Investment and Financing of Roadway Digital Infrastructure for Automated Driving

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Abstract

Connected automated vehicles (CAVs) are possessed with sensors, enabling them to scan and analyze their surrounding environment. This capability empowers CAVs to make informed and efficient decisions regarding their motion; however, their limited spatial range and resolution present challenges for achieving full autonomy. While enhancing the mobile sensors mounted on CAVs can improve driving autonomy, cooperative sensing through vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications offers an alternative approach to enrich CAVs' environmental understanding. This study explores the optimal investment policy for vehicular connectivity and stationary sensor deployment under varying traffic conditions and the extension of the self-financing theorem to the case of digital roads and investigates whether an optimal toll can cover the construction cost and equip digital components to roads. Our stylized model of CAV mobility considers the interplay between stationary sensors installed roadside as a part of the infrastructure and mobile sensors of CAVs. Results indicate that under constrained budgets and low traffic flow, investing in infrastructure improvement is preferred. However, as traffic flow increases, prioritizing connectivity and data sharing among CAVs becomes more lucrative. Notably, in high-flow scenarios, a shift back to investing in stationary sensors may occur, depending on system settings. Our findings provide insights into budget allocation to enhance CAV performance, advancing the development of efficient and safe automated driving systems. Our analyses on the self-financing theorem show that an optimal toll cannot cover the costs and the theorem does not hold for digital infrastructure. However, if the safety benefits of digitalization are considered by social planners, constructing digital infrastructure can be self-financed. In addition, the self-financing theorem can be held for the digitalization of existing roads, if their flow-capacity ratio is greater than some threshold.

Contents

Page

Abstract **ii**

Contents **iii**

List of Tables **vi**

List of Figures **vii**

1 Introduction **1**

1.1 Background 1

1.2 Objectives 2

1.3 Scope 2

2 Literature Review **5**

2.1 Automation in Driving 5

2.1.1 Classification of Automated Vehicles 6

2.1.2 Implementation of Automated Vehicles 7

2.1.3 Benefits of Achieving Automated Driving 9

2.1.3.1 Safety 9

2.1.3.2 Traffic Capacity 10

2.1.3.3 Environmental 12

2.1.4 Challenges in Achieving Automated Driving 13

2.1.4.1 Safety 14

2.1.4.2 Cyber Security 14

2.1.4.3 Financial Costs 15

2.2 Sensing Technologies in Automated Vehicles 15

2.2.1 RADAR 16

2.2.1.1 Shortcomings of RADARs 17
2.2.2 LiDAR 17
2.2.2.1 Shortcomings of LiDARs 18
2.2.3 Camera 19
2.2.3.1 Shortcomings of Cameras 19
2.2.4 Sonar 19
2.2.4.1 Shortcomings of Sonars 20
2.2.5 GNSS 20
2.3 Connectivity Technologies in Automated Vehicles 21
2.3.1 Types of Connectivity 22
2.3.1.1 Vehicle-to-Vehicle (V2V) 22
2.3.1.2 Vehicle-to-Infrastructure (V2I) 23
2.3.1.3 Vehicle-to-Everything (V2X) 24
2.3.2 Applications and Benefits of Connectivity in Automated Vehicles 24
2.3.2.1 Benefits of Vehicle-to-Vehicle (V2V) Connectivity 25
2.3.2.2 Benefits of Vehicle-to-Infrastructure (V2I) Connectivity 26
2.4 Cooperative Sensing 29
2.4.1 Applications and Benefits of Cooperative Sensing 31
2.5 Financing Methods for Smart Infrastructure 35
2.5.1 Self-financing Theorem of the Roads 37
2.5.1.1 Extensions to Self-financing Theorem 37

3 Optimal Investment in Stationary Vs. Mobile Sensors 40
3.1 Sensor Range and Resolution 40
3.2 CAVs' Speed 44
3.3 Flow Characterization 46
3.4 Modeling Bottleneck With Point Queue 48
3.5 Mathematical Model 49

3.6 Analytical Closed-form Solutions 51
3.7 Numerical Analyses for Optimal Investment 54

4 Financing of Digital Roads **59**
4.1 Self-financing Theorem 62
4.1.1 Constructing Physical Roads 62
4.1.2 Constructing Digital Roads 63
4.1.3 Digitizing Existing Roads 63
4.2 Modified Models 65
4.2.1 Manufacturing Automated Vehicles and Constructing Digital Roads 65
4.2.2 Safety Benefits of Enabling Automated Driving 68
4.3 Numerical Analyses for the Self-financing Theorem 71

5 Conclusion **73**
5.1 Summary of Results 73
5.2 Future Research Directions 74

Bibliography **75**

Appendices **99**
A Proof of Lemma 1 99
B Closed-form Solutions of the Optimization Problem 100
C Nomenclature 104

List of Tables

1 Classification of automated driving levels in SAE [1]. 6

2 Summary of characteristics of sensors used for automated driving. 21

3 Classification of digital infrastructure levels in ISAD. 31

4 Default values used for parameters in the numerical analyses. 54

5 Default values for parameters of numerical examples. 71

6 Construction of a digital road representative solutions. 71

7 Digitizing of an existing road representative solutions. 72

List of Figures

1 Vehicle-to-everything (V2X) communications [2]. 25

2 Sensor range and resolution profile for mobile and stationary sensors (The darker color shades indicate a higher resolution). 41

3 Speed-density diagram for (a) mobile sensor governed region, and (b) stationary sensor governed region. 46

4 Fundamental diagram for (a) mobile sensor governed region and (b) stationary sensor governed region 47

5 (a) Transitioning from stationary sensor region to mobile sensor region and (b) the disparity between the flow capacity of those regions 49

6 Optimal vehicular connectivity level (β^*), optimal stationary sensor coverage (δ^*), and average travel time for various available budgets (B) and for different σ_β values. (a, b, and c) $\sigma_\beta = 1$, (d, e, and f) $\sigma_\beta = 2$, and (g, h, and i) $\sigma_\beta = 2.5$. 55

7 Optimal investment policy for vehicular connectivity level and stationary sensors coverage in different traffic flows and budgets for different σ_β and γ values. (a) $\sigma_\beta = 1$ and $\gamma = 500$, (b) $\sigma_\beta = 1$ and $\gamma = 2000$, (c) $\sigma_\beta = 1.5$ and $\gamma = 500$, (d) $\sigma_\beta = 1.5$ and $\gamma = 2000$, (e) $\sigma_\beta = 2$ and $\gamma = 500$, and (f) $\sigma_\beta = 2$ and $\gamma = 2000$. . . . 57

8 Schematic of the probability of accident on a link, $N(\delta_a)$, as a function of its portion covered by roadside sensing, δ_a. 69

9 Schematic of a network with one O-D pair and multiple links. 70

1 Introduction

The emergence of connected automated vehicles (CAVs) is set to significantly transform the movement of people and goods in the near future, enhancing safety and accessibility. The current approach to enabling automated driving has been mainly vehicle-centric, in which CAVs can independently perceive their surroundings and navigate without human driver input. This approach, however, faces challenges in achieving fully automated driving despite significant research and development.[3, 4, 5] While enhancing on-board sensors and AI-based control systems is one way of improving perception and vehicle autonomy, equipping all CAVs with highly advanced sensors and computation power is neither cost-effective nor robust. The potential benefits of cooperation between traffic agents, such as vehicles through vehicle-to-vehicle (V2V) and infrastructure through vehicle-to-infrastructure (V2I) communications [6, 7, 8, 9], has led to the consideration of an alternative strategy, where connectivity and cooperation between vehicles and infrastructure plays a central role in enabling automated driving systems. While there is strong evidence of a positive effect of V2V and V2I communication on advancing CAV operations, it remains unclear which approach is ideal for different traffic conditions.

1.1 Background

The literature has highlighted the advantages of data sharing and communication in the context of CAVs, supporting the notion that enhanced connectivity can significantly boost the operational performance of CAVs.[10, 11, 12, 13, 14, 15] For instance, Kong [16] proposes the idea of installing LiDAR sensors on road-side lamp posts for sharing among passing vehicles, avoiding the need to install expensive sensors on-board each vehicle. Geissler et al. [17] introduce an optimal sensor placement method for installing sensors on the infrastructure to achieve the best coverage in such systems. In addition, Vignon et al. [18] conduct an economical analysis of vehicle-infrastructure cooperation for automated driving and demonstrate that such vehicle-infrastructure cooperation is socially optimal. In the most related study, Nourinejad et al. [19] explore the trade-offs between individual and cooperative sensing with data shared among CAVs. Their findings identify a critical traffic density threshold beyond which the sensors of adjacent CAVs exhibit adequate overlap in their detection range, leading to increased driving speeds as CAVs benefit from an enhanced vision of their surroundings.

1.2 Objectives

In this study, we expand Nourinejad et al. [19] by considering the smart infrastructure concept, which is to install road-side sensors to achieve comprehensive and seamless sensing coverage. This integration introduces an intriguing trade-off between stationary road-side sensors installed in the infrastructure and on-board CAV sensors. This study aims to determine the optimal investment policy concerning two technologies. Hence, our first research question concerns investigating the optimal allocation of a limited budget in enhancing V2V or V2I under different traffic characteristics of roads.

Our second research question concerns the financing of such smart infrastructure. Mohring and Harwitz [20] studied the financing of a regular highway and showed that if a planner selects road capacities and tolls optimally, the generated toll revenue, in the long run, is equal to the construction cost of roads if there are neutral scale economies in road construction and congestion technology. Since then, there has been a substantial body of literature that has extended the results for various scenarios (for reviews, see [21] and [22]). Studies show that Mohring and Harwitz's conclusions hold for the network as a whole but do not hold if only a subset of links in a network is tolled.[23, 24] However, to the best of our knowledge, the self-financing theorem for digital infrastructure has not been investigated yet. Hence, we are interested in evaluating whether revenue from optimal tolls can cover the cost of constructing digital roads.

1.3 Scope

To address the first question regarding the strategic placement of road-side sensors considering a limited budget where road-side sensors cannot be installed throughout the road, we develop a stylized model of CAV mobility considering the properties of road-side and on-board sensors. In developing the model, it is assumed that the corridor under study consists of a single lane, exclusively serving CAVs, with no unexpected appearance of other objects anticipated. Our analysis reveals that in cases of low vehicle density that limits the efficacy of V2V data sharing, it is optimal to allocate the budget to improve the infrastructure through installing road-side sensors. However, as traffic flow increases, investing in CAVs' connectivity and data sharing becomes increasingly beneficial. Nonetheless, depending on the system's settings, there are instances in high-flow scenarios where investing in road-side sensors once again becomes more optimal. To address the second question regarding the financing of roadway digital infrastructure, we extend the conventional self-financing theorem of highways to the vehicle-infrastructure cooperative approach. More specifically, we consider not only choosing the optimal physical capacity of roads (conventional self-financing theorem), but also selecting the optimal infrastructure digitalization (road-side sensing), and exploring whether revenue from optimal tolls can cover the cost of constructing digital roads. Our analyses show that the revenue from optimal toll is not enough to cover the cost of constructing digital infrastructure, including physical road construction and road-side sensor installation, and therefore, the self-financing theorem does not hold. We also consider the case of digitalization of existing roads and show that the revenue from the toll can cover the cost of installing road-side sensors only if the link flow-capacity ratio is greater than some threshold. Moreover, we consider two modified versions of the problem. In the first scenario, the social planner selects the CAVs' on-board sensing and data-sharing properties as well as the road-side sensing properties of the roads. Our analysis shows that in this scenario the travelers pay the full cost of CAVs' on-board sensing power and connectivity level. In the second scenario, the social planner additionally considers the safety benefits of the digitalization of roads. Our findings reveal the construction of digital roads can be self-financed when the safety benefits are also considered, demonstrating the significant impact of incorporating such benefits.

The remainder of this thesis is organized as follows: A review of the related works is presented in Chapter 2. In Chapter 3, we present a stylized model of CAV traffic, considering the configuration of both on-board and road-side sensors, followed by presenting the closed-form solutions for the optimization problem outlined earlier in the chapter and showcasing the numerical findings related to the properties of the optimal investment policies. Chapter 4 evaluates the self-financing theorem for different scenarios, and presents the mathematical model and its analytical solutions, followed by a numerical example highlighting the analytical findings. Finally, Chapter 5 provides the conclusions drawn from our research and outlines potential directions for future studies.

2 Literature Review

In this chapter, we conduct a comprehensive review of the existing literature on connected and automated vehicles (CAVs). Initially, we explore the concepts, challenges, and benefits associated with achieving automated driving. We examine the technological challenges related to the perception capabilities of automated vehicles (AVs), focusing on the various sensors used in their operation and their limitations. Subsequently, we examine research on the connectivity between AVs, emphasizing the concept of connected automated vehicles. We introduce different connectivity types, such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I), and evaluate their applications in enhancing CAV operations and the associated benefits. Furthermore, we explore cooperative sensing through vehicular connectivity, discussing how this technology can address the shortcomings of on-board sensors in CAVs. We also highlight a gap in the literature regarding the optimal connectivity path and the most effective investment strategies under varying budget constraints and traffic conditions.

In the final part of this chapter, we address the financial challenges associated with enabling infrastructure support for CAVs and digitalizing roadways. We begin by examining the difficulties in financing and funding road construction and reviewing traditional and innovative methods of securing necessary funds. We then investigate the self-financing theorem as a means of funding road construction, discussing its extensions from its foundational format in the literature. Additionally, we investigate methods to overcome the financial hurdles of installing road-side units (RSUs) and identify gaps in the literature concerning the application of the self-financing theorem to the construction of sensor-equipped roads.

2.1 Automation in Driving

In recent years, there has been a surge of interest and research endeavors in enabling automated driving. Between 2014 and 2018, the total investments directed to automated vehicle technologies reached a sum of 80 billion USD [25]. Furthermore, the global CAV market is anticipated to

Table 1: Classification of automated driving levels in SAE [1].

SAE level	Name	Responsibilities	
		Human driver	Automated system
0	No automation	All driving tasks	No assistance
1	Driver assistance	Monitoring road and steering control	Assist in acceleration, deceleration, and braking
2	Partial automation	Monitoring driving and able to take control at any time	Assist in steering, braking, acceleration, and deceleration
3	Conditional automation	Responding to requests to intervene	Maintain navigation, steering, acceleration, and braking
4	High automation	No responsibility	Control operational and tactical decision makings
5	Full automation	No driver required	All driving tasks

experience substantial growth, expanding from 5.68 billion USD in 2018 to an estimated 60 billion USD by the year 2026, which will result in more attention being paid to this field [26].

An automated vehicle (AV), also commonly known as an autonomous vehicle, is an intelligent vehicle equipped with the ability to perceive its surroundings, chart an optimal route to its destination, and navigate without human intervention using its automated driving system (ADS) [27]. The ADS comprises several modules: perception, motion planning, navigation, and behavioral decision-making. The perception module utilizes sensor data from tools like LiDAR and cameras to interpret the vehicle's environment. Motion planning handles executing low-level maneuvering actions to achieve higher-level navigation objectives. The navigation module localizes the vehicle, determining its current position within the driving environment. After assessing the surroundings, planning motion, and completing localization, the behavioral module makes decisions and issues commands for accelerating, braking, and steering [27]. The Society of Automotive Engineers (SAE) defines six levels of driving autonomy, ranging from zero (no automation) to five (full autonomy in all driving scenarios without human assistance) [1] which are further investigated in the following section.

2.1.1 Classification of Automated Vehicles

While there are several classifications for automated vehicles, the taxonomy proposed by the Society of Automotive Engineers is the most widely used and accepted. The SAE [1] defines six levels of driving automation, ranging from level 0 (no automation) to level 5 (full automation), as shown in Table 1. The critical distinction lies between levels 2 and 3. From levels 0 to 2, the human driver remains the primary actor responsible for the driving task. In the event of system faults, the human driver must react within less than one second and is not permitted to divert their attention away from driving [28]. At level 3, the ADS performs the entirety of the dynamic driving task, with the vehicle becoming aware of its surroundings. The human driver has an increased reaction time of several seconds, during which the vehicle will alert them to intervene if necessary. At this level, the human driver is allowed to engage in other activities while the vehicle is in motion. The fundamental difference between levels 3 and 4 is that level 4 vehicles can intervene independently during emergencies or system failures. For levels 4 and 5, the human driver's reaction time extends to a couple of minutes, and the driving process is considered fully adopted by the vehicle. At these levels, the vehicle becomes capable of reacting autonomously throughout the entire journey, even allowing the human driver to sleep while driving [28]. Level 5 represents full automation, where the system performs all aspects of the dynamic driving tasks under all roadway and environmental conditions without human driver input. At this level, the human driver may need to activate or deactivate the ADS. Once activated, the system monitors the driving environment and executes longitudinal and lateral dynamic driving tasks. Deactivation occurs only when the human driver takes over control, the vehicle reaches its destination, or if a failure occurs within the automated system [29]. Despite significant technological advancements, several challenges persist in achieving levels four and five of autonomy [30].

2.1.2 Implementation of Automated Vehicles

Over 40 corporations and more than 250 companies, spanning traditional car manufacturers, automotive suppliers, and tech firms, have made significant strides in the field of developing automated vehicles [31]. As one of the leaders of the industry, Waymo's self-driving vehicles have traversed over 20 million miles without human intervention [32]. Achieving these milestones required the development and application of advanced technologies, including high-precision sensors for data collection, sophisticated algorithms for data processing and vehicle control, and enhanced computational capabilities for real-time operations [33].

In 2015, Volvo unveiled its Autopilot system, a production-ready automated driving technology, and planned to deploy 100 automated vehicles on a 50-kilometer road for use by actual customers [34]. This initiative aims to integrate a large number of AVs into everyday use, especially under winter conditions [35, 36]. More recently, Volvo partnered with Uber to develop AVs for potential future automated ridesharing within Uber's network [37]. In another significant collaboration, Mercedes-Benz and BMW are jointly working on self-driving technology, with plans to release a vehicle featuring advanced driver assistance, highway automation, and parking capabilities up to level four autonomy by the mid-2020s [38]. As of April 2019, more than 9 million Tesla drivers had engaged Autopilot, accumulating a total of 66 million miles driven with the feature enabled and they are projected to achieve full autonomy (level 5) in the near future [39].

Moreover, automotive suppliers such as IBM, Bosch, Denso, and Magna International are actively competing to establish a foothold in the automated vehicle market [31]. In 2019, Bosch and Daimler initiated the first trial of a self-driving taxi service in San Jose, California, and also tested the world's first fully automated parking system at SAE Level 4 without a human safety driver [40]. In January 2019, Magna announced a collaboration with Waymo to build a factory in Michigan for manufacturing level 4 automated vehicles [41]. Technology giants like Apple, Google-Waymo, Nvidia, Huawei, and Baidu are leveraging their financial and technological resources to develop innovative automated vehicle features [31]. Apple has been testing a fleet of SUVs equipped with LiDAR and RADAR sensors in California [42]. Baidu, partnering with BMW, began testing automated vehicles on Beijing's streets in November 2016 and had 300 automated vehicles on urban roads by December 2019, accumulating over 1.8 million miles [31]. Service providers including Uber and Lyft are vigorously advancing their automated vehicle projects, alongside numerous other less prominent initiatives. Amazon has also invested billions in enhancing its delivery services over the past decade. In 2019 they announced a plan to deploy 100,000 electric automated vehicles by 2030 [43].

Optimistic projections from various sources [44, 45, 46, 47] have predicted that automated vehicles would hit the market by 2020. Prominent companies (e.g. Tesla, Waymo, and GM) announced that their automated vehicles would be available by this date. Nevertheless, these timelines got postponed. One primary reason for the delay is that automated vehicle technologies are still in their development and testing phases and need to undergo several more stages before they can be widely marketed, reliable, and affordable [48]. A more commonly accepted timeline suggests that most vehicles will operate autonomously between 2040 and 2050 [49].

2.1.3 Benefits of Achieving Automated Driving

The AVs are set to revolutionize everyday mobility and have huge impacts on the lives of people. Below we investigate the benefits that can be obtained from implementing this technology into our day-to-day lives.

2.1.3.1 Safety

Road safety is a crucial factor in the transition from human drivers to connected and automated vehicles [50, 51]. The driving habits of human drivers are the primary contributors to road crashes [52, 53]. The World Health Organization (WHO) reports that approximately 1.2 million people die on the road each year globally, with nearly 50 million sustaining injuries [54], and according to a survey by the United States Department of Transportation (USDOT), human errors account for approximately 90% of these car accidents [55].

Automated vehicle technology holds considerable potential to reduce these fatalities[33, 45, 48]. Research suggests that automated driving significantly enhances road transport safety and efficiency [56]. Studies argue that although automated vehicles may not always outperform an alert driver, their quicker response times can prevent accidents caused by poor drivers, thereby saving lives [57]. Furthermore, some studies claim that widespread deployment of automated vehicle technology not only enhances the safety of vehicle occupants but also improves the safety and environment for vulnerable road users such as pedestrians and cyclists [48].

Ni and Leung [58] observed that even basic technologies at levels 0 and 1, such as forward collision warning and lane departure warning, have the potential to reduce accidents. Studies estimated that the adoption of level 0 and level 1 technologies across all vehicles could prevent nearly a third of road accidents [56]. Advanced technologies at levels 3, 4, and 5 also hold significant promise for saving tens of thousands of lives annually [58]. According to Anderson et al. [33], level 3 automation, which enables drivers to cede control of safety-critical functions in certain scenarios, could substantially decrease the incidence of crashes, injuries, and fatalities. This reduction is attributed to level 3 vehicles' immunity to distraction, impairment, and reckless driving, thereby reducing accidents involving vulnerable road users (e.g. pedestrians and cyclists). Furthermore, it is projected that a significant portion of alcohol-related traffic fatalities could be averted as impaired drivers hand over control to fully automated vehicles once the shift from level 3 automation to level 5 occurs [33]. Nevertheless, the transition phase for level 3 vehicles raises specific concerns. The risk associated with drivers becoming inattentive or quickly disengaging once the vehicle assumes control poses a new hazard if the vehicle subsequently requires the driver to retake control [59]. Connectivity is set to further contribute to the positive safety effects of AVs and automated driving with connectivity is anticipated to reduce driver stress [48] and significantly decrease accidents caused by human error [45].

2.1.3.2 Traffic Capacity

As automated driving technologies advance, AVs offer the promise of more efficient road utilization and smoother driving capabilities compared to human-operated manual vehicles. The expectation is that AVs should be able to largely eliminate roadway congestion [45, 48]. For instance, technologies like adaptive cruise control (ACC), cooperative adaptive cruise control (CACC), and lane keeping assist (LKA) would enable AVs to travel much closer together and at higher speeds, resulting in improved traffic flows [60]. Atiyeh [61] estimated ACC-equipped vehicles could increase congested traffic speeds by 8-13% and fuel economy by 23-39%. However, market penetration needs to reach sufficient levels to observe significant improvements from these technologies [45, 62]. Studies have reported that 20% ACC market penetration could nearly eliminate all congestion on highways, and CACC-equipped vehicles will drastically increase lane capacity with reasonable market growth [57]. Additionally, it is estimated 10%, 50%, and 90% CACC penetration rates, would raise effective lane capacities by approximately 1%, 21%, and 80% respectively [63]. Other studies suggest that realizing just the safety benefits of AVs, such as reducing crashes and secondary incidents, would significantly mitigate traffic congestion [45].

On the other hand, some researchers have expressed concerns that AVs may actually increase roadway congestion levels. Forrest and Konca [64] indicated that in the early implementation stages when human-driven and automated vehicles share the roads, there could be more congestion due to confusion around how human drivers react to AVs and how well AVs integrate into traffic flows. Some studies also noted that congestion benefits only materialize if AVs reach a high market penetration, otherwise impacts would be non-existent or greatly diminished. Rates of congestion mitigation increase more substantially as AV market share grows beyond 10%, enabling smoother traffic flow as every lane would likely have regularly-spaced AVs during peak times [45]. Metz [65] suggested several other factors likely to exacerbate congestion with AVs: individually owned AVs traveling unoccupied on return trips; increased car usage demand from those previously unable to drive; and greater demand for lower-cost automated taxis drawing former public transit riders.

The automatic braking configured in AV systems will increase highway capacity, along with other advantages. This increased capacity may further induce overuse of roadways, reducing safe following distances between vehicles and increasing speeds due to the incorporation of ACC and CACC [66, 67]. Commercially deployed AVs are expected to reduce traffic congestion delays and subsequently increase traffic flow [68, 69]. Applications of ACC and CACC in AVs are estimated to increase highway capacity by 80% compared to human-driven traffic [63]. The Virginia Department of Transportation found highway capacity could increase by 28% for fully automated vehicles and 92% for connected AVs compared to legacy vehicles.

In summary, while full AV deployment with technologies like automatic braking, ACC, and CACC is projected to significantly boost road capacity and traffic throughput, concerns exist around induced demand from overuse eroding those gains if not properly managed. Low levels of automation were found to in fact worsen the capacity.

2.1.3.3 Environmental

The transportation sector comprises a substantial and growing source of air contamination and CO2 output globally. Reports from the World Health Organization (WHO) indicate road transport accounts for 70-90% of urban air pollution and 23% of worldwide energy-related CO2 emissions [70]. In the United States alone, an estimated 3.9 billion gallons of fuel are wasted due to traffic congestion, equating to around 16 million tons of CO2 released into the atmosphere [70]. A widely cited advantage of self-driving car technology relates to favorable impacts on the environment. The primary effects include reduced contributions to carbon dioxide (CO2) emissions, air pollution, greenhouse gases, noise levels, and land usage [48, 60].

Given the significant environmental toll of road transportation amid rising population and travel demands, advancements in eco-friendly vehicle designs have become imperative. While driver training in eco-driving techniques can yield fuel economy and emissions reduction benefits, automated driving capabilities are expected to have an even more pronounced positive impact [71]. Prior work identifies eco-driving practices like smooth acceleration, early upshifting, and avoiding sudden braking/acceleration as key strategies [33]. Other studies demonstrate that private vehicles equipped with existing autonomous technologies like ACC and employing eco-driving styles can improve fuel efficiency by 10% to 40% enhancement [46, 61].

Fagnant and Kockelman [45] have demonstrated that smoother acceleration and deceleration, along with improved traffic flow, can significantly reduce emissions. Forrest and Konca [64] found that the widespread adoption of automated vehicles could result in an average fuel savings of 25%, potentially saving billions of dollars annually in the US alone. These savings could increase further if traffic flow becomes more stable, as vehicles typically consume more fuel in stop-and-go conditions. Studies on connected and automated vehicles have further pointed out that CAVs, by minimizing stop-and-go driving patterns, should experience lower fuel consumption and emissions levels [33]. Additionally, implementing dampening functions instead of stop-and-go driving can notably decrease greenhouse gas (GHG) emissions, with reductions ranging from 15% to 75% [72]. However, achieving optimal GHG emission reductions may be difficult with low CAV penetration rates on roadways [73].

In addition to emissions reductions, automated vehicles can also lead to substantial land conservation. It was predicted in 2014 that approximately $50 trillion would be required for global infrastructure investments from 2013 to 2030 to meet the projected transportation demand [74]. Tientrakool et al. [67] demonstrated road capacity could increase by 43% with automated vehicles and by 273% with V2V communication. This would significantly reduce the road space required for vehicles, leading to decreased investment needs in road infrastructure [71, 75].

As the global population continues to grow, the space dedicated to parking will increase, reducing overall land use density. A study focusing on Los Angeles' central business district found that parking occupies about 81% of the district area. Similarly, across 41 major cities worldwide, parking spaces occupy an average of 31% of district areas [33]. The integration of automated vehicles could further a trend towards more dispersed and lower-density land use patterns around metropolitan regions. Furthermore, Alessandrini et al. [76] noted that automated vehicles could reduce the number of parked vehicles and the space required for parking, enhancing urban livability and providing more space for pedestrians and cyclists.

Research has shown that shared automated vehicles (SAVs) can greatly reduce the number of cars on the road and the demand for parking spaces, thereby decreasing land use requirements. For instance, Zhang [77] highlighted that the implementation of an SAV system could cut the required parking space for users by over 90%. Further studies illustrated that each SAV could lead to significant reductions in land use, energy consumption, greenhouse gas emissions, and air pollutants when the SAV system is adopted by approximately 5% of the population in the study area [45]. Additionally, SAV systems have the potential to nearly eliminate the need for on-street parking and significantly decrease off-street parking requirements.

2.1.4 Challenges in Achieving Automated Driving

Despite the advantages of AVs, several obstacles continue to hinder their rapid development and widespread adoption. Below we further discuss some of the key challenges in this path.

2.1.4.1 Safety

Safety concerns remain a key challenge for the commercialization of AVs. Wang et al. [78] conducted a statistical survey on AV testing by various manufacturers, finding that about 63% of accidents in a total of 3.7 million miles traveled occurred in autonomous mode.

A study conducted by Litman [48] stated that AV users may take additional risks (e.g. neglect to use seatbelts, operate at higher speeds or closer proximities) and as a result of feeling overly secure contribute to new safety hazards. Various studies suggest that automated vehicles may not be inherently safer than conventional human-driven vehicles and could potentially increase the number of accidents during the transition period when both automated and human-driven vehicles share the road [79] by complicating matters more for human operators[80] and traffic safety is estimated to decline in mixed environments of non-AVs and AVs [50].

Notably, the first recorded fatal accident involving a Tesla car using its semi-automated autopilot system occurred in 2016 [81]. Google-Waymo vehicles have also been involved in several crashes since the project's inception in 2009 [82]. These incidents underscore the critical safety issues that must be resolved. A survey has illustrated the majority of drivers preferred no automation or only partial automation over fully automated vehicles, expressing significant concerns about the safety of fully automated systems [83]. Similarly, a survey by Song et al. [84] revealed that over 75% of respondents were uncomfortable riding in a fully automated bus without a human operator. Moreover, regulatory issues regarding the deployment of CAVs and associated liability have not been adequately addressed and need improvements [85].

2.1.4.2 Cyber Security

Despite advancements in the technology of connected and automated vehicles, concerns about electronic security remain prevalent among automotive manufacturers and prospective AV owners [77]. Litman [48] noted that automated vehicles could introduce new risks, such as system failures, cyberterrorism, offsetting behaviors, and rebound effects. Fagnant and Kockelman [45] highlight the potential threat posed by computer hackers, terrorist groups, and hostile nations, who may target

AVs to cause collisions and disrupt traffic. The current AV industry lacks standardized protocols for vehicular communications to infrastructure or among vehicles. Without properly designed protocols, these technologies remain highly vulnerable to such malicious attacks [77].

2.1.4.3 Financial Costs

Gibson [86] examined policies related to automated vehicles and identified alongside safety and security concerns, cost is the other primary hurdle in achieving widespread adoption of AVs. The most costly component of an AV is the Light Detection and Ranging (LiDAR) sensor, with prices ranging from 30,000 USD to 85,000 USD [77]. For instance, an early model from Velodyne, widely used by self-driving technology companies, is priced at 75,000 USD [87].

A survey conducted by Kyriakidis et al. [88] revealed that 20% of participants were unwilling to pay additional costs for AV technology, and a mere 5% were ready to spend more than 30,000 USD on a fully automated vehicle. Further research in this area indicated that potential buyers are more sensitive to the costs and incentive policies associated with automated vehicles than to other factors such as fuel efficiency, safety, or environmental benefits [89].

2.2 Sensing Technologies in Automated Vehicles

Automated vehicles, despite design variations among manufacturers, operate on roads using three core components: (1) input devices or sensors to perceive the environment, (2) control systems with advanced software to process inputs and determine the travel path, and (3) output devices or actuators to manage steering, wheels, brakes, and other functions [90]. These components are often analogized to the vehicle's eyes, heart, and hands, respectively [91]. During the perception phase, data captured by sensors and prior information are used to map and localize the surrounding environment. This information is crucial for the planning phase, where travel paths are determined. The control phase, involving both lateral and longitudinal controls, ensures that the vehicle follows the planned trajectory accurately [92].

This section examines various sensors employed in automated vehicle perception and their potential applications for traffic sensing. Commonly used perception sensors installed on AVs include cameras, stereo vision cameras, LiDAR, RADAR, and sonar [93]. The most representative sensors that form the sensor suite of automated vehicles are RADAR, LiDAR, sonar (ultrasonic) sensors, global navigation satellite system (GNSS), and cameras. These sensors measure various waveforms and detect a wide array of physical phenomena. Each sensor has distinct characteristics that enable it to perform specific tasks under designated conditions. In this section, we explore these sensors in greater detail, discussing their operational mechanisms, benefits, and limitations [94].

2.2.1 RADAR

Radio Detection and Ranging (RADAR) is a technology that employs radio waves to detect objects within a certain range. When these transmitted waves encounter an object, they are reflected back, and the RADAR antenna collects the returning signal (echo) within its field of view (FOV). By measuring the round-trip delay time and using the known speed of radio waves, the system can accurately determine the object's distance and velocity [95]. The range of RADAR sensors is influenced by several factors, including the transmitted power, the wavelength used, and the cross-sectional area of the target. Additionally, it is inversely proportional to the distance between the sensor and the target.

RADAR systems in AVs typically operate at different frequencies designated for different ranges: short-range RADAR (SRR), medium-range RADAR (MRR), and long-range RADAR (LRR) [96]. SRR and MRR are commonly used for functions such as blind spot detection, parking assistance, and collision warning, with an effective range of approximately 20 meters [97]. However, neither SRR nor MRR are suitable for traffic sensing. In contrast, LRRs primarily employed for adaptive cruise control, have a range of about 150 meters and are capable of detecting vehicles in the same lane ahead, making them a potential tool for traffic sensing [98]. Modern AV RADAR systems utilize arrays of micro antennas that create multiple antenna lobes. The integration of such devices in the automotive sector has been driven by advancements in smart vehicle technology to enhance safety. Applications include adaptive cruise control (ACC), collision avoidance systems (CAS), blind spot detection (BSD), and lane change assist (LCA) [95].

2.2.1.1 Shortcomings of RADARs

RADAR sensors are capable of operating in various weather conditions due to their wide-spectrum wavelength and the absence of mechanical moving parts, unlike passive visual sensors which have limited effectiveness in different climates. Nevertheless, rain is a major factor affecting RADAR signal attenuation [99]. Because droplet sizes are comparable to RADAR wavelengths, the rain backscatter effect significantly impacts performance. The attenuation effect reduces the signal strength, while the backscatter effect introduces interference at the receiver [100]. These issues are also relevant in the presence of snow or mist. In the case of hail, millimeter-wave RADAR signals lose some of their power as they pass through the weather conditions [101, 102]. The mathematical models for attenuation and backscatter in snow and mist are consistent with those for wet conditions [103].

2.2.2 LiDAR

Light Detection and Ranging (LiDAR), is a technology developed in the 1970s for use on space and airborne platforms. Similar to RADAR, LiDAR operates by measuring the time it takes for a pulse of light—emitted in the infrared or near-infrared range from a laser diode—to travel to a target and return to the receiver, a principle known as time-of-flight (ToF). In ToF technology, LiDAR emits a light pulse of a specific duration (τ), which starts an internal clock within a timing circuit. The reflected light pulse is detected by a photodetector, generating an electrical signal that stops the clock. The distance to the reflection point is calculated using this electronically measured round-trip ToF [104].

LiDAR systems primarily operate at wavelengths of 905 nm and 1550 nm, selected based on atmospheric transmission windows and the availability of high-power pulsed sources [104]. Initially, 905 nm pulsed LiDAR systems were used in the early development of automated vehicles due to their accessibility. However, these systems faced significant limitations, including high costs, inefficient mechanical scanning, susceptibility to interference from other light sources, and eye-safety power constraints that restricted their detection range to about 100 meters [95]. These drawbacks led to a transition towards the 1550 nm band, which is safer for the human retina. Since atmospheric water begins to absorb energy at 1400 nm, this shift allows for higher pulse powers, extending the detection range to between 200 and 300 meters [104]. The LiDAR systems used in vehicles are classified as Class-1 [105], ensuring safety under all normal usage conditions.

LiDAR technology employs a pulsed laser beam to measure the distance to objects, also capturing their 3D shape. LiDAR systems on automated vehicles typically offer 360° coverage, with detection ranges varying from 30 to 150 meters depending on the manufacturer, detection algorithms, and weather conditions [94]. Both LiDAR and cameras are capable of vehicle detection and 3D mapping. However, cameras, while more affordable, have a higher system latency (the time delay for processing data) compared to LiDAR [4]. Although theoretically, either LiDAR or cameras could be used to develop a comprehensive AV perception system, most current automated vehicles rely on LiDAR as their primary sensor.

2.2.2.1 Shortcomings of LiDARs

LiDAR sensors are susceptible to precipitation conditions such as snow, hail, sleet, and rain, as illustrated in Figure 20. Despite this vulnerability, LiDAR, with its short wavelength technology, can detect small objects and generate a precise 3D monochromatic image, which RADAR might not achieve. Adverse weather conditions can significantly impair object perception and reduce detection range. The decreased intensity contrast can lead to increased misclassifications and erroneous detections [106]. When raindrops are close to the laser emitter, there is a high likelihood of incorrect detection. This is because the laser beam interacts with particles, creating a flash of light similar to that from a small surface, producing a return peak akin to that of a road object [107].

2.2.3 Camera

Cameras can detect shapes and colors and are extensively used in AVs for object detection, identifying signals, pedestrians, vehicles, lane markings, and overall interpreting AV's surroundings [108, 109]. Based on the electromagnetic spectrum, cameras are typically categorized as visible (VIS) or infrared (IR). VIS cameras, which include monocular [110, 111, 112, 113] and stereo vision [114, 115], capture wavelengths from 400 to 780 nm, similar to human vision. They are favored for their low cost, high resolution, and ability to distinguish colors. Due to their affordability, multiple cameras can be installed on a single automated vehicle. By pairing two or more VIS cameras at a specific focal distance, stereo vision is achieved, enabling the derivation of depth information for each pixel from the slightly different images captured by the cameras and creating a 3D representation of the vehicle's environment [95]. However, even with stereoscopic vision systems, the depth accuracy is lower compared to active range finders like RADAR and LiDAR. Modern automated vehicle prototypes often integrate cameras with stereo vision systems or LiDAR to better perceive their surroundings [94].

2.2.3.1 Shortcomings of Cameras

Cameras provide dependable environmental information and can function effectively in various weather conditions [116]. For self-parking, a visual navigation system can detect nearby obstacles and position the vehicle accurately, assuming a comprehensive and precise view of the surroundings is maintained within the limited space. This can be achieved through the application of stereo vision techniques. By extracting real-time depth maps, a detailed and accurate map can be constructed through a sequence that includes depth map extraction, obstacle identification, and fusion across multiple camera frames, ensuring precise estimation [117].

2.2.4 Sonar

Sonar sensors, also known as ultrasonic sensors, are widely used for various detection tasks in industrial settings due to their ability to detect solid, liquid, granular, or powdery objects. Sonar sensors, have a detection range of 3 to 5 meters, In automotive applications are often used for blind spot detection and parking assistance [94]. These sensors utilize sonic transducers to emit sound waves within the 40 kHz to 70 kHz frequency range, which is inaudible to humans and thus safe for human ears. This is particularly important as a car's parking system can produce sound pressures exceeding 100 dB, comparable to the noise of a jet engine. Similar to LiDARs, the ultrasonic sensors operate on the principle of measuring the time-of-flight (ToF) of sound waves between their emission and reception. The ToF measurement is then used to determine the distance to an object or reflector within the sensor's range.

2.2.4.1 Shortcomings of Sonars

Sonar sensors, are primarily utilized for detecting nearby obstacles and assisting with parking. Their limited range which is commonly less than 5 meters, and poor angular resolution mean they cannot reliably track the location and velocity of vehicles on the road [118]. Additionally, ultrasonic sensors can be disrupted by noisy environments, such as roads, streets, and highways. Efforts to extend their coverage range can result in loud emissions from the emitter, which can be harmful to both people and the environment. Therefore, sonar systems are best confined to environments like parking lots, where they can accurately detect obstacles [119]. To ensure optimal accuracy, the sonar sensors on the front and rear bumpers should be kept free of snow, ice, and dirt.

2.2.5 GNSS

The Global Navigation Satellite System (GNSS) is the most commonly used technology for providing precise positional information on Earth. The most renowned GNSS is the Global Positioning System (GPS), a world-renowned system that offers positioning, navigation, and timing (PNT) services. GPS's free, open, and reliable nature has made it a crucial component of the global information infrastructure, impacting every facet of modern life. To enhance the accuracy of positioning systems in vehicles, data from satellites are integrated with information from other vehicle sensors, such as inertial measurement units (IMU), LiDAR, RADAR, and cameras, to ensure reliable posi-

Table 2: Summary of characteristics of sensors used for automated driving.

Feature	LiDAR	RADAR	Camera	Ultrasonic
Main Technology	Laser beam	Radio wave	Light	Sound wave
Range	∼200 m	∼250 m	∼200 m	∼5 m
Resolution	Good	Average	Very good	Poor
Effect of weather	High	High	High	Low to none
Effect of lighting	Low to none	Low to none	High	Low to none
Speed detection	Good	Very good	Poor	No
Distance detection	Good	Very good	Poor	Good
Size	Large	Small	Small	Small

tional information [95].

In summary, the findings indicate that RADAR sensors are well-suited to current technology, as they can function effectively even in adverse weather conditions. However, their primary limitation is the need for a complementary perception system to enhance decision-making robustness. While LiDAR can be adapted to perform in challenging weather, it still requires an additional perception system to be fully effective. Cameras, on the other hand, struggle with reliability when lighting conditions change, weather is harsh, or visibility is poor. Issues like lighting and obstructions, such as dirt-covered signs or cameras, further compromise their reliability. Although LiDAR sensors are highly efficient for applications like spacecraft missions, including location and docking, they are less suitable for use in automated vehicles. Table 2 provides a qualitative summary of the strengths and weaknesses of the most commonly used perception-based sensors in automated vehicles. This evaluation is based on their technical characteristics as well as external factors like weather and lighting conditions.

2.3 Connectivity Technologies in Automated Vehicles

Connected and automated vehicles (CAVs) are the result of merging connected vehicle (CV) and automated vehicle (AV) technologies. Connected Vehicles (CVs) are part of the broader Smart Transportation network, which includes communication between vehicles and their surroundings via Dedicated Short-Range Communications (DSRC) [120]. This involves vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-everything (V2X) communication. The two primary components of CV technology are On-Board Units (OBUs) and Road-Side Units (RSUs). OBUs are installed within vehicles, while RSUs are positioned in road infrastructure, such as at intersections. OBUs gather data on vehicle speed, location, heading, and more, transmitting this information several times per second to nearby OBUs or RSUs through basic safety messages (BSMs) over DSRC. Nearby OBUs receive this data to alert drivers to probable risks of crashing [121]. Recently, the development of the next-generation cellular network, 5G, has become a revolutionary trend for advancing connected and automated vehicles [122], and evidence has shown the value of supporting drivers and providing advanced information through wireless communication between vehicles and infrastructure [123]. The effectiveness and reliability of DSRC communications have been studied, as well. Results from El-said et al. [124] indicate that changes in air density during foggy conditions do not affect DSRC transmission. The Safety Pilot Model Deployment (SPMD) project, led by the University of Michigan Transportation Research Institute, involved approximately 2,800 vehicles equipped with OBUs and 25 RSUs [125]. This project's data was used to evaluate the impact of weather conditions on DSRC transmission. Analyzing data from 2,581 clear days, 114 rainy days, and 227 snowy days revealed that severe weather conditions do not impact DSRC performance. This study concludes that DSRC is a promising and reliable technology under all weather conditions.

2.3.1 Types of Connectivity

In the remainder of this section, we will first explore the literature on various types of vehicular connectivity. Subsequently, we will examine existing research on the applications and benefits these technologies offer for enhancing automated driving.

2.3.1.1 Vehicle-to-Vehicle (V2V)

Vehicle-to-vehicle (V2V) connectivity is a technology that facilitates the exchange of crucial information between vehicles on the road. This communication system allows vehicles to share data such as speed, position, direction of travel, and braking status with other nearby vehicles. The primary goal of V2V technology is to enhance traffic safety, improve traffic flow, and reduce accidents by providing drivers and autonomous driving systems with real-time information about the driving environment. In the V2V framework, vehicles within communication range can exchange data about their speed, position, size, acceleration, brake status, travel direction, and other details [126, 127].

By sharing critical data in real-time, V2V technology enhances situational awareness for both human drivers and autonomous systems, significantly improving overall traffic safety and efficiency. One major use of this technology is supporting collision avoidance systems. For instance, if a vehicle suddenly brakes or encounters an obstacle, it can instantly send an alert to surrounding vehicles, enabling them to take preemptive actions to avoid a potential collision. This capability is particularly useful in situations where a driver's line of sight is obstructed, such as at intersections or in heavy traffic [127].

2.3.1.2 Vehicle-to-Infrastructure (V2I)

Vehicle-to-infrastructure (V2I) technology facilitates the transmission of data between vehicles and road infrastructure, primarily aimed at preventing or reducing motor vehicle accidents and supporting various safety, mobility, and environmental applications [127]. This technology enables the exchange of critical information between vehicles and infrastructure elements such as traffic signals, road signs, and other road-side units. V2I applications rely extensively on the data exchanged between vehicles and infrastructure elements to provide information such as advisories from the infrastructure to vehicles, informing drivers about safety, mobility, and environmental conditions. The development efforts of the government and transport organizations have predominantly concentrated on V2I-based applications to achieve safer, faster, and more environmentally friendly transportation systems [128]. By utilizing V2I connectivity, vehicles can receive alerts about traffic conditions, road hazards, and optimal driving speeds, while infrastructure systems can better manage traffic flow and respond to incidents. This integration of vehicle and infrastructure communication is essential for the development of intelligent transportation systems and the advancement of automated driving technologies. V2I connectivity aims to improve traffic safety, reduce congestion, and minimize environmental impacts by providing real-time data to both drivers and infrastructure systems [92].

2.3.1.3 Vehicle-to-Everything (V2X)

The term V2X, often used to describe a comprehensive system of interconnected road components, stands for vehicle-to-everything and represents an intelligent transportation system where vehicles are seamlessly linked with various elements of the infrastructure. This system includes both V2V (Vehicle-to-Vehicle) and V2I (Vehicle-to-Infrastructure) communications. As shown in Figure 1, in this context, 'X' can refer to any entity that interacts with the vehicle, such as other vehicles, infrastructure components like traffic lights and road signs, on-board devices within the vehicle, cloud technology for data processing and storage, or even pedestrians who may carry connected devices [129]. According to NHTSA [130], V2X technology enables automation systems to react more swiftly to situations by providing vehicles with a comprehensive awareness of their surroundings. Moreover, V2X offers a multi-service platform for V2V and V2I, which has the potential to enhance road safety and deliver beneficial mobility, environmental, compliance, and efficiency solutions for road users [131].

2.3.2 Applications and Benefits of Connectivity in Automated Vehicles

CAVs utilize wireless communication technology and on-board computing to exchange and process V2V and V2I messages and data, supporting various safety and mobility applications. In the short term, this innovative technology must be tested under realistic driving conditions before it can be introduced to the market and gain public acceptance. In the long term, existing transportation infrastructure will need to be upgraded, and agencies will have to plan and prioritize the addition of new infrastructure to support various types of vehicle connectivity under different levels of automation [1, 132]. Key issues to address regarding CAV deployment include determining the necessary infrastructure upgrades and improvements, from both hardware and software perspectives, to sup-

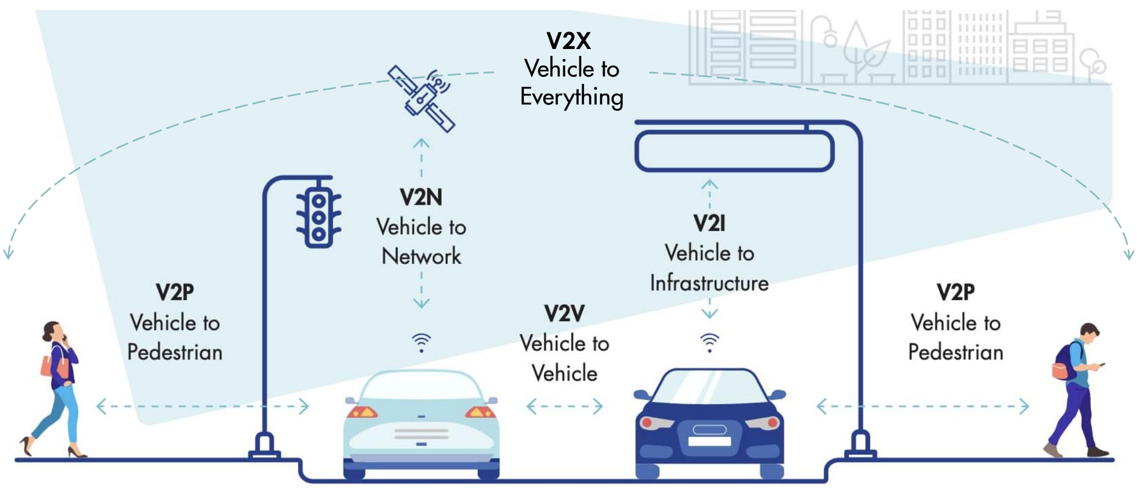


Figure 1: Vehicle-to-everything (V2X) communications [2].

port the adoption of CAVs; assessing the costs and benefits associated with these investments; and deciding which communication technology should be used for connected vehicles. Given these challenges, many benefits can be gained from implementing these technologies.

2.3.2.1 Benefits of Vehicle-to-Vehicle (V2V) Connectivity

This section discusses the existing work on the benefits of vehicle-to-vehicle (V2V) applications. V2V connectivity plays a critical role in the concept of platooning for AVs, where multiple vehicles travel in a coordinated formation with minimal gaps between them. This coordination is achieved through precise control systems and continuous communication among the vehicles, allowing the lead vehicle to dictate speed and direction while the following vehicles mimic these movements. The real-time data exchange enabled by V2V connectivity includes critical information such as speed, acceleration, braking, and positioning data, ensuring all vehicles in the platoon can react synchronously to any changes initiated by the lead vehicle, thus maintaining a consistent and safe distance [133].

The benefits of V2V connectivity in platooning are significant, including enhanced safety through simultaneous braking and acceleration, improved fuel efficiency by reducing aerodynamic drag, increased road capacity by allowing more vehicles to travel safely on the same stretch of road, reduced traffic congestion through smoother traffic flow, and environmental benefits due to lower greenhouse gas emissions. Despite these advantages, challenges remain in ensuring robust and secure communication channels, preventing data breaches, and developing standardized protocols for interoperability among vehicles from different manufacturers. Addressing these challenges is crucial for the widespread implementation of V2V-enabled platooning [48].

V2V systems provide significant safety benefits, such as preventing collisions and issuing electronic brake light warnings. For example, V2V can alert a driver about a braking vehicle ahead, prompting them to slow down or warn them that proceeding through an intersection is unsafe due to an approaching vehicle [134]. In other studies, a cooperative emergency electronic brake light (EEBL) system was proposed, utilizing BSM information and a camera sensor installed in each vehicle. The BSM includes the license plate information of the broadcasting vehicle [135]. However, using a camera to determine vehicle positions may fail in adverse weather and poor lighting conditions. Chen et al. [136] developed a forward collision warning (FCW) algorithm based on road friction. This algorithm focuses on preventing longitudinal collisions without considering the lane information of CVs. Yang et al. [137] proposed an FCW system providing distance and time to collision (TTC) algorithms, using heading angle information in a two-way two-lane scenario to exclude vehicles traveling in the opposite direction.

2.3.2.2 Benefits of Vehicle-to-Infrastructure (V2I) Connectivity

Infrastructure plays a pivotal role in advancing automated driving [138]. One essential function of infrastructure is to augment the sensing abilities of AVs by gathering, analyzing, and transmitting data about the driving environment, such as road conditions and traffic characteristics [139]. This information aids AVs in making strategic, tactical, and operational driving decisions [140]. Another critical role of infrastructure is to support AVs during challenging driving conditions, like adverse weather, obstructions from larger vehicles, or connectivity issues, which can impair sensing or navigation [141]. The USDOT's Automated Vehicle Comprehensive Plan underscores the necessity of updating regulatory frameworks and upgrading current transportation infrastructure to ensure the success of automated transport [142, 143]. Similarly, the American Association of State Highway and Transportation Officials emphasizes the importance of creating a safe driving environment for AVs through regulatory measures and smart infrastructure development [144]. Notably, McAslan et al. [145] observed that numerous regional planning agencies in the United States have implemented policies aimed at improving infrastructure maintenance to support the testing and deployment of AVs. Hence, the development of smart infrastructure is crucial for the effective and safe operation of automated vehicles. The analyses conducted by Tang et al. [146] indicate that with the support of smart RSUs, CAVs can be alerted to the presence of vulnerable road users much earlier than their on-board sensors would typically detect, thereby significantly reducing collisions. Additional research supports this finding, demonstrating that integrating perceived intelligence and capabilities from surrounding infrastructure, including RSUs, can effectively supplement current sensing techniques. This integration enhances perception and intelligence, which proves beneficial for accurate localization, particularly when GPS is unavailable, as well as for blind spot detection and navigating around corners [10, 17]. Rebsamen et al. [147] investigated the advantages of utilizing existing infrastructure sensors, such as traffic cameras, to enhance the safety and efficiency of automated vehicles. Their findings revealed that infrastructure sensors could provide critical information about the vehicle's surrounding environment, often capturing details that on-board sensors might miss. Furthermore, they demonstrated that leveraging existing infrastructure sensors, like speed cameras, not only improves the safety performance of CAVs but also reduces the need for multiple on-board sensors. A significant challenge for AVs is maintaining performance in complex urban environments, temporary work zones, and poor visibility due to adverse weather conditions.[148] Connectivity can offer a viable solution to this issue. Li and Washburn [149] argue that automated vehicles may not perform as well as human drivers in situations with limited line of sight unless V2I connectivity is implemented.

Xu et al. [150] propose a V2I (vehicle-to-infrastructure) cooperation system that optimizes both traffic signals and vehicle trajectories simultaneously for all road users. Similarly, Cai et al. [151] developed a state-space model using vehicle speed and position data obtained through V2I communication. They predicted travel times with a traffic model and optimized traffic signals using dynamic programming methods. Goodall et al. [152] employed simulation methods to forecast queue lengths and delays based on vehicle position and speed data from V2I communication, which then informed traffic signal timing optimization. Priemer and Friedrich [153] designed a decentralized adaptive traffic signal control system that estimated queue lengths and traffic flow using V2I communication data. Zhao et al. [154] created a V2I-based signal timing optimization method that considered individual vehicles' fuel consumption characteristics. In another study, Reitberger et al. [155] proposed a cooperative tracking approach for cyclists using smart devices and infrastructure-based sensors. They demonstrated that incorporating information from smart devices improved the accuracy and robustness of cyclist tracking. Furthermore, the digitalization of infrastructure can provide revenue-generating opportunities for service providers. Smart infrastructure facilitates the provision of digital services to users and simplifies the monetization of traffic data.[18]

Environmental benefits can also be obtained from V2I connectivity. Wu et al. [156] examined CAV testing facilities in the U.S. and cataloged California's CAV testbeds. The team developed a cellular network-based eco-approach and departure (EAD) application, designed to provide drivers with speed guidance to reduce fuel consumption and emissions while minimizing travel delays. This EAD application is intended for vehicles traveling within signalized corridors using both short-range wireless and cellular network communication. It was tested along the testbed to evaluate its effectiveness in enhancing mobility and environmental sustainability. The results indicated that the EAD application can reduce fuel consumption and CO2 emissions by 15.6% and decrease average travel time by 6.3%, compared to scenarios without speed guidance. Furthermore, the environmental benefits, in terms of reduced fuel consumption and CO2 emissions, from cellular-based EAD algorithms surpassed those from limited range wireless communication-based EAD algorithms by approximately 3%. This advantage is attributed to the greater transmission range, allowing vehicles more time to adjust their speed to navigate intersections.

The crucial role of infrastructure in ensuring the effective operation of AVs is also evident from the substantial investments made by various AV manufacturers and technology firms in dedicated infrastructure and supportive hardware, as well. A notable example is the "Test Tunnel" in Los Angeles, developed by Elon Musk's The Boring Company. This 1.2-mile-long tunnel was constructed to advance research and development for Musk's vision of an underground highway network.[157] Within this controlled setting, autonomous vehicles can travel at speeds as fast as 25 mph. Another innovative project is Mercedes-Benz's "Future Bus," which operates on exclusive bus lanes equipped with V2I connectivity. This system provides essential information about bus routes and station locations, allowing the bus to travel at 43 mph and make precise stops at designated stations.[157]

2.4 Cooperative Sensing

The transportation system is intricate, involving various elements such as vehicles, roads, pedestrians, the environment, and their complex interactions. Automated vehicles leverage various perception and sensing technologies, each offering unique advantages and disadvantages. The primary method is utilizing on-board sensors where AVs depend on sensors like cameras, RADARs, and LiDARs to detect their surroundings. However, due to the limited range and field of view (FOV) of these sensors, AVs are not always able to consistently and accurately perceive the environment[158, 159, 160] Connecting to external perception sources and using data shared from them can also be another method employed by AVs to survey their surroundings; however, it mostly plays a complementary role to the on-board sensors. Having discussed the literature on the aforementioned methods in the previous sections, in this section, we focus on the integration of both approaches through cooperative sensing.

The core concept of cooperative sensing on the road involves vehicles and infrastructure sharing local perception data through wireless communication. This allows drivers to foresee upcoming traffic conditions, which is particularly useful in situations like avoiding hidden obstacles, changing lanes safely, overtaking, and ensuring smooth braking and acceleration. Cooperative perception significantly extends the range of perception beyond the line of sight or field of view, covering the entire network of connected vehicles. This shared data can be visualized in forms such as see-through, lifted-seat, or satellite views, acting as advanced driving assistance tools.[161]

In the 1990s, the United States took its initial steps into intelligent transportation systems (ITS) research with the introduction of the cooperative vehicle infrastructure system (CVIS).[162, 163] CVIS was designed to establish a communication framework between vehicles and road infrastructure, aiming to develop collision avoidance systems and improve traffic safety. The advancement of wireless communication technology has significantly driven the progress of ITS. For instance, the US Department of Transportation initiated the IntelliDrive program in 2009 [164, 165], targeting the reduction of traffic congestion through the integration of road-side units and CAVs. This system leverages communication technology to provide real-time data to traffic management centers and drivers. In 2020, the US National Highway Traffic Safety Administration (NHTSA) launched an ITS program focusing on CAVs for the 2020–2025 period, offering policy support to foster ITS development.[159] This initiative primarily emphasized vehicle intelligence, with RSUs playing a supplementary role. In parallel, the European Institute for Intelligent Transport introduced the eSafety project [166], aimed at utilizing advanced information and communication technologies to expedite research and development, as well as the integrated application of safety systems. This project provides comprehensive safety solutions encompassing traffic management, freight and fleet management, vehicle navigation, hazard warnings, and driver information. Germany has also made strides in this domain by establishing an ITS test section in Berlin, equipped with over 100 sensors to gather real-time traffic information. These RSU sensors enable CAVs to detect objects within a 400-meter range. Japan, meanwhile, embarked on the SmartWay project in 1999 [167], with the goal of creating a vehicle-road network. The government implemented the Vehicle-Infrastructure Communication System (VICS) to facilitate the exchange of traffic information between vehicles and infrastructure. This initiative led to a significant increase in the adoption of electronic toll collection, with a penetration rate surpassing 98%. As policies evolve and in-

Table 3: Classification of digital infrastructure levels in ISAD.

Infrastructure type		Cooperation level	Information provided			
			Digital static map of road	Warnings (e.g. accident, weather)	Traffic status	Guidance (e.g. speed, lane changing)
Digital	A	Cooperative driving	•	•	•	•
	B	Cooperative sensing	•	•	•	–
	C	Digital dynamic information	•	•	–	–
Traditional	D	Digital static map support	•	–	–	–
	E	No automated driving support	–	–	–	–

formation technology advances rapidly, the development of CVIS has gained momentum. Both academic and industry sectors have made notable efforts to tackle the scientific and engineering challenges associated with autonomy. Globally, countries are building intelligent infrastructure to support automated driving, defining levels of intelligent infrastructure.[159]

The European Road Transport Research Advisory Council (ERTRAC) has published the Infrastructure Support Levels for Automated Driving (ISAD) [168, 169], categorizing infrastructure into five distinct levels, as outlined in Table 3. The ERTRAC Infrastructure Support Levels for Automated Driving (ISAD) outline five distinct levels of infrastructure capability to aid automated vehicles. At the lowest tier, Level E, there is no digital information or automated driving support, compelling AVs to depend solely on their on-board systems. In Level D, the infrastructure includes static digitized information like fixed road signs, but AVs must still interpret variable information such as traffic lights and dynamic road signs. Progressing to Level C, the infrastructure provides both static and dynamic information. This includes variable data such as traffic signals, alerts, accident notifications, and weather updates, which enhance the AVs' situational awareness. Level B introduces collaborative perception, allowing the infrastructure to perceive and transmit detailed traffic conditions to AVs. At Level A, the infrastructure supports collaborative driving. This level involves the infrastructure actively guiding automated vehicles, advising on speed, spacing, and lane usage through digital communication, thereby optimizing traffic flow and enhancing safety.

2.4.1 Applications and Benefits of Cooperative Sensing

One of the compelling aspects of cooperative perception is its affordability compared to conventional long-range sensors. The advantages are not limited to assisting human drivers. In critical situations, such as a sudden obstacle appearing in front of a fatigued driver, an automated system can automatically take over to prevent accidents. Additionally, far-sighted traffic information enables the detection of congestion ahead in each lane, allowing automated vehicles to make more strategic and informed lane-changing decisions.[161] This section provides a comprehensive summary of the current research status on cooperative sensing technology for automated driving. It first focuses on different information fusion methods, including image fusion, point cloud fusion, and the fusion of images with point clouds. Studies have determined that the integration of image and point cloud data from multimodal and multi-view perspectives offers the most effective approach for cooperative perception. Compared to single-vehicle multi-sensor fusion, cooperative perception information fusion significantly enhances sensing range, accuracy, and reliability.[170] Current methodologies in V2I cooperative sensing are generally categorized into three types: low-level fusion, feature-level fusion, and high-level fusion.[171] Each type has its unique strengths and limitations. Low-level fusion integrates raw data without any prior processing. Feature-level fusion involves extracting significant features from the raw data before merging them. High-level fusion, conversely, consolidates information based on the objects identified by individual sensors.[172]

An application of LiDAR sensors for smart infrastructure is proposed by Jun and Markel [173], providing data integration for both automated and non-automated vehicles in a cost-effective strategy. This data sharing strategy would enhance the robustness of automated vehicle decisions and provide connected vehicles and their operators with augmented visibility enhancing the opportunity to reduce collisions, and congestion and in the end improve traffic flow. Also, according to Geissler and Grafe [17] RSUs can act as well-informed authorities for traffic coordination, and therefore provide an improvement to the traffic flow. Geissler et al. [17] investigated the design requirements for a prototype setup of virtual vision or RADAR sensors positioned along one side of the road. They focused on analyzing road coverage and the likelihood of vehicle occlusions to assess the completeness of information captured by the sensor field. The study's findings highlighted how to optimally design the sensor network in terms of range, orientation, and opening angle to ensure effective traffic detection. The results suggested that this configuration could significantly support automated vehicles by providing comprehensive traffic data. Kim et al. [161] showcased augmented road-side sensing systems that leverage cooperative perception to offer see-through, lifted-seat, and satellite views. By extending the perception range, we demonstrated that road situation awareness can be significantly enhanced. This improved perception and situational awareness capability can lead to better decision-making and planning in automated driving. Masi et al. [174] harnessed computer vision technology to create a cooperative road-side vision system that merges data from both on-board and remote sensors to facilitate map-based tracking. This system was tested in real traffic at a roundabout, where it showed an enhanced field of view and improved accuracy in estimating vehicle positions. Similarly, Chen et al. [175] introduced a cooperative perception framework, which relies on the point cloud features of CAVs. This framework uses small-scale features to enable real-time edge computing, thereby preventing network congestion.

Jia and Ngoduy [176] developed a cooperative driving model based on vehicle platoons, utilizing realistic V2V communication links. They introduced innovative algorithms to manage the control of multi-platoon cooperative driving. Seeliger et al. [177] created a cooperative perception warning system to enhance active traffic safety, using object-oriented Bayes networks to model context dependencies like traffic rules and priorities. Deng et al. [178] developed a collision avoidance system based on cooperative perception, which estimates distances between CAVs and their neighbors via V2V communication to make overtaking decisions. Kamel et al. [179] introduced a misbehavior detection simulation framework designed to detect and prevent accidents in real-time, monitoring the semantics of V2X messages to identify potential perception errors. To tackle the challenge of occluded regions at urban intersections, several studies have focused on blind area detection through V2V. Kim et al. [180] suggested a cooperative perception system framework to minimize occluded areas on the road, while Xiao et al. [181] developed a system that aggregates information from multiple vehicles using unified bird-view maps, enhancing CAVs' perception capabilities by merging graphic and semantic data.

Miller et al. [182] developed a cooperative perception and localization system to boost object detection accuracy, allowing vehicles with low-fidelity sensors to benefit from the detection results of those with high-fidelity sensors. Chen et al. [183] proposed a 3D object detection approach using multiple registered LiDAR point clouds, improving accuracy by expanding the sensing area through the fusion of data from various positions. Wang et al. [184] investigated the network capacity requirements for V2V and V2I communication necessary for effective cooperative perception across different traffic densities and levels of automated vehicle penetration. Their findings indicated that when the proportion of automated vehicles is low, maintaining V2V communication links is challenging due to the distances between the vehicles. In such scenarios, with limited penetration and the need for high reliability, V2I communication becomes essential for data transmission. [19] investigated the trade-offs between individual and cooperative sensing through V2V data sharing among CAVs. Their study identifies a crucial traffic density threshold, beyond which the detection ranges of adjacent CAVs sufficiently overlap, thereby enhancing driving speeds due to improved situational awareness. To facilitate research in vehicle-to-vehicle cooperative perception for automated driving, Li et al. [185] introduced the V2X-Sim dataset, which comprises multi-modality sensor streams captured by vehicles and RSUs in real-world traffic scenarios.

Even though the long-term saving effects of setting up an infrastructure (e.g. adopting V2I communications) seem very promising, one can argue that the costs can represent an initial barrier. Upgrading infrastructure is expensive and there is a need for studies to be conducted to assess the real-time implementation of vehicular communication and its effect on planning.[10] Additionally, service providers are reluctant to invest in digital infrastructure, and vehicle manufacturers tend to over-equip their vehicles to avoid relying on infrastructure technology, even though these two technologies are complementary.[18] The literature lacks research comparing the effectiveness of V2V and V2I cooperative sensing under varying conditions. The unresolved question is whether it is more beneficial to install expensive road-side sensors on infrastructure in high-traffic areas or to leverage the high volume of vehicles for effective V2V data sharing in such environments, reserving infrastructure sensors for less congested roads. This study addresses this gap by exploring the trade-off between stationary road-side sensors and on-board CAV sensors, aiming to determine the optimal investment strategy for these technologies.

2.5 Financing Methods for Smart Infrastructure

Smart cities focus on sustainable development and enhancing residents' quality of life through the application of information and communication technologies. With urbanization accelerating, it is forecasted that by 2050, 68% of the global population will be living in cities, adding 2.5 billion people to urban areas.[186] This substantial increase will inevitably exert significant pressure on current infrastructures, resources, sustainability initiatives, and overall urban life quality.

It is predicted approximately 50 trillion USD would be required for global infrastructure investments from 2013 to 2030 to meet the projected transportation demand.[74] In 2016, global investments aimed at improving city infrastructures stood at around 550 billion USD. However, this figure is expected to escalate dramatically, reaching 2.57 trillion USD by 2025 and soaring to more than 40 trillion USD by 2037. This rapid growth in the smart cities sector highlights the growing view of these cities as key opportunities for digital technology investments.[187]

Historically, public funds have been the primary source of financing for city infrastructure investments, with governments taking the lead due to the inherent public interest in such projects. However, the inability to make necessary investments due to budget deficits, significant public debt, and the lack of expertise within the public sector has resulted in a reduction of public funds allocated to infrastructure in many economies. Without sufficient funding, no infrastructure project, whether smart or traditional, can be realized. Consequently, the financial dimension often becomes the most critical obstacle to initiating meaningful smart city projects and increases the likelihood of existing projects failing to reach completion. [188]

Achieving extensive deployment of V2I cooperation systems requires significant financial resources. Funding for these systems must come from diverse sources, including government agencies, automotive manufacturers, and telecommunications operators. Nonetheless, securing continuous investment for large-scale deployment remains challenging. Government budgets and policy shifts can impact funding availability, while corporate investments are often driven by market dynamics and profit motives.[189] The cost factor is a crucial aspect that demands attention. The initial construction phase involves substantial expenses. For vehicle-road cooperation to be effective, there must be a comprehensive deployment of road-side infrastructure, such as sensors, communication devices, and edge computing servers, along with developing and testing necessary software. Additionally, long-term maintenance and operational costs must be considered. As the number of vehicles increases, the system's capacity and coverage must also expand. This necessitates regular upgrades and maintenance of the infrastructure. Moreover, operational expenses, including data storage, processing, transmission, and ongoing maintenance, require consistent financial commitment.[189] Smart cities and their infrastructure extend beyond traditional physical structures. While some might categorize smart technology under information and communications technology due to the inclusion of fiber-optic networks, its defining feature is the inter-connectivity between various infrastructure systems. Unlike conventional infrastructure, smart cities can monetize the data collected on environmental and social performance through sensors embedded in the infrastructure. By charging access fees to third-party developers who wish to create applications utilizing this data (e.g., a parking space app), the revenue stream for smart infrastructure projects is significantly enhanced. This economic value of data adds a multiplier effect to the revenue potential compared to traditional infrastructure projects.[188]

Traditionally, infrastructure projects are financed through debt instruments, with cities obtaining capital from entities such as commercial and development banks via municipal bonds. This capital is allocated to cover construction costs, and there is typically a grace period during which repayment is deferred until the project's completion. Once the infrastructure becomes operational and begins generating revenue, these funds are used to repay the bond's principal and interest. This approach generally applies to large-scale projects, often valued at 100 million USD or more. The revenue generated from these assets is usually earmarked for debt servicing, a practice particularly relevant to project bonds rather than general obligation bonds.[188] These funding methods mainly include grants and subsidies, bank loans and leases, and municipal bonds [190].

Since enhancing citizens' living conditions is a primary government responsibility, smart city projects are frequently overseen by the public sector. However, public funds are often inadequate, complicating the timely and effective implementation of these initiatives.[190] The success of sustainable projects hinges on financial sustainability, which is closely tied to diversifying funding sources and developing innovative business models. Innovative methods for financing smart city projects include Public-private partnerships (PPPs), monetizing acquired data, etc.

2.5.1 Self-financing Theorem of the Roads

Another method of providing for the financial needs of smart infrastructure is the self-financing theorem. This theorem states that a road designed and priced optimally will generate enough toll revenue to cover its capital costs over the long term.[20] The self-financing outcome derived from the basic model introduced by Mohring and Harwitz [20] indicates a simple and direct correlation between infrastructure tolls and capacity costs: the degree of self-financing corresponds to the elasticity of the capacity cost function. In other words, the revenue from optimal toll is equal to the construction cost of optimal capacity if there are neutral scale economies in road construction and congestion technology. Since then, there has been a substantial body of literature that has extended the results to various scenarios.

2.5.1.1 Extensions to Self-financing Theorem

Growing Traffic Demand: As economies grow and populations rise, so too does the demand for road space. Continuously expanding roads incrementally would prove to be prohibitively expensive. The standard approach involves expanding road capacity beyond the optimal level for the current traffic conditions at the time of expansion. Traffic subsequently increases to and then exceeds this optimal level, necessitating further expansion. This leads to an intriguing question: in a growing economy with constant returns to scale in road production, would congestion tolls still cover the network's capital costs as they do in a steady-state economy? Arnott and Kraus [191] explore this question and conclude that the self-financing theorem remains valid in present value terms. This holds true as long as the size of capacity expansions is optimized in relation to the timing of investments, regardless of whether capacity is added continuously or intermittently and whether the timing of these investments is optimal.

Heterogeneous Users: Arnott and Kraus[192] further investigate the impact of user heterogeneity and determine that the self-financing theorem remains applicable as long as every user is charged optimally. The crucial condition is the implementation of marginal cost pricing for all users. If some users are exempt from charges or if the charges deviate from marginal cost pricing for any reason, the self-financing principle typically collapses.

Time-of-Day Dynamics: A notable simplification in the basic self-financing model is the treatment of congestion as a static, steady-state issue. While this assumption aids in clarity, it is not reflective of the complexities of real-world traffic congestion. Thus, it is essential to explore whether the self-financing outcome holds when accounting for the temporal dynamics of congestion and optimal congestion tolls. Arnott and Kraus [191] confirmed that the self-financing principle is maintained, provided tolls can be optimally adjusted over time. This conclusion is exemplified by the bottleneck model, initially proposed by Vickrey [193] and later examined in detail by Arnott et al.[194] In their research, Arnott and Kraus [191] addressed the issue of increasing demand over time, while Arnott et al. [194] focused on systematic demand variations throughout the day. Unlike Arnott and Kraus [191], Arnott et al. [194] considered the intertemporal substitutability of demand in their analysis.

Network Extensions: The self-financing outcome also persists when the analysis is broadened from a single road or bottleneck to an entire network.[24] illustrated that self-financing is applicable to each individual link within an optimally priced network, and therefore, to the entire network. However, this principle can break down due to network effects if other segments of the network are not priced optimally.[22]

Road Durability and Maintenance: Furthermore, the issue of self-financing in the context of road durability choices and maintenance expenses has been investigated. The results from the study concluded that if road construction exhibits constant returns to scale (for roads of specified strength) and if road use also demonstrates constant returns (with heavy vehicles evenly distributed across the road width), then the optimal road user charge, which includes both congestion and road damage fees, will be sufficient to cover all road-related costs, such as maintenance and capital interest.[195]

As extensively discussed in the preceding sections, securing sufficient funding for the development of smart road infrastructure is of paramount importance. While many methods involve financing projects through external sources such as loans and bonds, approaches like data monetization and the self-financing theorem focus on leveraging the road and its smart infrastructure for funding. It has been demonstrated that extending the basic model presented by Mohring and Harwitz [20] provides valuable additional insights.[22] Despite numerous extensions of the self-financing theorem explored in the literature, its application to the construction of digitized, sensor equipped roads has not been thoroughly investigated. This study aims to fill this gap by extending the self-financing theorem to the context of digitized roads. Specifically, we not only consider the optimal physical capacity of roads, as addressed in the conventional self-financing theorem but also examine the optimal level of infrastructure digitalization. Furthermore, we investigate whether revenue from optimal tolls can cover the costs associated with constructing digital roads.

3 Optimal Investment in Stationary Vs. Mobile Sensors

Consider a single-lane corridor exclusive to CAVs. The movement of CAVs is governed by the data collected from sensors that are either stationary (i.e., roadside) or mobile (i.e., placed on-board a CAV). As shown in Figure 2, the corridor is divided into two regions, the first region of the corridor is covered by stationary sensors, and in the remainder of the corridor there is no stationary sensor coverage available, and data gathered by mobile sensors is the only data source available to the CAVs. We denote δ as the portion of corridor length covered by stationary sensors. Later in Section 3.4 we will discuss why the portion covered by the stationary sensors should be the first part of the corridor.

3.1 Sensor Range and Resolution

Each sensor, whether stationary or mobile, has a range and resolution profile (See Figure 2). The range indicates the distance ahead and behind the sensor within which objects are detected, and the resolution profile expresses the data points per unit distance captured by the sensor.

Mobile sensors detect objects within a range of r_m ahead and behind the vehicle on which they are mounted. In this study, we further develop upon the resolution function (R_m), augmented resolution function (A_m), and sight function (T_m) developed by Nourinejad et al. [19] for the on-board sensors. We express $R_m(x)$ as the resolution of a point located x away from a vehicle, measured in data points per unit distance. Sensor resolution decreases with distance from the sensor, and the rate of decline relies on the type of sensor, weather conditions, and lighting [196]. Hence, the following properties are expected from mobile sensors' resolution: $\partial R_m(x)/\partial x < 0$, indicating that mobile sensor resolution decreases with distance between an object and the sensor, and $R_m(x) = 0$ for $x > r_m$ which specifies that mobile sensors cannot detect objects outside of the sensor's range. In addition to these properties, we assume the following in relation to the mobile sensor resolution: a) All mobile sensors have identical resolution profiles, b) Resolution is symmetric (behind and ahead of the vehicle), c) $R_m(x)$ is linearly decreasing with x, which also satisfies the above properties.

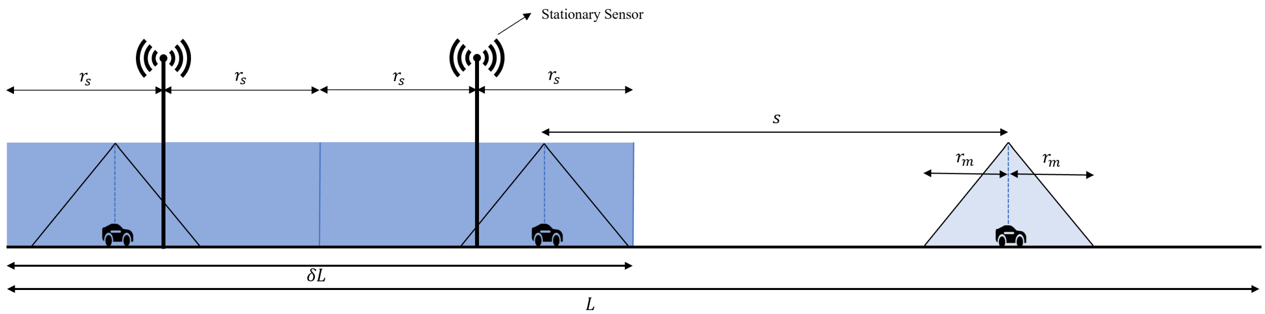


Figure 2: Sensor range and resolution profile for mobile and stationary sensors (The darker color shades indicate a higher resolution).

Following these assumptions, we present the functional form of resolution $R_m(x)$ as:

$$R_m(x) = \frac{\alpha}{r_m}(1 - \frac{x}{r_m}) \qquad \forall x \in [0, r_m], \tag{1}$$

where α is a parameter known as the sensor *power*, which is the area under $R_m(x)$ defined as

$$2\int_0^{r_m} \frac{\alpha}{r_m}(1 - \frac{x}{r_m})dx = \alpha, \tag{2}$$

where factor 2 accounts for the resolution behind and ahead of the CAV [19]. Based on Equation (1), sensor power increases resolution correspondingly at all points within the range.

Cooperative sensing allows each CAV to have an enhanced perception of its environment by using the data shared by other vehicles and stationary sensors in addition to its on-board sensors. Consider a pair of CAVs driving along the corridor. The leader and ego vehicles, respectively, are the one moving in front and the one following. The vehicles may achieve no-, partial-, or full-overlap in their range, determined by the spacing between the pair, denoted by s.

When $2r_m \leq s$, there is no overlap; when $r_m \leq s < 2r_m$, there is partial overlap but the vehicles themselves are not in each other's range; and when $s < r_m$, there is full overlap and the vehicles are in each other's range. $A_m(x,s,\beta)$, the augmented resolution of a point located at a distance x in front of the vehicle, is defined as

$$A_m(x,s,\beta) = R_m(x) + \beta R_m(s-x), \tag{3}$$

where s is the spacing between the pair of vehicles, and $\beta \in [0,1]$ is the connectivity level between the vehicles, indicating the percentage of the leader's collected data points that the ego vehicle can utilize and access. The assumption regarding augmented resolution is that the ego vehicle has full access to its sensor's resolution, $R_m(x)$; however, its access to the leader vehicle's sensor, $R_m(s-x)$, is limited because of the level of connectivity available between the vehicles, and for a given connectivity level, the additional resolution gained by communicating with the vehicle in the front is $\beta R_m(s-x)$. Where there is a quicker rate of data sharing or compatibility in fusing the data obtained from the leading sensor, the connectivity level (β) can be high. For instance, sharing sensor data amongst vehicles made by the same manufacturer may be more efficient. Vehicle connectivity also depends on the complementary nature of data, interoperability with other fusion systems [197], and redundancy with other fusion systems. Investments in communications networks like LTE and 5G [198], as well as the standardization of CAV sensors [199], and data fusion techniques [200], can improve connectivity and its level of efficiency among CAVs. At $\beta = 1$ the vehicles are fully connected and have complete access to each other's sensor data, whereas at $\beta = 0$ the vehicles are disconnected and cannot share any data. (For further details refer to Nourinejad et al. [19])

We denote θ as a safety performance threshold for the augmented resolution of sensors. Any point with augmented resolution above this threshold is considered to be within the sight range of the CAV and the CAV is able to accurately apprehend its characteristics such as size, distance (to the vehicle), and speed. We define T as the vehicle's sight, the distance between the vehicle and the furthest point with an augmented resolution above the θ threshold. Thus, sight is formulated as

$$T = \max\{x | A(x) \geq \theta\}. \tag{4}$$

While vehicles are outside the range of stationary sensors they rely on the mobile sensors and the connectivity among each other. We define T_m as CAVs' sight outside stationary sensors' range. Based on the spacing among CAVs and the overlap between mobile sensors' ranges, T_m will have different relations with spacing, range, connectivity, and safety threshold, which is

$$T_m = \begin{cases} s & 0 \leq s < r_m(1+\beta) - \frac{r_m^2\theta}{\alpha}, \\ \frac{(1+\beta)\alpha r_m - \alpha\beta s - r_m^2\theta}{(1-\beta)\alpha} & r_m(1+\beta) - \frac{r_m^2\theta}{\alpha} \leq s < 2r_m - \frac{r_m^2\theta}{\alpha}, \\ r_m(1 - \frac{r_m\theta}{\alpha}) & 2r_m - \frac{r_m^2\theta}{\alpha} \leq s. \end{cases} \tag{5}$$

Stationary sensors detect objects within the confines of their range r_s ahead and behind their location on the corridor. We assume the resolution of a stationary sensor at point $x \in [0, r_s]$ away from the sensor, in both directions, is R_s, measured in data points (dps) per unit distance, and zero at every other point beyond the range. This means that the resolution of a stationary sensor is fixed within its range and does not change with the distance from the sensor. In practice, this assumption can be interpreted as having high-definition mapped zones that have a number of sensors, not necessarily one, and can provide a standard data resolution within the boundaries of the zone. In our analysis, we express this setting as having one sensor with a fixed resolution within the sensor's range.

Once vehicles enter the stationary sensor covered region, they will solely rely on the data provided from their connection to the road-side unit where they happen to be within its range. We assume that stationary sensors have a sufficiently high resolution, R_s, where $R_s \geq \theta$ is always true. While relying on the stationary sensors, the adequate resolution across all points of their range results in a decision stretch extending to the end of their range. In other words, the maximum possible decision stretch is achieved when the CAV has just entered the stationary sensor's range. As the CAV travels through this range, the available decision stretch decreases until it reaches zero at the range's end. Therefore, it can be said that, on average, a decision stretch of r_s is available to CAVs throughout the stationary sensor's range. In circumstances where the spacing of the CAVs is high, the available sight for CAVs from stationary sensors is equivalent to the decision stretch. However, depending on spacing, it is possible that a CAV may not be able to see all the way to the end of the range if the CAV in front blocks its sight. In this case, even though the decision stretch extends to the end of the sensor's range, the available sight for the CAV is limited by the spacing between the vehicles. Based on the definitions above, we define the average sight within the stationary sensor range, T_s, as

$$T_s = \min(r_s, s). \tag{6}$$

The equation above states that if the spacing is smaller than the average available decision stretch (r_s), the sight will be limited and equal to the spacing (s).

3.2 CAVs' Speed

A vehicle with an extended field of vision can travel faster, as it possesses a better understanding of the longer section of the corridor ahead. Hence, the available sight becomes a determining factor for the allowable traffic speed. When a vehicle detects an object or obstruction on the road at a distance T away, it must come to a complete stop within a distance of $T - l$, where l represents the safety distance. This safety distance can be set as the average length of vehicles plus an additional safety margin between vehicles. Consequently, when cars come to a complete stop, they maintain a distance of l from the obstruction.

For our analysis, we have focused on corridors with restricted access, where only CAVs utilize the corridor, and no stationary objects are present or can suddenly appear. In this context, we define V as the average speed of the CAVs within the corridor. Additionally, τ represents the processing time, which refers to the duration required by the CAVs to survey their surroundings, process the collected data, and make driving decisions.

Exploiting the fact that no stationary objects can suddenly appear in restricted corridors, and considering that the ego vehicle maintains speed V for τ time units before applying the same deceleration rate as the leading vehicle, we can deduce from kinematic equations that:

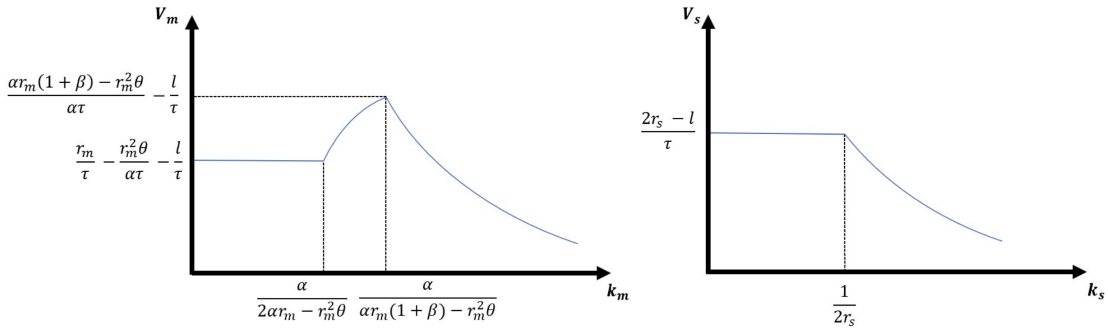
$$V = \frac{T - l}{\tau}. \tag{7}$$

Let k be the average vehicle density, which is equal to $1/s$, the inverse of spacing between the leader and ego vehicle. We define k_s and V_s as the average density and speed of vehicles traveling inside the confines of stationary sensors. For a given density k_s, V_s can be derived from Equations (6) and (7) as

$$V_s = \begin{cases} \frac{r_s - l}{\tau} & 0 \le k_s < \frac{1}{r_s}, \\ \\ \frac{1}{\tau k_s} - \frac{l}{\tau} & \frac{1}{r_s} \le k_s. \end{cases} \tag{8}$$

Similarly, k_m and V_m are the average density and speed of the vehicles outside of stationary sensors' range and relying only on their on-board sensors and vehicular connectivity for understanding their local surroundings. V_m for a given density k_m using Equations (5) and (7) is

$$V_m = \begin{cases} \frac{r_m}{\tau} - \frac{r_m^2 \theta}{\alpha \tau} - \frac{l}{\tau} & 0 \le k_m < \frac{\alpha}{2\alpha r_m - r_m^2 \theta}, \\ \\ \frac{(1+\beta) r_m}{(1-\beta)\tau} - \frac{r_m^2 \theta}{(1-\beta)\alpha\tau} - \frac{\beta}{(1-\beta)\tau k_m} - \frac{l}{\tau} & \frac{\alpha}{2\alpha r_m - r_m^2 \theta} \le k_m < \frac{\alpha}{\alpha r_m (1+\beta) - r_m^2 \theta}, \\ \\ \frac{1}{\tau k_m} - \frac{l}{\tau} & \frac{\alpha}{\alpha r_m (1+\beta) - r_m^2 \theta} \le k_m. \end{cases} \tag{9}$$



(a) (b)

Figure 3: Speed-density diagram for (a) mobile sensor governed region, and (b) stationary sensor governed region.

The speed-density profile for both stationary sensor governed and on-board sensor governed regions of the corridor are provided in Figure 3.

3.3 Flow Characterization

Let Q denote the flow of vehicles moving along the corridor. Q can be derived as a function of the speed and density of vehicles as $Q = kV$. We assume vehicles can enter or exit the corridor only at its ends and we can establish that the flow remains equal throughout all segments of the corridor. From Equations (8) and (9) we can see that both V_m and V_s are functions of density. Therefore, we have

$$Q = k_m V_m(k_m) = k_s V_s(k_s). \tag{10}$$

We define capacity as the maximum achievable flow, which is indicated by C given as

$$C = \max_k Q, \tag{11}$$

and critical density is the density at which the maximum flow, capacity, is achieved and given as

$$k^{cr} = \arg\max_k Q. \tag{12}$$

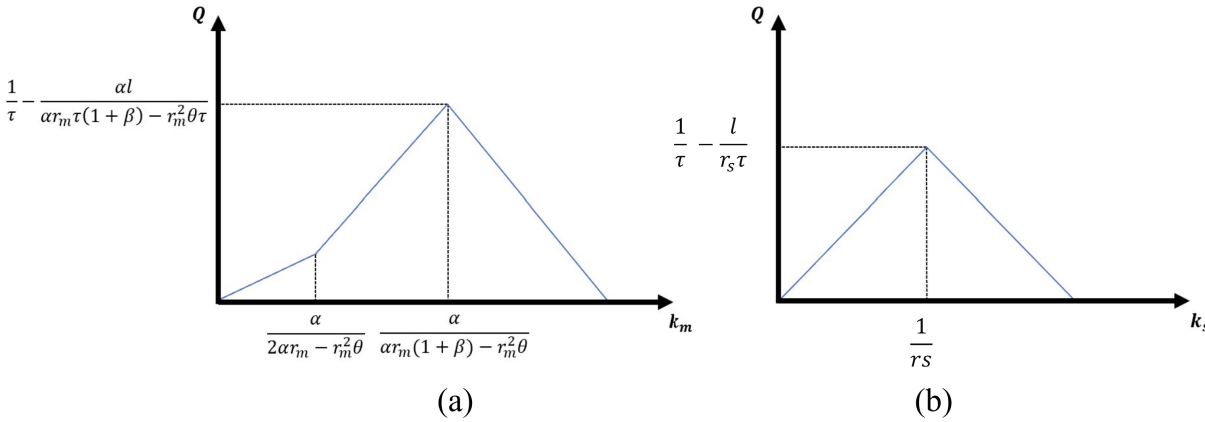


Figure 4: Fundamental diagram for (a) mobile sensor governed region and (b) stationary sensor governed region

We denote the capacity for the stationary sensor governed regions of the corridor by C_s and for regions that CAVs use the data from on-board sensors by C_m, and their respective critical densities by k_s^{cr} and k_m^{cr}. C_m and k_m^{cr} are derived as

$$C_m = \frac{1}{\tau} - \frac{\alpha l}{\alpha r_m \tau(1+\beta) - r_m^2\theta\tau}, \tag{13}$$

$$k_m^{cr} = \frac{\alpha}{\alpha r_m(1+\beta) - r_m^2\theta}. \tag{14}$$

Moreover, for the stationary sensor region, C_s and k_s^{cr} are

$$C_s = \frac{1}{\tau} - \frac{l}{r_s\tau}, \tag{15}$$

$$k_s^{cr} = \frac{1}{r_s}. \tag{16}$$

The fundamental diagram of both regions is depicted in Figure 4. The diagram for the mobile sensor governed region does not completely resemble the form of conventional fundamental diagrams (for reference, see Figure 9 of Shi and Li [201]) and that is due to the effects of connectivity on the traffic flows.

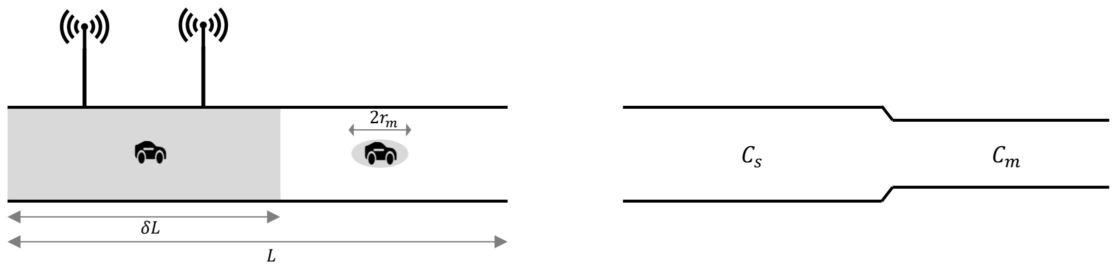
Lemma 1. *The capacity of the stationary sensor region (C_s) is higher than the capacity of the mobile sensor region (C_m) if the range of stationary sensors (r_s) is larger than the range of mobile sensors (r_m).*

Proof of lemma 1 is provided in Appendix A.

3.4 Modeling Bottleneck With Point Queue

According to lemma 1 the capacity of the stationary sensor-governed region (C_s) is larger than the capacity of the mobile sensor-governed region (C_m) if the range of stationary sensors is larger than the range of mobile sensors. We consider a capacity-prioritizing flow direction, which stipulates that flow is injected from the high-capacity segment into the low-capacity segment because it allows for the feasibility of a larger flow within the corridor. Thus, the stationary sensor governed region must supersede the mobile sensor governed region or we will be limiting our maximum traffic flow throughput (See Figure 5a). However, as a consequence of this capacity disparity, CAVs may encounter a bottleneck as they enter the mobile sensor governed region (See Figure 5b), leading to an increase in their total travel time. The occurrence of the bottleneck is contingent upon the flow of CAVs (Q) surpassing the capacity of the mobile sensor governed region (C_m). In such instances, where the inflow rate exceeds the capacity of the mobile sensor governed region, a queue appears, causing delays in the movement of CAVs. We employ a modeling approach that represents the queue resulting from the bottleneck as a point or vertical queue, without occupying any physical space. While it is acknowledged that modeling the bottleneck congestion with point queues may have certain limitations, such as the inability to predict spillover effects and the oversimplification of traffic flow at intersections [202], the utilization of point queues as a modeling approach remains a suitable choice to effectively capture the additional time added to the total travel time due to the bottleneck, while avoiding unnecessary complexities in the model setting.

We measure the average delay time of the bottleneck using the model developed by [203] for quadratic arrival functions. In the context of this research, the arrival rate is equal to the flow of CAVs, Q. It should be emphasized that the occurrence of the bottleneck is contingent upon the flow



(a) (b)

Figure 5: (a) Transitioning from stationary sensor region to mobile sensor region and (b) the disparity between the flow capacity of those regions

surpassing the capacity of the mobile sensor governed region, C_m; therefore, in cases where $Q \leq C_m$ no bottleneck delay will be experienced, and in the rest of the cases where it is experienced, the discharge rate is equal to the capacity of mobile sensor governed region, C_m. The average delay experienced by vehicles during the congestion period can be expressed as

$$t_b = \begin{cases} \frac{\gamma}{36} \cdot \frac{Q^3}{C_m^4} & C_m < Q \\ \\ 0 & Q \leq C_m, \end{cases} \tag{17}$$

where γ represents the inflow curvature parameter of the polynomial arrival function; For further details refer to 203. In two specific scenarios where δ equals either 0 or 1, no bottleneck delays are experienced. This absence of delays occurs because the CAVs in these cases do not undergo a transition between stationary sensor governed region and mobile sensor governed.

3.5 Mathematical Model

We focus on restricted access corridors and specifically examine the uncongested region of the fundamental diagram, as we aim to prevent undesirable traffic congestion that arises when the density exceeds its critical threshold, which maximizes the flow. To maintain efficiency, we exclude the congested portion of the fundamental diagram that is often observed during peak hours in major cities [204]. Our objective is to maximize the welfare of system users by minimizing the travel costs incurred when traversing this corridor. In this context, the cost is directly associated with the travel time experienced by users. Hence, maximizing welfare equates to minimizing user travel time.

The total travel time (t) of a CAV traveling along the corridor can be expressed as

$$t = \frac{\delta L}{V_s} + \frac{(1-\delta)L}{V_m} + t_b, \tag{18}$$

where L denotes the length of the corridor, and consequently, δL represents the coverage length of road-side sensors installed throughout the corridor. V_s, V_m, and t_b are obtained from Equations (8), (9), and (17), respectively. The first term of Equation (18) is the travel time for traversing the stationary sensor governed region of the corridor ($\frac{\delta L}{V_s}$), and the second term is for the mobile sensor governed region ($\frac{(1-\delta)L}{V_m}$). Additionally, the term t_b represents the average delay experienced by CAVs during possible bottleneck congestion, which was previously discussed in Section 3.4.

We seek to assess the optimal allocation of a limited budget to enhance the connectivity level of CAVs and/or the deployment of road-side stationary sensors and the aim is to improve the overall efficiency of the transportation system by minimizing user travel time. By investing in stationary sensors, speed can be increased, particularly in no-overlap conditions, albeit at potentially higher costs. On the other hand, improving connectivity can enhance speed in partial- and full-overlap scenarios. We assume that the cost of managing and maintaining one unit of stationary sensor coverage and one unit of connectivity between vehicles is σ_δ and σ_β, respectively. We minimize the total travel time of all users via the following mathematical model:

$$\min_{\beta,\delta} \quad Q\left(\frac{\delta L}{V_s} + \frac{(1-\delta)L}{V_m} + t_b\right), \tag{19a}$$

$$\text{s.t.} \quad \sigma_\delta \delta L + \sigma_\beta \beta Q \leq B, \tag{19b}$$

$$0 \leq \beta \leq 1, \tag{19c}$$

$$0 \leq \delta \leq 1, \tag{19d}$$

$$\frac{\alpha\beta}{\theta} \leq r_m. \tag{19e}$$

Constraint (19b) is the budget constraint, Constraints (19c) and (19d) ensure the variables do not exceed their boundaries, and Constraint (19e) ensures that the sensor power is sufficient enough for the CAVs to operate relying solely on their own sensors (See 19). Therefore, the mathematical problem (19a) is a nonlinear program with linear constraints.

3.6 Analytical Closed-form Solutions

The objective of this section is to determine the optimal solution for the objective function introduced in Equation (19a) within the uncongested travel region. However, due to the piece-wise nature of the functions V_m and t_b (as defined in Equations (9) and (17)) in the uncongested region, the travel time formulation can vary. To establish the relationship between flow and CAVs' density, we can rewrite the uncongested portion of Equation (9) in terms of flow Q as

$$V_m = \begin{cases} \frac{r_m}{\tau} - \frac{r_m^2\theta}{\alpha\tau} - \frac{l}{\tau} & Q \leq \frac{\alpha(r_m - l) - r_m^2\theta}{\tau(2\alpha r_m - r_m^2\theta)}, \\ \\ \frac{(1-\beta)\tau Q}{\beta + (1-\beta)\tau Q}\left(\frac{(1+\beta)r_m}{(1-\beta)\tau} - \frac{r_m^2\theta}{(1-\beta)\alpha\tau} - \frac{l}{\tau}\right) & \frac{\alpha(r_m - l) - r_m^2\theta}{\tau(2\alpha r_m - r_m^2\theta)} < Q \leq C_m. \end{cases} \tag{20}$$

In the equation above, the upper bound of Q in the second term is C_m, as exceeding this value indicates that the density k_m has surpassed the critical density k_m^{cr}, resulting in congestion. Similarly, for Equation (8), V_s in the uncongested traffic region is given by

$$V_s = \frac{r_s - l}{\tau} \qquad Q \leq C_s. \tag{21}$$

Using Equations (17), (20), and (21), we can derive the piecewise formulation of Equation (19a) below:

$$\begin{cases} \frac{\delta L\tau}{r_s-l}+\frac{\alpha(1-\delta)L\tau}{\alpha(r_m-l)-r_m^2\theta} & 0\leq Q\leq \frac{\left(\alpha(r_m-l)-r_m^2\theta\right)}{\tau(2\alpha r_m-r_m^2\theta)}, \\ \frac{\delta L\tau}{r_s-l}+\frac{(1-\beta)\alpha(1-\delta)L\tau}{\alpha r_m(1+\beta)-r_m^2\theta-\alpha l(1-\beta)}\left(1+\frac{\beta}{(1-\beta)\tau Q}\right) & \frac{\alpha(r_m-l)-r_m^2\theta}{\tau(2\alpha r_m-r_m^2\theta)}<Q\leq C_m, \\ \frac{\delta L\tau}{r_s-l}+\frac{\alpha(1-\delta)L\tau}{\alpha r_m(1+\beta)-r_m^2\theta-\alpha l}+\frac{\gamma Q^3}{36}\left(\frac{\tau(\alpha r_m(1+\beta)-r_m^2\theta)}{\alpha r_m(1+\beta)-r_m^2\theta-\alpha l}\right)^4 & C_m<Q\leq C_s. \end{cases} \tag{22}$$

This leads to three different cases for the travel time function, depending on the value of Q. The mathematical model is solved in each case to obtain the closed-form solution for the optimal values of vehicular connectivity level, β^*, and stationary sensor coverage, δ^*. Detailed solutions for the mathematical model in all cases are provided in Appendix B.

Case I. $Q\leq \frac{\alpha(r_m-l)-r_m^2\theta}{\tau(2\alpha r_m-r_m^2\theta)}$

In this case, traffic flow, and as a result, traffic density is not high enough for the mobile sensors to overlap with each other. Consequently, even high levels of connectivity do not yield benefits, as the shared data is useless for other CAVs. Therefore, the optimal investing policy dictates allocating the entire budget to stationary sensors and we have

$$\beta^*=0, \tag{23}$$

$$\delta^*=\frac{B}{\sigma_\delta L}. \tag{24}$$

Case II. $\frac{\alpha(r_m-l)-r_m^2\theta}{\tau(2\alpha r_m-r_m^2\theta)} < Q \leq C_m$

Here, with an increase in traffic flow, the role of vehicular connectivity becomes significant. The closed-form solution reveals that the budget is now allocated between investments in β and δ. The distribution of the budget between these factors is influenced by other variables in the system. Their values and the specific traffic characteristics of the setting dictate the proportion of the budget allocated to each component and we have

$$\beta^* = \frac{\alpha l - \alpha r_m + r_m^2\theta}{\alpha l + \alpha r_m} - \frac{\sqrt{\Delta}}{\alpha\sigma_\beta\sigma_\delta Q^2(l+r_m)(l-rs)(l-rs+Q\tau(r_m+r_s))}, \tag{25}$$

$$\begin{aligned}\Delta = Q^3\sigma_\beta\sigma_\delta^2(l-r_s)^3(&-\alpha B(l+r_m)+\alpha L\sigma_\delta(l+r_m)+Q\sigma_\beta(\alpha l-\alpha r_m \\ &+r_m^2\theta))(l-r_s+Q\tau(r_m+r_s))(\alpha l-r_m(\alpha-2\alpha Q\tau+r_m\theta(Q\tau-1))),\end{aligned} \tag{26}$$

$$\delta^* = \frac{B-\sigma_\beta\beta^* Q}{\sigma_\delta L}. \tag{27}$$

Case III. $C_m < Q \leq C_s$

It is important to note that in Case III, Q exceeds C_m. Here, we assume that the flow in the stationary sensor governed region reaches its capacity, resulting in CAVs traveling at the critical speed and density. The additional travel time caused by flow exceeding the capacity of this region is captured through the queue delay term, t_b. Moreover, Q does not exceed C_s since in such a scenario, the entire corridor would experience congestion, including the stationary sensor governed region. However, the equations derived from the KKT first-order conditions lead to a seventh-degree polynomial equation for β. The general polynomial equations of degree five and above are unsolvable in radicals, meaning an analytical closed-form expression for β^* and δ^* cannot be obtained.

3.7 Numerical Analyses for Optimal Investment

Our objective for conducting numerical experiments is to assess the impact of investing a limited budget in enhancing vehicular connectivity levels and/or deploying stationary sensors while minimizing the total travel time along the corridor under different traffic flow conditions. The default parameters for variables used in the numerical examples are presented in Table 4.

Figure 6 compares the optimal values for vehicular connectivity level (β^*) and stationary sensor coverage (δ^*) along with the average travel time of users for different σ_β values. The travel time plots in Figures 6 (c), (f), and (i) show the total corridor travel time divided by traffic flow, giving the average travel time per user. Interestingly, due to the connectivity benefit, at flows lower than the capacity (C_m), as the traffic flow increases, the average travel time of users either remains unchanged (the cases where all of the budget is invested only on stationary sensors) or decreases (the remaining of the cases), which is contrary to conventional human-driven vehicles' travel time behavior where the average travel time is an increasing function of traffic flow and highlights the effectiveness of vehicular connectivity and road-side sensors in reducing travel times. At traffic flows beyond C_m, the formation of bottleneck queue induces a noticeable increase in travel time as it was discussed in Section 3.4.

Table 4: Default values used for parameters in the numerical analyses.

Notation	Interpretation	Default value
α	Sensors' power	0.25 [dps]
l	Average length of vehicle	5 [m]
r_m	Mobile Sensors range	100 [m]
r_s	Stationary Sensors range	200 [m]
θ	Safety threshold	0.002 [$\frac{\text{dps}}{m}$]
τ	Processing time	1 [sec]
γ	Bottleneck delay parameter	500
L	Length of road	10[Km]
σ_β	CAV connectivity cost	\$1[$\frac{min}{veh}$]
σ_δ	Stationary sensor cost	\$6[$\frac{1}{km}$]

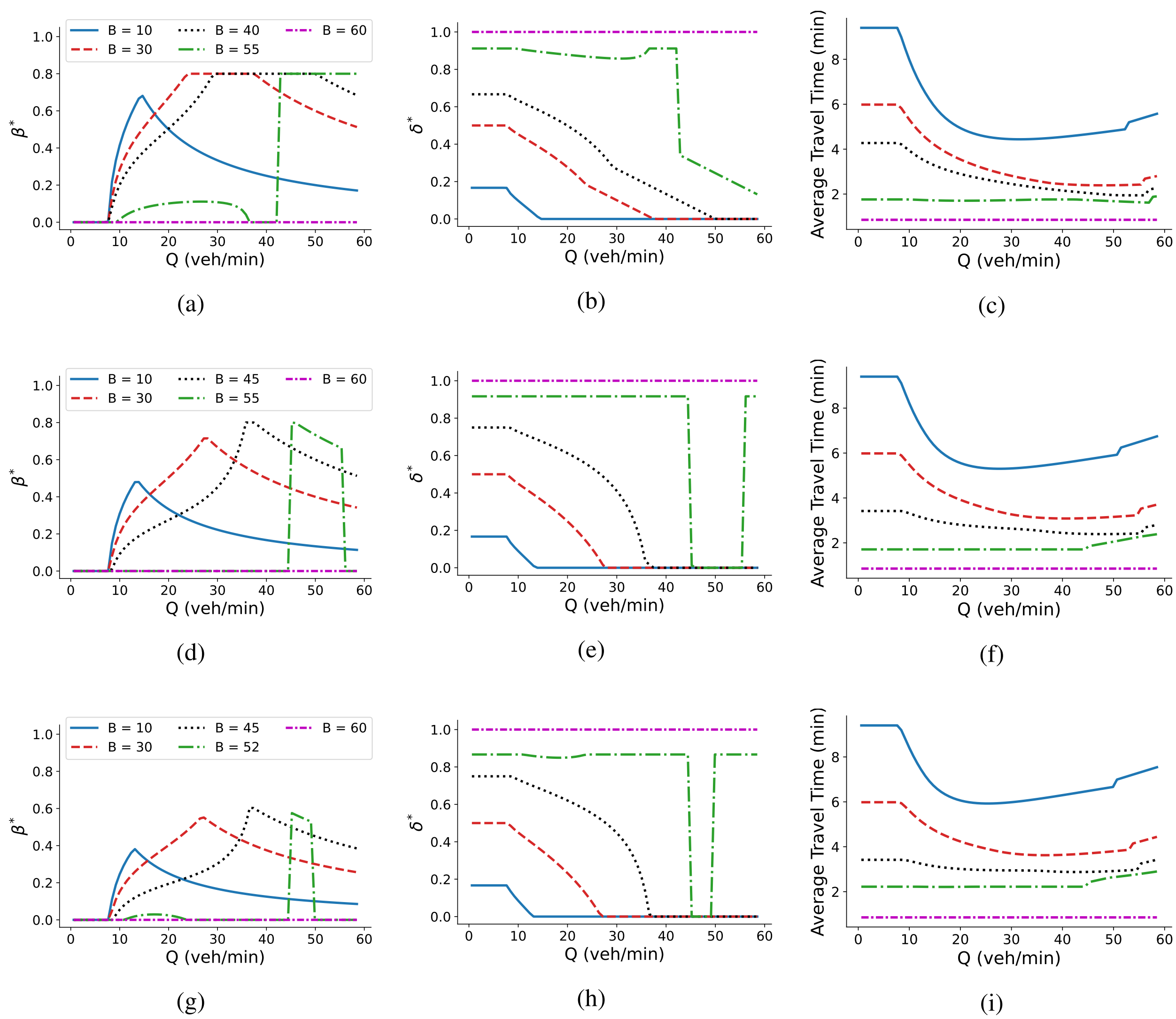
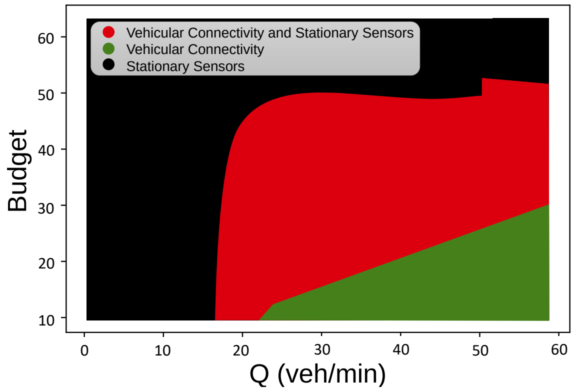


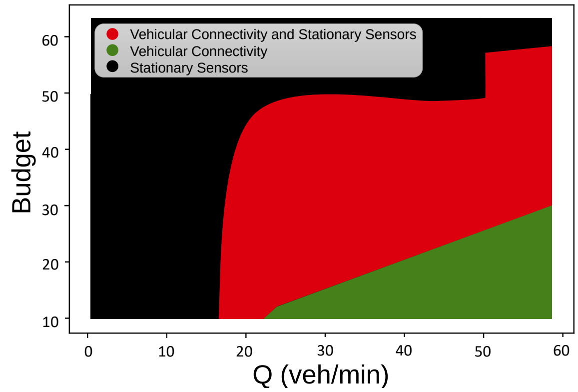
Figure 6: Optimal vehicular connectivity level (β^*), optimal stationary sensor coverage (δ^*), and average travel time for various available budgets (B) and for different σ_β values. (a, b, and c) $\sigma_\beta = 1$, (d, e, and f) $\sigma_\beta = 2$, and (g, h, and i) $\sigma_\beta = 2.5$.

Figures 6 (a-b), (d-e), and (g-h) reveal the patterns of optimal vehicular connectivity level (β^*) and optimal stationary sensor coverage (δ^*) across various budget levels and traffic flows. As anticipated based on the closed-form solutions, these results illustrate the complementary relationship between β^* and δ^*. In low traffic flows (Section 3.6 - Case I) where the density of CAVs on the road is insufficient for their ranges to overlap, and thus, vehicular connectivity offers no benefits, the optimal investment strategy is to allocate the entire budget to stationary sensors and improve δ. As traffic flow increases, vehicular connectivity becomes more beneficial and the investment plan shifts towards investing more in improving β, and δ^* gradually decreases. It is important to highlight that the decrease in β^* at higher traffic flow values is attributed to the escalating costs associated with maintaining connectivity among an increased number of CAVs within the system and the budget limitation dictates a reduction of vehicular connectivity to manage overall costs effectively (See Constraint (19b)). In addition, β^* and δ^* plots in Figure 6 allow us to notice an interesting pattern, for some given budgets, at traffic flows higher than C_m where queue delays begin to impact users' travel times, as well. As traffic flow increases, the total cost of vehicular connectivity also rises, necessitating a reduction in connectivity levels to comply with the budget constraint. As the level of connectivity decreases, we reach a critical value of β where investing all available resources in installing stationary sensors would yield more positive effects than maintaining vehicular connectivity at any lower level. This tipping point leads to the optimal investment shifting back to enhancing δ. These observed patterns underscore the significance of budget allocation and traffic flow conditions in determining the optimal investment policies for vehicular connectivity and stationary sensor deployment.

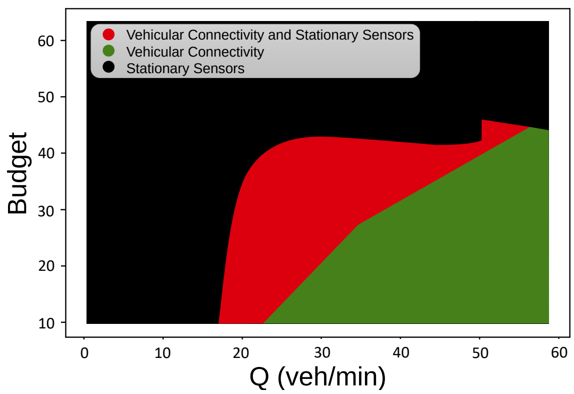
Analyzing the plots for β^* and δ^* reveals three distinct investment policies based on the available budget: (1) investing only in stationary sensors (δ), (2) investing only in vehicular connectivity (β), and (3) investing in both of the technologies. Figure 7 depicts the policy space plots, for these three distinct policies, for different σ_β and γ values. It is observed that for high budgets (relative to σ_β and σ_δ), all funds are allocated towards enhancing stationary sensors' coverage (δ), and this policy is observed to be the predominant investment strategy. In addition, at low traffic flow levels (Q), where vehicular connectivity lacks applicability due to the absence of mobile sensor range overlap, the optimal investment is again improving infrastructure and installing more stationary sensors. When neither an excessive budget is available, nor the traffic flow is small, it is best to invest in vehicular connectivity (β), and the lower the available budget and the higher the flow gets, vehicular connectivity becomes more and more lucrative in decreasing the CAV's travel time along the corridor. Figures 7 (a-b) show that when σ_β is small (relative to σ_δ), it is more possible to invest on both vehicular connectivity and infrastructure sensors; however, as σ_β increases (Figures



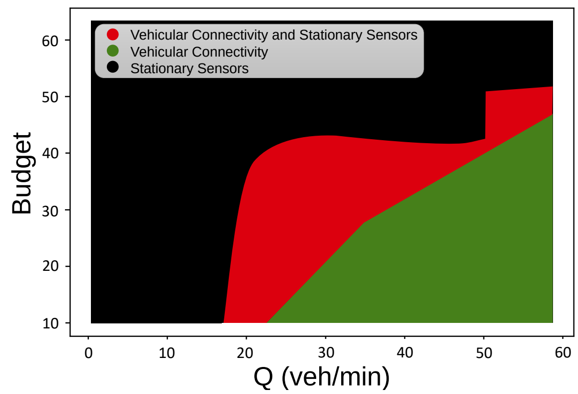
(a)



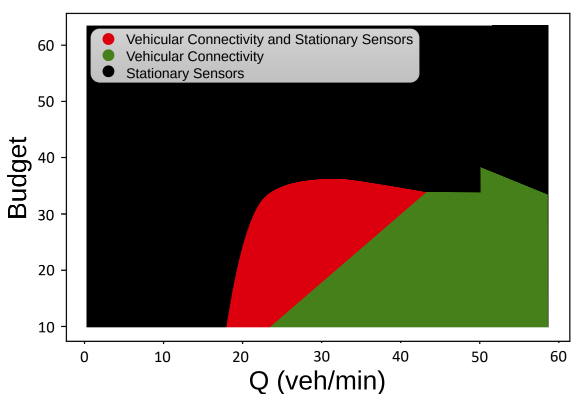
(b)



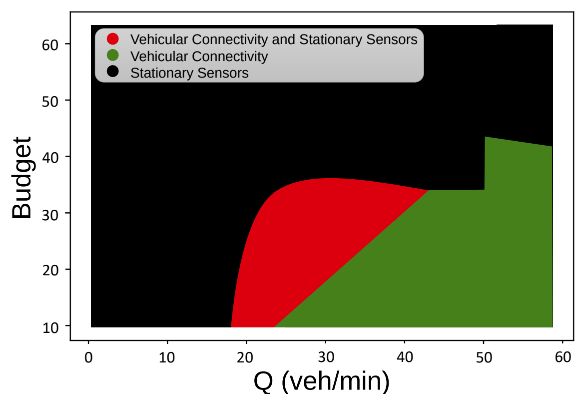
(c)



(d)



(e)



(f)

Figure 7: Optimal investment policy for vehicular connectivity level and stationary sensors coverage in different traffic flows and budgets for different σ_β and γ values. (a) $\sigma_\beta = 1$ and $\gamma = 500$, (b) $\sigma_\beta = 1$ and $\gamma = 2000$, (c) $\sigma_\beta = 1.5$ and $\gamma = 500$, (d) $\sigma_\beta = 1.5$ and $\gamma = 2000$, (e) $\sigma_\beta = 2$ and $\gamma = 500$, and (f) $\sigma_\beta = 2$ and $\gamma = 2000$.

7 (c-d) and (e-f)) decision makers need to pick either β or δ for improving as their investment policy; hence, smaller red areas. These policy space plots can help decision makers advocate the best policy based on the resources available at their hands.

Examining Figure 7, a noticeable spike occurs, which is once the traffic flow surpasses C_m. This spike is primarily attributed to the bottleneck queue formation within the corridor, a phenomenon explored in Section 3.4. As it is observed in Figures 7 (b,d, and f), an increase in γ corresponds to a higher spike. This suggests that an extended queue delay time leads to an even more pronounced spike in the figures, signifying the critical role of delay time in this context.

4 Financing of Digital Roads

In this chapter, we extend the conventional self-financing theorem of highways to the vehicle-infrastructure cooperative approach. We study a digitalized road network in which travelers choose their routes following user equilibrium conditions. Consider a set of directed links, denoted as A. Each link $a \in A$ has a travel cost function, $t_a(q_a, y_a, \delta_a)$, where q_a is the link flow, y_a is the link capacity (number of lanes), and similar to the previous chapter, δ_a is the density per unit distance by which the roadside sensing devices are installed. We also denote a set of origin-destination (O-D) pairs as W, and a set P_w of possible routes between each O-D pair $w \in W$. We assume that the demand function $d_w = D_w(c_w)$ for each O-D pair w is a continuous and decreasing function based solely on the generalized travel cost between the O-D pair. Additionally, the cost of the physical construction of a link is represented by the function $G_a(y_a)$, and the cost of adding sensing units to the link is represented by the function $U_a(\delta_a)$. The social planner maximizes the social surplus by selecting the capacity, and the portion of link length covered by roadside sensing units for all links of the network:

$$\max Z = \sum_{w\in W} \int_0^{d_w} D^{-1}(\omega)d\omega - \sum_{a\in A} q_a t_a(q_a, y_a, \delta_a) - \sum_{a\in A} G_a(y_a) - \sum_{a\in A} U_a(\delta_a) \tag{28a}$$

$$s.t.: \sum_{p\in P_w} n_p^w = d_w \qquad \forall w \in W, \tag{28b}$$

$$q_a = \sum_{w\in W} \sum_{p\in P_w} \eta_{ap}^w n_p^w \qquad \forall a \in A, \tag{28c}$$

where n_p^w is the flow on route p between O-D pair w, and η_{ap}^w is the link-route incidence matrix. Rewriting the travel time equation for each user (Equation (18)) for every link of the network defined in this section, we have

$$
t_a = \begin{cases}
\frac{\delta_a L_a \tau}{r_s - l} + \frac{\alpha(1-\delta_a) L_a \tau}{\alpha(r_m - l) - r_m^2 \theta} & 0 \leq q_a \leq \frac{y_a\left(\alpha(r_m-l)-r_m^2\theta\right)}{\tau(2\alpha r_m - r_m^2\theta)}, \\
\frac{\delta_a L_a \tau}{r_s - l} + \frac{(1-\beta)\alpha(1-\delta_a) L_a \tau}{\alpha r_m(1+\beta) - r_m^2\theta - \alpha l(1-\beta)}\left(1 + \frac{\beta y_a}{(1-\beta)\tau q_a}\right) & \frac{y_a\left(\alpha(r_m-l)-r_m^2\theta\right)}{\tau(2\alpha r_m - r_m^2\theta)} \leq q_a \leq \frac{y_a\left(\alpha(r_m(1+\beta)-l)-r_m^2\theta\right)}{\tau(\alpha r_m(1+\beta)-r_m^2\theta)}, \\
\frac{\delta_a L_a \tau}{r_s - l} + \frac{\alpha(1-\delta_a) L_a \tau}{\alpha r_m(1+\beta) - r_m^2\theta - \alpha l} + \frac{\gamma_a q_a^3}{36 y_a^3}\left(\frac{\tau(\alpha r_m(1+\beta) - r_m^2\theta)}{\alpha r_m(1+\beta) - r_m^2\theta - \alpha l}\right)^4 & \frac{y_a\left(\alpha(r_m(1+\beta)-l)-r_m^2\theta\right)}{\tau(\alpha r_m(1+\beta)-r_m^2\theta)} \leq q_a \leq \frac{y_a(r_s-l)}{r_s\tau},
\end{cases} \tag{29}
$$

where L_a is the length of the link, r_m and α are the range and power of CAVs on-board sensors, respectively, and β is the level of connectivity between CAVs. r_s is the range of road-side sensing units, l and θ are the safety thresholds, and γ_a is a constant for capturing the delay as a result of changes in link capacity depending on the type of digital infrastructure.

Now that we have revised the travel time function based on the characteristics of this problem, we discuss the first-order optimality condition of problem (28):

$$
D_w^{-1}(d_w) = \sum_{p \in P_w} \eta_{ap}^w \left(t_a(q_a, y_a, \delta_a) + q_a \frac{\partial t_a(q_a, y_a, \delta_a)}{\partial q_a} \right) \qquad \forall w \in W | d_w, q_a > 0, \tag{30a}
$$

$$
q_a \frac{\partial t_a(q_a, y_a, \delta_a)}{\partial y_a} + \frac{\partial G_a}{\partial y_a} = 0 \qquad \forall a \in A, \tag{30b}
$$

$$
q_a \frac{\partial t_a(q_a, y_a, \delta_a)}{\partial \delta_a} + \frac{\partial U_a}{\partial \delta_a} = 0 \qquad \forall a \in A. \tag{30c}
$$

Given the travel time function (29), we express the following derivatives as they appear in the KKT conditions.

$$\frac{\partial t_a(q_a,y_a,\delta_a)}{\partial q_a}=\begin{cases}0,\\ \\ \frac{-\alpha\beta(1-\delta_a)L_a y_a}{q_a^2\Big((1+\beta)\alpha r_m-r_m^2\theta-\alpha l(1-\beta)\Big)}\le 0,\\ \\ \frac{q_a^2\gamma_a\tau^4\Big(\alpha r_m(1+\beta)-r_m^2\theta\Big)^4}{12y_a^3\Big(\alpha r_m(1+\beta)-r_m^2\theta-\alpha l\Big)^4}\ge 0,\end{cases}\tag{31a}$$

$$\frac{\partial t_a(q_a,y_a,\delta_a)}{\partial y_a}=\begin{cases}0,\\ \\ \frac{\alpha\beta(1-\delta_a)L_a}{q_a\Big((1+\beta_a)\alpha r_m-r_m^2\theta-\alpha l(1-\beta)\Big)}\ge 0,\\ \\ \frac{-q_a^3\gamma_a\tau^4\Big(\alpha r_m(1+\beta)-r_m^2\theta\Big)^4}{12y_a^4\Big(\alpha r_m(1+\beta)-r_m^2\theta-\alpha l\Big)^4}\le 0,\end{cases}\tag{31b}$$

$$\frac{\partial t_a(q_a,y_a,\delta_a)}{\partial \delta_a}=\begin{cases}\frac{-L_a\tau\Big(\alpha(r_s-r_m)+r_m^2\theta\Big)}{(r_s-l)\Big(\alpha(r_m-l)-r_m^2\theta\Big)}\le 0,\\ \\ \frac{-L_a\left(q_a\tau\alpha r_s(1-\beta)+y_a\alpha\beta(r_s-l)-q_a\tau\Big(\alpha r_m(1+\beta)-rm^2\theta\Big)\right)}{q_a(r_s-l)\Big(\alpha r_m(1+\beta)-r_m^2\theta-\alpha l(1-\beta)\Big)},\\ \\ \frac{-L_a\tau\left(\alpha\Big(r_s-(1+\beta)r_m\Big)+r_m^2\theta\right)}{(r_s-l)\Big(\alpha r_m(1+\beta)-r_m^2\theta-\alpha l\Big)}\le 0.\end{cases}\tag{31c}$$

We know that $\frac{\partial G_a}{\partial y_a}>0$, and $\frac{\partial U_a}{\partial \delta_a}>0$. Hence, Equation (30b) can only hold true only for the third leg of $\frac{\partial t_a(q_a,y_a,\beta_a,\delta_a)}{\partial y_a}$, and the maximum social surplus can only happen if the link capacities are selected to ensure that the link travel times are in their third leg based on Equation (29). The third leg of the travel time function (Equation 29) has neutral economies of scale (constant return to scale) based on link flow-capacity ratio ($\frac{q_a}{y_a}$), and diseconomies of scale (decreasing return to scale) with respect to flow-sensing ($\frac{q_a}{\delta_a}$) ratio.

4.1 Self-financing Theorem

In this section, we discuss the self-financing theorem. More specifically, we evaluate whether the optimal toll collected by social planners can recover the costs for three different scenarios (1) constructing physical roads, (2) constructing digital roads, and (3) automating vehicles and constructing digital roads.

4.1.1 Constructing Physical Roads

Consider the absence of any digital infrastructure ($\delta_a = 0$), similar to the traditional self-financing theorem where the planner only determines the physical capacity of the links. The self-financing theorem holds if the revenue from the optimum toll covers the capital cost of constructing links:

$$q_a\mu_a - G_a(y_a) \geq 0. \tag{32}$$

Based on Equation (30a), the optimal toll is $q_a \frac{\partial t_a(q_a,y_a,0)}{\partial q_a}$. Hence, if there are constant returns to scale in constructing physical roads based on the link capacity, $G_a(y_a) = \lambda_a y_a$, and we have:

$$q_a\mu_a - G_a(y_a) = q_a^2 \frac{\partial t_a(q_a,y_a,0)}{\partial q_a} + q_a y_a \frac{\partial t_a(q_a,y_a,0)}{\partial y_a} = 0, \tag{33}$$

indicating that the revenue from the optimum toll covers the capital cost for constructing each road link, which is consistent with the conventional self-financing of roads summarized in Theorem 1:

Theorem 1. *The revenue from the optimum toll covers the capital construction cost for each road link.*

4.1.2 Constructing Digital Roads

When the planner decides about physical capacity and equipping a portion of it with roadside sensing units, the self-financing theorem holds if the revenue from the optimum toll covers the capital cost of constructing physical roads and installing roadside sensing of the links:

$$q_a\mu_a - G_a(y_a) - U_a(\delta_a) \geq 0, \tag{34}$$

where μ_a is the optimal toll charge for link a, and based on Equation (30a), the optimal toll is:

$$\mu_a = q_a \frac{\partial t_a(q_a, y_a, \delta_a)}{\partial q_a}.$$

If there are constant returns to scale in constructing physical and digital parts of roads, $G_a(y_a) = \lambda_a y_a$ and $U_a(\delta_a) = \zeta_a \delta_a$, from (34) we have:

$$q_a\mu_a - G_a(y_a) - U_a(\delta_a) = q_a^2 \frac{\partial t_a}{\partial q_a} + q_a y_a \frac{\partial t_a}{\partial y_a} + q_a \delta_a \frac{\partial t_a}{\partial \delta_a} = \frac{-q_a L_a \delta_a \tau \left(\alpha \left(r_s - (1+\beta) r_m \right) + r_m^2 \theta \right)}{(r_s - l)\left(\alpha r_m (1+\beta) - r_m^2 \theta - \alpha l \right)} \leq 0. \tag{35}$$

We can show that all terms inside the parentheses are positive based on the properties of parameters (for further explanations refer to Chapter 3 and [19]). Therefore, the nominator is negative, and the self-financing theorem does not hold for constructing roads and equipping them with digital components. This happens due to diseconomies of scale with respect to roadside sensing. Theorem 2 summarizes the findings for the financing of digital road construction:

Theorem 2. *The revenue from the optimum toll does not cover the construction and installation costs of roadside sensing units for each road link.*

4.1.3 Digitizing Existing Roads

Consider the case where the physical road network is well developed currently and there is not much interest in building new roads. However, there is a need to deploy digital infrastructure to enable automated driving. In this section, we consider a fixed physical capacity and investigate the decision of a social planner to maximize social surplus by selecting the optimal roadside sensing level. We then investigate the self-financing theorem for these joint investments.

The self-financing theorem holds if the revenue from the optimum toll covers the capital cost of installing roadside sensing for each link:

$$q_a\mu_a - U_a(\delta_a) \geq 0. \tag{36}$$

Based on Equation (30a), the optimal toll is $q_a \frac{\partial t_a}{\partial q_a}$. In this case, the first-order optimality condition can be satisfied for all three parts of the travel time function. Hence, if there are constant returns to scale in installing roadside sensing, $U_a(\delta_a) = \zeta_a \delta_a$ we have:

$$q_a\mu_a - U_a(\delta_a) \begin{cases} \leq 0 \quad \text{if } 0 \leq \frac{q_a}{y_a} \leq \frac{\left(\alpha r_m(1+\beta) - r_m^2\theta - \alpha l\right)}{\tau\left(\alpha r_m(1+\beta) - r_m^2\theta\right)} \sqrt[3]{\frac{12 L_a \delta_a \left(\alpha\left(r_s - r_m(1+\beta)\right) + r_m^2\theta\right)}{\gamma_a(r_s - l)\left(\alpha r_m(1+\beta) - r_m^2\theta\right)}}, \\ \\ > 0 \quad \text{if } \frac{\left(\alpha r_m(1+\beta) - r_m^2\theta - \alpha l\right)}{\tau\left(\alpha r_m(1+\beta) - r_m^2\theta\right)} \sqrt[3]{\frac{12 L_a \delta_a \left(\alpha\left(r_s - r_m(1+\beta)\right) + r_m^2\theta\right)}{\gamma_a(r_s - l)\left(\alpha r_m(1+\beta) - r_m^2\theta\right)}} < \frac{q_a}{y_a} \leq \frac{(r_s - l)}{r_s\tau}, \end{cases} \tag{37}$$

indicating that the optimal toll may or may not cover the cost of digitalization depending on the flow-capacity ratio.

Proposition 1. *For the digitalization of existing road links, the revenue from the optimal toll may cover the cost of installing roadside units for each road link if its flow-capacity ratio is higher than some threshold (f_a).*

4.2 Modified Models

This section examines a few modified versions of the problem and investigates whether self-financing can be held for these modified models.

4.2.1 Manufacturing Automated Vehicles and Constructing Digital Roads

First, we consider a scenario in which the social planner can also select the sensing properties of CAVs, α, and their connectivity, β to maximize the social surplus. This can be done through cooperation between all players as discussed in [18] or by enacting CAVs sensing properties rules. In this case, the social planners maximize social surplus:

$$\max Z_2 = \sum_{w \in W} \int_0^{d_w} D^{-1}(\omega) d\omega - \sum_{a \in A} q_a t_a(q_a, y_a, \delta_a, \alpha, \beta) - \sum_{a \in A} G_a(y_a) - \sum_{a \in A} U_a(\delta_a) - E(\alpha, \beta) \sum_{w \in W} d_w, \tag{38}$$

$$S.t. :(28\text{b}) - (28\text{c}).$$

The only difference between Equation (38) and Equation (28a) is the last term which captures the cost of CAV on-board sensing and CAVs connectivity level. This term is not link dependent and therefore we cannot evaluate the self-financing theorem for each link, however, it can be evaluated for the network as a whole. The first-order optimality condition for this scenario results:

$$D_w^{-1}(d_w) = \sum_{p \in P_w} \eta_{ap}^w \left(t_a(q_a, y_a, \delta_a, \alpha, \beta) + q_a \frac{\partial t_a(q_a, y_a, \delta_a, \alpha, \beta)}{\partial q_a} \right) + E(\alpha, \beta) \quad \forall w \in W | d_w, q_a > 0, \tag{39a}$$

$$q_a \frac{\partial t_a(q_a, y_a, \delta_a, \alpha, \beta)}{\partial y_a} + \frac{\partial G_a}{\partial y_a} = 0 \qquad \forall a \in A, \tag{39b}$$

$$q_a \frac{\partial t_a(q_a, y_a, \delta_a, \alpha, \beta)}{\partial \delta_a} + \frac{\partial U_a}{\partial \delta_a} = 0 \qquad \forall a \in A. \tag{39c}$$

$$\sum_{a} q_a \frac{\partial t_a(q_a, y_a, \delta_a, \alpha, \beta)}{\partial \alpha} + \frac{\partial E}{\partial \alpha} \sum_{w \in W} d_w = 0, \tag{39d}$$

$$\sum_{a} q_a \frac{\partial t_a(q_a, y_a, \delta_a, \alpha, \beta)}{\partial \beta} + \frac{\partial E}{\partial \beta} \sum_{w \in W} d_w = 0. \tag{39e}$$

Equation (39a) shows that the generalized travel cost between each O-D pair includes the travel time and toll of the links constituting the path between the O-D pair, and the full cost of CAVs on-board sensing power and CAVs connectivity level.

As the cost of on-board sensing is exactly equal to the amount that travelers pay, the link tolls are the only source of revenue for the social planner, which is equal to $q_a \frac{\partial t_a(q_a, y_a, \delta_a, \alpha, \beta)}{\partial q_a}$. Therefore, similar to the case of digital infrastructure discussed in the previous section, if there are constant returns to scale in constructing physical and digital parts of roads, $G_a(y_a) = \lambda_a y_a$ and $U_a(\delta_a) = \zeta_a \delta_a$, the self-financing theorem does not hold:

$$q_a \mu_a - G_a(y_a) - U_a(\delta_a) = q_a^2 \frac{\partial t_a}{\partial q_a} + q_a y_a \frac{\partial t_a}{\partial y_a} + q_a \delta_a \frac{\partial t_a}{\partial \delta_a} = \frac{-q_a L_a \delta_a \tau \Big(\alpha \big(r_s - (1+\beta) r_m\big) + r_m^2 \theta \Big)}{(r_s - l)\big(\alpha r_m (1+\beta) - r_m^2 \theta - \alpha l\big)} \leq 0. \tag{40}$$

Theorem 3. *When the social planner selects the CAVs on-board sensing power and properties of each link, travelers pay the full cost of CAVs on-board sensing and connectivity, $E(\alpha, \beta)$. Moreover, the revenue from the optimal toll does not cover the construction cost of each road link and equipping it with roadside sensing.*

In addition, if there are constant returns to scale with respect to CAVs on-board sensor power and connectivity level, $E(\alpha, \beta) = c_\alpha \alpha + c_\beta \beta$, based on Equations (39d) and (39e), we have:

$$E(\alpha, \beta) = c_\alpha \alpha + c_\beta \beta = -\frac{1}{\sum_{w \in W} d_w} \left(\alpha \sum_{a \in A} q_a \frac{\partial t_a(q_a, y_a, \delta_a, \alpha, \beta)}{\partial \alpha} + \beta \sum_{a \in A} q_a \frac{\partial t_a(q_a, y_a, \delta_a, \alpha, \beta)}{\partial \beta} \right),$$

where $\frac{\partial t_a}{\partial \alpha}$ and $\frac{\partial t_a}{\partial \beta}$ based on travel time function, Equation (29), are:

$$
\frac{\partial t_a(q_a,y_a,\delta_a,\alpha,\beta)}{\partial \alpha} = \begin{cases} \dfrac{-L_a(1-\delta_a)r_m^2\theta\tau}{\left(\alpha r_m - r_m^2\theta - \alpha l\right)^2} \leq 0, \\[3em] \dfrac{-L_a(1-\delta_a)r_m^2\theta\left(q_a\tau(1-\beta)+y_a\beta\right)}{q_a\left((1+\beta)\alpha r_m - r_m^2\theta - \alpha l(1-\beta)\right)^2} \leq 0, \\[3em] \dfrac{-(1-\delta)L_a r_m^2\theta\tau\left(9y_a^3(\alpha(l-(1+\beta)r_m+r_m^2\theta))^3\right)+\gamma_a l q^3 r_m^2\theta\tau^4\left(\alpha r_m(1+\beta)-r_m^2\theta\right)^3}{9y_a^3(\alpha(l-(1+\beta)r_m+r_m^2\theta))^5}, \end{cases} \tag{41}
$$

$$
\frac{\partial t_a(q_a,y_a,\delta_a,\alpha,\beta)}{\partial \beta} = \begin{cases} 0, \\[3em] \dfrac{-\alpha(1-\delta_a)L_a\left(q_a\tau(2\alpha r_m - r_m^2\theta) - y_a\left(\alpha(r_m-l)-r_m^2\theta\right)\right)}{q_a\left((1+\beta)\alpha r_m - r_m^2\theta - \alpha l(1-\beta)\right)^2} \leq 0, \\[3em] \dfrac{\alpha^2 r_m\tau\left(-9y_a^3(1-\delta_a)L_a\left(\alpha(r_m(1+\beta)-l)-r_m^2\theta\right)^3-\gamma_a q_a^3\tau^3 l(\alpha(1+\beta))r_m-r_m^2\theta)^3\right)}{9y_a^3(\alpha(r_m(1+\beta)-l)-r_m^2\theta)^5}. \end{cases} \tag{42}
$$

Then, based on Equations (39d) and (39e), we have:

$$
\alpha^* = \sqrt{\frac{r_m\theta c_\beta}{c_\alpha}}, \tag{43}
$$

which is the same as the result for optimally assigning a fixed budget between sensor power and connectivity to maximize the road capacities derived by [19].

Proposition 2. *When the social planner selects automated vehicles' on-board sensing properties and connectivity in addition to road link properties to maximize the social surplus, the optimal CAVs' on-board sensing power is equal to the case when social planners assign a limited budget between CAVs' on-board sensing and connectivity to maximize link capacities.*

4.2.2 Safety Benefits of Enabling Automated Driving

So far we assume that the generalized cost of travelers is only a function of their travel time and toll for using each road link. However, safety is a primary determinant for enabling automated driving [45, 205, 206, 207]. Therefore, in this section, we consider the safety benefits of automated driving and digitalization of infrastructures. For this purpose, we define $N_a(\delta_a)$ as the probability of accidents on link a. We know that $\frac{\partial N_a}{\partial \delta_a} < 0$, which means that the probability of accidents on links decreases with an increase in the digitalization of road links. In this case, the social planners maximize social surplus:

$$\max Z_3 = \sum_{w \in W} \int_0^{d_w} D^{-1}(\omega) d\omega - \sum_{a \in A} q_a t_a(q_a, y_a, \delta_a) - \sum_{a \in A} q_a N_a(\delta_a) - \sum_{a \in A} G_a(y_a) - \sum_{a \in A} U_a(\delta_a), \tag{44}$$

$$S.t. :(28\text{b}) - (28\text{c}),$$

where the third term in objective function (44) captures the safety cost. The first-order optimality condition results:

$$D_w^{-1}(d_w) = \sum_{p \in P_w} \eta_{ap}^w \left(t_a(q_a, y_a, \delta_a) + q_a \frac{\partial t_a(q_a, y_a, \delta_a)}{\partial q_a} + N(\delta_a) \right) \quad \forall w \in W | d_w, q_a > 0, \tag{45a}$$

$$q_a \frac{\partial t_a(q_a, y_a, \delta_a)}{\partial y_a} + \frac{\partial G_a}{\partial y_a} = 0 \quad \forall a \in A, \tag{45b}$$

$$q_a \frac{\partial t_a(q_a, y_a, \delta_a)}{\partial \delta_a} + q_a \frac{\partial N_a(\delta_a)}{\partial \delta_a} + \frac{\partial U_a}{\partial \delta_a} = 0 \quad \forall a \in A. \tag{45c}$$

Again, the self-financing theorem holds if the revenue from the optimum toll covers the capital cost of constructing physical roads and installing roadside sensing of the links:

$$q_a \mu_a - G_a(y_a) - U_a(\delta_a) \geq 0, \tag{46}$$

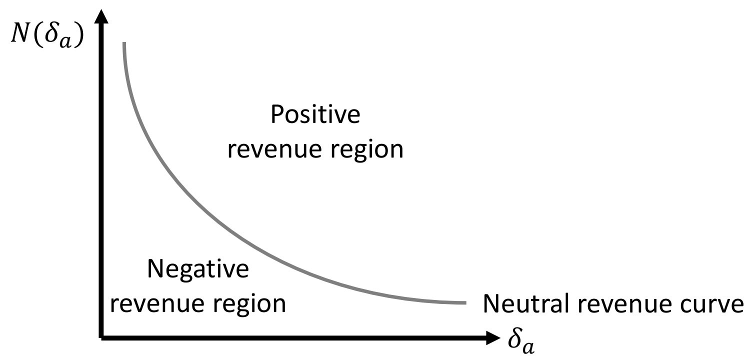


Figure 8: Schematic of the probability of accident on a link, $N(\delta_a)$, as a function of its portion covered by roadside sensing, δ_a.

where μ_a is the optimal toll charge for link a, and based on Equation (45a), the optimal toll is:

$$\mu_a = q_a \frac{\partial t_a(q_a, y_a, \delta_a)}{\partial q_a} + N(\delta_a).$$

Hence, the toll of each link has two components. The first component is congestion based and is equal to $q_a \frac{\partial t_a}{\partial q_a}$, and the other one depends on the accident probability and is equal to $N(\delta_a)$. If there are again constant returns to scale in installing roadside sensing for each link, $U_a(\delta_a) = \zeta_a \delta_a$, based on Equation (45c) we have:

$$\zeta_a = -q_a \left(\frac{\partial t_a(q_a, y_a, \delta_a)}{\partial \delta_a} + \frac{\partial N_a(\delta_a)}{\partial \delta_a} \right). \tag{47}$$

Therefore, Equation (46) can be simplified to:

$$\begin{aligned} q_a\mu_a - G_a(y_a) - U_a(\delta_a) &= q_a^2 \frac{\partial t_a}{\partial q_a} + q_a N_a(\delta_a) + q_a y_a \frac{\partial t_a}{\partial y_a} + q_a \delta_a \frac{\partial t_a}{\partial \delta_a} + q_a \delta_a \frac{\partial N_a(\delta_a)}{\partial \delta_a} \\ &= q_a N_a(\delta_a) + q_a \delta_a \frac{\partial N_a(\delta_a)}{\partial \delta_a} - \frac{q_a L_a \delta_a \tau \Big(\alpha \big(r_s - (1+\beta) r_m \big) + r_m^2 \theta \Big)}{(r_s - l)\big(\alpha r_m (1+\beta) - r_m^2 \theta - \alpha l \big)}. \end{aligned} \tag{48}$$

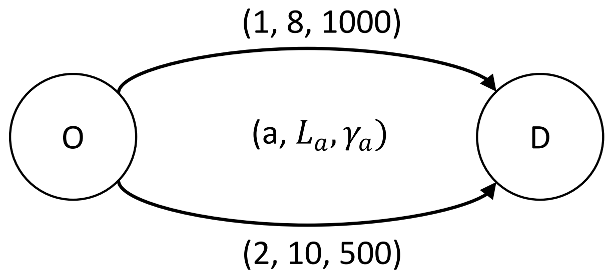


Figure 9: Schematic of a network with one O-D pair and multiple links.

If we assume that the revenue from optimal toll exactly covers the cost of constructing roads and installing roadside sensors, Equation (48) becomes an ordinary differential equation, and solving it results:

$$N_a(\delta_a) = \frac{L_a\tau\Big(\alpha\big(r_s-(1+\beta)r_m\big)+r_m^2\theta\Big)}{2(r_s-l)\big(\alpha r_m(1+\beta)-r_m^2\theta-\alpha l\big)}\delta_a + \frac{c}{\delta_a}, \tag{49}$$

where c is a constant. Figure 8 shows a schematic of $N(\delta_a)$ based on Equation (49). For any safety function laying above this line, the revenue is positive and the optimal toll charged per link is greater than the cost of constructing the link and equipping it with roadside sensing. We label this area as a positive revenue region. On the other hand, for any probability function curve laying under the revenue neutral curve, the optimal toll cannot cover the cost of constructing the digital link, and the self-financing theorem is refuted again. We label this region as a negative revenue region.

Proposition 3. *If the social planner also considers the safety benefit of digitalization of infrastructure, the revenue from optimal toll may cover the cost of constructing roads and installing roadside sensing units for each road link.*

Table 5: Default values for parameters of numerical examples.

Notation	Interpretation	Default value
α	Sensors' power	0.25 [dps]
β	CAVs' connectivity ratio	0.5
l	Average length of vehicle	5 [m]
r_m	Mobile sensors range	100 [m]
r_s	Stationary sensors range	200 [m]
θ	Safety threshold	0.002 [$\frac{\text{dps}}{m}$]
τ	Processing time	1 [sec]
$\overline{D_w}$	Potential demand	50400 [$\frac{veh}{hr}$]
n	Demand function parameter	100 [sec]
λ_1	Link1's coefficient of physical cost function	80
λ_2	Link 2's coefficient of physical cost function	100
ζ_1	Link 1's coefficient of sensing units' cost function	100
ζ_2	Link 2's coefficient of sensing units' cost function	200

Table 6: Construction of a digital road representative solutions.

	$q_a[\frac{veh}{hr}]$	$y_a[lane(s)]$	$\frac{q_a}{y_a}[\frac{veh}{hr \cdot lane}]$	δ_a	$t_a[min]$	μ_a $[min]$	Profit
Link 1	5848	1.75	3348	0.53	1.72	1.50	-47.3
Link 2	1548	0.47	3348	0.17	2.47	0.75	-30.0

4.3 Numerical Analyses for the Self-financing Theorem

In this section, we employ a network with multiple routes connecting an origin-destination (O-D) pair to illustrate the insights from the previous section. Figure 9 provides an overview of this network. The labels on the links provide information about each link, including its id, length (L [Km]), and delay parameter (γ). We consider a demand function in the form of $D_w = \overline{D_w} exp(\frac{-C_w}{n})$, where $\overline{D_w}$ is the potential demand, C_w is the generalized cost of traveling between O-D pair, and n is a parameter of the model. We assume that both the physical cost and the digitalization cost functions have linear dependencies on y_a and δ_a, respectively, characterized by $G_a(y_a) = \lambda_a y_a$ and $U_a(\delta_a) = \zeta_a \delta_a$. All parameters are set at their default values as presented in Table 5. From Table 5 it can be observed that links of our network have different λ and ζ values. The reason for this discrepancy is the influence of corridor length on its costs. Longer roads incur higher expenses when it comes to construction and sensor deployment over their spans.

Table 7: Digitizing of an existing road representative solutions.

	q_a $[\frac{veh}{hr}]$	$\frac{q_a}{y_a}[\frac{veh}{hr \cdot lane}]$	δ_a	t_a $[min]$	μ_a $[min]$	$f_a[\frac{veh}{hr \cdot lane}]$	Profit
Link 1	6696	3348	0.92	1.20	1.50	3153	74.88
Link 2	3348	3348	0.48	1.94	0.75	3448	-54.35

Upon solving the optimization problem outlined in Equations (28a-c) for this network, we present the results in Table 6. Analyzing the outcomes, it becomes apparent that at the network's equilibrium, both links encounter equal total costs, which is sum of travel time (t_a) and toll (μ_a). Furthermore, the negative profit values for both links indicate that the revenue generated from the optimal tolls cannot cover the physical and digitalization costs of these links, as elaborated in Section 4.1.2. Then, we consider the case that the two roads of our network exist, and the social planner only adds digital components to it. For this example, the number of lanes (y_a) for each link is assumed to be fixed on $y_1 = 2$ and $y_2 = 1$. The links are also different in terms of the delay parameter, γ, and length, L. The optimal sensor coverage and traffic flow traveling through each link are presented in Table 7. For Link 1, the f_a threshold based on Equation (37) is 3153 $[\frac{veh}{hr \cdot lane}]$ which is lower than 3348 $[\frac{veh}{hr \cdot lane}]$, and the revenue can cover the digitalization costs, which results in having a positive profit. However, in Link 2, the f_a threshold based on Equation (37) is 3448 $[\frac{veh}{hr \cdot lane}]$ which is higher than this link's traffic flow, 3348 $[\frac{veh}{hr \cdot lane}]$, and the revenue from optimal toll cannot cover the digitalization costs.

5 Conclusion

This study highlights the role of cooperative sensing and connectivity in enhancing the capabilities of CAVs. We focused on investigating the optimal investment policy, considering the paradigms of improving vehicular connectivity among vehicles and installing stationary robust sensors as part of the infrastructure to aid CAVs in overcoming their inherent sensor limitations.

5.1 Summary of Results

We presented a stylized model of CAV mobility, accounting for the characteristics of both stationary and mobile sensors. Our investigation aimed to understand how each investment paradigm impacts CAV operations under varying traffic conditions and budget constraints. The findings of our study shed light on the trade-offs and benefits associated with the two investment paths. Specifically, when budgetary constraints limit the installation of stationary sensors throughout the road and low traffic flows indicate low vehicle density, the more optimal approach is to allocate the entire budget towards improving the infrastructure through additional stationary sensor deployment. As traffic flow increases and a greater number of CAVs operate on the road, investing in enhancing vehicular connectivity and facilitating data sharing among CAVs becomes more lucrative. However, intriguingly, depending on the specific system settings, instances in high-flow scenarios arise where investing in stationary sensors once again becomes more optimal. The identification of these optimal investment patterns allowed us to propose three distinct investment policies based on the optimal level of connectivity among CAVs and optimal stationary sensors' coverage of the corridor, providing policymakers with valuable insights for making informed decisions.

Furthermore, we extended the conventional self-financing theorem of road networks which states that a social planner can cover the cost of constructing roads if optimally selects road capacities and their tolls for the whole network, to the case of constructing physical roads and equipping them with roadside sensing units. We showed that self-financing will not hold for constructing digital roads because, unlike the flow-capacity ratio, the travel time function has diseconomies of scale with respect to the flow-sensing ratio. In addition, we showed that for existing roads, the optimal toll can generate profit for links with a flow-capacity ratio higher than some threshold but cannot cover the costs for the links with lower flow-capacity ratios. We then extended our study and considered two modified versions of the problem in which the social planner also selects the sensing and connectivity properties of CAVs, and considers the safety benefits of the digitalization of roads. We show that in the former scenario, travelers cover the full cost of CAVs' on-board sensors, and therefore the construction of digital roads is not self-financed. However, in the latter scenario, the construction of digital roads may be self-financed depending on the safety benefits of installing roadside units.

5.2 Future Research Directions

Future research could explore scenarios where conventional human-driven vehicles coexist with CAVs. Understanding the dynamics and performance of connectivity and cooperative sensing among CAVs in an environment shared with conventional vehicles could uncover challenges and opportunities for seamless integration. Moreover, exploring the incorporation of heterogeneous sensing capabilities within CAVs' on-board sensors and studying the implications of varying levels of sensing proficiency represents an avenue for further research. Furthermore, exploring additional benefits of road digitalization, such as monetizing traffic data information and how it can be a supplementary revenue source in self-financing of the roads holds promise for future investigation.

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Appendices

A Proof of Lemma 1

To prove Lemma 1 we shall use the backward proving method. From the capacity of the stationary region being higher than the capacity of the mobile region, we have

$$C_s > C_m \Rightarrow \frac{1}{\tau} - \frac{l}{r_s\tau} > \frac{1}{\tau} - \frac{\alpha l}{\alpha r_m \tau(1+\beta) - r_m^2\theta\tau}. \tag{50}$$

By simplifying both sides we have

$$r_s > \frac{\alpha r_m + \alpha\beta r_m - r_m^2\theta}{\alpha}. \tag{51}$$

From Equation (19e), we have $\beta \leqslant \frac{r_m\theta}{\alpha}$. Since α is always positive we can rewrite as $\alpha\beta \leqslant r_m\theta$. Therefore, for the right side of Inequality (51) we have

$$\frac{\alpha r_m + (r_m\theta) r_m - r_m^2\theta}{\alpha} \geqslant \frac{\alpha r_m + (\alpha\beta) r_m - r_m^2\theta}{\alpha}. \tag{52}$$

Since the left side of Inequality (52) is r_m, we can say that if $r_s > r_m$ is true, $C_s > C_m$ is true as well, and Lemma 1 is proved.

B Closed-form Solutions of the Optimization Problem

In this section, we provide the solution to the optimization problem introduced in Equation (19a). Since Constraints (19c), (19d), and (19e) are boundary limits, and in cases where they are binding the variables are simply bounded to their upper and lower limits, here, we seek the solution for cases where the budget constraint (19b) is binding.

Rewriting the problem in standard form, we have

$$\min_{\beta,\delta} \quad Q\left(\frac{\delta L}{V_s} + \frac{(1-\delta)L}{V_m} + t_b\right), \tag{53a}$$

$$\text{s.t.} \quad \sigma_\delta \delta L + \sigma_\beta \beta Q - B \leq 0, \tag{53b}$$

and the Lagrangian function can be derived as

$$\mathcal{L} = Q\left(\frac{\delta L}{V_s} + \frac{(1-\delta)L}{V_m} + t_b\right) + \lambda(\sigma_\delta \delta L + \sigma_\beta \beta Q - B) \tag{54}$$

where λ is the Lagrange multiplier.

From the first order condition we have

$$\frac{\partial \mathcal{L}}{\partial \beta} = (1-\delta)L\left(-\frac{1}{V_m^2}\frac{\partial V_m}{\partial \beta}\right) + \frac{\partial t_b}{\partial \beta} + \lambda(\sigma_\beta Q) = 0, \tag{55a}$$

$$\frac{\partial \mathcal{L}}{\partial \delta} = \frac{L}{V_s} - \frac{L}{V_m} + \lambda(\sigma_\delta L) = 0, \tag{55b}$$

$$\frac{\partial \mathcal{L}}{\partial \lambda} = B - \sigma_\delta \delta L - \sigma_\beta \beta Q = 0, \tag{55c}$$

where t_b, V_m, and V_s are given from Equations (17), (20), and (21), respectively.

Case I. $Q \leq \frac{\alpha(r_m - l) - r_m^2\theta}{\tau(2\alpha r_m - r_m^2\theta)}$

In this case, an examination of Equations (17) and (20) reveals that both $\frac{\partial V_m}{\partial \beta}$ and $\frac{\partial t_b}{\partial \beta}$ equal zero. Consequently, solving Equations (55a), (55b), and (55c) yields

$$\lambda_1 = 0, \tag{56a}$$

$$\beta_1 = 0, \tag{56b}$$

$$\delta_1 = \frac{B}{\sigma_\delta L}. \tag{56c}$$

In this case, the Lagrange multiplier λ becomes zero, indicating a specific solution for β and δ, and highlighting the significance of δ as determined by Equation (56c).

Case II. $\frac{\alpha(r_m - l) - r_m^2\theta}{\tau(2\alpha r_m - r_m^2\theta)} < Q \leq C_m$

In Case II, we have $\frac{\partial t_b}{\partial \beta} = 0$, but from Equation (20) we have

$$\frac{\partial V_m}{\partial \beta} = \frac{Q\left(\alpha l - r_m(\alpha - 2Q\alpha\tau + r_m\theta(Q\tau - 1))\right)}{\alpha(\beta + Q\tau(1-\beta))^2}. \tag{57}$$

Substituting this into Equations (55a), (55b), and (55c), and solving for λ, β, and δ, we obtain

$$\lambda_2 = \frac{\sigma_\delta Q(r_s - l)(r_s - Q\tau(r_m + r_s) - l) + \frac{\sqrt{\Gamma}}{\sigma_\delta L(l + r_m)\alpha + \sigma_\beta Q(l\alpha - r_m\alpha + r_m^2\theta) - B(l + r_m)\alpha}}{\sigma_\delta^2 Q^2 (l + r_m)(r_s - l)^2}, \tag{58a}$$

$$\beta_2 = \frac{\alpha l - \alpha r_m + r_m^2\theta}{\alpha l + \alpha r_m} - \frac{\sqrt{\Delta}}{\alpha\sigma_\beta\sigma_\delta Q^2(l + r_m)(r_s - l)(r_s - Q\tau(r_m + r_s) - l)}, \tag{58b}$$

$$\delta_2 = \frac{B - \sigma_\beta \beta_2 Q}{\sigma_\delta L}, \tag{58c}$$

where Γ and Δ are as below

$$\Gamma = \sigma_\beta \sigma_\delta^2 Q^3 (l - r_s)^3 (-B(l + r_m)\alpha + \sigma_\delta L(l + r_m)\alpha + \sigma_\beta Q(l\alpha - r_m\alpha + r_m^2\theta))(l - r_s + Q(r_m + r_s)\tau)(l\alpha - r_m(\alpha - 2Q\alpha\tau + r_m\theta(Q\tau - 1))), \tag{59}$$

$$\Delta = Q^3 \sigma_\beta \sigma_\delta^2 (l - r_s)^3 (-\alpha B(l + r_m) + \alpha L\sigma_\delta(l + r_m) + Q\sigma_\beta(\alpha l - \alpha r_m + r_m^2\theta))(l - r_s + Q\tau(r_m + r_s))(\alpha l - r_m(\alpha - 2\alpha Q\tau + r_m\theta(Q\tau - 1))). \tag{60}$$

Notably, the Lagrangian multiplier in Equation (58a) is non-negative based on the characteristics of the problem's parameters, indicating that the budget constraint is binding, yielding the optimal values for β and δ.

Case III. $C_m < Q \leq C_s$

For case III, since Q is larger than the capacity of the moving region, C_m, the vehicles traveling in this region are bound to the critical density and speed of the moving sensor governed region, and based on Equations (13) and (14) we can obtain critical speed as

$$V_m^{cr} = \frac{C_m}{k_m^{cr}} = \frac{\alpha r_m(1 + \beta) - \alpha l - r_m^2\theta}{\alpha\tau}. \tag{61}$$

Therefore, from Equations (17) and (61) we have

$$\frac{\partial t_b}{\partial \beta} = \frac{\gamma\alpha^2 r_m(\alpha r_m(1 + \beta) - r_m^2\theta)^3 Q^3 \tau^4 l}{9(\alpha l - \alpha r_m(1 + \beta) + r_m^2\theta)^5}, \tag{62a}$$

$$\frac{\partial V_m}{\partial \beta} = \frac{r_m}{\tau}. \tag{62b}$$

Replacing Equations (62a) and (62b) in Equation (55a) will yield a seventh-degree equation of β.

Since solving general polynomial equations of degree five and above in radicals is not possible, an analytical closed-form solution for this case cannot be obtained for β and δ.

C Nomenclature

α	mobile sensor's power
β	vehicular connectivity ratio
δ	stationary sensor coverage ratio
η_{ap}^{w}	the link-route incidence matrix
γ_a	the bottleneck delay parameter of a link a
λ_a	the sensing units' cost function's coefficient of a link a
μ_a	the optimal toll of a link a
$\overline{D_w}$	the potential demand between O-D pair w
σ_β	the cost of CAVs' connectivity
σ_δ	the cost of stationary sensors
τ	processing time
θ	the safety threshold of resolution
ζ_a	the physical cost function's coefficient of a link a
A	the set of all links
a	a link $a \in A$
A_m	augmented resolution
B	budget

C_m the capacity of the mobile sensor governed region

C_s the capacity of the stationary sensor governed region

C_w the generalized cost of traveling between O-D pair w

d_w the demand function for each O-D pair w

$E(\alpha, \beta)$ the cost of CAV on-board sensing and CAVs connectivity level

f_a the flow-capacity threshold of a link a

G_a the cost of the physical construction of a link a

k_m the vehicle density of the mobile sensor governed region

k_m^{cr} the critical density of the mobile sensor governed region

k_s the vehicle density of the stationary sensor governed region

k_s^{cr} the critical density of the stationary sensor governed region

l safety distance

L_a the length of a link a

n demand function parameter

N_a the safety cost of a link a

n_p^W the traffic flow on route p between O-D pair w

p a path or a route $p \in P_w$

P_w the set of all possible routes between each O-D pair $w \in W$

Q traffic flow

q_a the traffic flow of a link a

R_m mobile sensor's resolution

R_s stationary sensor's resolution

r_s mobile sensor's range

r_s stationary sensor's range

s spacing

t_a the travel time on link $a \in A$

t_b the bottleneck travel time delay

T_m mobile sensor governed region's sight

T_S stationary sensor governed region's sight

U_a the cost of adding sensing units to a link a

V_m speed in the mobile sensor governed region

V_s speed in the stationary sensor governed region

W the set of all O-D pairs

w an O-D pair $w \in W$

y_a the capacity of a link a

Z social welfare