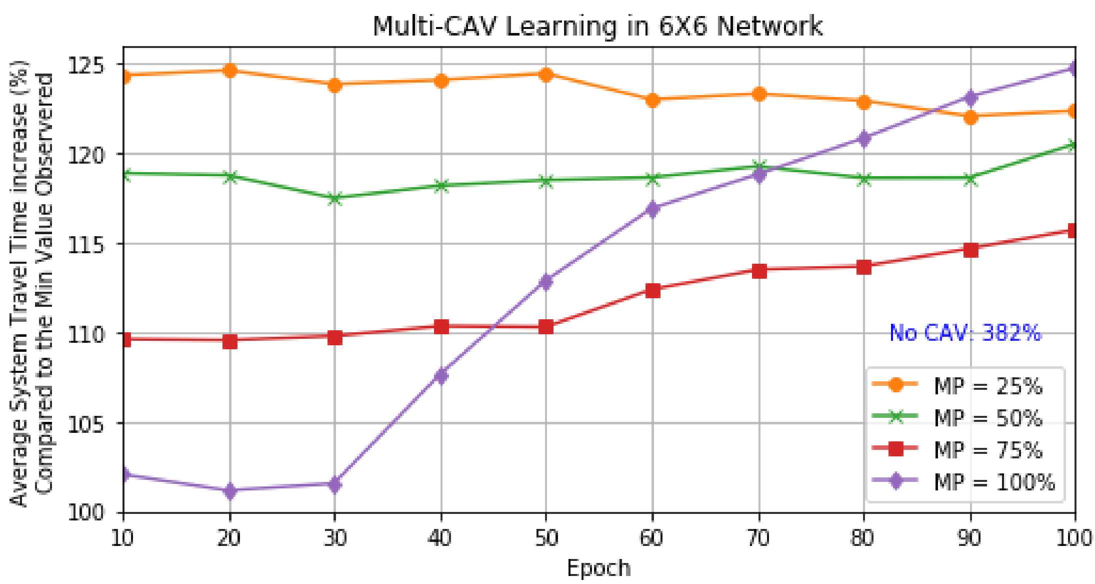
## 4.5 Multi-CAV Learning Results

To assess the performance of the Multi-CAV learning process, we analyzed the average system travel time as a function of learning procedure (epoch) for different CAV market penetration. Figure 4.7 shows the average system travel time increase (%), over the minimum system travel time observed over the course of simulation, which incorporates all the vehicles in the network (CAV and Non-CAV). To assess the impact of network size and how the system scales, we presented this performance for two network sizes of $3X3$ and $6X6$. Interestingly, looking at the results for a $3X3$ network shown in Figure 4.7a, the system performance converges to the minimum average travel time when the $MP = 75\%$. The fact that $MP = 100\%$ does not improve the system performance under this learning environment shows the deficiency of the learning-based methods in multiagent domains with high number of agents. Moreover, it can be seen that the learning deteriorates the system performance for $MP$ of 75% and 100%, as the system travel time increases with learning. This suggests that the random routing behavior that is practically the start of learning yields a lower overall network travel time. On the other hand, the system performance for a $MP$ of 25% or 50% intelligent agents improves over simulation time. Therefore, it is reasonable to conclude that there exists a critical threshold between 50% and 75%, above which the system performance deteriorate, and below which the system performance improve over the simulation horizon.

Previous studies have attempted to alleviate the issue of learning without communicating (Sen et al., 1994; Schaerf et al., 1994), however, most of these studies work with low number of agents, often less than 10 (Bu et al., 2008). In addition, this suggests that as the number of intelligent agents increase, a convergence to the optimal solution becomes harder or even impossible. This is due to the fact that when all of the agents are trying to optimize their utility function with conflicting interests, reaching an optimal solution is becoming infeasible (Claus and Boutilier, 1998; Panait and Luke, 2005). In this case, having 100% of intelligent agents is even worse than all other three different scenarios ($25 \leq MP \leq 75$). However, it has to be noted that this does not mean that introduction CAVs into the system is not beneficial. Note the difference between the average system travel time when $MP = 100\%$ (118% Travel Time Increase) and $MP = 25\%$ (106% TTI).




(a) $3X3$ network




(b) $6X6$ network

Figure 4.7: Average travel times for different percentage of intelligent agents

Similar patterns are observed from the experiment with higher network size, $6X6$, shown in Figure 4.7b. It can be seen that the performance of a fully CAV penetrate system deteriorates as learning goes on, to the point that it even gets worse than the system with $MP = 25\%$. The results also show that it takes about 4 times longer for a larger system to converge, as the state-space action increases exponentially with increase in the network size. This longer convergence time is also partially due to complexities added as a result of the stochasticity in the policies that depend on the policy of the other agents (Scerri et al., 2006). One other interesting observation is the substantial improvement in the 6X6 network travel time compared to the case with no CAV (382%) which is significantly more than the same impact in a smaller network. This suggests that in the effects of CAVs are more discernible in large-scale deployment.

## 4.6 Conclusion

In this chapter, a CAV learning algorithm is proposed to optimize the shortest path for the these vehicles and to optimize the system travel time under the limitation that CAVs are unable to communicate with each other or the infrastructure at any capacity. It is assumed that CAVs are *smart* in the sense that they can *learn* the shortest path to their destinations, only based on their previous experiences. Non-CAVs on the other hand do not change their route throughout the simulation horizon. A Q-learning algorithm with eligibility trace is applied for the CAVs to learn the optimal shortest path within a grid network. At first, the algorithm was applied to a single CAV learning environment, during which different coefficients have been evaluated, analyzed, and tuned based on their impact on the algorithm's performance. Secondly, the learning algorithm is implemented in the Multi-CAV systems with different CAV market penetration. Although significant improvements were observed in terms of system travel time with the introduction of CAVs into the transportation network, the results revealed that as the percentage of CAVs increases, it is more difficult to converge to the optimal solutions (Yu et al., 2015). It can be explained that when all of the agents are trying to optimize their utility function in a competitive system with competing goals, reaching an optimal solution is not feasible. This theory is in line with previous studies on similar subjects (Bu et al., 2008; Tumer et al., 2002). In addition, this study found that the there is a critical threshold of market penetration at which the final converged total travel times reaches its minimum. The results of competitive learning environment in this study suggest that the scope of the threshold would lie between 50% and 75%, above which the system deteriorates with learning, while below which the system improves over the simulation horizon. This further validates the fact that increasing percentage of CAVs does not necessarily improves the performance of the system, and to our surprises, the system travel time converges to the minimum observed value at market penetration of 75%.

The findings of this chapter reveals that proper coordination between the CAVs relies on a robust communication system and proper information sharing capabilities for this ever-changing technology. This chapter is a motivation to study such systems under different levels of communication capabilities and to develop algorithms and procedures to reach a social optimal state and minimize the transportation network travel time, which will be the focus of the next two chapters of this dissertation.

# Chapter 5: On the Impacts of Minimal Information Sharing on Connected and Autonomous Vehicle Routing Optimization: Percolation Phenomenon in CAV Networks

## 5.1 Introduction

This chapter introduces a multiagent approach, coupled with percolation theory and network science, to measure the mobility impacts (i.e., mean travel time of the system) of minimal information sharing over the connected and autonomous vehicle (CAV) network at varying levels of CAV market penetration. It is assumed that CAVs share their location and travelling speed with the other CAVs in their communication cluster, and this information is used by the CAVs to find the current shortest path to their destination at each stage in the trip and reroute accordingly. The characteristics of a CAV network, i.e., node degree distribution, vehicular clustering, and giant component size were captured to verify the existence of percolation phenomenon, and further connect the emergence of mobility benefits to the percolation phase transition in the CAV network. The results show that the percolation phase transition properties appear in a dynamic CAV network with time-correlated link and node dynamics. An analytical framework was developed to evaluate the CAV network attributes with varying market penetrations (MP) and connection ranges (CR) to identify percolation phenomenon in a mixed CAV and Non-CAV environment. In addition, a multiagent CAV simulation platform was created to further measure (1) how varying MPs and CRs affect the network-wide mobility measured by the mean travel time of the network; and (2) when percolation transition occurs in CAV network to capture the critical MP and CR. Percolation phenomenon in CAV network was further validated with the analytical assessments. The results show that (1) percolation phase transition phenomenon is a function of both market penetration and communication range; (2) percolation phase transitions in both mobility and CAV network are highly correlated; (3) the application can reduce the average travel time of the system by up to 20% with reasonable market penetration and communication range; (4) critical market penetration is sensitive to communication range, and vice versa; (5) at least 70% of the CAVs on the network are required to show in the same cluster for mobility benefits to appear; and (6) for high levels of MP or CR, a low probability of connectivity (PC) does not dramatically change the mean travel time. These results provide solid supports to create evidence-driven frameworks to guide future CAV deployment and CAV network analysis.

The rest of this chapter is organized as follows. Section 5.2 shows the development of the multiagent CAV simulation platform in NetLogo (Wilensky and others, 1999), and describes the simulation settings and modeling procedures. In Section 5.3, the different components and the details of the analytical formulation is discussed. Section 5.4 presents the analytical and simulation results, and compares the outcomes of two methods. Section 5.5 and 5.6 provide a discussion and conclude with the major findings. Throughout this chapter, I used abbreviations for frequently used variables as summarized in Table 5.1.

Table 5.1: List of abbreviations

| **Variable** | **Notation** | **Explanation** |
|---|---|---|
| Market Penetration | MP | The percentage of the CAVs |
| Communication Range | CR | The radius that a CAV's connection can reach |
| Mean Travel Time | MTT | The average travel times of all the vehicle |
| Giant Component Size | GCS | The relative size of the largest cluster |

## 5.2 Multiagent CAV simulation platform

This section presents the development of a CAV modeling and simulation platform through an agent-based modeling environment. The simulation setting, algorithm, and behavior of CAVs are further discussed to explain the system dynamics through an iterative Monte Carlo simulation framework.

### 5.2.1 Simulation network setting

A $4 \times 4$ square lattice with 400 vehicles were considered in this chapter, in which the MP of CAVs is increased from 0% to 100%. On top of the MP, the CR also varies, which governs the dynamics of CAV clustering, and the shared information cloud that CAVs will use to optimize their routes to destinations. The information cloud is formed via DSRC system with the flooding-type information transmission strategy as experimented by Talebpour et al. (2016). It is worth noting that it is not the main focus of this study to analyze different communication and networking protocols, as the main contribution is to assess the impacts of vehicle-to-vehicle communication on mobility benefits. It is expected that advancements in network technology or new communication protocol will overcome the communication interference in the near future. Despite this, since there have been studies suggesting that physical barrier and frequency interference would lead to signal and information loss (Talebpour et al., 2016), a scenario considering the probability of connectivity (PC) is also conducted in this chapter.

The scenario replicates a morning peak commute in a small network with the size of 6000ft $\times$ 6000ft where origins and the destinations of the vehicles are uniformly distributed to the arrival and departure intersections on both sides of the network, as shown in Figure 5.1. There are 100 agents in each origin heading to one of the destinations. The simulation reflects a transportation network in between residential area and central business district. Thus, the origins and destinations are in fact pseudo ODs, mimicking where vehicles enter and exit the portion of the network that is being simulated. Therefore, this grid network can also be considered as a subnetwork of a larger regional transportation network. Accordingly, the assumption of origins and destinations on either side of the network leads to an approximation of a real scenario. The north-south links are bi-directional, and the east-west links are uni-directional towards the destinations.

Based on the origins, destinations, uniformly distributed travels, and given the routing algorithm for the conventional vehicles show in figure 5.1, the traffic is concentrated towards the middle right side of the network. As shown in black color, almost 40% of the vehicles use the east-west links on the right side of the

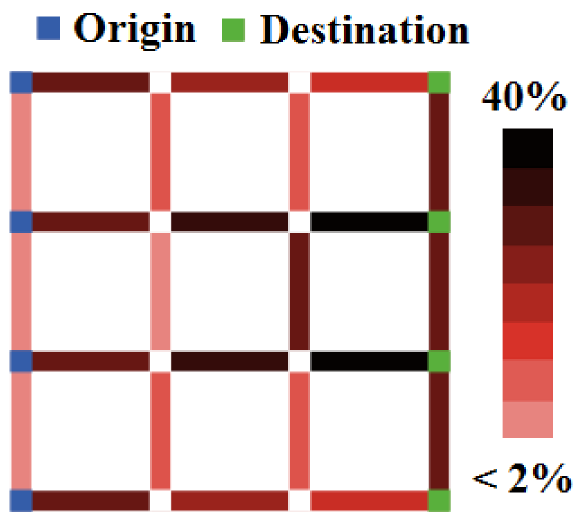



Figure 5.1: Schematic transportation network and routing behavior.

network. On the other hand, north-south links, especially on the left side of the network are used less often, knowing that less than 2% of the vehicles travel on them.

A small lattice network is chosen primarily to reduce the computational intensiveness in the agent-based modeling platform. Specifically in the case of routing optimization, allowing all the agents running on the network with a realistic car-following model is computationally expensive. Replicating a large network increases the routing algorithm runtime exponentially to a point that the simulation is no longer computationally feasible based on the accessible resources. Using a small network made it possible to replicate the congestion dynamics of the mixed traffic flow. In addition, the simulation replicates an arterial grid network with a block size of 2000ft. Although larger network would be preferred, and adds additional validity to the simulation results, It was found that the dependency of the CAV network on the transportation network size and shape will not shift the magnitude of simulation results dramatically. Thus, changes in the transportation network size will have minimal impacts on the CAV network and its associated attributes. The CAV network size is mostly governed by the MP of CAVs and CR which is explained as a fraction of the block size. Thus, based on the aforementioned reasoning, I believe that a larger transportation network will result in similar outcomes from the CAV Network point of view.

### 5.2.2 Simulation environment and parameters

The simulation environment was coded in NetLogo (Wilensky and others, 1999), which is a widely used agent-based modeling and simulation platform (Wang et al., 2016). Vehicle movements are bounded by a maximum driving speed of $v = 35$ mph. The speed of each vehicle is governed by $5^{th}$ generation general motors car-following model with the parameters presented in Table 5.2 and the formula shown in Equation 5.1, which would lead to a realistic model of congestion propagation over the network.

$$a_{n+1}^{t+\delta t} = [\frac{\alpha_{l,m}(v_{n+1}^{t})^{m}}{(x_{n}^{t} - x_{n+1}^{t})^{l}}](v_{n}^{t} - v_{n+1}^{t}) \tag{5.1}$$

Parameters described in Table 5.2 lead to the Greenshield's speed-density relationship. The $\alpha$ is estimated with the assumption of $K_j = 210$vpm (jam density) and $V_f = 30$mph (free-flow speed). Vehicle arrival in the network follows a Poisson distribution with parameter $\lambda = 720$ veh/hour. As a result, the vehicle headway

Table 5.2: Car-following model parameters

| Parameter | Notation | Value |
|---|---|---|
| Distance Headway Exp. | $l$ | 2 |
| Speed Exp. | $m$ | 0 |
| Perception-Reaction Time | $\delta t$ | 0 |
| Sensitivity Coef. | $\alpha$ | 0.14 |

follows a negative exponential distribution with $\mu = 5$ seconds.

### 5.2.3 Routing algorithm and behavior

Routing decision is the major task of communication in the CAV network. Each equipped vehicle optimizes the fastest route using the $A^*$ algorithm (Hart et al., 1968), with regard to the travel time information of the CAVs in its communication cluster. While all the non-CAVs follow the predefined diagonal route to their destinations, mainly due to the fact that the commuters that are traveling within the same OD pair, are most likely to choose the same route. The routing algorithms for both CAVs and non-CAVs are discussed hereafter.

#### 5.2.3.1 Non-CAV routing behavior

As the non-CAVs have no information regarding the travel time of the links in the network, either congested or uncongested state will not change an individual routing, even if they will use the fastest path algorithm, since in the lattice there are multiple routes with the same Manhattan distance between each pair. Therefore, all the non-CAVs, choose their routes depending on only their origin and designation based on the following equation:

$$\text{Shortest Route} = \begin{cases} \overbrace{R....R}^{(4-d_y)}\overbrace{RU..RU}^{d_y} & d_y \geq 0 \\ \underbrace{R....R}_{(4-|d_y|)}\underbrace{RD..RD}_{|d_y|} & d_y < 0 \end{cases} \tag{5.2}$$

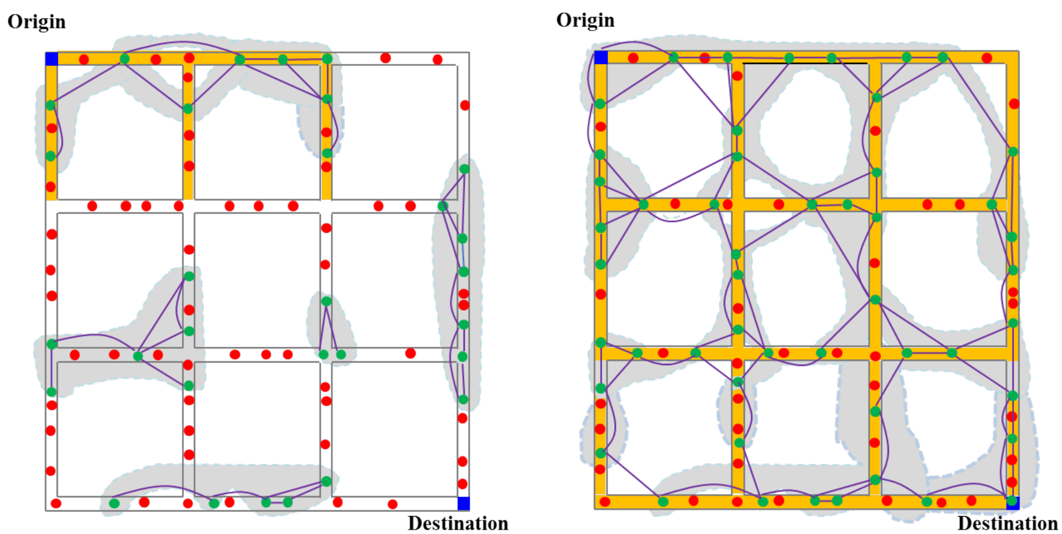
Where $d_y = Y_{\text{Desination}} - Y_{\text{Origin}}$ and R, D, and U represent the direction of movement in sequence.

Considering the routing behavior for Non-CAVs, formulated above, Figure 5.1 shows the traffic demand exposed to the transportation network in a scenario when there is no CAV in the network. It can be seen that the traffic is more concentrated towards the middle right of the network. At the same time, there exist quite a few links that are highly underutilized. Therefore, the route distribution in the hypothetical network is extensively insufficient, mostly due to the concentration of traffic as it happens in a real transportation network with similar demand patterns as well.

#### 5.2.3.2 CAV routing behavior

The exchange of travel time information within connected CAV clusters through V2V communication will inform an individual routing decision-making behavior and facilitate the use of available road network capacity (Jia and Ngoduy, 2016). The formation of CAV clusters is highly dependent on the CR and geo-location of the CAVs over the network, which is mainly governed by MP and the demand pattern. Therefore, different combinations of MP and CR result in distinct network dynamics and clustering behavior (i.e., cluster size and distribution). Figure 5.2 and 5.3 schematically show the formation of clusters under varying combinations of CR and MP. To measure the benefits of connectivity and information-sharing among CAV clusters, it was assumed that CAVs share their individual speed and travel time information within their CAV cluster. The average speed of CAVs traveling on the same link is used to estimate the travel time of that link, which is ultimately used for route optimization by the CAVs in the cluster. Although estimating the link travel time solely based on the average speed of CAVs on the link might not be accurate due to the presence of congestion pockets, the results of this study show that this is not necessarily true, as mobility benefits were emerged in the results even with this simplistic prediction model.

However, it is rather common that the travel time of some roadway links are unknown, namely partial information of the network are provided. Therefore, the problem of optimization under partial information arises. The results from this study have shown that partial information lattice path optimization will not generate significant mobility benefits or travel time decrease. The reason is that there is hardly any reliable way to predict the travel time of the missing link. For instance, it can be either fully congested with non-CAVs, or empty. In both cases, there will not be any information regarding the link travel time. However, the speed of the link is zero and free-flow speed respectively. These uncertainties lead to failure in proper fastest path optimization. In other words, fastest path algorithm under partial information does not practically produce an optimal solution, even with the use of heuristic methods to estimate the travel time of the missing link. Figure 5.2 presents two hypothetical cases of partial and complete information. Low market penetration or short connection range tends to yield partial information scenarios in a network.




(a) Partial information

(b) Complete information

Figure 5.2: Partial information vs. Complete information.

Figure 5.2 explains the difference between partial and complete information cases. For example, in this case, and based on these set of origin and destination, the entire network travel time information is desired for a CAV to make an informed routing decision. Green dots represent the CAVs and red dots show the non-

CAVs. Highlighted roadways are the ones that are covered by the CAV cluster, and therefore the travel time information will be shared with the cluster members. (a) replicates the case that $MP = 30\%$, and although a CAV is connected to a cluster of CAVs, the cloud does not cover the area of interest, and thus, it is less beneficial in terms of route optimization. On the other hand, (b) shows a rich CAV network, where $MP = 50\%$, that covers all of the links. The shared information among this cluster will be used for routing decisions.

In the simulation setting, each CAV updates its route using $A^*$ algorithm at every intersection based on the available information (i.e., current location, destination, and the cluster information cloud) to find the fastest path. Therefore, the dynamics of the clusters and information cloud enable CAVs to update and search for the fastest route at each intersection. It is of note that the modeling of the message communication protocols was not the focus of this work, and thus simplified. It was assumed that messages can be uploaded to the information cloud, and be circulated through the cluster in minimal or negligible time. However, as mentioned before, in order to demonstrate the impacts of signal loss on mobility, a case study is conducted to illustrate the impact of the probability of connectivity. Moreover, since the information is used for route choice when a CAV reaches an intersection, the usage of the information is thus not very frequent.

### 5.2.4 CAV network connectivity

MP and CR are the two major variables that characterize the network connectivity of CAVs. As discussed, the presence of CAVs in the network does not generate mobility benefits by itself. Travel time benefits of CAVs is largely driven by rich connectivity that facilitate prevalent information sharing required for route optimization. Figure 5.3 shows the dependency of the number of CAVs that have complete information on MP and CR. It was found that higher MP or larger CR alone are not particularly effective to generate a CAV network with sufficient amount of information coverage. Instead, the combination of both is required to achieve the desired benefits. In other words, only when MP is high and CR is large, the CAV network will be richly connected, and that's when significant mobility benefits appear.

In Figure 5.3, the orange dots represent the Non-CAVs, and the blue dots show CAVs with partial or no information. Green dots on the other hand show CAVs that have complete and necessary information to optimize the fastest route to their destinations. The connectivity between two vehicles is represented by a light magenta-colored link, depending on the corresponding CR. When $CR = 0.25$, it can be observed that even with MP = 100%, the number of cars with complete needed travel time information is minimal. Therefore, market penetration cannot achieve desired mobility benefits by itself. Analogously, when MP = 20%, even CR = 1.0 does not lead to great increase of CAVs with proper information. As both MP and CR go higher, high percentages of fully informed CAVs will start to

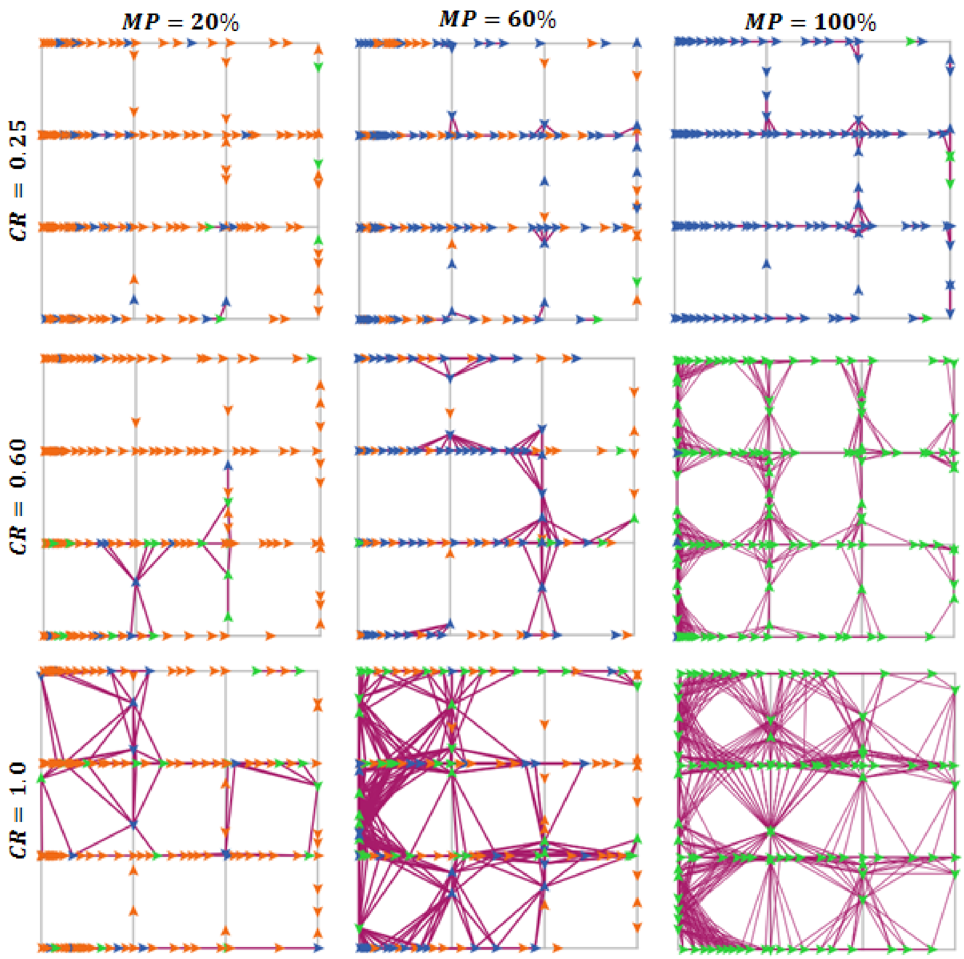



Figure 5.3: The impact of CR and MP on connectivity.

appear, which lead to optimal route decision, and thus lower travel times.

### 5.2.5 System dynamics

An integrated agent-based modeling, using NetLogo, and Monte Carlo simulation approach, through RNetLogo (Thiele, 2014), is used in this study to evaluate the emergent collective behaviors and patterns, and to capture stochasticity of the simulation. Varying MP from 0 to 100 and CR from 0.25 to 1.0 block size (1 block = 2000 ft), each simulation setting has been iterated for 100 times. At the end of each run, the following information have been recorded for further assessment.

- Mean travel time of the system
- Degree distribution of the CAV Network
- CAV cluster size distribution
- Giant component size of the CAV Network

The aforementioned data is used to interpret the relativity of CAV Network characteristics to mobility benefits in terms of the MTT of the system. In addition, CAV network characteristics are dynamic throughout each simulation run. As shown in Figure 6.3, the network attributes vary dramatically from the beginning of the simulation when the vehicles enter the network to the end when vehicles leave the network. In order to provide an accurate estimation of the vehicle connection, the first and last 5 minutes are eliminated. That is to say, the data is collected through a fully-loaded network, truncating loading and unloading phases. The average of the truncated attributes (e.g., mean cluster size and giant component size) over the simulation period is used to estimate reliable CAV network characteristics that are static representatives of the underlying dynamic network. Next section is dedicated to analytically deploy percolation theory on the simulated CAV network to have a benchmark to validate simulation results further in the chapter.

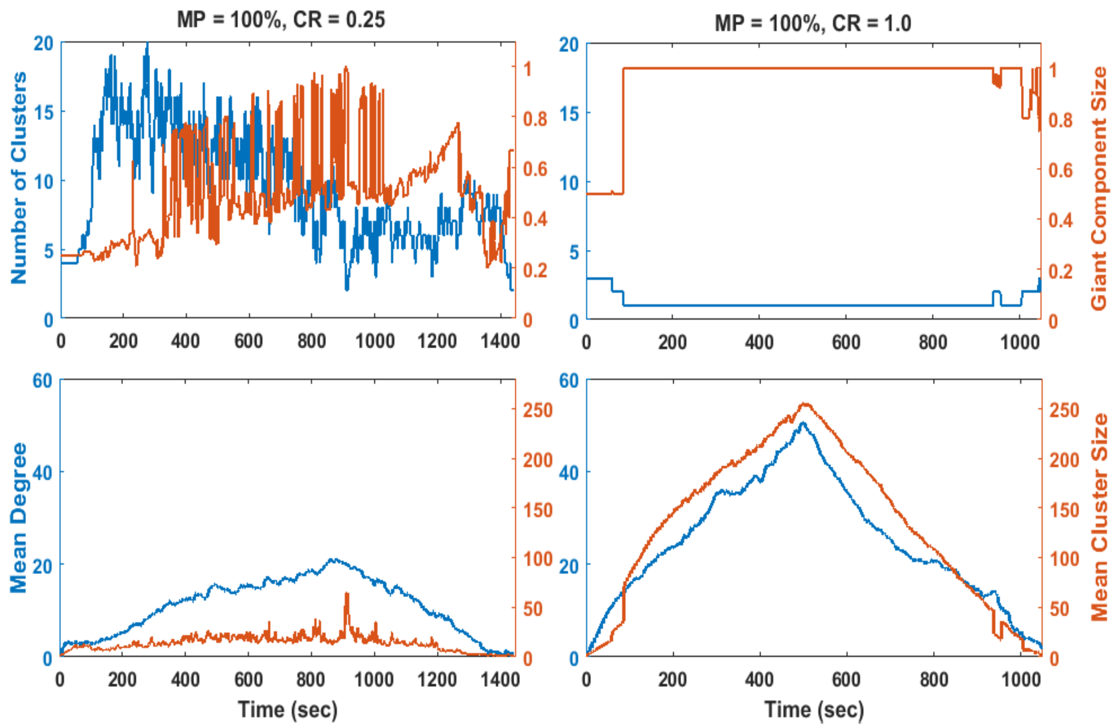



Figure 5.4: Simulation dynamics.

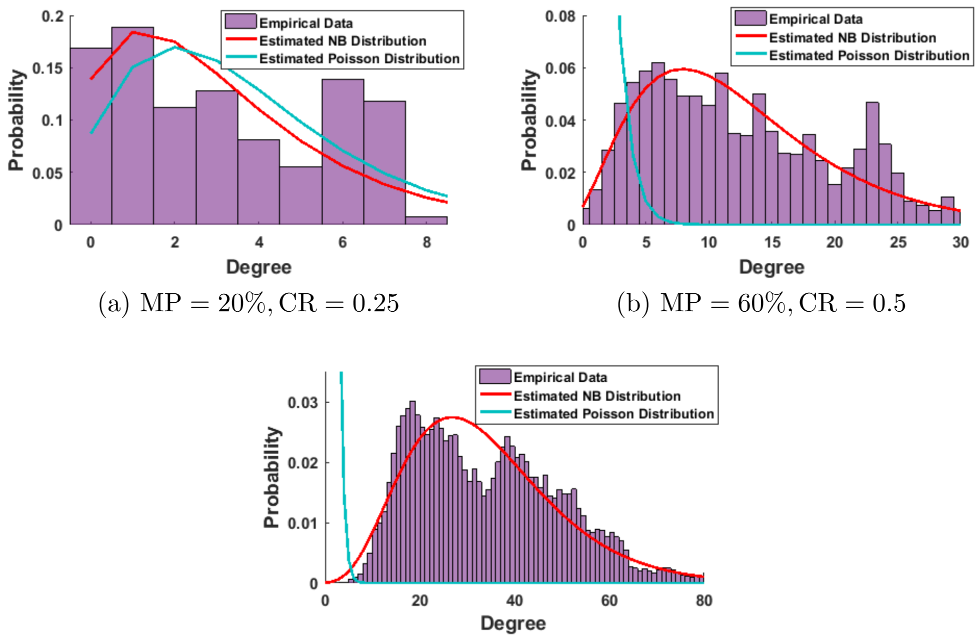
As observed in the Figure 6.3, in the first row, the blue curve represents the number of clusters, and orange curve delineates the size of the giant component (cluster). In the second row, the blue curve shows the mean degree (average number of communication links) of the CAVs on network at each second, and orange curve describes the mean cluster size of the simulation. At MP = 100%, different simulation behaviors exist under different CRs. Comparing the number of clusters between CR = 0.25 and CR = 1.0, the number of clusters fluctuates around 10 and giant component size never goes up to 1. As CR gets higher, the number of clusters get lower and giant component size stays at 1. That is because when the CR is larger, vehicles are more connected, and they form a giant component. Similarly, as CR increases, a CAV can reach out to more other CAVs, which leads to the larger mean degree and mean cluster size. It also suggests that throughout the simulation, mean degree and mean cluster size are constantly changing. As the network is loading, they both increase, and after the network is fully loaded, around 500 seconds, they both decrease while unloading the network.

## 5.3 Analytical formulation

This section presents the essential components of the proposed integrated approach combining network science (Gao et al., 2013, 2015), percolation theory (Grimmett, 1999), and percolation in a dynamic connected vehicle network (Jin et al., 2011b,a).

### 5.3.1 Degree Distribution

The mixed driving environment can be viewed as a graph containing two types of nodes: CAV and non-CAV. Within the connection range CR, CAVs can detect other equipped vehicles and exchange the essential travel information, while the non-CAVs are separated. In Figure 5.5, the histogram represents the collected simulation data on the distribution of node degrees in the CAV network. The red curve is estimated Negative Binomial distribution plotted by using the estimated $r, p$. The blue curve is estimated Poisson distribution plotted by estimated $\lambda$.



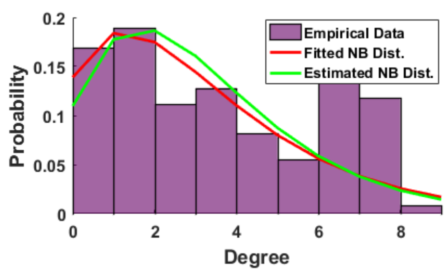

(a) MP $= 20\%$, CR $= 0.25$

(b) MP $= 60\%$, CR $= 0.5$

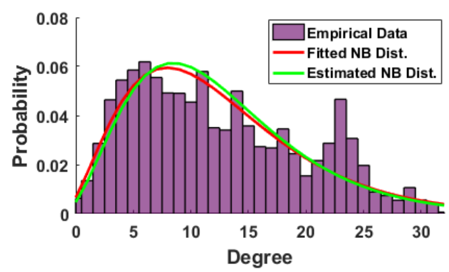
(c) MP $= 100\%$, CR $= 1.0$

Figure 5.5: Degree Distribution Fitting Comparison.

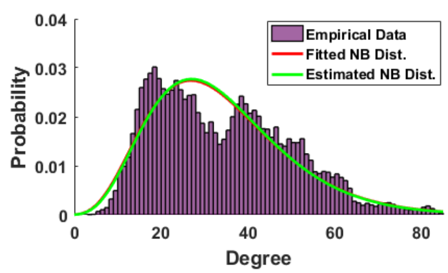
Existing research have investigated the degree distribution of connected vehicle networks in highway settings. For example, Nagel (2010) investigated the degree distribution under different following distances. Akhtar et al. (2015) characterized the VANET topology over time and space for a highway scenario, and presented the node degree in different channel models. However, degree distribution in network scenarios is inadequate. Therefore, in this research, a simulation based technique is adopted to capture the degree distribution on a grid transportation network. The degree distribution of three sampled CAV networks throughout the simulation with different MPs and CRs are summarized. Different discrete distributions are fitted to the empirical data and plotted in Figure 5.5. The shape of the node degree distributions is similar to the results in Meireles et al. (2009). Fiore and Härri (2008) also tested the impact of road layout on activity patterns. It was found that the node degree distribution from Fiore and Härri (2008) also resembles a bimodal distribution as shown in the Figure 5.5. Clearly, Negative Binomial distribution fits the empirical data the best. This can also be concluded by comparing the Akaike information criterion (AIC), Bayesian information criterion (BIC), and Negative Log likelihood. In addition, the fitted and estimated Negative Binomial distributions are plotted in Figure 5.6. Fitted curve is directly generated from the simulation data, while the estimated curve is plotted through the distribution with the estimated $(r, p)$ based on the simulation data. Through the investigation of the fitted (red) curve, among discrete distributions, namely Poisson and Binomial distributions, it was found that the degree distribution of the CAV network follows a Negative Binomial distribution NB$(r, p)$. In order to estimate the distribution parameter with empirical data, degree information, i.e. mean ($\mu$) and variance ($\sigma^2$), are collected throughout the simulation at different simulation settings. Based on the theoretical formulation $\mu = \frac{r(1-p)}{p}$ and $\sigma^2 = \frac{r(1-p)}{p}$, for each MP and CR, the corresponding $(r, p)$ can be therefore estimated. The green curve shows the estimated NB distribution, and it can be seen that the result fits the fitted curve well at high MP and wide CR scenarios. That is because NB distribution can describe the degree distribution when the sample variance ($\sigma^2$) is larger than the mean ($\mu$). When the MP is low, the standard deviation of degrees is low (Figure 5.8b). Despite NB distribution is limited in the case of low variance, it is still the best fit among various discrete distribution. In addition, when MP is lower, the degree range is narrower, and thus, the mean will be smaller as well. This generates a variance which is less likely to be greater than the mean. However, when the degree range goes up to 80 ($\mathrm{MP} = 100,\ \mathrm{CR} = 1.0$), variance will be larger than mean. This yields a better approximation of the NB in higher MPs. In Figure 5.6, the histogram represents the collected simulation data. The red curve is fitted negative binomial distribution based on the shape of the histogram. The green curve is plotted by using the parameters estimated via the mean and variance of node degree.




(a) $\mathrm{MP} = 20\%, \mathrm{CR} = 0.25$




(b) $\mathrm{MP} = 60\%, \mathrm{CR} = 0.5$




(c) $\mathrm{MP} = 100\%, \mathrm{CR} = 1.0$

Figure 5.6: Degree Distribution.

Therefore, the probability that a randomly chosen CAV connects to $k$ other CAV follows a negative binomial distribution as below,

$$p_k = \begin{pmatrix} r+k-1 \\ k \end{pmatrix} p^r(1-p)^k \tag{5.3}$$

Empirically, $k$ can be interpreted as the number of successes, $r$ is the number of failures ($r \in \mathbb{R}$. In theoretical sense, they can be real numbers to more accurately carve the distribution), and $p$ is the probability of success. In this complex problem, the empirical data was utilized to identify the best-fit distribution. Therefore, in the context of percolation in connected vehicle network, $(r, p)$ serves as shape parameters to describe the degree distribution information of the different clusters.

### 5.3.2 Generating function

Given a network, the probability that a randomly chosen node from the network that has degree $k$ is $p_k$. The generating function for this probability distribution $p_k$ is,

$$G_0(x) = p_0 + p_1x + p_2x^2 + p_3x^3 + \cdots = \sum_{k=0}^{\infty} p_kx^k \tag{5.4}$$

The average degree $z$ of a node can be calculated by,

$$z = \langle k \rangle = \sum_k kp_k = G_0^{'}(1) \tag{5.5}$$

The $G_0(x)$ encapsulates all the information contained in the probability distribution $p_k$. Say $G_0(x)$ "generates" the probability distribution $p_k$ (Newman, 2010).

Following by a randomly chosen edge, the node at either end of the edge has degree $k$ with a probability proportional to $kp_k$. It is because there are $k$ times as many edges connected to a node of degree $k$ than to a node of degree 1. This is called the excess degree of the node. The probability $q_k$ of having excess degree $k$ is,

$$q_k = \frac{(k+1)p_{k+1}}{\sum_k kp_k} = \frac{(k+1)p_{k+1}}{z} \tag{5.6}$$

Therefore, another generating function $G_1(x)$ can be represented as,

$$G_1(x) = \sum_{k=0}^{\infty} q_k x^k = \frac{1}{\langle k \rangle} \sum_{k=0}^{\infty} (k+1)p_{k+1}x^k = \frac{G_0'(x)}{G_0'(1)} = \frac{G_0'(x)}{z} \tag{5.7}$$

Suppose $k$ follows the negative binomial distribution with parameter $(r, p)$, the corresponding generating function would be,

$$G_0(x) = \sum_{k=0}^{\infty} p_k x^k = p^r(1-(1-p)x)^{-r} = (\frac{p}{1-(1-p)x})^r \tag{5.8}$$

According to the generating function's feature,

$$G_1(x) = \frac{G_0'(1)}{z} = \frac{rp^r(1-p)}{[1-(1-p)x]^{r+1}} \times \frac{p}{r(1-p)} = \left(\frac{p}{1-(1-p)x}\right)^{r+1} \tag{5.9}$$

$G_0(x)$ and $G_1(x)$ are used to calculate the mean degree distribution of the network and the GCS. The empirical results suggest the degree distribution of dynamic CAV network follows a negative binomial distribution. Derivation of $G_0(x)$ and $G_1(x)$ allow us to obtain the giant component size analytically. Different degree distributions have distinctive forms of $G_0(x)$ and $G_1(x)$, Equations 5.8 through 5.9

are detailed procedures to derive the generating function. The same procedure can be applied to calculate generating functions for other types of degree distribution such as Poisson distribution.

### 5.3.3 Percolation process

Consider the mixed CAV network in which some fraction of the nodes are CAV and the rest of them are non-CAV. The percolation process is parameterized by the fraction of the CAV present in the network. When more CAVs are present, the network tends to be more connected. The giant component was defined as the cluster that has the maximum number of connected vehicles. When the percentage of CAV decreases, there exists a transition point where the giant component breaks apart. The point at which the percolation transition occurs is of our central interest, called the critical percolation threshold ($p_c$). The logic behind this is that although small cluster can form in the network, they will not create significant impact to the mobility due to the scarce information they obtained from the network. Only when the cluster size reaches a critical point, namely, percolation threshold, the benefits start to appear. Therefore, the relative size of the giant component to the size of the whole network was used. In order to connect to the giant component, CAV $A$ must be connected to the giant component via at least one of its neighbors. That is to say, $A$ does not belong to the giant component if (and only if) it is not connected to the giant component via any of its neighbors. Define $u$ as the average probability that a CAV is not connected to the giant component through its neighbors. If CAV $A$ has degree $k$, then the probability that it is not connected to the giant component via any neighbors is $u^k$. Hence, the average probability that a node is not in the giant component is $\sum_k p_k u^k = G_0(u) = \sum_{k=0}^{\infty} p_k u^k$. This probability also equals to the $1-S$, where $S$ is the fraction of the CAV that belongs to the giant component (Newman, 2010). Therefore, we have,

$$S = 1 - G_0(u) \tag{5.10}$$

Again, the probability that a CAV is not connected to the giant component via a particular neighboring CAV is equal to the probability that this CAV is not connected to the giant component through any of its neighbors. If there are $k$ of these neighbors, then the probability is $u^k$. Since it connects to a neighboring CAV through an edge, $k$ is following the excess degree distribution $q_k$. Thus, it is formulated as,

$$u = \sum_{k=0}^{\infty} q_k u^k = G_1(u) \tag{5.11}$$

Equations 5.10 and 5.11 provide a complete solution procedure to identify the size of giant component in a CAV network. Analytical giant component size with respect to theoretical NB$(r, p)$ is illustrated in Figure 5.7.

Through the collected simulation node degree data, i.e., mean and variance, we can estimate the $(r, p)$ for each degree distribution as a function of MP and CR as explained in earlier Section 5.3.1. This enables us to generate theoretical percolation phenomenon on CAV network associated with different MPs and CRs,

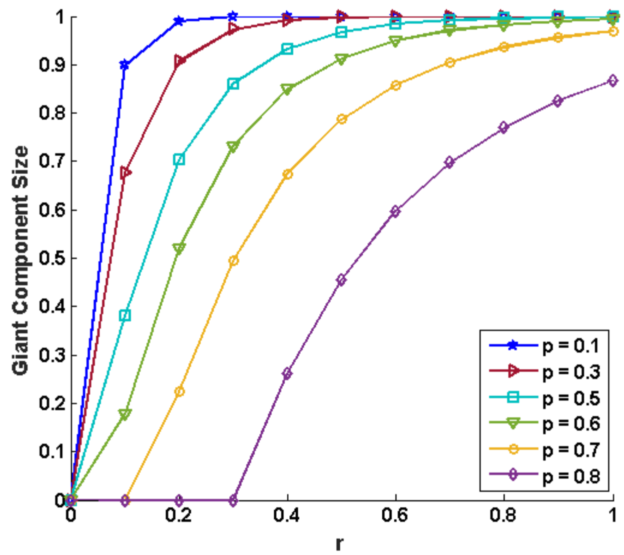


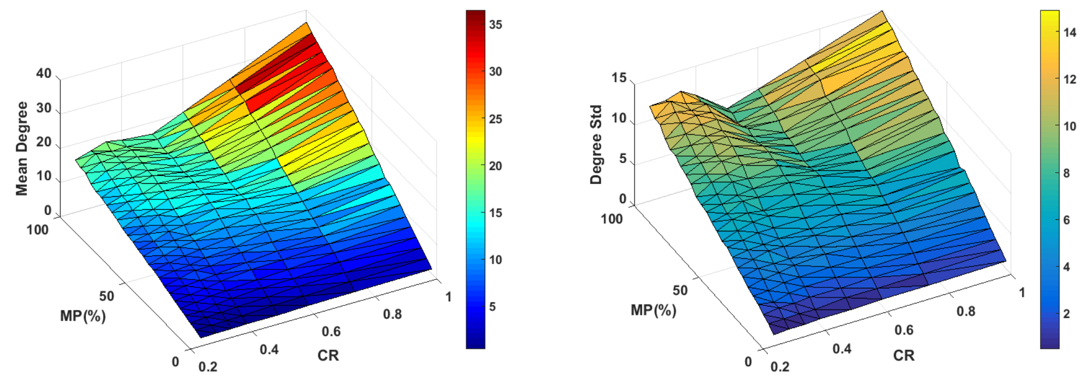

Figure 5.7: Giant component size with theoretical $(r, p)$

and compare the theory with the simulated results, as is shown in Figure 5.14. The next section elaborates on the dependency of CAV network degree distribution on MP and CR as a dynamic network.

### 5.3.4 Dynamic connected vehicle network

Conventional percolation research mainly focuses on empirical networks such as the Internet, power grid etc., and the theoretical network such as ER network (Gao et al., 2013, 2015), random network with power-law or Poisson degree distribution etc (Callaway et al., 2000). However, in a vehicular network, the degree of each node is varying over time. A vehicle network is featured by the movement of vehicles, which creates challenges in modeling the degree distribution of the CAV network. Due to the different destination assignments, a CAV may leave the cluster at the intersection, while others can join the cluster. This behavior further adds complexity to the nodes' degree modeling. Although it is challenging to apply percolation theory to a dynamic network structure, percolation has been applied to dynamical transportation network to detect the bottlenecks on the network (Li et al., 2015a). Furthermore, it can depict the network evolution in the scenario where traffic state is largely static. For example, percolation can be used for planning purpose to create a resilient network under extreme events (Latora and Marchiori, 2005). In this study, a multiagent platform was created to approximate the behavior of the vehicles, and the degree of each node at each simulation step was constantly recorded, and the descriptive statistics are presented in Figure 5.8a and 5.8b. The results show that the mean degree of a CAV is controlled by the corresponding MP and CR. As discussed in Section 5.3.1, the degree distribution is found to follow a negative binomial distribution with parameter $(r, p)$ which can be estimated by the mean and standard deviation of the sample. Figure 5.8 shows the increasing trend in both mean and standard deviation of the degree distribution with the increase in both MP and CR.

CAVs who belong to the giant component are more likely to exchange information to optimize their travel performance. However, there are small clusters of connected vehicles that are not connected to the giant component, but they can still benefit the mobility in varying degrees. This motivates us to study the cluster size and its distribution. As shown in Figure 5.9a, the mean cluster size grows as MP and CR increase. Between 0.3 to 0.5 of CR, the mean cluster size exhibits a

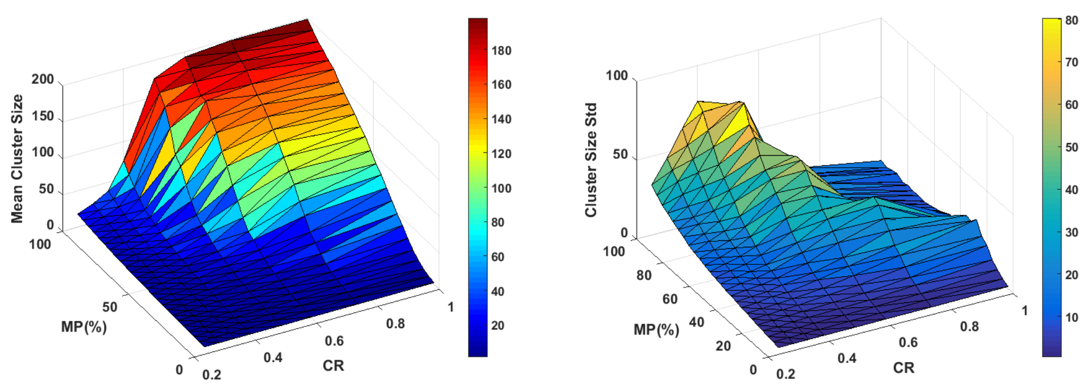



(a) Mean Degree Distribution

(b) Std of Degree Distribution

Figure 5.8: Degree Distribution Parameters

big jump. As the MP and CR both reach the higher end, the mean cluster size tends to be more steady. Figure 5.9b demonstrates the standard deviation of the cluster size. It shows that at the lower and higher ends of CR and MP, the mean cluster size tends to be steady, while the variation is high in the middle.




(a) Mean Cluster Size Distribution

(b) St.d of Cluster Size Distribution

Figure 5.9: Cluster Size Distribution Parameters

To summarize the approach, Figure 5.10 presents the integrated multiagent and percolation theory framework that was created to address this intriguing research question striking the balance between mobility benefits and market penetration. This innovative framework involves verification of GCS observed from simulation with the analytical results. Specifically, the degree distribution computed from the simulation was used to analytically calculate the GCS based on the estimations of CR and MP. Then, the results of GCS from the simulation were verified with the same results from analytical procedure to validate the accuracy of the simulation. Next, the mobility results were drawn from the simulation for further discussion and investigation.

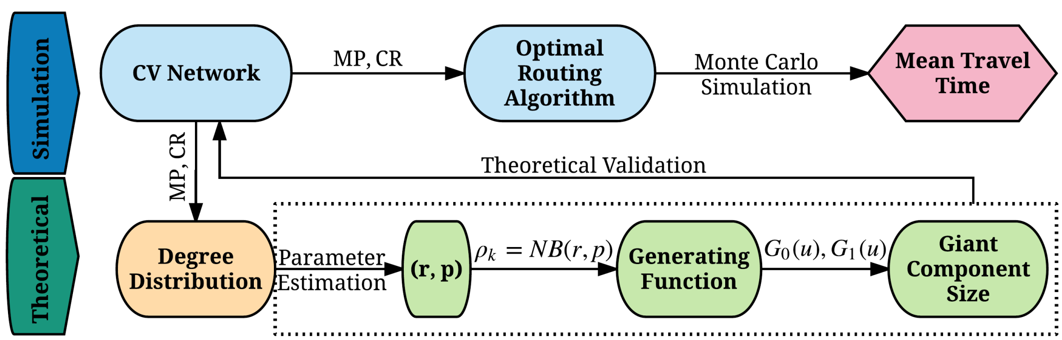



Figure 5.10: Experiment procedure

## 5.4 Results Analysis

This section presents the impacts of market penetration (MP) and communication range (CR) of CAVs on mobility. The results will be coupled with the CAV network characteristics from both simulation and theoretical points of view. Although the results are expected to be robust to changes in size and shape of the transportation network and demand, this work intends to prove the concept that mobility benefits driven by CAV technologies are highly dependent on the CAV network connectivity and its characteristics. Therefore, generalizations should be used with caution. The numbers are presented to better measure the scale in the graphs and results in a quantitative way, not necessarily to define specific threshold values as varying parameters and settings can shift the magnitude of the results. It is of note that the critical percolation threshold could vary when the assumptions and simulation scenarios differ.

### 5.4.1 Mobility Impacts of Market Penetration (MP)

As mentioned earlier, the mobility benefits of CAVs are primarily dependent on both MP of CAVs and CR that they can accommodate. Figure 5.11 shows the variation of mean travel time (MTT) of the system alongside with giant component size (GCS) of the CAV network with changes in MP, for different CRs. These measurements are calculated from the simulation results with the following formula.

$$\text{MTT} = \frac{\sum_{i=1}^{N} \text{Travel Time}}{N} \tag{5.12}$$

$$\mathrm{GCS} = \frac{\max\limits_{j \,\in\, \text{CAV Clusters}} N_j}{N_{\mathrm{CAV}}} \tag{5.13}$$

Where $N$ is the number of cars in the entire simulation window, 400 in this study. $N_j$ is the size of the cluster $j$, and $N_{\mathrm{CAV}}$ is the number of CAVs on the network at the time of recording as explained in Section 5.2.5. As shown in the Figure 5.11, for lower CRs (e.g., CR = 0.3), there is hardly any decrease in MTT, even when MP goes up to 100%. As CR reaches 0.4, MTT starts decreasing when MP goes greater than 70%. The MP that beyond which mobility benefits start to reveal and MTT begins to decrease is defined as the critical market penetration from a mobility perspective, $\mathrm{MP}^{\mathrm{Mob}}_{\mathrm{Critical}}$. For instance, when CR = 0.5, $\mathrm{MP}^{\mathrm{Mob}}_{\mathrm{Critical}} =$ 50%, and for CR = 0.6, $\mathrm{MP}^{\mathrm{Mob}}_{\mathrm{Critical}} = 30\%$. As results show, $\mathrm{MP}^{\mathrm{Mob}}_{\mathrm{Critical}}$ decreases as CR increases, and it gets fairly close to 0 % when CR = 1.0.

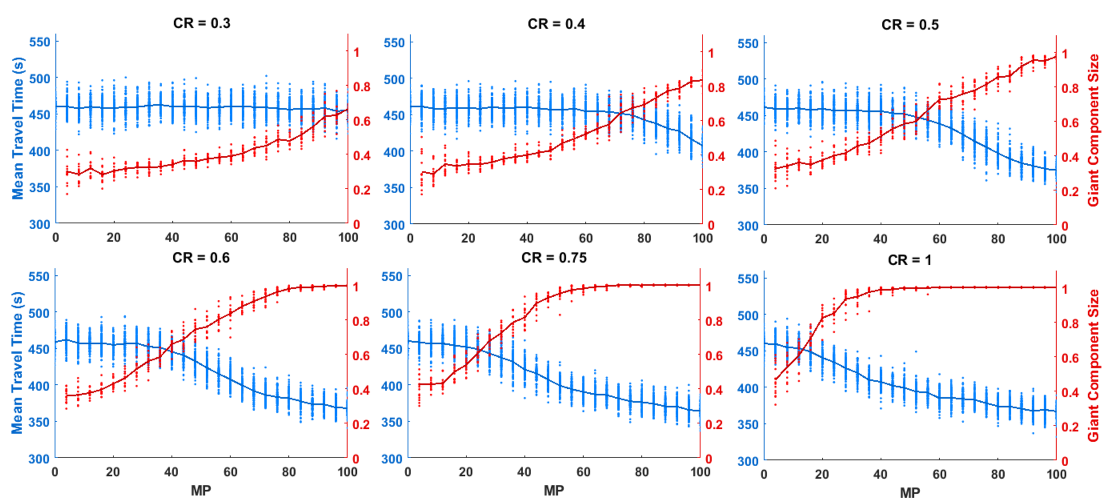



Figure 5.11: MTT and GCS with varying MP under each CR

The blue dots in Figure 5.11 represent the travel time at each run under specified MP and CR. To capture stochasticity, each combination of CR and MP has been run for 100 times, and the average of the MTT is calculated and plotted in blue curve. Analogously, the red dots are the giant component size at each simulation with specific MP and CR, and the red curve represents the mean GCS over the simulation horizon.

At the same time, GCS grows when MP increases, regardless of CR. However, GCS will not reach 1.0 for CRs lower than 0.5, even if MP is 100%. Above CR = 0.5, GCS reaches to 1.0 at a certain point with increasing MP, indicating that all the CAVs on the network have created a giant cluster. In addition, the MP required to achieve the mentioned state, decreases from 100% for CR = 0.5, to 40% for CR = 1.0. The MP at which GCS reaches 1.0 is defined as the critical MP from a network science perspective, $\mathrm{MP}^{\mathrm{GC}}_{\mathrm{Critical}}$. It was found that, for every CR, $\mathrm{MP}^{\mathrm{Mob}}_{\mathrm{Critical}}$ is lower than $\mathrm{MP}^{\mathrm{GC}}_{\mathrm{Critical}}$. The physical interpretation is that the emergence of mobility benefits does not necessarily demand a fully connected network. Rather, a partially connected network can still generate effective information sharing through the cloud. As a result, the exchange and sharing of travel information are central to identify optimal routes and reduce average travel time in the network. Moreover, from Figure 5.11, it was found MTT continues to decrease even after GCS reaches 1.0 while CR is greater than 0.6. This shows that more travel time information is generated and shared in a richly connected CAV network. A significant coverage of the majority of links in a transportation network will enable informative routing decisions.

### 5.4.2 Mobility impact of communication range (CR)

Measuring the impact of CR on both GCS and mobility in terms of MTT is of great significance since it directly corresponds to the design of the technology. Figure 5.12 clarifies the dependency of MTT and GCS on CR, for different levels of MP. For low levels of MP (i.e., under 20%), an increase in CR barely affects the MTT. This is mainly due to the fact that, increasing CR will help farther vehicles to connect to each other. However, what makes a difference in mobility is the travel time information that is circulating in the information cloud. Without sufficient MP, the travel time information is inadequate, and thus, optimal decision is unlikely to be made. As MP reaches 20%, the decrease and the dropping point in MTT starts to appear at a specific MP which is defined as critical CR with respect to mobility in this work, $\text{CR}^{\text{Mob}}_{\text{Critical}}$. For example, $\text{CR}^{\text{Mob}}_{\text{Critical}} = 0.50$ for MP = 20%, and $\text{CR}^{\text{Mob}}_{\text{Critical}} = 0.40$ for MP = 40%, and it keeps decreasing to 0.30 as MP goes up to 100%.

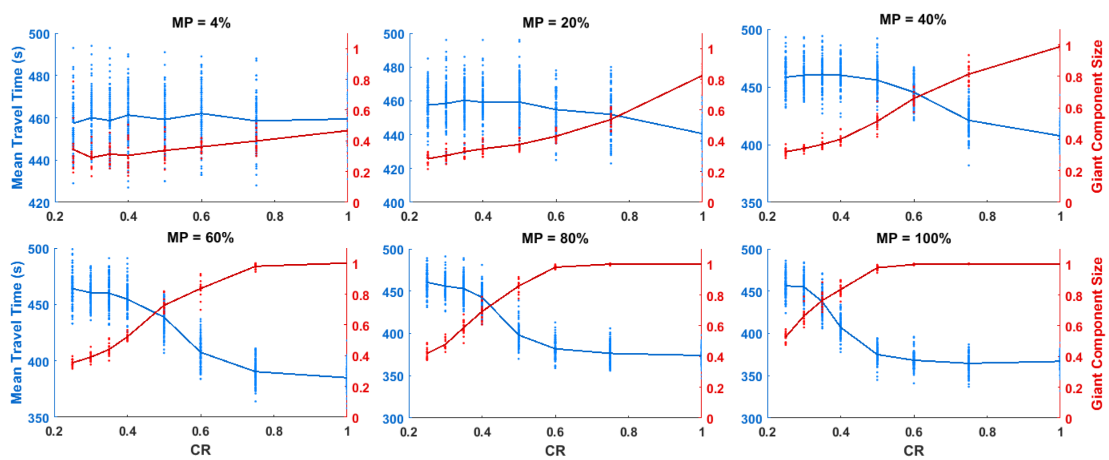


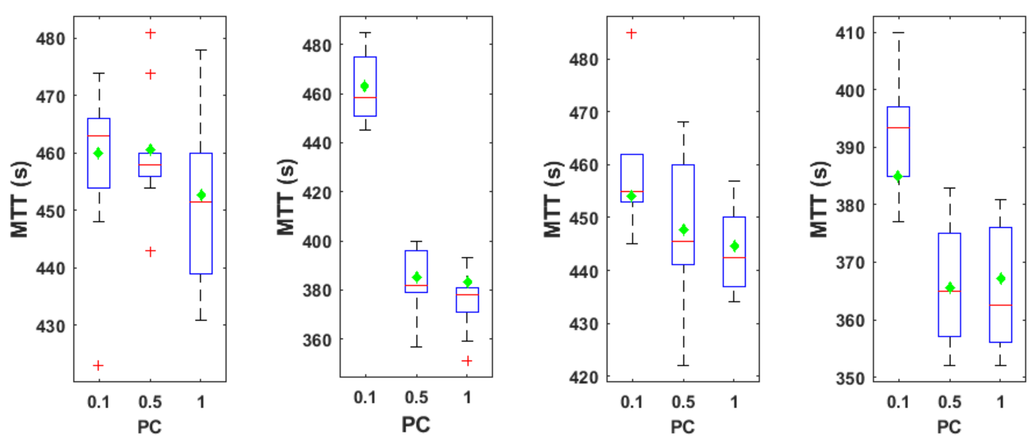

Figure 5.12: MTT and GCS with changing CR under different MPs

In Figure 5.12, the blue dots represent MTT recorded from 100 simulation runs at specified MP and CR, and the blue curve depicts the average of the repetitions. Similarly, the red dots are the calculated GCS at each run under selected MP and CR, and the red curve stands for the mean GCS over multiple runs.

Interestingly enough, it is hypothesized that the GCS increases when CR goes higher from the CAV Network perspective. However, the results show the GCS does not necessarily go up to 1 for all the MP levels. It was found that for MPs lower than 40%, GCS hardly reached 1, even when CR equals to 1 block size. On the contrary, for MP levels above 40%, beyond a specific CR, the giant component will cover all the CAVs on the network. This CR is called critical CR from the percolation transition perspective, $\mathrm{CR}^{\mathrm{GC}}_{\mathrm{Critical}}$. For instance, this value for MP = 40% is 1.0, and for MP = 60% is 0.75. $\mathrm{CR}^{\mathrm{GC}}_{\mathrm{Critical}}$ decreases as MP increases, to the extent that for MP = 100%, it reaches 0.50. One of the major findings here is that $\mathrm{CR}^{\mathrm{GC}}_{\mathrm{critical}}$ is often greater than $\mathrm{CR}^{\mathrm{Mob}}_{\mathrm{Critical}}$. In other words, a giant component that includes every single CAV in the network is not required for the mobility benefits to emerge. Practically, even if the giant component partially covers the CAVs on the network, they still benefit from message communication and shared information system within the cluster to some extent. In addition, the minimum MTT occurs when GCS reaches 1, beyond which, increasing CR does not affect either GCS or MTT. This has been verified for MPs greater than 60%. This happens because for a fixed MP, increasing CR beyond the point where the giant component has already established will only create connections that do not bring new information into the shared cloud.

### 5.4.3 Mobility Impacts of Probability of Connectivity (PC)

CAVs are assumed to be communicating through DSRC technologies or WiFi networks in this study. Therefore, physical barriers (e.g., other vehicles, buildings, and power lines etc.) and frequency interference (e.g., microwave, wireless devices, and other WiFi networks) would interfere with the signal (Talebpour et al., 2016). Due to the signal interference, the communication may not be established even when the distance between CAVs falls into the CR. Therefore, the concept of probability of connectivity was incorporated to replicate the real scenario. In the simulation, CAVs can transfer information if and only if they are connected, corresponding to the probability of connectivity (PC).




(a) CR=.5, MP=20 (b) CR=.5, MP=100 (c) CR=1, MP=20 (d) CR=1, MP=100

Figure 5.13: Probability of Connectivity Impact on Mobility

Figure 5.13 presents the mean travel time comparison under different MPs, CRs and PCs. The green dot represents the mean of the MTT to the corresponding MP and CR. Four extreme cases with varying levels of CR and MP were tested. From all four figures, it can be concluded that as PC increases, the mean travel time generally decreases. This makes sense because when more vehicles are connected, the cluster will have more information to optimize the routing, which further leads to the reduction of travel time. The results show that in case of high levels of MP or CR, even if the PC is as low as 0.5, there will not be any significant difference in MTT comparing to the case where $PC = 1.0$. This is mostly due to the fact that under these settings, the network is densely connected that even removing half of the links does not impact the clustering behavior, and thus the impact on shared information among the members of the cluster is minimal. It is also worth mentioning that when PC is as low as 0.1, although that the network might be filled with CAVs, the information is not shared adequately. Thus, the mobility is at very lower performance, compared to the cases with $PC \geq 0.5$. These experiments illustrate that even though signal interference deteriorates the network connectivity on high MP or high CR, where the transmissions are highly frequent, the results of this study with the assumption of $PC = 1.0$ are still valid.

### 5.4.4 Comparison of simulation and theoretical results

The theoretical and empirical giant component sizes are plotted in Figure 5.14. As shown in the Figure, when MP is high, theoretical discrepancy match the empirical data very well. As MP decreases, theoretical GCS shows a sharp decline, while the empirical results cover between $[0.3, 0.5]$. This is because, at low MP, NB distribution is limited in describing the degree distribution as discussed in Section 5.3.1, which leads to the unsatisfied approximation. This issue stems from the differences between dynamic and static networks. However, for higher MPs (approximately when GCS is above 0.4) the analytical framework fits the empirical results very well. From Figures 5.11 and 5.12, it was proved that the mobility benefits start to appear when the GCS falls in $[0.4, 0.6]$ range, where the theoretical and empirical results match. In figure 5.14, different colors represents the giant component size under different CR and MP. Dashed line describes the empirical giant component size obtained from the simulation, and the solid line represents the theoretically calculated giant component size.

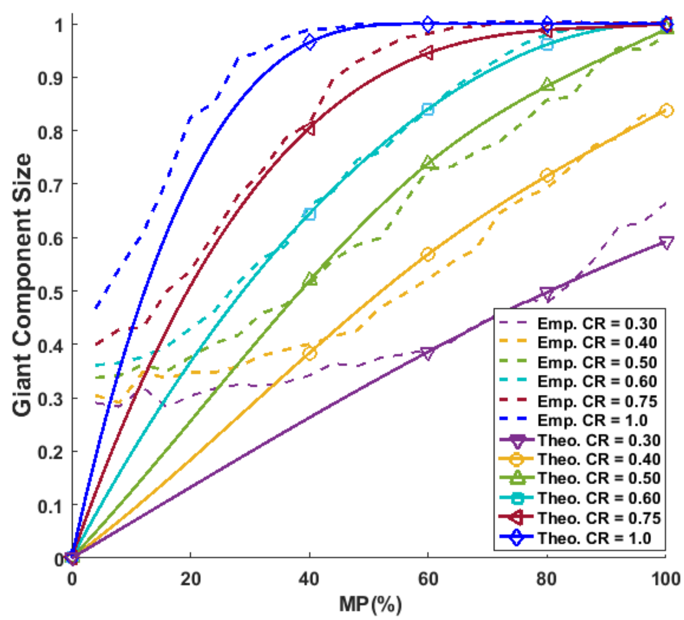



Figure 5.14: Comparison between empirical and theoretical GCS analysis

## 5.5 Discussion

In the previous section, the impact of MP and CR on mobility and the formation of giant components were presented. However, the combined effect of MP and CR remains elusive. Figure 5.15 combines and summarizes the results presented in the previous section. The top two figures show the variation of GCS with respect to CR and MP. Generally, GCS increases with increase in MP and CR respectively. It is also worth mentioning that not all the GCS goes up to 1. On the top right of the figures, it was discovered that the GCS grows from 0.2 to 0.5, which differs from analytical and mathematical percolation models. This is largely due to the fact that theoretical percolation models exhibit distinctive features when applied to static, random, or large networks. Despite stochastic nature of this problem, it was shown that the CAV Network in low CRs and MPs is far from random and large network mostly due to the low number of nodes. Therefore, it is reasonable that for low CRs and MPs, the results do not perfectly match the theory. The bottom two figures show the decreasing trend of MTT with increase in CR and MP. When CR = 1 and MP = 100%, MTT is reduced by almost 20% from 460 to 360 seconds. On the contrary, when CR $<$ 0.30 or MP $<$ 20%, the mobility change is minor. Similarly to GCS, the marginal decrease in MTT climbs as either MP or CR increase. The transition between subcritical and supercritical state is clearly displayed in all four graphs. This transition in the context of complex network and giant component size is well-known in percolation theory (Gao et al., 2013, 2015; Li et al., 2015b). Moreover, in terms of mobility, this transition in a CAV network corresponds to the emergence of the decrease in travel time and increase in travel time reliability. In the subcritical state, routing optimization under partial information has marginal benefits. On the other hand, in the supercritical state, V2V communication is prevalent in the CAV network that leads to a fully-informed decision on the choice of routes, beyond which increasing the MP will not decrease the MTT in the network.

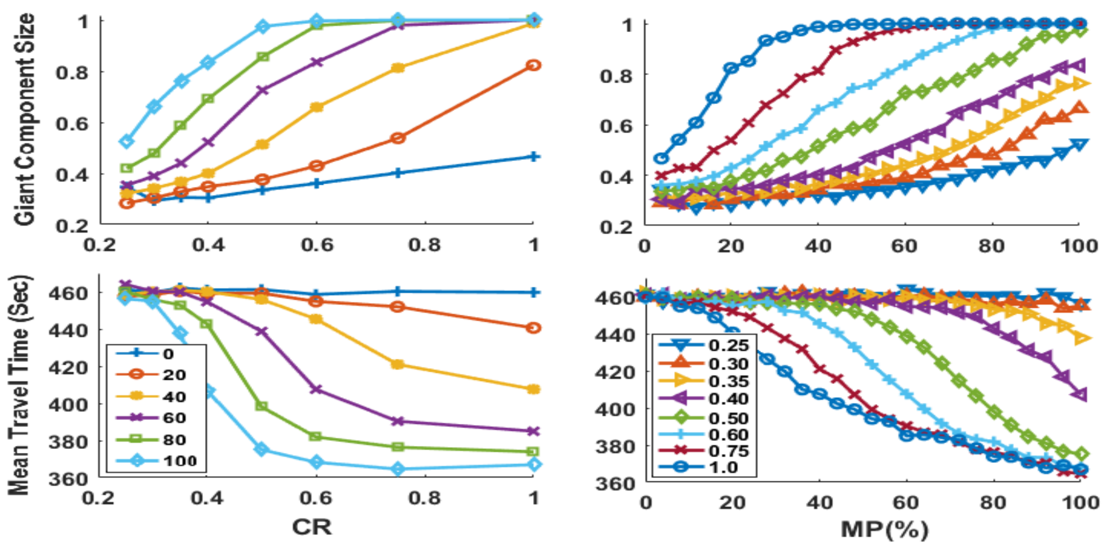
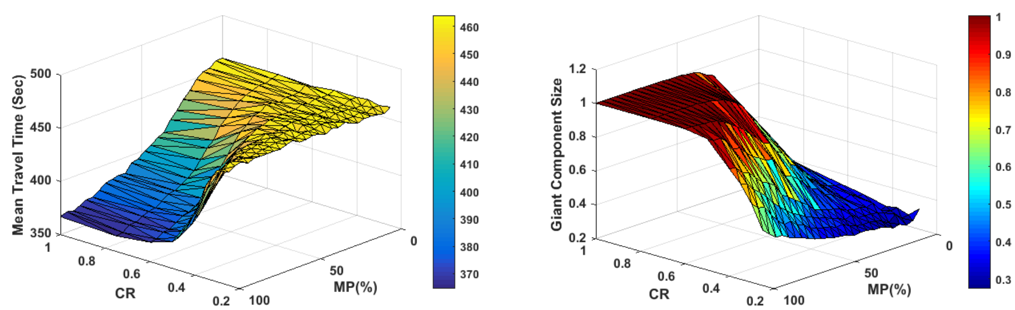



Figure 5.15: GCS and MTT vs. CR and MP

Figure 5.16 presents a 3D representation of the relationship of MTT and GCS versus CR and MP. Top two figures show the variation of GCS versus CR and MP. Generally, with increase in MP and CR the GCS increases, and goes up to 1 for high CR and MP combinations. Similarly, the bottom two figures show the variation of MTT versus CR and MP. It can be seen as the GCS goes up, MTT decreases. It is obvious that GCS is correlated with MTT. High MPs and long CRs create richly connected and dense network which is likely to cover a larger transportation network. Therefore, CAVs will have the travel time information of the entire network to optimize their routes. Red color in Figure 5.16b and blue color in Figure 5.16a reflects these cases where GCS equals to 1 and MTT is at its minimum. On the other hand, low MPs and short CRs do not generate a proper network for travel information collection. Blue color in Figure 5.16b and yellow color in Figure 5.16a corresponds to the aforementioned state where MTT is at its maximum and GCS is at its minimum. Note that in the other two cases (High MP and Short CR - Low MP and Long CR), they do not generate either larger GCS or lower MTT. This further verified the results in Section 5.4 that it requires both MP and CR to grow to result in desired outcomes.

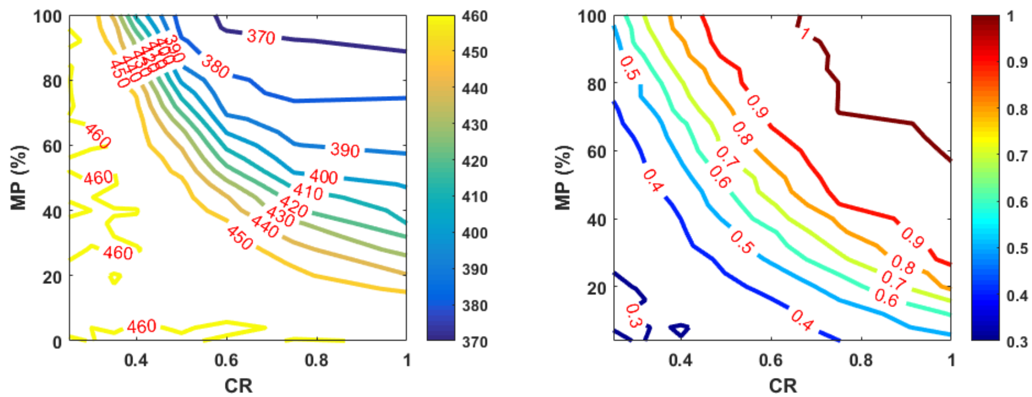



(a) Mean Travel Time

(b) Giant Component Size

Figure 5.16: 3-D representation of MTT and GCS with varying MP and CR

It is obvious that there is a reverse correlation between MTT and GCS shown in Figure 5.16. Obviously, when GCS is at its minimum (low MP and short CR - right side of the surfaces) MTT is at its maximum. Conversely, for the MPs and CRs that GCS reaches to 1 (high MP and Long CR - left side of the surfaces) MTT goes to its minimum.




(a) Mean Travel Time Contour

(b) Giant Component Size Contour

Figure 5.17: MTT and GCS contour line with varying MP and CR

In Figure 5.17, the contour lines shows the ranges of MP and CR that mark the transition area for both MTT and GCS. The dense cluster of contour lines reflects the transition area where slight changes in either MP or CR results in significant change in MTT or GCS. For instance, looking at (a), CR $\in [0.30,\ 0.50]$ and MP $\in [20\%,\ 60\%]$ marks the transition area of MTT for the cases that $MP = 100\%$ and $CR = 1.0$ respectively. Similarly, (b) shows that the transition area of GCS is marked by CR $\in [0,\ 0.50]$ and MP $\in [0\%,\ 40\%]$.

Another important task of this study is to capture the critical MP and CR when MTT starts dropping, defined earlier as $\text{MP}^{\text{Mob}}_{\text{Critical}}$ and $\text{CR}^{\text{Mob}}_{\text{Critical}}$ respectively. Figure 5.17a shows that when MP $= 100\%$, at a CR range of $[0.3, 0.5]$, cluster of contour lines which marks the transition regime, a small increase of CR would yield a rapid decrease of MTT. In this case, at the start of a phase transition or the critical threshold is at $\text{CR}^{\text{Mob}}_{\text{Critical}} = 0.25$ which corresponds to contour line of 450 seconds. Similarly, when CR = 1.0, slight increase in MP within range of $[20\%, 60\%]$ would result in large decline in MTT. In this case, the critical threshold is at $\text{MP}^{\text{Mob}}_{\text{Critical}} = 20\%$. Again, the critical threshold is located on the contour line of 450 seconds. Therefore, contour line of MTT $= 450s$, shows the 2-tuples of $(\text{CR}^{\text{Mob}}_{\text{Critical}}, \text{MP}^{\text{Mob}}_{\text{Critical}})$ that practically is the critical transition in MTT. Mapping these coordinates onto Figure 5.17b, this contour overlaps with the GCS contour line at GCS = 0.7. The physical interpretation is that a market penetration of 70% of CAVs in the network are demanded to form a giant CAV cluster to produce significant mobility benefits regardless of the value of MP and CR. This finding lays the foundation of CAV network design and a critical step in the CAV deployment roadmap for varying CAV applications.

In addition, from Figure 5.17a, when MP is in range of $[80\%, 100\%]$, an increase of CR from 0.7 to 1 does not significantly change MTT. This indicates that at a certain MP, CAVs will all be connected, and increasing CR has negligible benefits. In another extreme case when CR $< 0.25$, increase of MP does not affect travel time performance. This suggests when inter-vehicle transmission technology is immature, even increasing CAVs on the network will not help improve the system performance in terms of travel time. Comparing the two figures, it is also worth noting that when travel time decreases rapidly, GCS climbs up. This further validates the findings presented in section 5.4.1 and 5.4.2.

## 5.6 Conclusion

This study evaluates the potential mobility benefits of multiagent coordination in a group of Connected and Autonomous vehicles (CAV). In order to reduce the network travel time, it examines mixed traffic flow environment where the CAVs share minimal information regarding their location and travelling speed with other CAVs within their communication cluster. Both analytical and simulation models were developed to measure how varying market penetration (MP) and connection range (CR) of CAVs affect the system-wide mean travel time (MTT) through an information sharing system in vehicular cloud network (Lee et al., 2014). This communication will inform the CAVs to optimize their choices of routes which will affect the MTT and the network throughput. A 4x4 lattice transportation network was simulated, reflecting a subnetwork of a larger transportation network with similar traffic demands as morning peak hour travel pattern. Through the multiagent coordination system implemented in this chapter, the results showed that MTT of the system can be reduced by up to 20% for higher MPs and larger CRs. In addition, the results reveled there exists a critical MP and a critical CR, beyond which mobility benefits of CAVs start to emerge. Moreover, the percolation phenomenon in CAV network was studied. The mobility benefits of communication and coordination between CAVs were further tied to the characteristics of the CAV network such as the node degree distribution, cluster size distribution, and giant component size (GCS) which can be analyzed and explained using percolation theory. The findings of this study showed that percolation phase transitions

CAV network is highly correlated with the mobility benefits. Through the multi-agent connected vehicle simulation platform, it is found that the node degree of a dynamic CAV network follows a negative binomial distribution. This is partially attributed to the lattice grid transportation network, the distribution of the OD pairs, the distribution of CAVs, and the vehicle arrival time assumption. The evolution of the GCS change in the dynamic CAV network was captured throughout the simulations and later compared to the the theoretical percolation analysis using the random network with degree distributions estimated from the simulated CAV network characteristics. It was observed that the theoretical and simulation results are consistent when MPs and CRs are both high. However, for lower MPs and CRs, where clusters of CAVs are rare, the expected CAV network is not quite compatible with analytical assumptions (e.g., static, random, and large), and hence the discrepancy between analytical and simulation results. The final key finding of this work is that mobility benefits do not necessitate the presence of a fully connected network. In fact, the tipping point in MTT is associated with a GCS of 0.7. In other words, 70% of the CAVs need to form a cluster in order for mobility benefits to reveal. Finally, the probability of connectivity (PC) is incorporated to capture the impacts of signal interference. The results show that in the case of high MP or CR, the PC has minor effects on the MTT. The findings of this research will inform decision-makers and officials regarding the investment decisions and resource allocations on the components to achieve the higher benefit-cost ratio, as well as the design of the infrastructure to facilitate the future large-scale deployment of CAV applications and CAV network.

# Chapter 6: Connected and Autonomous Vehicle Routing under Extensive Communication: A Decentralized Collaborative Time-dependent Shortest Path Algorithm

## 6.1 Introduction

The advent of Connected and Autonomous Vehicle (CAV) technology calls for better and more intelligent routing behavior in transportation systems. Ultimately, this would yield lower travel times, lower idle times, and a more efficient utilization of the full transportation network by intelligent agents. As the overall transportation system tends toward a higher percentage of CAVs, however, individual CAVs must be able to communicate and coordinate better. This will allow CAVs to avoid competing goals, and more easily reach an optimal state. In this chapter, we study the behavior of such systems under *Extensive Communication* capabilities. More specifically, we introduce a Decentralized Collaborative Time-dependent Shortest Path Algorithm (*Dec-CTDSP*) with which the CAVs optimize their route according to the communicated mobility messages regarding the location, speed, and the preferred path of the other CAVs within their cluster through a multi-hop wireless network (Kosch et al., 2002). This algorithm is an extension of regular TDSP proposed by Dreyfus (1969) and Dijkstra (1959) where the time-dependency of the links are calculated based on the information communicated from the other CAVs in the cluster, which makes this algorithm both decentralized and collaborative. Additionally, we analyzed the impacts of this optimization scheme under various levels of CAV Market Penetration (MP) and communication radius (CR). Furthermore, the network utilization corresponding to the proposed routing algorithm is analyzed.

The rest of this chapter is organized as follows. The domain, framework, and the methodology used for this study are further elaborated in Section 6.2. The results of the experiments with CAV Market Penetration (MP) and Communication Radius (CR) are presented in Section 6.3. Specifically, MSTT, MSS, and Network Usage Distribution are studied along with their prediction reliability level. Moreover, Dec-CTDSP performance and its runtime is benchmarked with a few common routing algorithms in Section 6.4. And finally, Section 6.5 discusses the major findings of this study and concludes with the key contribution.

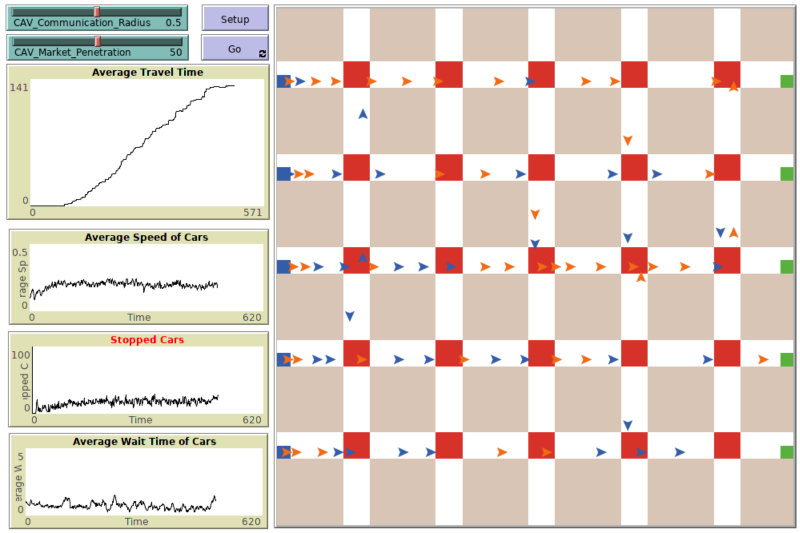
## 6.2 Methodology

This study intends to investigate the behavior of a transportation system with a varying percentage of CAV market penetration (MP) and Communication Range (CR). We modeled a grid transportation network where the vehicles aim to travel from one edge to the other in a continuous pattern (Fig. 1.2a). We assume that basic mobility messages regarding the location, speed, and preferred path of each CAV can be communicated to its own CAV cluster through multi-hop connections. This communication and coordination between the CAVs, and consequently the distribution of traffic onto different links, in turn, can reduce the travel time and congestion of the system significantly.

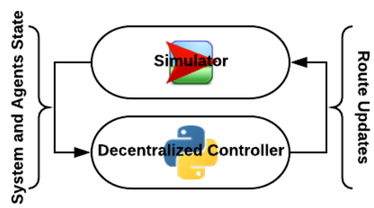
### 6.2.1 Domain

Figure 6.1a shows a snapshot the domain. Each red square shows an intersection which is modeled as a four-way stop sign. All the north-south streets are two-way and all the east-west streets are assumed to be one way towards the east and the destinations. All the links have the same speed limit. The blue squares on the left side show the origins, whereas the green squares on the right side show the destinations. There are 100 vehicles uniformly distributed across 5 origins. Similarly, their destinations are randomly and uniformly assigned to one of 5 destination nodes. The proportion of CAVs and Non-CAVs are governed by MP. Blue agents represent CAVs and the orange agents represent Non-CAVs. Each vehicle returns to its origin after reaching the destination, making the problem domain sequential and open-ended. CAV MP and CR can be adjusted in the simulation, and in turn, the Mean System Travel Time (MSTT) and Mean System Speed (MSS) can be monitored from the simulator, along with the number of the stopped cars, and the average delay.

The domain of this study is coded in NetLogo, expanding the existing model in NetLogo Library, “Traffic Grid” (Wilensky, 2003), and adding the CAV communication and coordination capabilities. NetLogo is a flexible agent-based modeling platform and has been used in a wide range of fields for prototyping purposes




(a) Domain




(b) Framework

Figure 6.1: Domain Snapshot and the Simulation Framework

(Wilensky and others, 1999). In addition, Figure 6.2 describes the speed-density relationship in the simulator. This relationship is an artifact of the car-following coded into the platform as explained by Mostafizi et al. (2017). The decentralized controller for each CAV is coded independently in Python, bridging the gap with PyNetLogo library (Jaxa-Rozen et al., 2018). At each point in time, system and CAV states are transferred to the controller which processes the information for each CAV independently and sends back the route updates to the simulator. Figure 6.1b shows the general optimization workflow. The System and Agent State

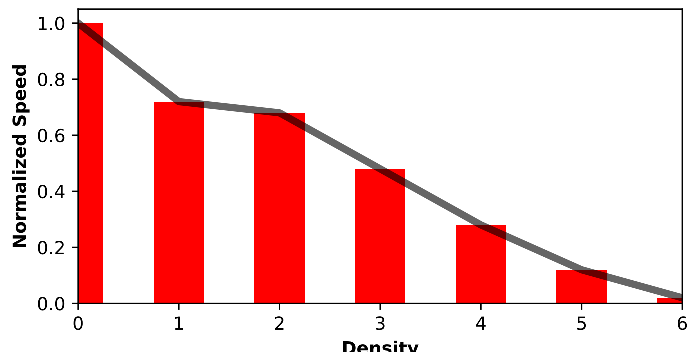



Figure 6.2: Speed Density Relationship

refers to all the CAVs' information that efficiently represents the entire environment (i.e., location, speed, and the preferred path of the CAVs). However, other CAVs' information is not readily available to any other CAV. The communication is governed by the CR and the location of CAVs that governs the clustering behavior at any point in time. Our Dec-CTDSP algorithm uses this information to reroute the CAV to an underutilized path, and thus, reduces the system travel time. The details of the routing behavior for both Non-CAVs and CAVs are discussed hereunder.

### 6.2.2 Routing Behavior for Non-CAVs

Routing behavior for Non-CAVs in this work follow the same pattern as Mostafizi et al. (2017), as shown in the following equation,

$$\text{Shortest Route} = \begin{cases} (5-d_y) \quad d_y \\ \overbrace{R....R}\overbrace{RU..RU} \quad d_y \geq 0 \\ \underbrace{R....R}\underbrace{RD..RD} \quad d_y < 0 \\ (5-|d_y|) \quad |d_y| \end{cases} \tag{6.1}$$

Where $d_y = Y_{\text{Desination}} - Y_{\text{Origin}}$ and R, D, and U represent the direction of movement in sequence. This predetermined routing behavior is set to replicate the predictability in the behavior of the vehicles in the rush hour and when they are not provided with any navigational information (Evans et al., 2002; Ponieman et al., 2013).

### 6.2.3 Decentralized Collaborative Time-dependent Shortest Path

The CAVs use the Dec-CTDSP Algorithm to find the shortest path with the following procedure. Each CAV at every intersection gathers the speed, location, and the preferred path of the other CAVs in its communication cluster. This information is used to to create a time-dependent abstraction of the network and the edge travel times with Algorithm 2.

In this algorithm, $CurrentTravelTime$ is calculated based on the number of vehicles predicted to be on a link at time step $t$ and the speed-density relationship presented in Figure 6.1a (bottom right). This relationship is also used to $SimulateVehicleMovement$ abstractly. The results of Algorithm 2 is a time-

**Algorithm 2** Building the Time-dependent Travel Time Network

**Input:** Graph $\boldsymbol{G} = (V, E)$ Directed Transportation Network,
List of Cars in the CAV Communication Cluster $\boldsymbol{C}$,
$PlanningHorizon$ for the abstract time-dependent network

**Result:** Graph ***TDep-G*** $= (V^{'}, E^{'})$ Time Dependent Travel Time Network

```
foreach e ∈ E' do TravelTimeList = [];
if C is empty then
    foreach e ∈ E' do
        TravelTimeList = [(0, FreeFlowTravelTime),
          PlanningHorizon, FreeFlowTravelTime)]
    end
    Return TDep-G
end
for i ← 0 to PlanningHorizon do
    foreach c ∈ C do SimulateVehicleMovement(c);
    foreach e ∈ E' do
        AppendToTravelTimeList(i, CurrentTravelTime)
    end
end
Return TDep-G
```

dependent network, representing travel time of each link at each point in time. Therefore, the time-dependent shortest path can be calculated from Algorithm 3 as discussed in Dreyfus (1969), which is a modification of the original Dijkstra shortest path algorithm (Dijkstra, 1959).

$GetTravelTime$ is the key function here that extracts the travel time of link $u - v$ at time $t = f[u]$ from ***TDep-G***. This results in $f[i]$ being the least travel time to node $i$ from the $Source$. As the $f$ value of the nodes are updated and the destination has been reached, $ReconstuctPath$ builds and returns the shortest path in the time-dependent network that minimizes the arrival time to the $Target$.

**Algorithm 3** Optimizing the TDSP

**Input:** Graph ***TDep-G*** $= (V^{'}, E^{'})$ Time-dependent Travel Time Network,
$Source$ The current intersection of the CAV
$Target$ Destination of the CAV

**Result:** $\boldsymbol{R}$ Sequence of Intersections representing the optimal shortest path

```
VertexSet = []
foreach v ∈ V' do
    f[v] = ∞
    prev[v] = None
    AppendToVertexSet(v)
end
dist[Source] = 0
while Q not empty do
    u = v in VertexSet with minimum dist[v]
    Remove u from VertexSet
    if u = Target then
        R = ReconstructPath
        Return R
    end
    foreach v ∈ Neighbors(u) do
        if v ∉ VertexSet then Skip;
        d_uv(t) = GetTravelTime(TDep-G, u, v, f[u])
        alt = f[u] + d_uv(t)
        if alt < f[v] then
            f[v] = alt
            prev[v] = u
        end
    end
end
```

Since the shortest path is calculated considering the decisions and the information of the other CAVs, this algorithm is named *collaborative* time-dependent shortest path. Note that this algorithm is based on general Bellman's principle that holds under the assumption of first-in-first-out (FIFO) (Dreyfus, 1969; Ziliaskopoulos and Mahmassani, 1993) which is the case in transportation applications, specifically the way it is modeled in our platform.

### 6.2.4 Simulation Dynamics

As mentioned earlier, to compare the future results from the Dec-CTDSP method, the authors performed tests on MSTT and MSS under different MP and CR levels. MSTT is estimated by the number of time steps in the simulator, that it takes on average for the vehicles to travel from their start point to destination. This value later is compared to the base case with CAV MP of 0%. MSS was analyzed with the same procedure. It has to be noted that as the domain is modeled in a continuous format, where the vehicles continuously start at their origin upon reaching their destination, the most recent trip time from origin to destination is considered towards the calculation of MSTT. This results in MSTT and MSS to converge to a final value, after a certain time, which depends on the routing behavior of the vehicles, the MP of CAVs, and their CR. These dynamics are shown in Figure 6.3.

Note that for each scenario, the simulation is run until the MSTT of the system converges. This event has been flagged by the standard deviation of the last 200 readings to drop below a certain threshold, less than 2%. From Figure 6.3 it can be seen that different levels of CAV MP and CR converge to different MSTT and MSS. In general, higher MP and higher CR yield lower travel times and higher speeds. The highlighted area around each curve shows the standard deviation of

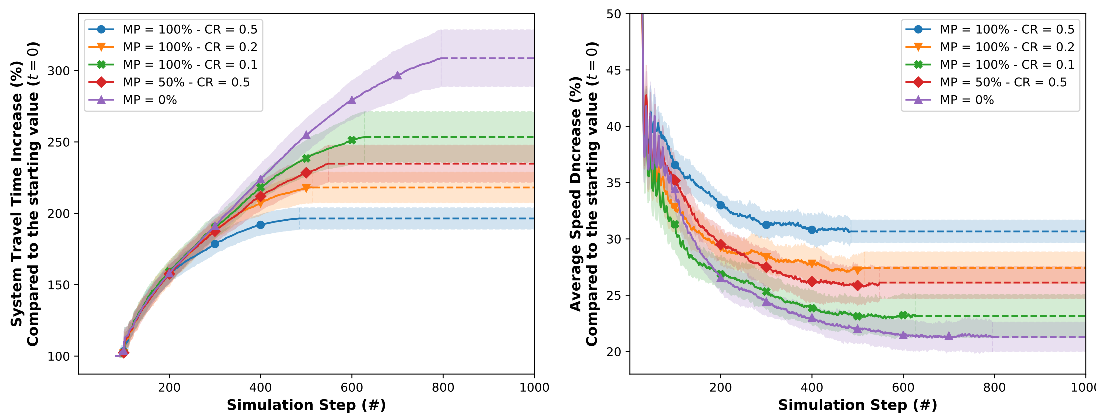



Figure 6.3: Dynamics and Convergence of System Travel Time and Speed

numerous monte-carlo simulations. As it appears, higher MP and CR increase both MSTT and MSS reliability. Also, under such circumstances, the system converges to its final travel time state earlier. These findings are further discussed in later sections.

## 6.3 Results

The performance of the Dec-CTDSP algorithm implemented in this work has been assessed by analyzing the Mean System Travel Time (MSTT), Mean System Speed (MSS), the reliability of the predicted values, as well as the distribution of the link usage towards a more efficiently utilized transportation network. All of these factors, under various levels of MP and CR, are discussed hereunder. Lastly, the performance of the algorithm is benchmarked against other semi- and un-coordinated Dijkstra-based and random routing algorithms.

### 6.3.1 Mean Travel Time

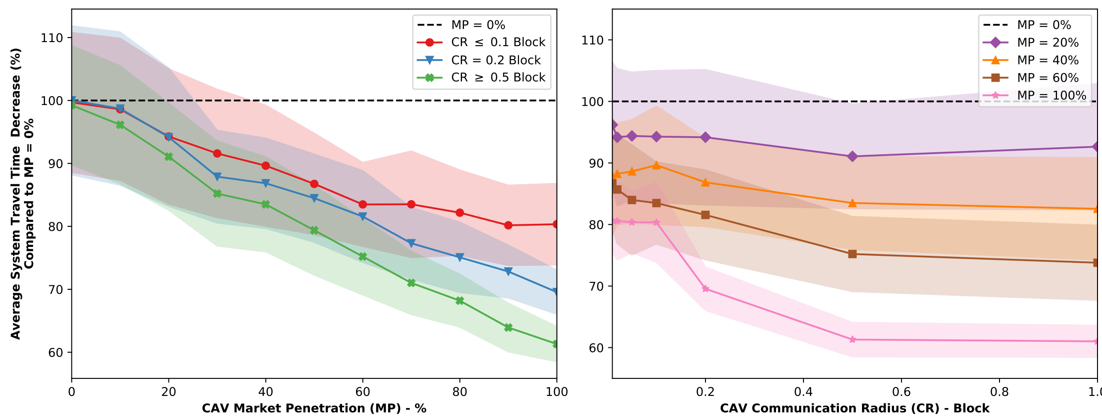
Figure 6.4a shows the final converged MSTT of the system, compared to $MP = 0\%$, as a function of MP and CR. The results show that the MSTT decreases rather linearly with increase in MP. In addition, the reliability in MSTT increases as MP increase. This reliability is characterized as the reverse of the standard deviation of numerous monte-carlo simulations until the standard shows no significant change with an increase in the sample size. Moreover, it can be seen that the performance of the system does not change for $CR \leq 0.1$ $Block$ as well as $CR \geq 0.5$ $Block$. This suggests that the algorithm requires a sufficient amount of information being circulated in the CAV communication cluster for the benefits to show. This threshold is marked by $CR = 0.1$ $Block$, below which the benefits in terms of MSTT are the same. Beyond this threshold, the CAV cluster enlarges, and the abundance of information shared regarding the preferred path of the CAVs with each other leads to lower travel time, until $CR = 0.5$ $Block$. Our simulation reveals that increasing CR beyond this threshold does not drastically improve the CAV cluster. In other words, $CR = 0.5$ $Block$ yields a fully connected CAV network through multi-hop connections, where each CAV is connected to any other CAV in the network. This is an interesting finding, proving that for the Dec-CTDSP algorithm to yield its optimal results, high levels of communication are not required. Also, it is noteworthy that the reduction in MSTT is more drastic with the increase in CR for higher levels of MP.

Moreover, it has to be noted that an increase in MP, even with insufficient

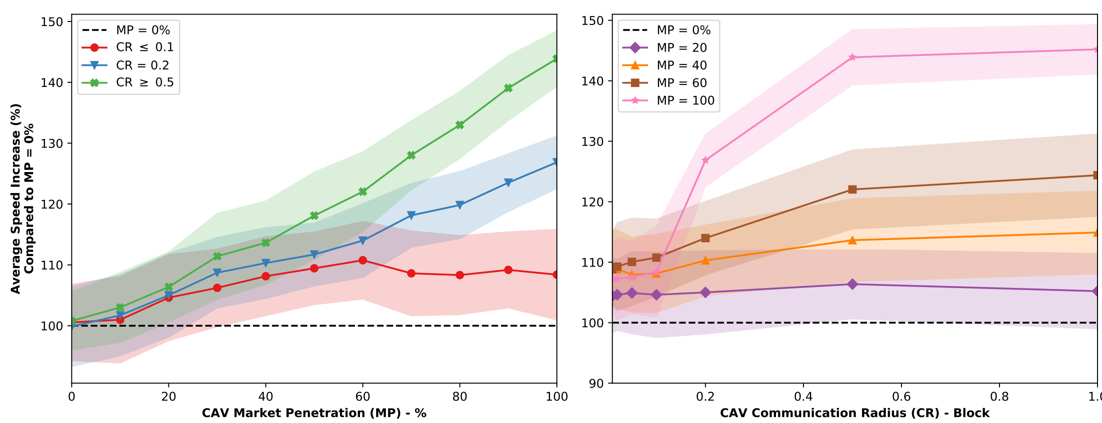
CR ($CR \leq 0.1$ $Block$) still exhibits some benefits in terms of MSTT since it adds randomness into the routing behavior of CAVs under limited information, as opposed to the fixed predefined routing behavior of Non-CAVs, as defined in Equation 6.1. In other words, the CAVs that do not have sufficiently sized CAV cluster choose their path to their destination randomly, since they cannot have any valid heuristic as to what the traffic level of different links is. This random behavior inherently dissipates the traffic onto the network somewhat uniformly, more than what predefined path for Non-CAVs does, leading to a reduction in MSTT. Our results show maximum of 20% reduction in MSTT at $Mp = 100\%$, compared to $MP = 0\%$, when CR is not large enough ($CR \leq 0.1 Block$). This reduction goes up to 40% when CR is greater than 0.5 Block and for a fully CAV penetrated system.

### 6.3.2 Average Speed

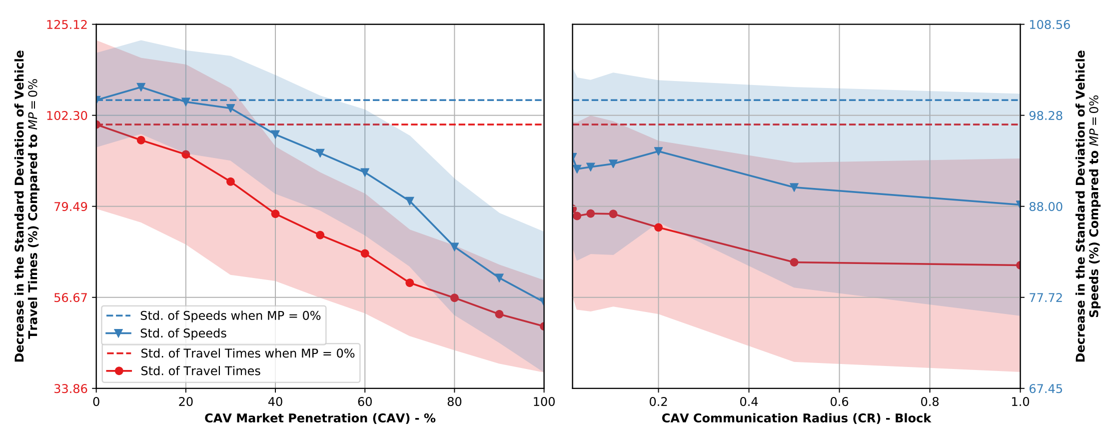
Figure 6.4b shows the increase in MSS, compared to the base case ($MP = 0\%$). Although MSS seems to generally follow the reverse trend of MSTT, however, looking at the speeds along with the travel time uncovers interesting behavior for the algorithm. The results show that the range of impact is noticeably more significant on the MSTT, compared to the MSS. When CR is relatively low ($CR \leq 0.1$ $Block$) even with $MP$ of 100%, the impact on the MSS is less than 10%, compared to 20% reduction in MSTT. This shows that the reduction in MSTT is solely an artifact of the random routing behavior of CAVs under lack of information, and not *intel-*




(a) Mean System Travel Time (MSTT)




(b) Mean System Speed (MSS)




(c) Reliability in Mobility Measures

Figure 6.4: Mobility Measures under different levels of MP and CR

*ligent* routing behavior. However, for high levels of CR, greater than 0.5 Block, the reduction in MSTT is comparable to the increase in MSS. The results reveal that, although the increase in speed for lower MP levels ($MP < 40\%$) is minimal (less than 15%), for a fully CAV penetrated system, the increase in MSS can go up to 45%.

### 6.3.3 Reliability in Mobility

We quantified the reliability in our estimations for MSTT and MSS with the average of the standard deviation of the travel time and the speed of all the vehicles over the monte-carlo simulation runs. This shows how accurately MSTT and MSS can be translated into each vehicle's travel time and speed. Needless to say that the lower the average standard deviation is, the more stable and transferable the estimations are to each vehicle. Figure 6.4c shows this average standard deviation both for the speeds and travel times of the vehicles, compared to the same statistics of the base case ($MP = 0\%$), as a function of MP and CR. Note that the curves are averaged over all the tested CR levels in the left figure and all the MP levels in the right figure.

The results show that reliability in travel time estimations (red curve) increases monotonically with an increase in MP, as shown as a decrease in standard deviation. However and surprisingly, the standard deviation of the speeds (blue curve) increases minimally when the MP hits 10% and then start to decrease. This is due to uncertainties in clustering behavior in a heterogeneous environment that is minimally CAV penetrated. Unlike the strong correlation between the reliability and the MP, CR shows no strong association with the standard deviation of either speeds or travel times, and accordingly, the reliability. The abstract interpretation of this would be that a fully CAV penetrated system is more reliable in terms of travel time and speed prediction, regardless of its CR level, than a system with lower MP but with higher level of technology sophistication.

### 6.3.4 Network Usage Distribution

We calculate the expected network usage from the planned route of the vehicles at the time of convergence. In other words, we monitor how many times a link is to be used based on the current route of all the vehicles when the system is converged to its final state (MSTT is converged). This measurement will provide an accurate estimate of how the traffic is to be distributed onto the network with the current routing behavior of the vehicles. Figure 6.5 shows various aspects of this measure and its relationship with mobility and MSTT specifically, and how it is impacted by MP and CR. The left panel shows how positively average link usage is correlated with the MSTT (green line). Average link usage is defined as the average of the link usage distribution, or in other words, it shows how many times on average a link is to be traveled by the vehicles in the system. The results show that higher MP levels (yellow) generally yield lower MSTT (C and B), regardless of the average link usage of the network. This is partially due to the random routing behavior of CAVs when the MP is high, but the CR is not sufficient enough (B). These circumstances, although resulting in somewhat low MSTT, do not dissipate the traffic properly (mid to high average link usage), and therefore do not reach minimal MSTT. However, it can be seen that the low end of MSTT, that also has the lowest average link usage (C), corresponds with high MP as well as high CR levels. This shows that high MP and high CR with the Dec-CTDSP algorithm results in more efficient dissipation of traffic, hence low average link usage, and accordingly lowest possible MSTT. This suggests that CR, the information shared within the CAV cluster, and finally the use of this information by Dec-CTDSP is the key factor in traffic dissipation. This is also shown with a greater correlation between average link usage and MSTT when $CR \geq 0.5$ *Block* (orange line), compared to the opposite scenario where $CR < 0.5$ *Block* (blue line). Moreover, on the other end of the spectrum, low MP, regardless of CR, yields high MSTT with mid-level average link usage (A).

The right two panels in Figure 6.5 show the average histogram of the link usage counts and the distribution of the average network usage for the three zones marked in the left panel. Zone $A$ represents low MP ($\approx 25\%$) and low CR (0.24 *Blocks*) levels that result in high average link usage ($\approx 6$), and therefore high MSTT. From the histogram, it can be seen that a larger portion of links are scheduled to be used by a high number of vehicles, according to their planned route. The imbalance in the link usage can also be interpreted from the heatmap that shows extreme usage of the middle and right side of the network, as opposed to the other links. This pattern is fairly similar to that of $MP = 0\%$ shown in Figure 1.2b). Zone $B$, on the other hand, represents high MP ($\approx 90\%$) but rather low CR ((0.04 *Block*)) that

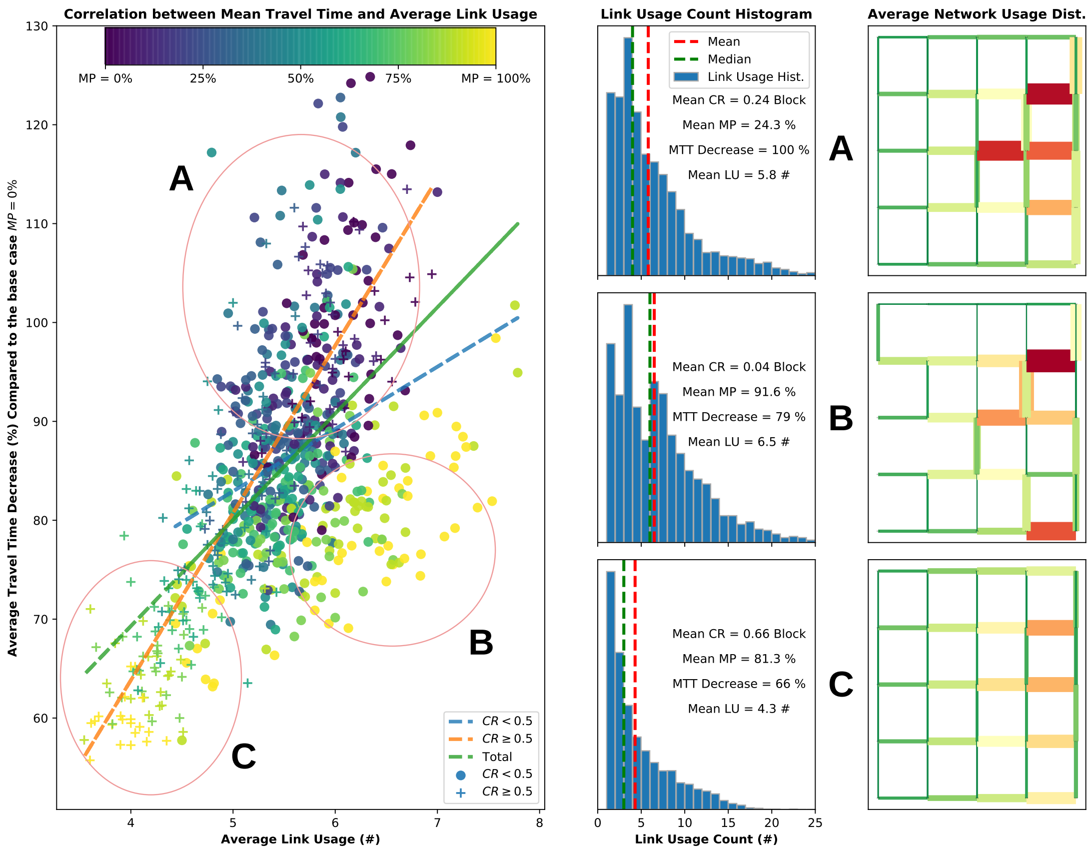



Figure 6.5: Network Usage

does not lead to a high decrease in MSTT. The imbalance in the network usage still persists, slightly less severe to the one with low levels of MP (A). At the other end of spectrum, zone $C$ with not necessarily very high MP level ($\approx 80\%$), but rather high CR (0.66 *Block*), shows low average link usage ($\approx 4$) where majority of the links are only scheduled to be used by one vehicle, and there are no links that are to be traveled by more than 18 vehicles. The balanced use of network under these circumstances are shown in the heatmap, specifically in the ending links towards the right side of the network where the most congestion is expected. Note the difference between the other two discussed cases and Figure 1.2b that shows the base usage under naive routing.

## 6.4 Discussion

### 6.4.1 Benchmark

To benchmark the performance of Dec-CTDSP algorithm in terms of increase in mobility, we tested it against a few simplistic routing behaviors as following,

- *Static Random Routing*: Each CAV calculates a random shortest path to their destination at the beginning of the simulation and sticks to it until the end in all iterations. This algorithm assumes no observability.
- *Dynamic Random Route*: Each CAV takes a different random shortest path at each iteration. Note that there are multiple shortest paths between each pair in a grid network. This algorithm assumes no observability.
- *Dijkstra*: Each CAV updates its route at each intersection with Dijkstra algorithm to find the shortest path in time, based on the current state of the network as shared through its own CAV cluster, similar to Mostafizi et al. (2017) where their results showed approximately 20% improvement in system travel time at 100% market penetration. Note that the path with the shortest travel time is typically not the same as that with the shortest

distance. Also, as the state dynamically changes, the quickest path at $t_0$ is not necessarily the same at $t_0 + \delta t$.

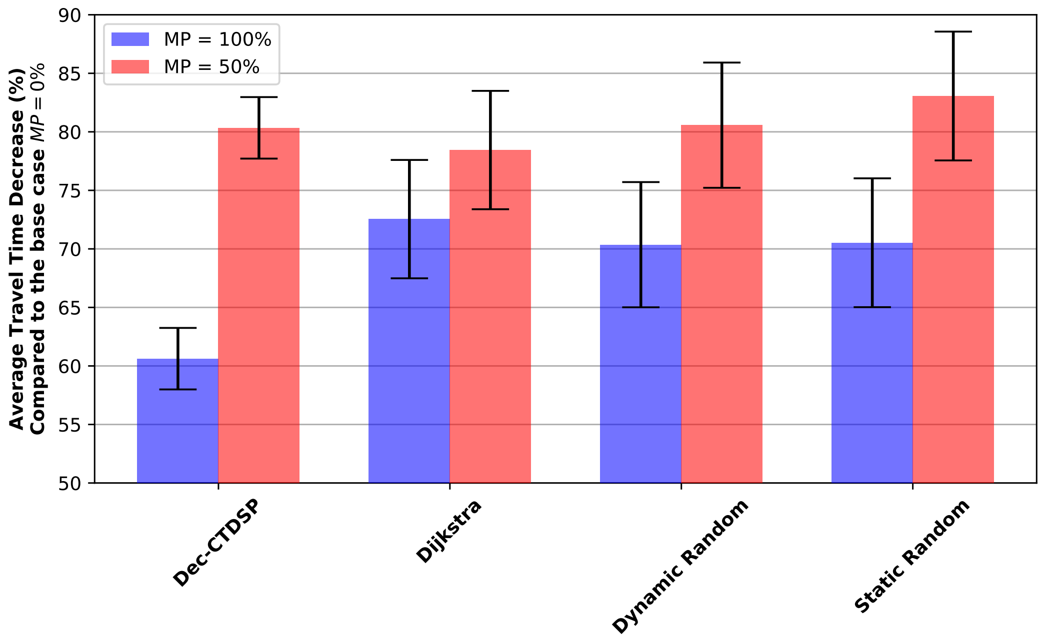



Figure 6.6: Benchmark

Figure 6.6 shows the performance of Dec-CTDSP algorithm compared to the other algorithms under different MP levels (50% and 100%) and with sufficient CR ($\geq 0.5$ *Block*). As expected, Statically and Dynamically random route assignment algorithms perform almost the same under both levels of MP. However, dynamic random assignment performs slightly better as it increases the randomness in routing behavior, and thus, more uniform dissipation of traffic.

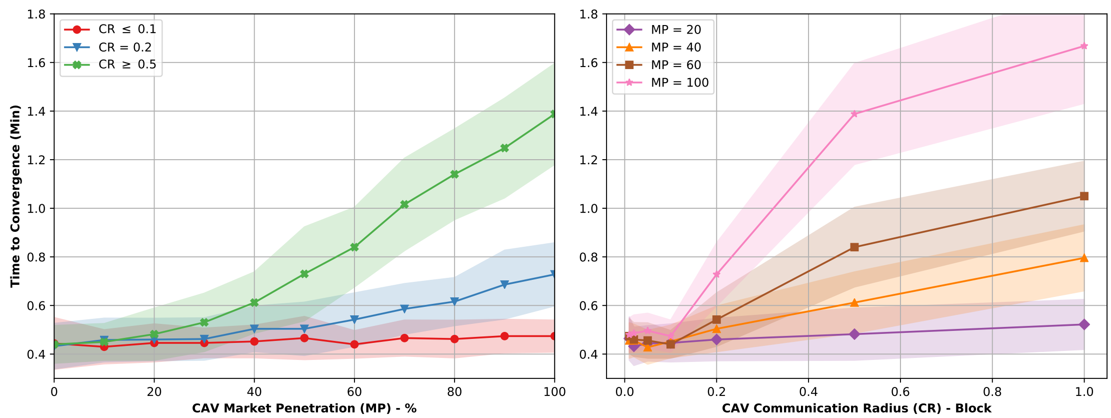
Interestingly, the results show that although Dijkstra performs better than random routing under low MP of 50%, as the number of CAVs increase, the performance drop even below random routing behavior. This is because under this algorithm, CAVs choose the routes that they perceive to be underutilized at the time of decision. However, as several CAVs do the same, the actual travel time is higher than initially estimated. This is a classic issue arising in congestion games (Helbing et al., 2005) and the coordination of multiagent systems with competing goals. Lack of coordination between the agents and the fact that there is no traffic dynamics prediction model taken into consideration results in multiple agents heading towards a less congested route, and thus, increasing the travel time. This issue is addressed to a great extent in the Dec-CTDSP algorithm with the notion of collaboration (Wolpert et al., 1999; Tumer and Wolpert, 2004).

To our surprise, the Dec-CTDSP performs worse than the Dijkstra algorithm, and almost similar to random routing behavior when the MP is as low as 50%. This confirms that for the Dec-CTDSP algorithm to benefit the system, there needs to be a properly connected CAV network that does not appear on low MP levels. In the absence of this CAV network, the CAVs behave randomly which is the underlying reason behind the similarity in performance with Static and Dynamic Random routing behavior. However, when it matters the most, and under MP of 100%, as the CAV communication network is densely populated, the performance of Dec-CTDSP is significantly better than the other tested algorithms.

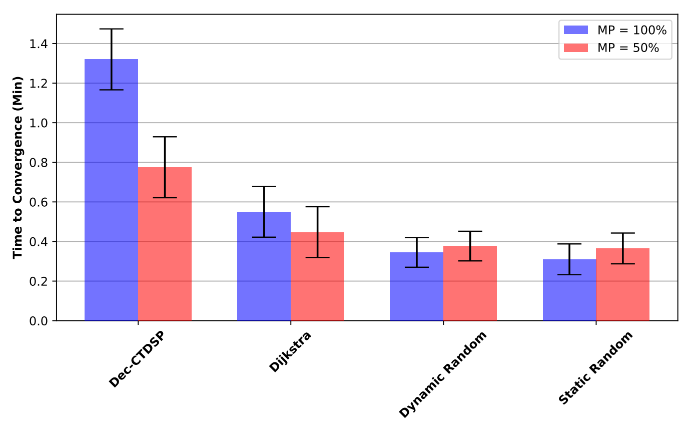
### 6.4.2 Runtime

A thorough analysis has been done on the runtime of the algorithm as a function of MP and CR, that basically control the complexity of the optimization task at hand. Besides, the runtime has been benchmarked with the other tested algorithms. Figure 6.7 shows the results of this analysis. Looking at Figure 6.7a it can be seen that the runtime increases exponentially with an increase in MP if the CR is large enough for the CAV network to form. However, for $CR \leq 0.1$, as the CAV network is not dense enough, the runtime is the same regardless of the MP. Figure 6.7b and 6.7c compare how long and how many simulation steps respectively would take the algorithms to converge to their final state. The results reveal that although Dec-CTDSP converges earlier that the other tested algorithms when $MP = 100\%$, it takes almost 3 times longer in time to optimize the route for all the CAVs. This difference is less sever for the case where $MP = 50\%$. Note that the simulation where conducted on a quadcore Intel Core i5 CPU @ 1.80GHz with 4GB RAM.

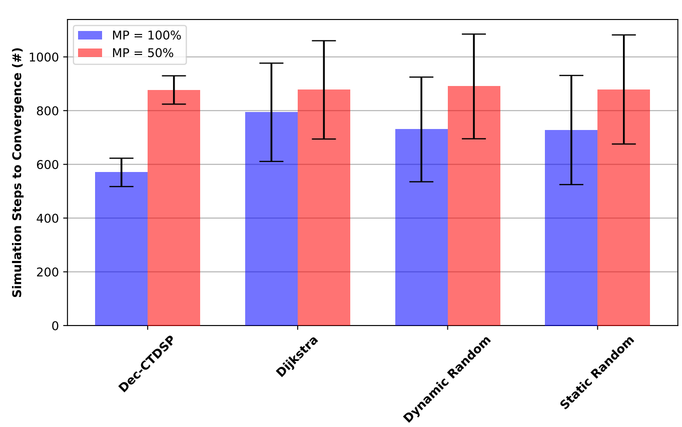
The results of this work will inform the CAV network design to achieve significant mobility benefits under different CAV Market Penetration and Communication levels. In addition, this work bridges the gap between network-wide CAV impact analysis and multiagent coordination and robotics concepts that need to be further analyzed for successful large-scale deployment of the technology.




(a) Runtime of Dec-CTDSP




(b) Runtime Comparison




(c) Convergence Step Comparison

Figure 6.7: Runtime

## 6.5 Conclusion

This study introduces a decentralized and collaborative time-dependent shortest path (Dec-CTDSP) routing algorithm implemented in heterogeneous Connected and Autonomous Vehicle systems (CAV) to improve the mobility and the efficiency in utilization of congested transportation networks. The communication capabilities of the CAVs make it possible for these vehicles to share information regarding their location, speed, and preferred route and accordingly avoid congestion. This information is used towards more coordinated routing behavior for CAVs by which traffic dissipates uniformly throughout the network, reducing the average system travel time. Our algorithm expands the idea of time-dependent shortest path where the dependency is governed by the joint state and action of the other vehicles in the system. With this, each CAV can intelligently reroute to a path that not only minimizes its own travel time but also reduces the system travel time as a whole. This decentralized approach heavily relies on the communication capabilities of the CAVs and the information shared over CAV network clusters. To model a mixed CAV environment, we introduced our agent-based traffic simulation domain as well as our decentralized routing controller framework. Our results showed that Dec-CTDSP significantly enhances the system performance in terms of travel time, and travel time reliability by up to 40% and 45% respectfully for high CAV Market Penetrations. We also analyzed these benefits under different levels of CAV communication radius. The result revealed that for moderate CAV Market Penetration, 0.5 Block Communication Radius yield in fully connected

CAV network beyond which the system performance does not observe significant improvements. Moreover, our findings showed a great correlation between the mobility and transportation network utilization, and the fact the Dec-CTDSP works towards a more uniformly utilized network, not necessarily requiring high CAV market penetration levels, but only sufficient communication levels. Lastly, we benchmarked our results with Dijkstra-based and random routing algorithms. The results revealed that Dec-CTDSP outperforms all other algorithms at high CAV Market Penetration levels. The results of this work provide insights into future development and deployment of CAV technologies and bridges the gap between multiagent coordination concepts and transportation systems.

# Chapter 7: Concluding Remarks

This dissertation discusses the mobility benefits that emerging Connected and Autonomous Vehicles (CAV) bring to increasingly congested networks. Particularly, it focuses on *how* a transportation system and vehicles within can be *coordinated* in a *decentralized* regime to reduce the travel time of the system. This work reveals the significance of vehicle coordination in the form of routing behavior and its contribution to transportation system efficiency. As an example, a route that is to be travelled by a large proportion of the vehicles at the same time can be avoided by the vehicles communicating and collaborating with each other. This dissertation reveals *how* and *to what extent* the communication capabilities of the CAVs can be utilized to enable more efficient dissipation of traffic, and therefore, lower system travel times. CAV Market Penetration (MP) and Communication Radius (CR) are two key factors investigated to realistically inform routing behavior and the expected mobility gain in the transition period. Besides, the benefits of CAV technologies are mapped to the required CAV network that facilitates the information-sharing infrastructure as well as the transportation network utilization. This work analyzes CAV coordination under three levels of communication between the CAVs as follows,

- ***No Communication***: where the CAVs do not communicate with each other to any capacity

- ***Minimal Communication***: where CAVs communicate regarding their current location and speed with the other CAVs in their communication cluster through a multi-hop network

- ***Extensive Communication***: where the CAVs not only share their current location and speed with the other CAVs in their cluster but also they share their intent regarding the preferred path that they are about to traverse.

## 7.1 Research Summary

Chapter 3 discussed the core car-following behavior in a mixed environment where CAVs and Non-CAVs interoperate. The characteristics of the traffic flow behavior, such as average travel time, throughput, and shockwave backpropagation, are then analyzed in a highway section with a speed reduction zone. Travel trajectories and platooning behavior have also been inspected. The results revealed that the benefits of CAV technologies, Cooperative Adaptive Cruise Control (CACC) in particular, surface generally beyond CAV market penetration of 50-60%, yielding a 45% decrease in average highway travel time and an 80% increase in the throughput for MP of 100%. On the other hand, the reliability in these estimates increases rather monotonically with an increase in MP. Also, platooning of the CAVs appear as they maintain relatively shorter headways in the highway section due to CACC application. Moreover, the shockwave does not backpropagate in a fully CAV-penetrated system. The traffic flow studied in this section is the core of the CAV and Non-CAV interactions in the simulations conducted in this dissertation.

Chapter 4 investigated the CAV coordination benefits where no communication capability exists among the CAVs in the system. Under this circumstance, the CAVs *learn* the optimal route to their destination through a reinforcement learning algorithm based on only their previous route, actions, and travel times. A CAV learns to avoid the routes that were previously found to be congested and gets a reward if it chooses the route with low travel time, eventually optimizing its route. The results revealed significant mobility improvements as a result of an increase in the number of CAVs that add randomness to the routing behavior of the system. However, this system works well under low levels of MP where only a small number of CAVs try to optimize their route. As the MP exceeds 75%, convergence to the optimal joint action policy for the CAVs become extremely complex. In other words, in the absence of communication capabilities, a system with MP of 75% yields the minimum system travel time.

Chapter 5 enhanced the communication to a minimal level where CAVs are capable of sharing their location and speed with their CAV cluster through a multi-hop connection network. CAVs share this information within their cluster, which is further used to optimize their route to their destination. The results showed that there is a critical *joint* threshold in MP and CR, beyond which the mobility benefits emerge. The proposed routing scheme reduced the average travel time by up to 20% for high levels of MP and CR. Furthermore, the mobility benefits were mapped to the CAV network characteristics formulated as percolation theory, giant component size, node degree distribution, and clustering behavior. The findings showed a strong correlation between the characteristics of the CAV network to the mobility of the transportation system. In general, at least 70% of the CAVs are needed to form a giant cluster so that sufficient information can circulate the cluster in order to make more intelligent and accurate routing decisions. This chapter also showed that communication degradation at high levels of MP and CR, where this concern is at its extreme, has minimal effect on the clustering behavior and the system mobility. Moreover, the comparison between analytical percolation behavior and the simulation results showed fair compatibility under densely populated CAV networks.

Chapter 6 introduces a novel Decentralized and Collaborative Time-dependent Shortest Path (Dec-CTDSP) algorithm where the time-dependency comes from the joint action of CAVs that are communicating with each other. In other words, the CAVs share their location, speed, and preferred path with any other CAV within their CAV cluster through multi-hop connections. Each informed CAV builds a dynamic abstract representation of the network within its planning horizon that reflects the travel time of each link at any time, through which a CAV optimizes its route. This algorithm is designed with a decentralized perspective that scales linearly. Similar to Chapter 5, the mobility of the transportation network was analyzed as a function of MP and CR. The results show a 40% decrease and 45% increase in travel time and its reliability respectively for high MP levels. Moreover, this chapter discussed the correlation between mobility and uniformity in the dissipation of traffic onto the transportation network. The results revealed that Dec-CTDSP distributes the traffic relatively uniformly onto the network, resulting in an increase in average speed and decrease in system travel time.

## 7.2 Future Work

This series of research provides invaluable insights into the CAVs routing behavior and enormous opportunities for further development in terms of multiagent coordination; yet, there remains some limitations to be improved in the future studies. As previously stated, the model design mainly focuses on the proof-of-concept, and is not tested in the real-world traffic conditions. A hypothetical transportation network is used throughout this work and in the multiagent simulations to illustrate the proposed methodological coordination framework. Traffic configurations, geometries, operating environments, traffic signals can all indirectly affects the dynamics, shape, and degree distribution of the CAV network, and it is crucial to further expand this research to a real transportation network with empirical Origin-Destination travel matrix.

There is also a multitude of factors influencing wireless communications performance that need to be further incorporated in the simulation platform. For instance, the connectivity and message passing through the vehicular information cloud need to follow proper protocols that were simplified in this work. On top of these, signal interference, information loss in connections, and V2I communication system have to be incorporated in future models to capture authentic CAV connectivity in urban environments.

In addition, the demand, the arrival time distribution of the CAVs, and their spread over the network also influence the formation of the CAV network and the mobility estimation. Therefore, expanding on the modeling perspective, and applying these components to more varied and diverse scenarios may yield more insightful results or perhaps further evidence in support of the findings from this study.

From the multiagent coordination perspective, there are also a few possibilities that can further improve the performance of the system, such as Auction-based or negotiation-based routing. In terms of multiagent learning, Cooperative Co-evolutionary Algorithm, Swarm Intelligence, Potential-based reward Shaping, and Difference Reward can be alternatives to what has been implemented in this work that further need to be benchmarked against. These improvements can lead to large scale simulation platform development similar to Flow (Kheterpal et al., 2018)). However, the core findings of this work that the advent of CAVs will drastically impact mobility characteristics remain unquestionable.

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