# Final Report

# Socially Responsible Road Charging for Online Retailers to Support Disadvantaged Urban Communities

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# Disclaimer

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**16. Abstract**

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## Abstract

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# Introduction

## Problem Statement

The recent pandemic has led to a significant increase in profits for online retailers, often at the expense of many small businesses that have been forced to close their stores or are struggling to survive financially (*1, 2*). The World Economic Forum predicts a 36% increase in delivery vehicles from 2019 to 2030 (*3*).This trend not only undermines the economic wellbeing and vitality of small businesses in urban areas, but also has a devastating impact on disadvantaged urban communities, who may be more oriented to utilize local businesses. On the other hand, the drastic changes in transportation patterns, such as increased e-commerce deliveries, raise concerns about the socially responsible use of roadways. This issue has been recognized in the relevant literature (*4*–*6*).

While delivery services can reduce the number of individual shopping trips, they also lead to a decrease in gas tax revenue, which is essential for road repairs and infrastructure maintenance (*5*, *7*). Most current approaches to address this problem focus on supply-side strategies, including the deployment of electric vans, route optimization, and improved pick-up points (*5*). Although having fewer vehicles on the roads offers some wider societal benefits, it does not necessarily provide more funding for road maintenance, and supply-side strategies do not provide any solutions in terms of collected revenue. Despite the prevalence of pricing strategies in other transportation sectors, they have yet to be applied to e-commerce deliveries.

Many researchers have found that increased e-commerce deliveries contribute to pollution, congestion, and emissions (*6*, *8*). Given these externalities, one might wonder why pricing strategies are not imposed on the online retailers. Few studies have examined the application of taxes to e-commerce deliveries (*5*). However, no research has been conducted on how to implement similar charging policies through traffic control at signalized intersections. Thus, it is important to consider charging e-commerce retailers more for increased road usage, as their profit-driven model directly impacts government funding for infrastructure maintenance.

The current lack of targeted pricing mechanisms means that EDVs continue to utilize public roadways without adequately compensating for their impact on traffic congestion, pollution, and infrastructure wear and tear. Thus, implementing a socially responsible road charging system will help redistribute the financial burden of road maintenance, ensuring that e-commerce companies contribute their fair share.

This research endeavors to develop a socially responsible road charging system for e-commerce delivery vehicles (EDVs). The proposed system includes an annual base fee paid by EDVs and a pay-for-priority traffic control system, allowing priority for a nominal fee in specific cases. Implemented as traffic control priority at signalized intersections, the proposed system is tested across diverse traffic demands and EDV penetration rates. The primary objective is to introduce and assess a socially responsible road charging model for EDVs, aiming to maximize revenue collection while preserving existing traffic conditions.

The methodology of this project is divided in three main components. Firstly, we propose an innovative annual base fee for retailers, designed to ensure that e-commerce companies contribute equitably to public infrastructure maintenance. This charge is a novel approach that aligns the financial responsibilities of retailers with their use of urban roadways, thereby promoting fairness. Secondly, we introduce a fuzzy logic-based pay-for-priority system, which allows EDVs to request priority at signalized intersections for a nominal fee. This system not only enhances the efficiency of delivery operations but also provides a flexible mechanism for managing traffic flow in congested urban areas. Lastly, we implement these concepts in a real-world-like case study, emulated through a rigorously validated PTV Vissim model. Thus, this research marks one of the first attempts to simulate delivery vehicles with multiple random deliveries within such a sophisticated microsimulation framework, offering insights into the dynamics of e-commerce logistics and urban traffic management.

### Research Objectives

The primary goal of this project is to introduce and explore a socially responsible road charging model for Online Merchandise Delivery Vehicles (OMDVs). It also aims to improve the efficiency and reliability of delivery services while raising government tax revenue. This goal has been achieved by executing several research objectives, which are given below.

The primary objectives are:

1. Develop pricing system for basic road usage based on literature review and factors like the frequency of vehicle use on the road network, its contribution to congestion, size, mass, and other relevant factors.
2. Develop a three-stage fuzzy logic-based pricing-priority traffic control system.
3. Develop microsimulation environment and necessary supporting scripts to test the proposed system.
4. Evaluate the benefits of the proposed pricing-priority system in the microsimulation environment.

The aforementioned objectives, when combined, represent the major overarching purposes of this project.

## Literature Review

The research team identified relevant topics related to transit signal priority, freight priority, road pricing, congestion pricing, equity in transportation, and gas tax studies. The team also explored the applications of fuzzy logic in providing priority at signalized intersections. These topics are directly related to the broader context of road charging and urban transportation management, which are essential components of socially responsible road charging. Understanding how these aspects work and their implications is crucial for designing an effective road charging system that supports disadvantaged communities. Each of the mentioned topics is discussed in a subsection of its own.

## Traffic Signal Priority

### *TSP at Signalized Intersections*

In the scenario of implementing TSP (Traffic Signal Priority) on intersecting bus routes, the challenge lies in addressing conflicting priority requests at the signals where these routes cross paths. Various methods can be employed to resolve such conflicts, ranging from straightforward rules like "first come, first served" to more sophisticated optimization techniques aimed at prioritizing the "best" request.

Stevanovic et al. (2008) created a tool designed to enhance the optimization of transit priority settings for traffic control on roads accommodating both private and transit vehicles (*9*). Christofa and Skabardonis (2011) introduced a system designed to identify optimal signal settings that minimize the overall person delay in the network (*10*). This system prioritizes transit vehicles based on their passenger occupancy. Zlatkovic, Stevanovic, and Martin (2012) demonstrated through simulation that the first-come-first-served approach might not be optimal for resolving conflicting transit routes, proposing an algorithm that significantly reduced bus rapid transit delays (*11*). Shu, Zhao, and Han (2018) delved into the issue of transit signal priority at near-saturated intersections (*12*). Recently, Xu et al. (2019) presented optimization model to address conflicting transit signal priority requests at arterial corridors, employing a genetic algorithm to solve the proposed model (*13*). Cvijovic et al. developed CV-based algorithms which use transit vehicle speed and the estimated time that the vehicle needs to arrive at an intersection to trigger TSP initiation (*14*). Wang (2014) developed transit signal priority supported by a wireless sensor network, utilizing a fuzzy logic system to address conflicts between buses and vehicles at intersections (*15*). In addition, there are models grounded in fuzzy logic dedicated to signalized intersection control and the bus priority problem (*15–17*).

### *Case Studies*

Numerous case studies, encompassing both real-world implementations and simulation-based analyses, have scrutinized the travel time benefits associated with TSP. An early field trial conducted in Louisville, Kentucky, assessed unconditional TSP, reporting a substantial time savings ranging from 9% to 17% when compared to express buses operating without TSP (*18*). The study also noted positive effects on traffic in the corridor, attributing them to inadequate signal timing in the base case. A pioneering field trial in Miami, comparing various bus priority strategies, revealed a significant reduction in bus travel time by 19% to 26% with unconditional TSP (*19*).

However, it noted a slight decline in schedule reliability. Subsequent research supported the argument that conditional signal priority is crucial for improving reliability, as unconditional TSP, without schedule control, fails to enhance reliability due to the uniform treatment of all buses (*20*, *21*). A simulation study focusing on Columbia Pike in Virginia (*22*) indicated travel time savings of 2.3% to 2.5% for express buses, a 4.8% improvement for local buses, and an 18% increase in average travel time for all traffic when priority was granted to all buses. A master thesis on the US-1 corridor in Virginia (*23*) revealed that a TSP strategy employing only 10-second green extensions could reduce bus travel times by 4%, accompanied by a modest increase in the maximum queue length on side streets by 1.23%. Muthuswamy, McShane, and Daniel (2007) evaluated a transit signal priority algorithm through simulation on a signalized arterial (*24*). Consoli et al. (2015) evaluated conditional transit signal priority in central Florida (*25*). Liu (2016) explored the effectiveness of active priority strategies in a typical intersection in China using VISSIM simulations (*26*). Currie and Shalaby (2008) provided insights into experiences with transit signal priority for streetcars in Melbourne and Toronto (*27*). Marnell, Zebell, Koonce, and Quayle (2017) explored diverse approaches to the bus priority problem in Portland, Oregon (*28*). Zlatkovic et. al (2012) evaluated different transit signal priorities TSPs for a future bus rapid transit (BRT) corridor in West Valley City, Utah (*29*).

*Optimization of Bus Schedules and Headway Control Strategies*

Various research studies have explored the optimization of bus schedules in light of TSP, as discussed by (*20*, *21*, *30*). The fundamental concept is that TSP empowers buses to operate at increased speeds, necessitating a corresponding adjustment in schedules to capitalize on this advantage. If buses are required to delay their priority requests to remain on-schedule, the frequency of priority requests becomes contingent on the schedule itself. Anderson and Daganzo (2020) have demonstrated that relying solely on conditional TSP can effectively maintain bus schedules, provided an appropriate schedule speed is adopted (*21*). Moreover, they assert that schedules slower than unconditional TSP can be upheld through the combined use of TSP and schedule control.

Gordon (1978) addressed the issue of headway instability, also referred to as bus bunching, proposing the utilization of traffic signals to either expedite or defer buses as needed (*31*). Recent developments include headway control strategies involving holding buses at stops, explored in works such as (*32–35*), with field trials validating their effectiveness (*36*). The notion of employing traffic signals for headway control resurfaced in Ma et al. (2010), suggesting the use of signals for both accelerating buses (via green extension/early green) and impeding buses (using red extension/early red) (*37*). Chow and Li (2017) implemented a headway control strategy (*38*) based on the actions proposed by Daganzo (2009) (*34*). However, strategies employing signals to delay buses may encounter practical challenges due to the volume of requests from buses and the potential impact on traffic. To overcome this hurdle, Anderson and Daganzo (2020) put forth an extended headway control strategy (*21*).

Niittymaki and Maenpaa (2001) pioneered the utilization of fuzzy logic techniques in modeling public transit priority, showcasing promising results from their field tests (*39*). Chada and Newland (2002) elaborated on various concepts related to bus signal priority (*40*), while Dion and Hellinga (2002) introduced a real-time, traffic-responsive model named Signal Priority Procedure for Optimization in Real-Time (SPPORT) (*41*). Their findings indicated that the rule-based transit control, based on different traffic demand patterns, resulted in reduced delays for both private and public transit vehicles. Liu, Skabardonis, and Zhang (2003) implemented a transit vehicle priority system, determined by a weighting factor assigned to each transit priority call (*42*). The authors derived this factor from considerations such as traffic demand, queuing conditions, and the lateness of the transit vehicle. A heuristic algorithm developed by He et. al reduces average bus delay in congested conditions by about 50% (*43*).

### *Impact of TSP on Other Users*

Several studies have explored strategies to mitigate the impact of TSP on other road users. Bowen et al. (1994) suggested a nuanced approach by advocating for the adjustment of TSP parameters at the intersection level based on spare capacity (*44*). Sunkari et al. (1995) undertook a field study in College Station, Texas, to provide precise estimates of the delay experienced by other vehicles when TSP is activated (*45*). Al-Sahili and Taylor (1996) conducted a simulation study of a corridor in Ann Arbor, Michigan, revealing heightened delays to car traffic with TSP implementation, which the authors attributed to high volumes and interruptions in signal progression (*46*). The ratio of arterial to cross street volumes emerged as a crucial factor influencing these delays. Balke et al. (2000) conducted a simulation study incorporating hardware-in-the-loop (HIL), concluding that TSP can be effectively employed at Volume-to-Capacity (V/C) ratios up to 0.9 without causing significant delays to cross street traffic (*47*). Hu et al. (2015) introduced the concept of leveraging connected vehicle technology to monitor traffic conditions, advocating for TSP activation when it reduces signal delay per person (*48*). Chow et al. (2017) adopted a comprehensive approach, employing both priority actions (green extension/early green) and delay actions (red extension/early red) in an optimal control formulation (*49*). The goal was to minimize both schedule deviation and traffic delays, highlighting a holistic strategy to address the impact of TSP on road users.

### *Technology and TSP*

The evolution of TSP (Traffic Signal Priority) technology has been a subject of exploration, with recent studies shedding light on potential shifts in priority strategies. One notable analysis by Hounsell et al. (2008) delves into London's shift from an AVL system relying on roadside beacons to one leveraging GPS technology (*50*). Their predictions suggest a 2% to 5% reduction in bus delay savings due to the lower location accuracy of GPS. However, they also anticipate the emergence of novel priority strategies. Another significant contribution comes from Hu et al. (2014), who advocate for the implementation of TSP with connected vehicle technology (*48*). This technology facilitates two-way communication between buses and signals, opening avenues for innovative TSP strategies. Numerous studies have examined the impact of various parameter values on the benefits of TSP. Early work by Jacobson and Sheffi (1981) modeled the traffic effects of bus priority at a basic isolated intersection, recommending parameter adjustments such as cycle length and phase length to enhance TSP benefits (*51*). Rakha and Zhang (2004) delved into the sensitivity of TSP benefits to signal timing and bus location parameters (*52*). Their simulations within a coordinated corridor highlighted higher benefits to buses with increasing congestion and signal phases. Additionally, they observed a decrease in systemwide benefits with prolonged near-side dwell time. In a more recent study, Anderson and Daganzo (2020) demonstrated that tuning a lateness threshold parameter could effectively eliminate mean schedule deviation (*21*). This underscores the ongoing exploration and fine-tuning of TSP strategies for optimal transportation outcomes.

In conclusion, TSP presents a valuable tool for transit agencies aiming to reduce bus travel times, minimize variability, and enhance headway reliability. The challenges lie in resolving conflicting priority requests at intersections, which many studies address through methods ranging from simple rules to sophisticated optimization techniques. Case studies demonstrate substantial time savings with TSP, though the effectiveness varies based on the implemented strategy. Optimization of bus schedules and headway control strategies further explores the synergy between TSP and scheduling adjustments. The evolving landscape of TSP technology, from AVL systems to GPS and connected vehicle technology, indicates a continuous quest for optimal strategies. Despite the complexity and interplay of technologies, rules, and parameters, TSP remains a crucial asset in the pursuit of optimal transportation outcomes for transit agencies.

**Freight Signal Priority**

While TSP strategies primarily target transit vehicles to minimize travel time and delay, FSP strategies aim to mitigate hard stops and red-light running in the context of freight movements. This part of literature review addresses noteworthy studies conducted in recent years on FSP, shedding light on its potential and impact.

Saunier pioneered a prototype truck signal priority system utilizing video sensors for the efficient and safe movement of freight (*53*). This system, tested with real-world data from the Next Generation SIMulation project (NGSIM), achieved a high recall for truck detection (78% to 95%) and a low false alarm rate (below 0.5%). This underscores the effectiveness of automated video-based sensors in facilitating truck signal priority. Kari and team (*54*) introduced a Freight Signal Priority algorithm based on multi-agent systems (MAS). The algorithm aims to minimize network-wide energy and emissions. Demonstrating versatility, it can be tailored to various measures of effectiveness, such as emissions and travel delay, and extended to multiple arterial intersections. Results indicated that the Eco-Friendly Freight Signal Priority algorithm improved network conditions, providing fuel and travel time savings for both freight and nonfreight traffic.

Zhao and Ioannou proposed a novel truck priority system evaluated on signalized urban intersections, benefiting both freight movements and overall traffic flow (*55*). The researchers employed a co-simulation-based optimization control approach, utilizing real-time simulators for traffic state prediction. Implemented near the twin ports of Long Beach/Los Angeles, the results demonstrated significant improvements in truck and passenger vehicle movements, including reduced traffic delays, stops, fuel consumption, and vehicle emissions. In a study conducted by Park et al. (2019), the energy and environmental effects of FSP in a connected vehicle environment were assessed (*56*). The findings indicated a substantial decrease in fuel consumption and emissions for both connected trucks and general passenger cars with the implementation of FSP. In their work for Florida DOT, Kaisar et al. and Iqbal et al. evaluated freight and transit signal priority strategies in multi-modal corridor and developed guidelines for implementing TSP/FSP (*57*, *58*). Mahmud's master thesis analyzed the benefits of freight services at a high truck density intersection (*59*). Employing the VISSIM simulation tool, FSP was implemented by extending green light duration. The analysis revealed that prioritizing trucks through green time extension enhanced service reliability, reduced red-light running, improved safety, minimized overall travel and stopped delays and carbon emissions. Importantly, this was achieved with minimal impact on other vehicular traffic.

The National Center for Sustainable Transportation, through Giuliano et al.'s report (*60*), delved into managing the impacts of freight movements in California. The report outlined current and anticipated impacts, developed methodologies to identify congestion caused by freight mobility, and applied these to Los Angeles and San Francisco. The analysis also explored various mitigation strategies, emphasizing the importance of FSP application across the U.S. to reduce truck delays.

In summary, this part of literature review highlights the effectiveness of FSP strategies in optimizing freight movements. Studies, utilizing different approaches such as video sensors, multi-agent systems, and simulation tools, consistently demonstrate significant improvements in trucks and overall traffic flow. FSP not only reduces delays, stops, fuel consumption, and emissions but also enhances service reliability and safety at signalized intersections. The findings emphasize the potential and impact of FSP, advocating for its widespread application to reduce truck delays across the U.S.

## Congestion Pricing

Congestion pricing is a transportation policy that aims to manage traffic flow by charging vehicles for using certain roads or entering specific zones during periods of high congestion. The primary goal of congestion pricing is to reduce traffic congestion, enhance the efficiency of transportation systems, and encourage the use of alternative modes of transportation. Examples of congestion pricing programs include:

- London Congestion Charge: Implemented in 2003, it charges vehicles operating within a specified zone during peak hours.
- Stockholm Congestion Tax: An example of a cordon pricing system with multiple control points.
- Singapore's Electronic Road Pricing (ERP): Involves variable tolls based on location and time.

*Facility-based schemes*

Facility-based tolling schemes have been a longstanding practice, with tolls applied to roads, bridges, and tunnels. Although tolls targeting congestion are relatively recent, they are limited to specific facilities. These tolls can be implemented across all lanes or selectively on designated toll lanes, such as in the case of HOT lane facilities. The U.S. has introduced the concept of 'Managed lanes,' integrating tolls, vehicle eligibility restrictions, and access control to manage demand effectively.

*Cordons*

Moving on to toll cordons, this area-based charging method involves vehicles paying a toll to cross a cordon, whether inbound, outbound, or both. While existing schemes focus on single cordons, the Stockholm congestion charge is an exception with eighteen control points. Other notable examples include Singapore's Electronic Road Pricing (ERP), which combines facility-based tolls and cordons, varying tolls every half hour.

*Zonal schemes*

Zonal schemes, also known as area charges, require vehicles to pay a fee upon entering or exiting a defined zone. London's congestion charge, initiated in 2003, serves as an operational example, employing a flat charge within the charging zone on weekdays. The scheme has evolved over the years, adjusting toll amounts, and expanding the charging zone. Travel along the boundary of the charging zone is free. Several vehicle categories are exempt, and residents of the charge area receive a 90% discount.

*Distance-based schemes*

Distance-based schemes involve charges that vary with distance traveled, either linearly or nonlinearly. Some U.S. states and European countries have implemented distance-based charges for heavy goods vehicles, primarily to cover infrastructure costs. For instance, four US states have implemented distance or weight-based charges for heavy goods vehicles, and these charges are intended to mitigate infrastructure costs imposed by heavy vehicles rather than manage demand (*61*). National distance-based heavy goods vehicle tolls exist in Switzerland, Austria, Germany, the Czech Republic and the Slovak Republic, and other European countries are developing or considering them.

*Degree of time differentiation*

In terms of time differentiation, pricing schemes can be flat, time-of-day, or responsive. Flat tolls remain constant, while time-of-day tolls vary based on predetermined schedules. Responsive tolls adjust in real-time based on prevailing traffic conditions. Responsive tolls are “reactive” in the sense that they are set, with a short time lag, as a function of current congestion levels. Yin and Lou (2009) develop two approaches for setting tolls on toll lanes (*62*). One (a feedback-control approach) increases the toll if lane occupancy exceeds a target level. The other (a reactive self-learning approach) learns motorists’ willingness to pay a toll and iteratively adjusts the toll to maintain free-flow conditions on the tolled lanes while maximizing throughput. Lou et al. (2011) built on (*62*) by using a more realistic representation of traffic dynamics and an explicit formulation for toll optimization (*63*). HOT lane facilities often employ responsive tolls to maintain free-flow speeds. Anticipatory or predictive schemes take a step further, basing tolls on forecasted congestion, though implementation faces challenges in information, communications, and computational requirements. Dong et al. (2011) developed an algorithm to implement predictive pricing on a HOT lane facility and show that it can anticipate breakdowns in flow and maintain higher throughput than reactive pricing (*64*). Predictive pricing has long been envisaged as a tool for traffic management, but the information, communications, and computational requirements are challenging.

This part of literature review shows that anticipatory or predictive pricing schemes, while challenging with respect to information and computational requirements, hold promise for enhancing traffic management and throughput. The diversity and adaptability of these tolling strategies offer policymakers a range of tools to address congestion and manage transportation demand effectively. While congestion pricing is implemented in various cities worldwide and has shown success in reducing traffic congestion, improving air quality, and promoting sustainable transportation alternatives, its effectiveness depends on factors such as the specific design of the pricing system, public acceptance, and the availability of viable alternative transportation options.

## Equity in Transportation

Since the 1960s, scholars in the field of transportation have delved into the impact of transport disadvantages on social exclusion and individual well-being. Notable works by researchers like Kain (1968) and Wachs and Kumagai (1973) pioneered the exploration of three interconnected types of transport-related inequalities that significantly influence people's well-being (*63*, *65*). These include disparities in transport-related resources, observed daily travel behavior, and transport accessibility levels. Numerous studies concentrate on the uneven distribution of transport-related resources, such as car ownership and proximity to transport services and infrastructure, as highlighted by (*66–68*). Given the heterogeneous nature of people's needs, preferences, and abilities, a narrow focus on resources fails to fully capture individuals' capacity to utilize these resources for mobility and access to goods and services. Proximity to transit services, for instance, may be of little use if affordability is an issue, if the transport system is not disability-friendly, or if it fails to connect essential travel destinations. Even the use of bicycles for daily transportation requires not only a suitably built environment and cycling infrastructure but also a level of health and fitness that is not universal.

In contrast, other researchers center their attention on disparities in daily travel behavior, examining variations in trip frequency, distances traveled, and travel time. The conventional assumption in academic literature positions transport decisions as primarily matters of individual choice and personal responsibility (*69*). However, discerning the extent to which inequality in travel behavior arises from voluntary choice or contextual constraints beyond individual control is challenging. For instance, longer commutes may result not only from the availability of affordable housing in distant locations but also from preferences for suburban living. This emphasis on observed travel behavior often overlooks the unmet needs of less mobile groups and disregards the suppressed demand for trips constrained by social and economic factors. Consequently, an analysis solely based on travel behavior data fails to capture the actual range of places the transport system makes accessible to the population.

A more promising avenue is to concentrate on inequalities in accessibility levels. Accessibility, conceptualized and measured in several ways, can be viewed from different ethical perspectives. Justice considerations position accessibility as the ease with which individuals can reach places and opportunities from a given location, shaped by the interplay of individual characteristics, the transport system, and land use. The literature on inequalities in transport accessibility, including works by (*70–72*), views accessibility as a necessary but not sufficient condition for expanding people's freedom of choice and promoting equality of opportunities in employment, healthcare, education, and more. From the standpoint of social justice and the environment, policies that enhance people's actual mobility differ significantly from those that increase their capability to access desired destinations. This perspective, advocated by Banister and Hickman (1994), underscores the importance of distinguishing between the places people actually visit and the range of places they can potentially reach (*73*). Some studies applying political and social equality to walking and cycling policies (*74*) or proposing a non-market-based distribution of transport accessibility (*75*), offer moral perspectives. However, these remain the minority. Others explore the link between accessibility and general principles of equality and basic needs, introducing various ethical principles to guide transport policies, yet without committing to a specific justice theory.

In summary, this part of literature review underscores the long-standing exploration of transport-related inequalities, focusing on disparities in resources, observed travel behavior, and accessibility levels. While studies on resource distribution and daily travel behavior provide valuable insights, the emphasis on accessibility emerges as a promising variable. Accessibility, viewed through the lens of justice considerations, is recognized as a crucial factor for expanding freedom of choice and promoting equality of opportunity. Ethical perspectives in conceptualizing and measuring accessibility become imperative given the diverse viewpoints presented by various justice theories. The literature calls for informed policies that address inequalities in accessibility to create a more equitable and inclusive transportation system.

### Gasoline Tax

Emissions from vehicles pollute air that harms human health, diminishes visibility and contributes to global warming (*76*). Gasoline taxes play a vital role in generating transportation revenue, operating at both the state and federal tiers. Despite this, there has been a notable lack of tax rate increases by both the federal government and several states over the past years, resulting in a decrease in the real value of tax revenues collected due to inflation (*77*). Gas taxes are intended to fund the construction and maintenance of roads, bridges, and other transportation infrastructure. The revenue generated is critical for financing transportation projects.

With advancements in fuel efficiency and the increasing popularity of electric and hybrid vehicles, future gas tax revenue faces challenges. These vehicles consume less traditional fuel, impacting the funds generated through gas taxes (*78*). Studies have found that an emissions tax is efficient, but measuring each car's emissions is inaccurate and expensive. Fullerton and West (2002) found similar efficiency for different models, including emissions tax, gasoline tax based on fuel type, engine size, and pollution control equipment (PCE), mileage-dependent vehicle tax, or a combination of uniform gas and engine size tax with a PCE subsidy—all with identical consumers (*76*). For varied consumers, efficiency is possible with a vehicle-specific gas tax or mileage-specific vehicle tax, but not with flat rates.

The foundational concept of using taxation to address externalities traces its origins to Pigou (1932) (*79*). Pigou demonstrated that in a free market, the optimal allocation of resources in an economy could be achieved by implementing a tax on the good causing externalities, equivalent to the marginal external damages at the optimal quantity (*79*). A direct tax on gasoline serves as a Pigouvian remedy since the externality correlates directly with the gallons of gasoline consumed, irrespective of the consumer or their consumption method. However, in the context of local air pollution, vehicles emit varying levels of emissions based on engine technology and driving conditions. Consequently, the Pigouvian approach for local air externalities involves taxing emissions, but this proves impractical given the limitations of current technologies. Although a gasoline tax falls short of complete efficiency, Fullerton and West (2000) approximated that it delivers approximately two-thirds of the advantages of the optimal emissions tax (*80*). This constitutes a substantial portion of the benefits attainable under the most feasible policy.

Sallee (2011) claims that despite the efficiency justifications for fuel taxation, gasoline taxes remain low in the United States (*81*). This is commonly attributed to political limitations, as increasing the gasoline tax is deemed politically unpopular and, therefore, not a viable option. As an alternative, the United States employs other strategies to curb gasoline consumption, such as fuel economy regulations and taxation. To replicate the efficiency of a gasoline tax, fuel economy policies would have to establish a consistent price for gasoline consumption applicable to all vehicles, manufacturers, consumers, and timeframes (*81*).

While gas taxes are prevalent across the United States (US), mileage taxes are not widely implemented. Most states primarily depend on gas taxes to generate revenue for transportation infrastructure. Nevertheless, ongoing discussions explore mileage-based fees as an alternative, with some states conducting pilot programs or studies to assess the feasibility of such systems. Gas tax rates vary significantly among states, with some, like California, imposing higher taxes to fund extensive transportation projects, while others, like Arizona, have lower rates. Pennsylvania holds the highest gasoline tax rate at $0.576 per gallon, followed closely by California at $0.511 per gallon. The federal gas tax has remained at 18.4 cents per gallon since 1993, causing it to lose nearly half its real value due to a lack of indexing for inflation (*82*). State taxes, on the other hand, may consist of both fixed and variable components, with variable elements tied to a percentage of fuel prices or linked to inflation.

This part of literature review highlights the significant role of gasoline taxes in generating transportation revenue, essential for funding infrastructure projects. The challenges posed by vehicle emissions and the evolving landscape of fuel-efficient and electric vehicles underscore the need for effective taxation policies. While studies suggest the efficiency of an emissions tax, practical limitations necessitate alternative approaches. The Pigouvian remedy through a direct gasoline tax, despite its shortcomings, emerges as a feasible strategy, providing substantial benefits. Political considerations, however, hinder the increase of gasoline taxes in the United States, leading to the exploration of alternative strategies such as fuel economy regulations. The ongoing discussions on mileage-based fees indicate a potential shift in taxation methods. Notably, the variation in gas tax rates among states and the federal stagnation since 1993 highlight the complexities of tax structures. As we navigate the challenges of revenue generation, consideration of both the economic and environmental impacts remain crucial for devising effective and equitable transportation taxation policies.

Many researchers have developed priority systems; however, none have created a system that utilizes the collected revenue in a socially responsible way. Thus, in this research, we develop a fuzzy logic system that determines, in a socially responsible manner, whether an EDV should have priority at the intersection.

# Methodology

The methodology of this research is structured through five distinct tasks. First, we define the problem and introduce the "base price" concept for the pay-for-priority system. Second, we outline the mechanism enabling EDVs to request priority service via V2I communications with the infrastructure. Third, we provide a detailed description of the pay-for-priority system. Fourth, we explain the microsimulation testbed case study. Finally, we present the experimental setup, including key assumptions made.

**Formulation of the problem**

We formulate a socially responsible pay for priority system for EDVs, by utilizing a common fully actuated traffic signal control. We also assume the availability of suitable technology (e.g., knowledge of the importance/value of transported goods and precise EDV locations). The preference for prioritizing EDVs over private cars is influenced by the trade-off between minimizing disruption to regular traffic and maximizing the efficiency of high-value deliveries. As the number of conflicting private cars decreases, the impact of granting priority to EDVs is reduced, making it a more favorable decision. Similarly, higher-value goods justify a greater need for expedited delivery, thus increasing the preference for giving EDVs the right of way. Conversely, if the value of the goods transported by the EDVs is relatively low (or if the EDV operator pays a smaller base price), priority given to EDVs would be reduced.

Let us introduce few key variables:

- *BP* – base road usage price (in dollars),
- *D* – relative delay of conflicting phases' demand (%),
- *SD* – relative behind-the-schedule delay (%)
- *I* – importance/value of transported goods

Let us explain each of the previously introduced variables. The base price for road usage is a concept proposed in this research to address road pricing for EDVs due to their increased road usage. To determine base price for EDV's road usage we utilize factors such as vehicle miles traveled per year (*VMT*), average fuel economy of the EDV ($\bar{F}$), size (*S*), and mass (*m*) of the EDV. Based on ranges of values for given inputs, the authors calculated that the base price would range from $1/year to $4/year for an EDV depending on the mentioned factors.

$$BP = f\ (VMT, \bar{F}, S, m) \tag{1}$$

Four different categories of EDVs are defined within microsimulation software PTV Vissim, as described below, and base price is different for each of them:

- Small or medium vans carry payloads between 500-1,000kg, with an average fuel economy of 40mpg.
- Large vans carry payloads up to 1,250kg, with an average fuel economy of 30mpg.
- Extra-large vans carry payloads up to 10,000kg, with an average fuel economy of 20mpg.

- Box trucks carry payloads up to 27,000kg, with an average fuel economy of 10mpg.

Another important variable for the system is relative delay of the vehicles to be served during the next traffic signal phase (*D*). For intersection *i*, relative delay of the next signal phase is calculated as total delay of the next phase(s') *j* demand divided with total intersection delay *i* ($d_{t_i}$):

$$D = \frac{\sum_{j=1}^{cp} d_j}{d_{t_i}} \tag{2}$$

Relative Behind-Schedule Delay (*SD*) is a variable that describes whether an EDV is late for delivery or not. To calculate *SD,* we use a following formula:

$$SD = \frac{CD - FFD}{FFD} 100\% \tag{3}$$

where *CD* is the current time of delivery, and *FFD* is a delivery time that an EDV would travel at free flow speed.

The importance of transported goods (*I*) is communicated at the time of placing the priority request. It is assumed that the driver or company would have this importance ready and available at any time, based on the value of the goods.

We employ three-stage Type-2 fuzzy logic because it extends the concept of traditional (Type 1) fuzzy logic by allowing for uncertainty in both membership grades and membership functions. This additional flexibility enables more detailed and accurate modeling of complex systems where uncertainty plays a significant role.

**Three-stage fuzzy logic type 2-based signal priority system formulation**

As mentioned previously, it has been established that Type 2 fuzzy logic systems outperform Type 1 systems because they introduce uncertainty into the system. In the case of type-2 fuzzy sets, we operate with an upper membership function $\mu_u(x)$ and a lower membership function $\mu_l(x)$ (**Figure 1**). The lower membership function $\mu_l(x)$ is less than or equal to the upper membership function $\mu_u(x)$ for all possible input values. The area between the upper and the lower membership function is called the footprint of uncertainty (FOU).

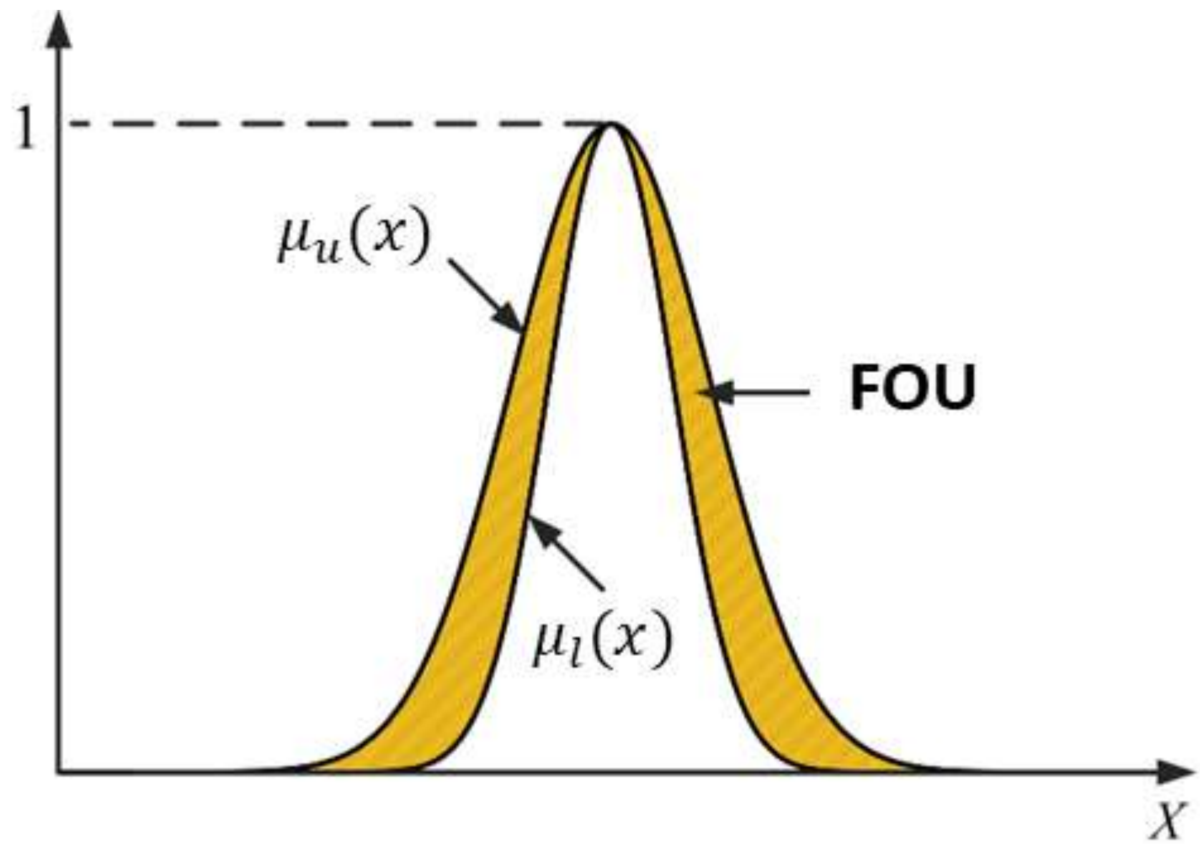


**Figure 1** Gaussian type-2 membership function.

For each input and output variable, we design the upper or primary membership functions $\mu_u(x)$ as it would be done in traditional (Type 1) fuzzy logic. These functions represent the degree of membership of an element in the fuzzy set corresponding to each linguistic term (**Table 1**). Then, for Type 2 fuzzy logic, for each primary membership function we define its secondary membership function. The secondary membership function represents the degree of membership of the primary membership function itself. The purpose of secondary membership functions is to introduce FOU into the system.

The detailed framework of the proposed concept is presented in **Figure 2**. This system comprises several components and processes. Each vehicle in the system pays an annual base price fee, which serves as one of the inputs for the pay-for-priority system. Additionally, while some EDVs request priority, others do not. This reflects the real-world scenario where not every company would choose to request priority, even if given the opportunity. The proposed pay-for-priority system incorporates a three-stage fuzzy logic system, with the main output being the urgency index, which is described later. If priority is granted to an EDV, the logic for implementing this priority is then executed.

The primary goal of our pay-for-priority system is to maximize revenue collected from EDVs, while keeping the delays of other passenger cars the same or similar to that in the "Do nothing" scenario. The system developed for this project comprises three stages, where the crisp outputs from the first and second stages feed into the third stage, which yields an urgency index

(UI) value. If the UI value is higher than a certain threshold (e.g. 0.5), the priority is provided to the requesting EDV.

$$UI > UI^* \tag{4}$$

where:

$UI$ – urgency index calculated by fuzzy logic in range (0,1)

$UI^*$ – the threshold determined by the researcher.

It is worth mentioning that the urgency index threshold ($UI^*$) should be predetermined, as this parameter significantly influences the outcomes of the pay-for-priority system and the collected revenue. For this project, the authors set this parameter at 0.5. Additionally, when $UI^* = 0$, EDVs always receive priority ("Unconditional Priority"). Conversely, when $UI^* = 1$, EDVs do not receive priority, and the system operates as a "No Priority System."

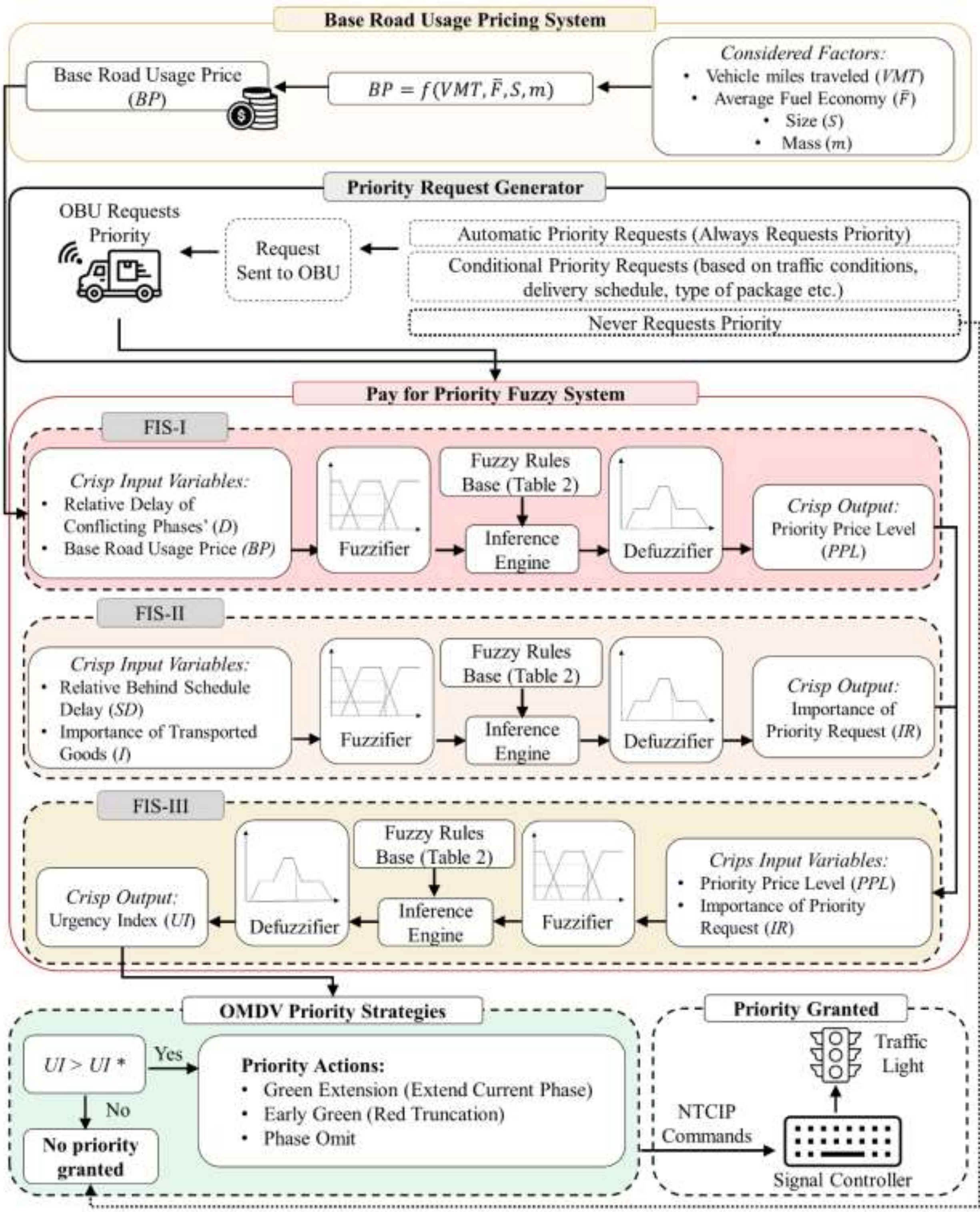


**Figure 2** Priority system framework.

In **Table 1**, we define all linguistic expressions for fuzzy sets whereas the membership functions of the fuzzy sets are presented in **Figure 3.**

**Table 1** Linguistic expressions for fuzzy sets, and membership functions

| Stage | Linguistic expression | Fuzzy set |
|---|---|---|
| 1 | Low Relative Delay of Conflicting Phases | LD |
| | Medium Relative Delay of Conflicting Phases | MD |
| | High Relative Delay of Conflicting Phases | HD |
| | Low Base Price | LBP |
| | Medium Base Price | MBP |
| | High Base Price | HBP |
| | Low Price Priority Level | LPPL |
| | Medium Price Priority Level | MPPL |
| | High Price Priority Level | HPPL |
| 2 | Low Relative Behind-Schedule Delay | LSD |
| | Medium Relative Behind-Schedule Delay | MSD |
| | High Relative Behind-Schedule Delay | HSD |
| | Low Importance of Transported Goods | LI |
| | Medium Importance of Transported Goods | MI |
| | High Importance of Transported Goods | HI |
| | Low Importance of Priority Request | LIR |
| | Medium Importance of Priority Request | MIR |
| | High Importance of Priority Request | HIP |
| 3 | Low Price Priority Level | LPPL |
| | Medium Price Priority Level | MPPL |
| | High Price Priority Level | HPPL |
| | Low Importance of Priority Request | LIR |
| | Medium Importance of Priority Request | MIR |
| | High Importance of Priority Request | HIP |
| | Low Urgency Index | LUI |
| | Medium Urgency Index | MUI |
| | High Urgency Index | HUI |

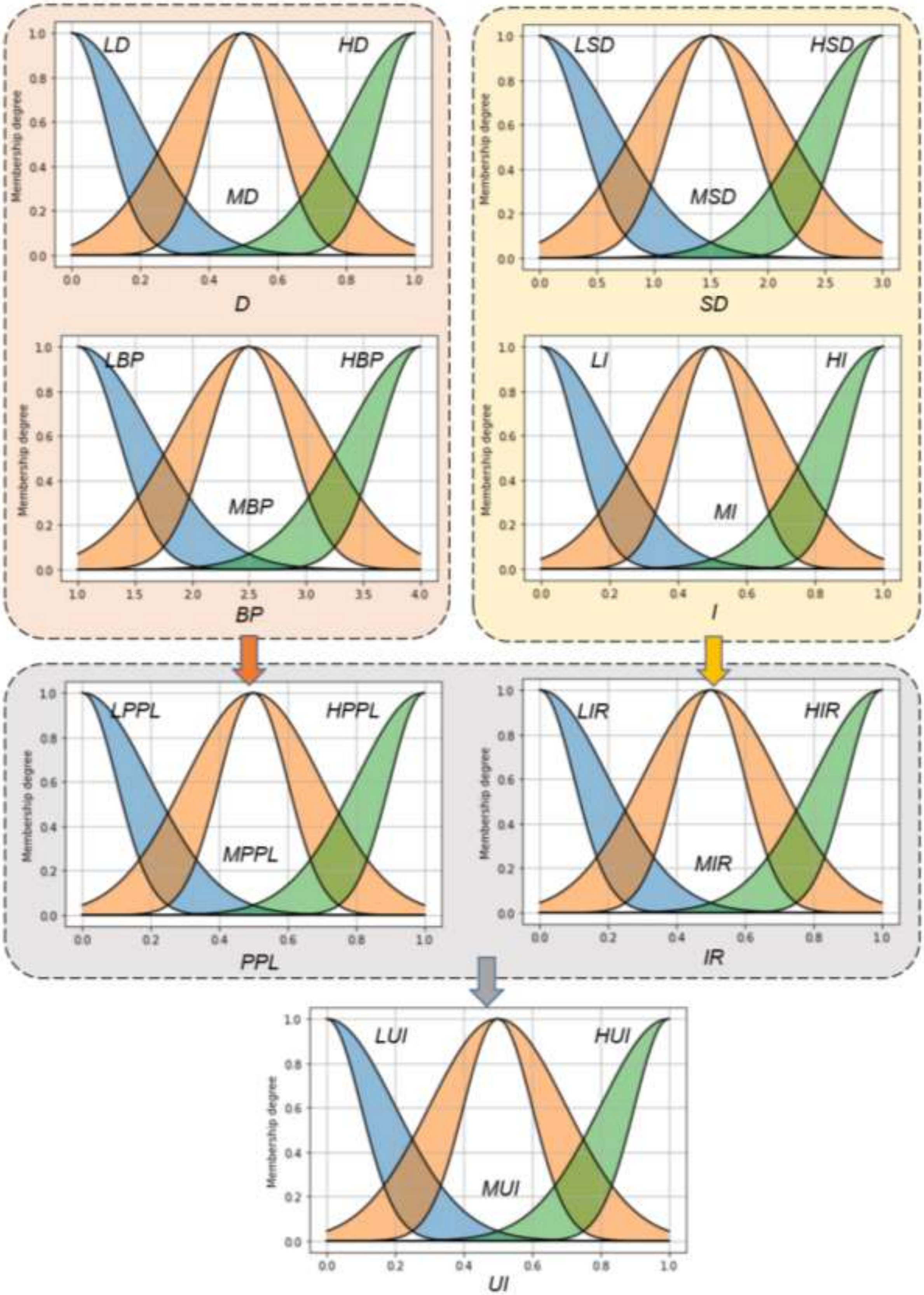


**Figure 3** Membership functions of the fuzzy sets

The pay-for-priority system can be formulated through a set of descriptive rules. These rules represent our knowledge in a descriptive manner and are presented to the computer in ambiguous and vague terms. Zadeh (1965, 1973) introduced a groundbreaking approach to describe human knowledge through the fuzzy rules (*83*, *84*). Fuzzy logic serves as the framework through which we can navigate the fuzziness. Zadeh (1973) coined the term "fuzzy" logic to describe the incorporation of imprecise rules within a specific control strategy (*84*). These fuzzy rules employ descriptive terms like "small," "medium," or "large" to delineate linguistic input and output variables. Assembled into a coherent set, these rules form the backbone of a fuzzy control algorithm, which is the core of our control strategy.

**Table 2** Fuzzy rules base.

| Stage | Rule Number | **IF** Relative Delay (*D*) is | **AND** *BP* is | **THEN** Priority Price Level (*PPL*) is | Weight Factor |
|---|---|---|---|---|---|
| 1 | 1 | LD | HBP | HPPL | 1 |
| | 2 | MD | HBP | MPPL | 1 |
| | 3 | HD | HBP | LPPL | 1 |
| | 4 | LD | MBP | HPPL | 1 |
| | 5 | MD | MBP | MPPL | 1 |
| | 6 | HD | MPB | LPPL | 1 |
| | 7 | LD | LBP | HPPL | 1 |
| | 8 | MD | LBP | MPPL | 1 |
| | 9 | HD | LBP | LPPL | 1 |
| **Stage** | **Rule Number** | **IF** Relative Behind Schedule Delay (*SD*) is | **AND** Importance of Transported Goods (*I*) is | **THEN** Importance of Priority Request (*IR*) is | **Weight Factor** |
| 2 | 1 | LSD | LI | LIR | 1 |
| | 2 | MSD | LI | MIR | 1 |
| | 3 | HSD | LI | HIR | 1 |
| | 4 | LSD | MI | MIR | 1 |
| | 5 | MSD | MI | MIR | 1 |
| | 6 | HSD | MI | HIR | 1 |
| | 7 | LSD | HI | HIR | 1 |
| | 8 | MSD | HI | HIR | 1 |
| | 9 | HSD | HI | HIR | 1 |
| **Stage** | **Rule Number** | **IF** Price Priority Level (*PPL*) is | **AND** Importance of Priority Request (*IR*) is | **THEN** Urgency Index (*UI*) is | **Weight Factor** |
| 3 | 1 | LPPL | LIR | LUI | 1 |
| | 2 | MPPL | LIR | LUI | 1 |
| | 3 | HPPL | LIR | MUI | 1 |
| | 4 | LPPL | MIR | MUI | 1 |
| | 5 | MPPL | MIR | MUI | 1 |
| | 6 | HPPL | MIR | HUI | 1 |
| | 7 | LPPL | HIR | MUI | 1 |
| | 8 | MPPL | HIR | MUI | 1 |
| | 9 | HPPL | HIR | HUI | 1 |

In **Figure 4**, a detailed algorithm of the proposed pay for priority system is presented. After determining whether an EDV should be granted priority, we employ one of the well-known priority strategies to allow EDVs to move through the intersection more swiftly (**Figure 4**):

- Green extension (extends the current phase)
- Early green (red truncation)

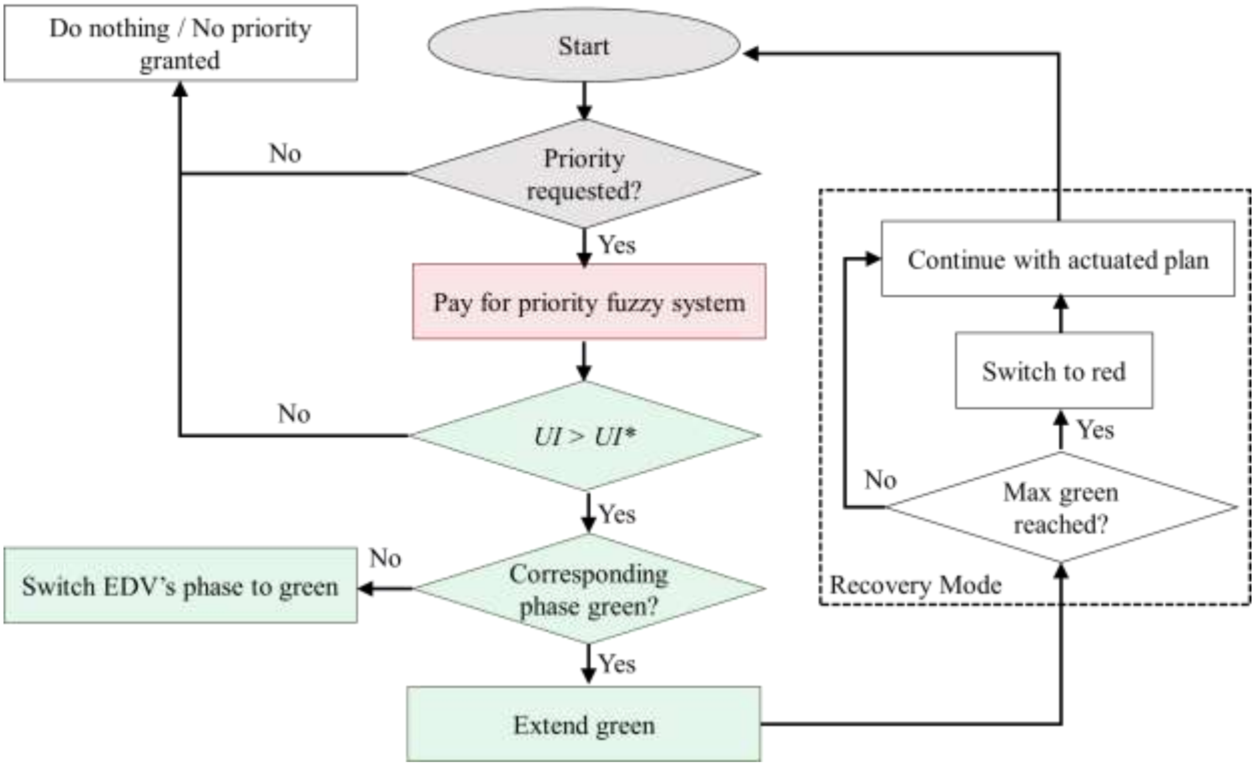


**Figure 4 Algorithm of the pay for priority system – signal operations.**

### V2I communication mechanism for pay for priority system

V2I communication allows vehicles to receive real-time traffic information from infrastructure such as traffic lights, road signs, and traffic management centers. Thus, for the proposed system this type of communication is required (**Figure 5**). By equipping wireless vehicles and traffic signals with communication devices and GPS, an exchange of information between the communication devices within an assumed range of up to 300 meters is possible. Within the communication range, they can send information to the traffic signal via the IEEE 802.11p standard. It is assumed that each record consists of the vehicle's identification number (ID), position, turning movement at the signal, and speed data, as well as a timestamp indicating when the information was created.


**Figure 5** Vehicle-to-infrastructure communication mechanism

## Implementation in microsimulation

*Modeling delivery vehicles using COM interface*

Python COM interface and the relevant libraries (e.g., PyIT2FLS) were utilized to implement the developed system in the microsimulation environment. Before implementing the developed priority system, it was necessary to simulate places where delivery vehicles park (to deliver goods) in a microsimulation environment. In our research, we lacked real-world data to determine headways between delivery vehicles and could not use public transport lines to simulate freight and delivery vehicles, as in some previous works (*85*). Instead, we opted to use on-street/curbside parking spaces, which are available in our case study and very common in the USA, in general. However, such an effort had not been done before. Therefore, the authors developed two main functions within a Python COM script.

The first function selects delivery stops for each EDV and assigns the next stop of that EDV. Additionally, this function calculates the travel time of EDVs to determine behind-schedule delay. The second function is a routing decision function, which adjusts the relative flow of parking routes for a specific vehicle category (EDVs). In other words, the second function assigns a binary variable of 1 to an EDV that crosses a parking route decision point if its next stop is the parking lot associated with that routing decision point.

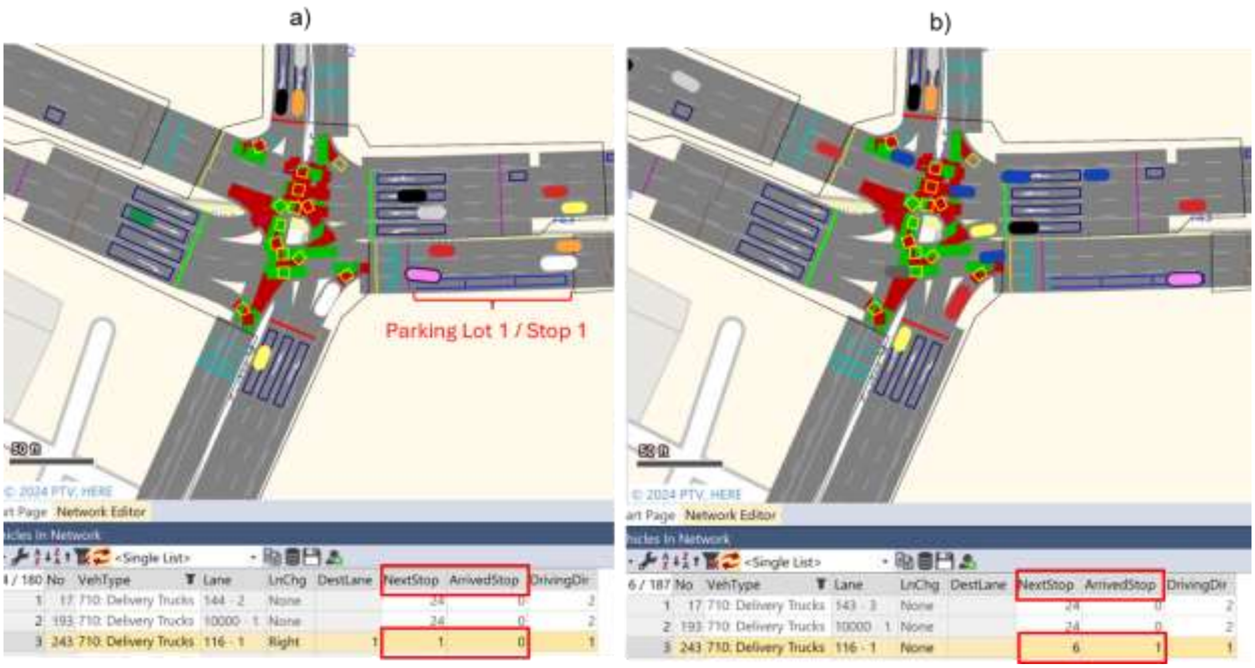


**Figure 6** EDV delivery modeling using parking routes and spaces; (a) The relative flow for a parking route is adjusted, and the EDV stops at the assigned stop; (b) The next stop is updated.

*Test-bed corridor*

To test the developed system, the authors used a simulated 11-intersection corridor along Martin Luther King (MLK) Blvd in Chattanooga, Tennessee (**Figure 7**). This network was chosen for three reasons. Firstly, the size of the studied network is small enough to ensure traceability of various inputs. Secondly, the network is large enough to provide relevant results for investigating the pay-for-priority system. Lastly, the studied network is equipped with all necessary infrastructure for the system's implementation and can thus serve as a future field test bed.

Moreover, this network has been utilized in many previous studies and is a proven test bed for new control systems (*86*, *87*).

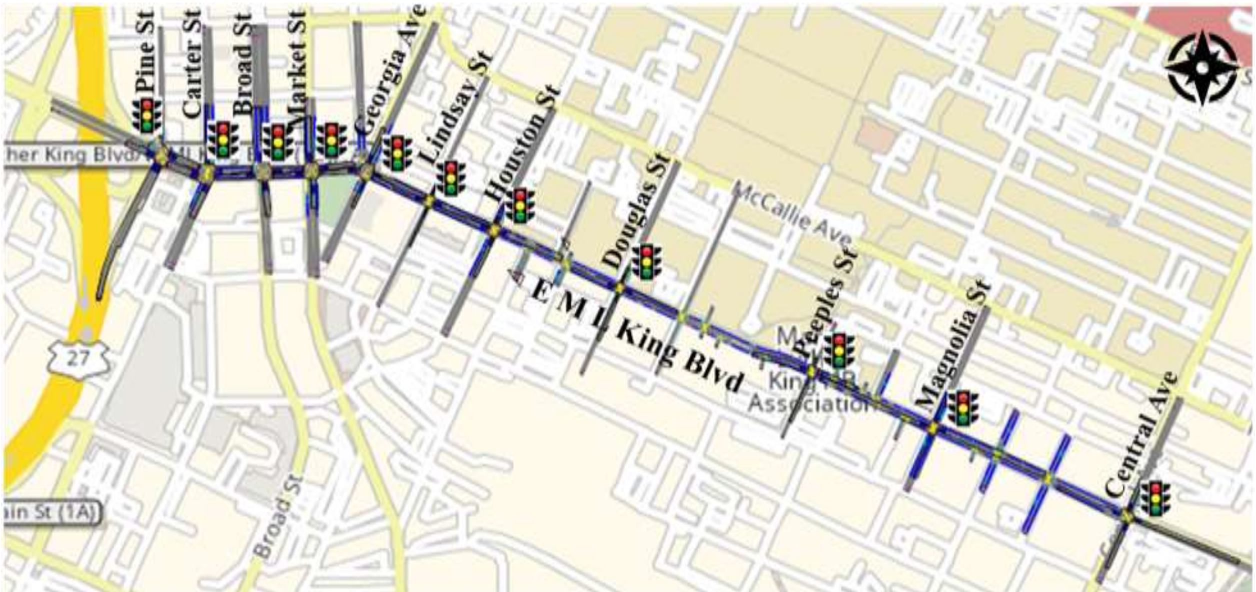

**Figure 7** Test-bed corridor (Chattanooga, TN)

**Experimental Setup**

Three signal control scenarios with three different demand levels of EDVs (5%, 10%, and 15%) and three different traffic demands (low, medium, high) are tested, as shown in **Figure 8**. It is worth mentioning that EDV demand was added to the field counts, taking a more conservative approach and assuming that e-commerce deliveries increase overall trips.

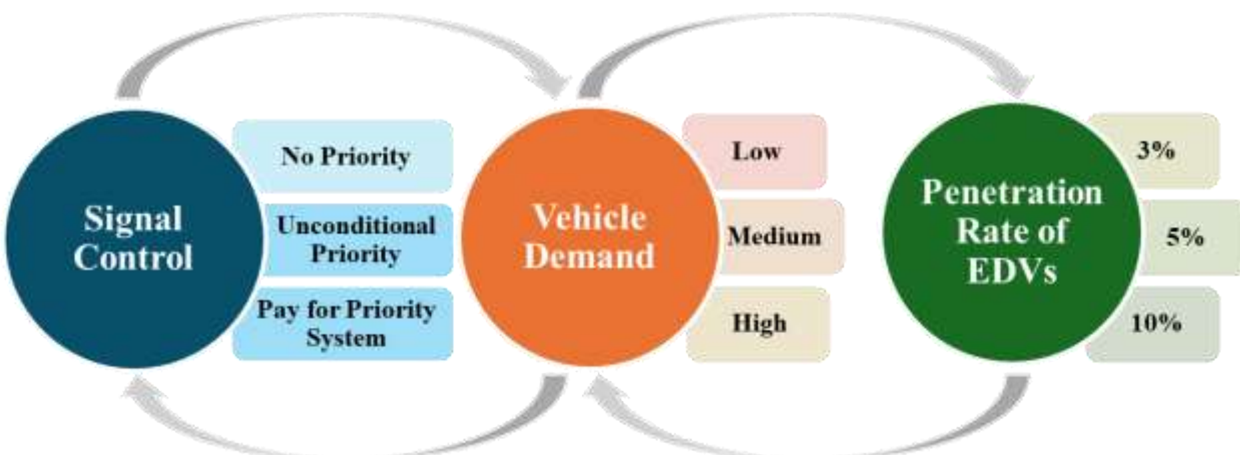

**Figure 8** Experimental setup

The following assumptions are made:

1. Dwell time is defined as the time that delivery staff spend performing out-of-vehicle activities while their vehicle is parked. The lengths of dwell time were assumed based on previous studies that used 2-5 minutes uniform distribution (*85*).
2. Each EDV executed 3 randomly selected deliveries in the analyzed network. Considering the size of the network, it is quite realistic to limit the number of deliveries to 3 per vehicle.
3. Only existing parking spaces were utilized for deliveries. Because the distances in the study were deemed to be walkable, no additional parking was introduced, thus removing the need for additional parking lots. Furthermore, this research did not model delivery vehicles stopping in traffic lanes (to make deliveries), thus avoiding unnecessary traffic bottlenecks (**Figure 6**).
4. Deliveries are made only in the main corridor, as the network has the shape of a linear corridor.
5. The urgency index was determined as soon as a vehicle enters the link leading towards the signalized intersection.
6. The authors assumed an equal number of trucks from each category described previously in the formulation of the problem.

To account for the stochastic nature of vehicle arrivals in the simulation model, multiple VISSIM simulation runs were executed for all scenarios using various random seeds. Each simulation lasted for one hour and fifteen minutes, consisting of a 15-minute warm-up period followed by one hour of evaluation.

# Results

The results section is divided into two distinct parts. First, we present operational results, including average delays and travel time of EDVs and other cars. Next, we delve into a cost-benefit analysis of the proposed pay-for-priority system and explore viability of such an investment.

### Operational Results

**Figure 9** illustrates the average delay of EDVs for each scenario. The results clearly demonstrate that the average delay of EDVs decreases when a pay-for-priority system is implemented. Moreover, the lowest average delay is observed in the unconditional priority scenario. Furthermore, the results indicate that the UI threshold selected by the authors was a good choice, as the average delay of EDVs in the pay-for-priority scenario falls between the no priority and unconditional priority scenarios, which was an expected outcome.

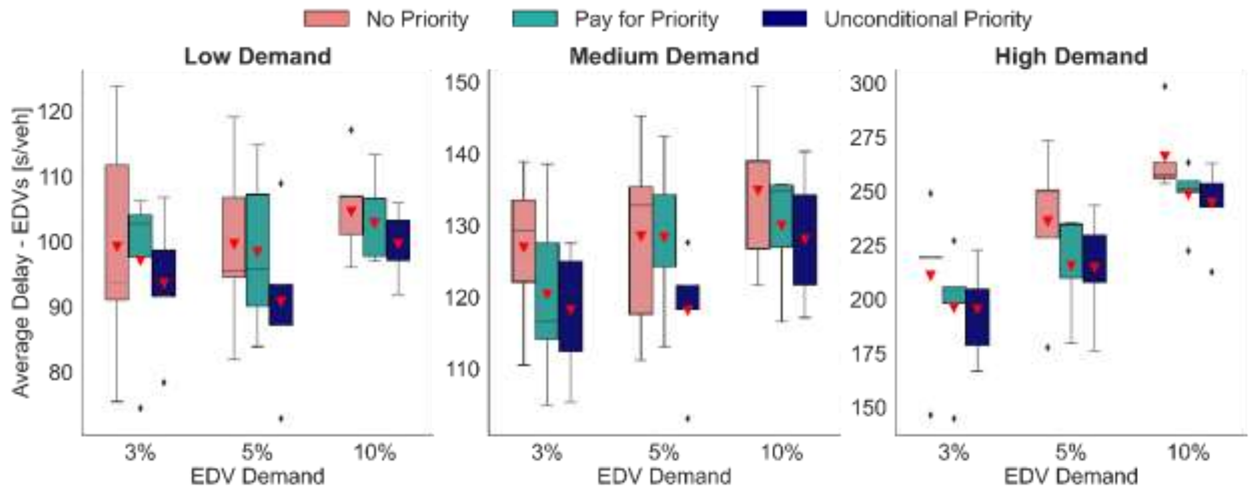


**Figure 9** Statistical Analysis of Average Delay for EDVs

**Figure 10** illustrates the average travel time of EDVs. Like the average delay, EDV travel times decrease under the pay-for-priority system. Interestingly, despite the fact that the EDVs are added on top of the existing traffic demand, the proposed system still offers benefits to EDVs that opt to pay extra for priority service (even in the high demand scenarios).

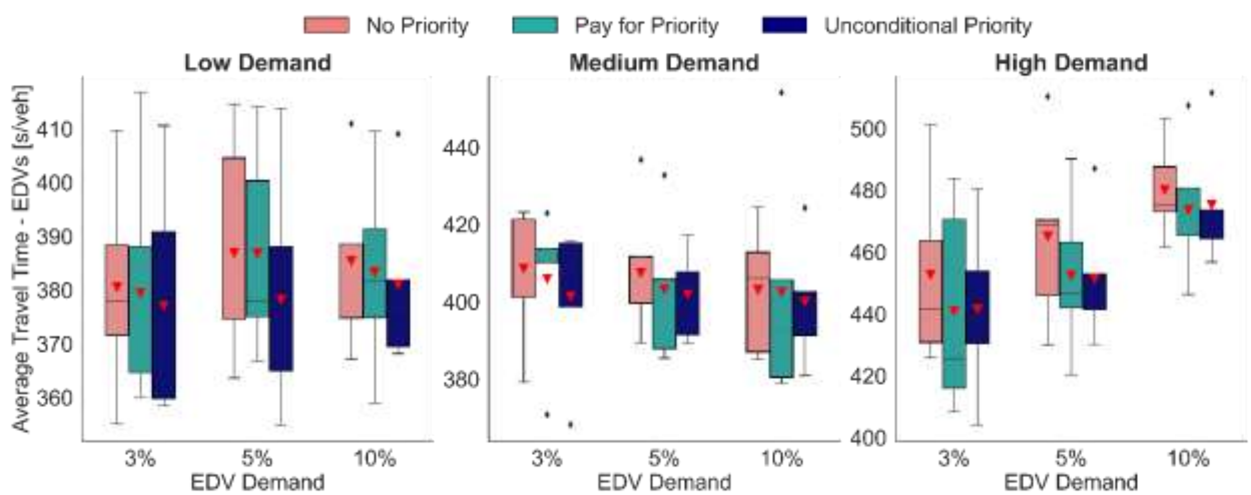


**Figure 10** Statistical Analysis of Average Travel Time EDVs

The objectives of the proposed system are to reduce the delays of EDVs, generate extra revenue, and keep similar delays for passenger cars. **Figure 11** was developed to illustrate these results. It is evident that the delay for passenger cars is only slightly higher in high demand scenarios and unconditional priority scenarios. In contrast, for the pay-for-priority system, these differences are negligible compared to the no priority scenarios.

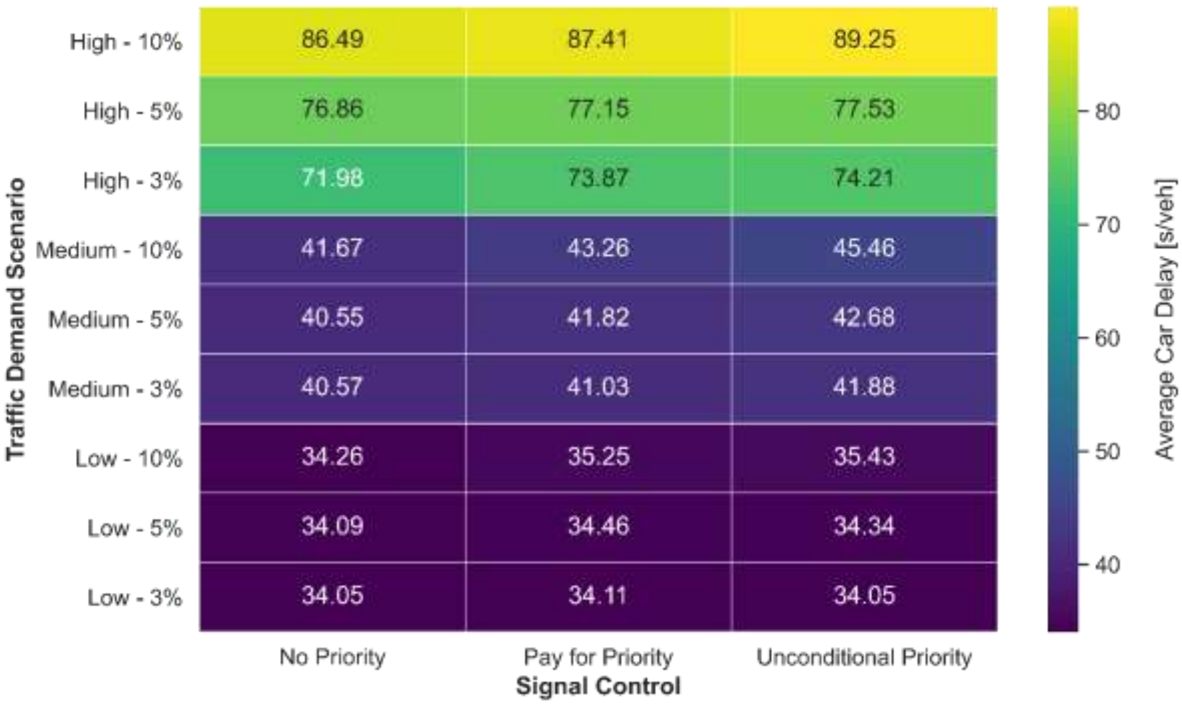


**Figure 11** Impact of signal control strategy on average passenger car delay

Another interesting finding is presented in **Figure 12**, which shows the average number of approved requests per EDV in the network. As **Figure 12** illustrates, the average number of approved requests decreases as the number of EDVs and level of traffic demand increase. This outcome shows that the priority system does not grant priority to EDVs when there is a high relative delay expected for the next signal phase.

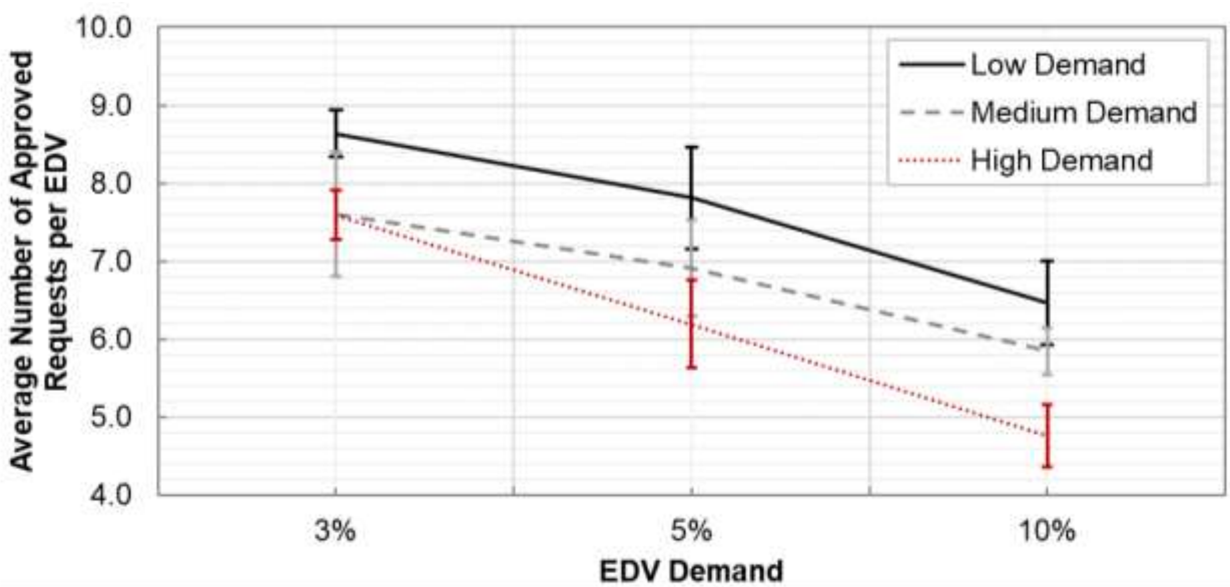


**Figure 12** Impact of traffic demand on number of approved priority requests

## Cost/Benefit Analysis

In this subsection, we present the cost-benefit analysis for the pay-for-priority system. For a project to be considered a viable investment, the benefit-cost ratio should be greater than 1.00. A conservative assumption was made that the 1-hour afternoon peak simulated in this research generates one-third of the daily weekday traffic (whereas in reality this proportion would be much lower, e.g., around 10%). Thus, the peak hour revenue was multiplied by 3 and then by 260 (the number of weekdays in a year) to get the results shown in **Table 3**. The price of the priority request was set at $0.01422/request, similar to what was used in (*88*) for high priority requests of connected vehicles.

According to other works (*89*), the capital costs to implement TSP range from $5,000 per intersection (if existing software and controller equipment are used) to $20,000 to $30,000 per intersection (if software and control equipment are replaced). The authors assumed that the lowest value of TSP per intersection would be $12,000 and the highest $30,000. These values were then converted to annual costs assuming a 5% interest rate and a 5- and 10-year payback period. The annual system cost per intersection is estimated to range from $2,772 to $6,929 and $1,554 to $3,885 for the 5- and 10-year payback periods, respectively, and assumed capital costs. For analysis, these costs are multiplied by 11, the number of signalized intersections in the study network.

Based on current market factors, the estimated cost for in-vehicle equipment, such as on-board units (OBUs) that enable vehicle-to-vehicle (V2V) communications and support security management functions, would be approximately $350 per vehicle in 2020. However, this price is not included in the system cost as it is assumed that retail companies would need to supply their vehicles with the necessary technology.

The results of the cost-benefit analysis are presented in **Table 3**. It is evident that the base price generates the highest portion of the revenue. Furthermore, the system would be more justifiable for higher traffic demand scenarios, which is logical, as there is little need for such a system if e-commerce can travel smoothly without it. In the case of a system cost of $30,000, the system would be justified with a 10-year payback period, but not with a 5-year payback period.

**Table 3 Cost/Benefit Analysis of the Proposed Pay for Priority System**

| Traffic Demand Scenario | Total No. of EDVs per hour | Average No. of Requests per EDV per hour | Pay for Priority System [$/hour] | Base Price [$/hour] | Pay for Priority System [$/year] | Base Price [$/year] | Total Collected Revenue [$/year] |
|---|---|---|---|---|---|---|---|
| Low – 3% | 22 | 8.6 | $2.70 | $0.07 | $2,107.40 | $42,900.00 | $45,007.40 |
| Low – 5% | 32 | 7.8 | $3.56 | $0.10 | $2,772.90 | $62,400.00 | $65,172.90 |
| Low – 10% | 73 | 6.5 | $6.71 | $0.23 | $5,235.24 | $142,350.00 | $147,585.24 |
| Medium – 3% | 28 | 7.6 | $3.03 | $0.09 | $2,362.51 | $54,600.00 | $56,962.51 |
| Medium – 5% | 45 | 6.9 | $4.42 | $0.14 | $3,449.49 | $87,750.00 | $91,199.49 |
| Medium – 10% | 90 | 5.8 | $7.48 | $0.29 | $5,834.18 | $175,500.00 | $181,334.18 |
| High – 3% | 32 | 7.6 | $3.46 | $0.10 | $2,695.26 | $62,400.00 | $65,095.26 |
| High – 5% | 56 | 6.2 | $4.93 | $0.18 | $3,848.79 | $109,200.00 | $113,048.79 |
| High – 10% | 110 | 4.8 | $7.44 | $0.35 | $5,800.91 | $214,500.00 | $220,300.91 |

| | Yearly Cost (5-year payback) - $12,000 | Benefit-Cost Ratio | Yearly Cost (10-year payback) - $12,000 | Benefit-Cost Ratio | Yearly Cost (5-year payback) - $30,000 | Benefit-Cost Ratio | Yearly Cost (10-year payback) - $30,000 | Benefit-Cost Ratio |
|---|---|---|---|---|---|---|---|---|
| Low – 3% | $30,488.70 | 1.48 | $17,094.55 | 2.63 | $76,221.64 | **0.59** | $42,736.54 | 1.05 |
| Low – 5% | $30,488.70 | 2.14 | $17,094.55 | 3.81 | $76,221.64 | **0.86** | $42,736.54 | 1.52 |
| Low – 10% | $30,488.70 | 4.84 | $17,094.55 | 8.63 | $76,221.64 | 1.94 | $42,736.54 | 3.45 |
| Medium – 3% | $30,488.70 | 1.87 | $17,094.55 | 3.33 | $76,221.64 | **0.75** | $42,736.54 | 1.33 |
| Medium – 5% | $30,488.70 | 2.99 | $17,094.55 | 5.34 | $76,221.64 | 1.20 | $42,736.54 | 2.13 |
| Medium – 10% | $30,488.70 | 5.95 | $17,094.55 | 10.61 | $76,221.64 | 2.38 | $42,736.54 | 4.24 |
| High – 3% | $30,488.70 | 2.14 | $17,094.55 | 3.81 | $76,221.64 | **0.85** | $42,736.54 | 1.52 |
| High – 5% | $30,488.70 | 3.71 | $17,094.55 | 6.61 | $76,221.64 | 1.48 | $42,736.54 | 2.65 |
| High – 10% | $30,488.70 | 7.23 | $17,094.55 | 12.89 | $76,221.64 | 2.89 | $42,736.54 | 5.15 |

**Note:* Bolded values are the only cases in which the proposed system is not a viable investment.

## Conclusions

This project introduces a novel pay-for-priority system to charge e-commerce vehicles for the negative externalities they create for public roads. Such a system is pertinent given declining gas tax revenues and the rapid growth of e-commerce platforms in recent years. A unique fuzzy logic system was developed to determine the urgency of priority requests. Additionally, for the first time in the literature, parking spaces in a microsimulation model were used as delivery locations. The pay-for-priority system was simulated in a field-like microsimulation corridor, yielding promising results. Moreover, a cost-benefit analysis indicates that the system would be a viable investment.

Key conclusions of this project are:

- The developed system demonstrated a decrease in delays and average travel times for EDVs, while maintaining low delays for passenger cars.
- Additionally, we showed that a small annual fee per e-commerce delivery vehicle could generate sufficient revenue to justify such a project. Our findings indicate that this system would only be unjustified low traffic and low EDV demand scenarios.
- Moreover, implementing such priority systems can yield secondary benefits. Once installed, traffic signal priority infrastructure can be used to provide priority to transit vehicles, bicyclists, etc. in addition to EDVs. This flexibility enhances the overall efficiency and effectiveness of urban traffic management.

Future research should focus on investigating this concept in a grid-like network where deliveries are made on side streets. This would provide a more comprehensive understanding of the system's impact and further validate its potential benefits. Furthermore, future research should consider delivery vehicles that close a lane while delivering goods, as these obstacles cause significant bottlenecks and congestion.

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