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Reduced Fuel Emissions through Connected Vehicles and Truck Platooning

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ABSTRACT

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Vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication enable the sharing, in real time, of vehicular locations and speeds with other vehicles, traffic signals, and traffic control centers. This shared information can help traffic to better traverse intersections, road segments, and congested neighborhoods, thereby reducing travel times, increasing driver safety, generating data for traffic planning, and reducing vehicular pollution. This study, which focuses on vehicular pollution, used an analysis of data from NREL, BTS, and the EPA to determine that the widespread use of V2V-based truck platooning—the convoying of trucks in close proximity to one another so as to reduce air drag across the convoy—could eliminate 37.9 million metric tons of CO_2 emissions between 2022 and 2026.

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Chapter 1. Introduction

Connected vehicles (CVs) could help to reduce the environmental impact of internal combustion engines by improving the efficiency of vehicular travel. Vehicle internal combustion engines produce pollutants that include SO_2, CO, CO_2, and other greenhouse gases. The Texas A&M Transportation Institute reports that congestion in 439 urban areas during 2017 accounted for 8.8 billion hours of extra drive time and 3.3 billion gallons of wasted fuel at a cost of $166 billion (Schrank et al., 2019).

CVs reduce pollutants and greenhouse gases by reducing fuel consumption, idling, and vehicle travel miles. CV technology could reduce vehicular stops, starts, and idling by coordinating arrivals at traffic intersections, suggesting alternate routes around congestion, directing drivers to free parking spaces, and enabling the formation and management of vehicular platoons. By reducing spacing between vehicles, platooning improves road utilization and reduces drag, thereby reducing fuel consumption, operating costs, and emissions.

In 2019, according to the Environmental Protection Agency's (EPA's) "Overview of Greenhouse Gases and Sources of Emissions", humans generated 6,558 million metric tons of CO_2 equivalents—5,769 million metric tons of CO_2 equivalents after accounting for sequestration from the land sector (Environmental Protection Agency, 2021). The EPA further noted that actions can be taken to reduce emissions. For example, from 2018 to 2019, after accounting for sequestration, emissions decreased by 1.7%. The decrease in emissions from fossil fuel combustion was driven in part by the decrease in total energy use in 2019 as compared to 2018 (ibid.). In the electric sector, a continued shift from coal to natural gas and renewables also contributed to the decrease in emissions. EPA data also indicate that greenhouse gas emissions in 2019 were 13 percent below 2005 levels after accounting for sequestration from the land sector. According to the Greenhouse Gas Emissions website, CO_2 makes up 80% of overall greenhouse gas emissions, 29% of which come from the transportation industry (ibid.).

One effort in the transportation industry toward reducing CO_2 emissions is the implementation of truck platooning. The current study's analysis of Heavy-Duty Vehicle (HDV) traffic statistics shows that platooning could eliminate 37.9 million metric tons of CO_2 emissions between 2022 and 2026. In the study, RStudio software was used to build a predictive model for HDV traffic and expected fuel usage between 2022 and 2026. Based on the predicted diesel fuel usage, likely CO_2 emissions were calculated using the diesel to CO_2 conversion established in 2010 by the EPA and the Department of Transportation (Environmental Protection Agency, n.d.). The difference between likely CO_2 emissions when platooning and when not platooning was then compared to calculate the results.

Limitations on the results include conservative estimates for future heavy-duty vehicle miles and choosing MAPE as the sole guide to test the accuracy of the predictions. Possibilities for future work include applying the method to other CV approaches such as coordinated traffic intersections, and applying additional predictive analytics approaches such as regression.

Chapter 2. Literature Review

In "Clean Mobility and Intelligent Transport Systems", Fiorini and Lin provide an overview of considerations related to integrating communication and transportation (Fiorini & Lin, 2015). Intelligent Transport Systems (ITS)—systems that use information technology to manage traffic—have been proposed as a means to reduce traffic congestion, energy consumption, and traffic emissions; increase public and private market share of clean vehicles and transport system efficiency; and enhance road safety. ITSes apply information and communication technologies to road transport, including infrastructure, vehicles, users, traffic management, and mobility management. ITS technologies include vehicle-to-infrastructure (V2I) systems and vehicle-to-vehicle (V2V) technology. V2V and V2I can provide real-time information on vehicular locations and speeds, communicating this information to other vehicles, traffic signals, and traffic control centers.

ITSes could benefit drivers and communities by reducing travel times, increasing driver safety, reducing vehicular pollution, and generating data for improving traffic management plans. Other benefits could include rerouting traffic to avoid obstacles caused by road construction or accidents and using traffic signal control to coordinate traffic signals for vehicles approaching an intersection, thereby reducing stop and go events. Drivers needing parking spots could be directed to an available spot immediately without having to search for a spot.

Given ITS's potential benefits, Fiorini and Lin (2015) argue for establishing policy goals that contribute to efficient traffic management. If government and industry establish sustainability as a goal for emerging ITS technology and transportation systems, smart transportation, in theory, can help to reduce the impact of automobile travel on society and the natural environment, In “A Decentralized Energy-Optimal Control Framework for Connected Automated Vehicles at Signal-Free Intersections”, Malikopoulos et al. analyze strategies for maximizing connected autonomous vehicle (CAV) traffic through an intersection by minimizing gaps between vehicles while minimizing energy consumption (Malikopoulos, 2018). The authors’ study simulates traffic through a Merging Zone (MZ), an intersection where vehicles cross, together with a Control Zone (CZ), a surrounding region within which vehicles can receive communications from a coordinator. Decision-making is assumed to be decentralized; the CAVs, rather than the coordinator, manage their speed and changes in velocity.

When a CAV reaches an intersection’s CZ, the coordinator assigns it a unique identity and grants it access to all information about the CZ’s other CAVs. A standard methodology used in optimal control problems establishes the CAV’s intersection crossing time. First, an unconstrained crossing time is calculated based on current velocity. If that crossing time conflicts with another CAV’s crossing time, the times are desynchronized by making slight adjustments to each CAV’s speed. If the resulting crossing times conflict with a third CAV’s crossing time, the three routes are adjusted in combination with one another. The process is repeated until there are no conflicts.

The authors evaluated the proposed strategy’s effectiveness using a MATLAB-based study of 20 simulated vehicles. The study was then repeated using VISSIM to simulate a 448-vehicle traffic flow. The studies’ results were compared to a comparable scenario involving an intersection with traffic lights with fixed switching times. The simulations showed a 46.6% improvement in fuel consumption and a 30.9% improvement in travel time. Fuel consumption was improved because momentum is conserved when vehicles do not have to stop, and transient engine operation is minimized when the need to accelerate and decelerate is reduced.

In “A Survey on Congestion Detection and Control in Connected Vehicles”, Paranjothi illustrates the importance of a reliable vehicle network (Paranjothi, 2020). CAVs use devices known as On-Board Units (OBUs) and roadside communication devices known as Roadside Units (RSUs) to establish V2V and V2I communications. The resulting communications networks, known as vehicular ad hoc networks (VANETs), are a subclass of mobile ad hoc networks (MANETs). MANETs are collections of mobile nodes that act as routers and hosts in an ad hoc wireless network and that dynamically self-organize without pre-established infrastructure (Munoz, 2021). Nodes in MANETs typically broadcast messages that reach only nearby nodes. Since CAVs may move rapidly, VANET topology can change rapidly and in unpredictable ways.

VANETs, when overloaded with network traffic, can potentially delay or drop messages that would otherwise contribute to road safety. Network overload, known as network congestion, is typically identified by detecting packet loss. Classic strategies for congestion management limit transmission ranges and rates and allocate bandwidth using priority scheduling. Networks then respond by reducing nodes’ bandwidth utilization—ideally before congestion becomes significant.

Congestion management in VANET offers challenges not seen in traditional network environments. Additional strategies for managing VANET congestion could include reinforcement learning and deep learning. Reinforcement learning is a subfield of machine learning (ML) that uses trial and error to identify and select strategies for solving problems (Osiński, 2018). A design team initially equips a learning algorithm like a router-based congestion management algorithm with knowledge about a set of desired outcomes. This algorithm can then learn to make optimal decisions based on ad hoc changes to the network topology caused by a sudden increase in nodes connecting to the network.

Deep learning, another subfield of ML, analyzes raw data more completely and builds response strategies based on that data. Like reinforcement learning, deep learning uses trial-and-error to identify strategies for problem management. Unlike reinforcement, it learns from simulations produced using a high-performance computing environment; the results are then programmed into network AI. The integrated AI then has a much deeper foundation with which to work at managing network challenges.

In "A Cooperative Autonomous Traffic Organization Method for Connected Automated Vehicles in Multi-Intersection Road Networks", Wang emphasizes the importance of network reliability for traffic management (Wang, 2020). Reliable vehicle communication and computing technologies ensure that CAVs can efficiently exchange information with other vehicles and infrastructure. Wang argues that these technologies should be used to manage vehicular traffic more efficiently: i.e., to replace signal controllers at intersections with strategies for organizing traffic that improve traffic efficiency and ride comfort and reduce energy consumption. These strategies should account for crossings at intersections, trajectory optimization in road segments, and route planning in road networks.

Design challenges for CAVs include evaluating the types of conflicts that arise at intersections, optimizing trajectories, and accommodating the different types of vehicles that share roads. Wang's (2020) proposed system addresses the need to coordinate heterogeneous decision-making behaviors and assess the impact of different proportions of CAVs with heterogeneous decision-making behaviors on global system performance. It includes an autonomous crossing strategy for CAVs at unsignalized intersections, an improved model to optimize vehicle trajectories in road segments that connect intersections, and a strategy that combines cooperative and autonomous decision making for CAVs to plan routes in multi-intersection road networks.

Wang's (2020) research used a model intersection with four entrances, each of which has a left lane for left turns, a center lane for through traffic, and a right lane for going straight or turning right. Wang's algorithm seeks to assure that, vehicles in the conflict area maintain maximum crossing speeds to maximize crossing efficiency, with two exceptions. One is that turning speeds are reduced to ensure that turns execute safely. Also, if a vehicle's trajectory conflicts with a vehicle scheduled to arrive ahead of it, this vehicle's trajectory is adjusted to prevent a collision. Wang assumes a communication range that covers the intersection and road segments, allowing enough time to plan vehicle trajectories. Vehicles approaching the intersection receive information about other vehicles in the communication range. A conflict resolution algorithm establishes a traffic-situation-dependent minimum safe headway, or distance between vehicles, for any two vehicles that could arrive at the same conflict point at roughly the same time. It does so by adjusting the time when vehicles enter the intersection.

For trajectory optimization, an intersection's autonomous crossing strategy is determined well in advance of a vehicle's arrival at the intersection, based on time, speed, acceleration, and location. For energy savings, acceleration is minimized, and for comfort, vehicle jerk is minimized. The resulting, iterative model for trajectory optimization adjusts speeds based on analyses of evolving conditions. These optimized trajectories provide safe, energy-saving, and comfortable ride experiences.

The third need that Wang (2020) addressed is cooperative decision making. Although each individual CAV can plan its route, cooperative decision enables vehicles to help balance road network traffic demand. Each CAV submits service requests in advance to an established information center. The request includes origins and destinations, departure time, and trajectory optimization objectives. The customized routes are then planned cooperatively and transmitted to the vehicles before their travels, enabling them to save travel time and reducing road congestion.

Wang (2020) tested his strategies using MATLAB-based simulation experiments. His simulations assume a road network with 10 entrances and 6 identical intersections. Using his cooperative autonomous traffic organization method, Wang ran multiple trials using four different scenarios. In the simulations, no collisions occur, and trajectories are smooth with small jerks and accelerations. Compared to fixed time signals and actuated signals for traffic control, the proposed method reduces the average delay of CAVs by over 85%. While the results are encouraging, Wang acknowledges that the study does not address hybrid flows that include HDVs. In addition, high quality V2V and V2I communications are required.

Unlike Wang, Avedisov studied the operation of ITSes with hybrid traffic (Avedisov, 2019). Mixed traffic that includes CAVs, conventional human driven vehicles (HVs), and connected human driven vehicles (CHVs) will dominate highways in the next several decades. In “Effects of Connected Automated Vehicles on Traffic Flow”, Avedisov develops a prototype CAV to study its effects on traffic patterns amongst human driven vehicles. The prototype is first programmed to follow a CHV at a desired distance. The CAV is then placed in an experimental configuration with two HVs to determine the effectiveness of CAVs using beyond-line-of-sight (BLOS) information for smoothing traffic flow in a mixed environment.

BLOS information includes information from outside of the normal visible range of a human driver and automated vehicle (AV) sensors. BLOS information is gradually being made available to CAVs via vehicle-to-everything (V2X) communication. The primary competing protocols for V2X communication are dedicated short range communication (DSRC) and

Cellular V2X (C-V2X). DSRC, the initial standard, was developed to improve HV safety by providing data for safety critical applications like forward collision warning, blind spot warning, and intersection movement assist. In November 2020 the FCC reallocated spectrum reserved for DSRC, making the lower 45 GHz available for unlicensed operations, and reserving the upper 30 MHz for cellular vehicle to everything (C-V2X) transmissions. This decision to allocate spectrum for C-2VX communication was seen by many providers as a positive move. Initial field experiments show that C-V2X provides a longer communication range than DSRC and, unlike DSRC, allows for packet retransmission. C-2VX can also potentially enable equipped vehicles to communicate with pedestrians and vehicles with cellular phones in addition to other vehicles and the infrastructure.

Avedisov (2019) used the framework developed in his dissertation to assess how connectivity affects traffic flow in DSRC networks. While the study assumed that all AVs are equipped with V2X, the CAVs still function when no other vehicle in the neighborhood has V2X. Avedisov's study also accounts for CAV penetration: i.e., the percentage of CAVs in a traffic environment. If a CAV cannot communicate with other CAVs, it essentially operates as an AV and can only use information from its immediate predecessor obtained from its sensors to control its longitudinal motion (forward motion of the vehicle in line with other traffic). This type of control strategy is referred to as adaptive cruise control (ACC). The presence of at least two CAVs in a connected vehicle network enables the use of connected cruise control (CCC). With CCC, a CAV can use BLOS information from a downstream CV for longitudinal control and line of sight and BLOS information from upstream CVs. Because it does not require a pre-defined connectivity structure, CCC is effective for small penetrations of CVs and CAVs. In an environment with high CAV penetration, CAVs can implement cooperative adaptive cruise control (CACC), where all CAVs use V2V communication to coordinate their motion.

To determine how the prototype CAV could mitigate congestion and promote a stable flow of traffic, Avedisov (2019) used simple car-following models without communication to characterize traffic patterns in HV traffic. Avedisov's experimental CAV follows cars like a human driver, while exploiting BLOS information by means of V2V communication. An experimental framework was also designed for a three-car CV network with one CAV and two CHVs. The setup allows traffic pattern observation with a wide range of traffic densities and speeds and helps determine whether the network would tend to create uniform flow or permit the development of congestion waves. The setup also helps evaluate the effects of introducing BLOS-enabled CAVs. Experiments were completed in a real three-car connected network, and conclusions were confirmed in a simulated environment.

Based on his study, Avedisov (2019) concluded that using BLOS communication to control a CAV adds stability and throughput to a CV network. The study showed that to significantly improve traffic flow in the CV network at low penetration, the CAVs must use information from BLOS vehicles. Increasing the penetration of CHVs would enable a small percentage of CAVs (on the order of 10 - 20 % out of all the cars) to significantly improve traffic flow.

In "Reducing Gasoline Consumption in a Mixed Connected Automated Vehicles Environment: A Joint Optimization Framework for Traffic Signals and Vehicle Trajectory", Yao observes that reducing gasoline consumption and improving transportation efficiency could help the environment while reducing driver frustration and inconvenience (Yao et al., 2020). In 2017, traffic jams on urban roads led Americans to waste an average of 41 hours a year during peak traffic hours, at an estimated cost of nearly $305 billion. In 2018 143 billion gallons of gasoline were used through a daily average of 391 million gallons.

Yao (2020) sees CAV technologies as a means of reducing fuel consumption, transportation emissions, and traffic congestion. Through VANET-enabled I2V communication, data on traffic signal status, road conditions, and vehicular identification, position, speed, and acceleration can be used to manage vehicle trajectories and traffic signaling, leading to reduced gasoline consumption.

Studies prior to Yao's (2020) used three approaches to optimize traffic signals. One, which used information from CAVs to adjust traffic signals in real time to optimize flow, showed that CVs could reduce vehicle delay and travel time significantly; they failed, however, to optimize CAV trajectories while minimizing gasoline consumption and transportation emissions, relative to a fixed traffic signal timing plan. A second approach, which showed that platooning improves fuel consumption improves in CVs and other vehicles the CVs influence, failed to optimize signal timing at intersections. The third approach, which considered joint optimization of traffic signals and CAV trajectories, ignored the impact of human driving vehicles (HDVs).

Yao (2020), by contrast, focuses on optimizing delays in traffic signals and vehicle trajectories in mixed CAV-HDV environments, while reducing gasoline consumption and transportation emissions. Yao's approach uses a two-level optimization framework that optimizes vehicle trajectories at the first level and traffic signals at the second. The first level uses model predictive control (MPC), an approach to process control that accounts for constraints, to optimize vehicle trajectories while accounting for gasoline consumption. The second level uses a two-stage dynamic programming (DP) algorithm to control traffic signals based on vehicle arrival. It uses a state variable to calculate a feasible set of decision variables, which are then used to optimize signal timing. In its first, forward, stage, the algorithm calculates an optimal objective function at each time step. The algorithm's second, backward stage then uses the objective function to find the best traffic signal plan.

Yao (2020) used his algorithm to control the movement of simulated vehicle platoons of HDVs and CAVs through simulated, signaled intersections. These experiments were intended to determine a set of speeds for the platoons together with a traffic signal plan that minimizes the platoon's total gas consumption. Each platoon featured a leading CAV, whose speed and acceleration was optimized for reduced gasoline consumption. For comfort and safety, the algorithm assumes that the platoon passes the intersection at a fixed velocity. Yao's framework proceeds by assuming an initial traffic signal plan; calculating a potential arrival time for each vehicle platoon; then using MPC to generate vehicle trajectories. Optimal traffic signal plans are then developed based on vehicle arrival times. Iterating between the MPC and DP processes optimizes the signal plan as well as vehicle trajectories.

Yao (2020) tested fifteen scenarios on a standard desktop computer with an Intel 3.6 GHz processor and 8 GB of memory. The study considered volumes of 200, 400, and 600 vehicles per lane per hour with five penetration rates of CAVs, from 0.2 to 1.0 with a 0.2 step. Each scenario ran for 900 seconds and was repeated 5 times. Yao found that average vehicle delays decrease significantly under CAV-based control and that CAV based control outperforms actuated control in all experimental scenarios. By optimizing vehicle trajectories, the framework reduces average vehicle delay by up to 57%, even as traffic penetration rates increase. In addition, gasoline consumption is reduced by as much as 22% and CO_2 emissions by as much as 18%. Average CO_2 emissions are lowered as traffic penetration increases. Based on the results, Yao asserts that CAV-based control can significantly improve the traffic capacity of intersections, and that the application of CAV can reduce CO_2 emissions significantly.

Ghiasi (2017), who likewise studied traffic control at intersections, considered additional means for enhanced traffic capacity (Ghiasi et al., 2017). Experiments with CAVs suggest that V2V communication and automated control can improve traffic highway capacity by reducing headway: the time difference between successive vehicles when they cross a given point. CAV platooning enables consecutive CAVs to function like concatenated cars in a train, greatly reducing headways typical of disconnected HDVs. Studies of pure automated traffic with computer simulation and analytical models predict that highway capacities will be maximized in the far future when all vehicles are platooned CAVs.

Ghiasi (2017) uses a novel framework to assess the impact of lane management on highway capacity in mixed CAV-HDV traffic. Lane management, the establishment of dedicated lanes for routing different types of traffic, has improved capacity in traditional HDV traffic. Ghiasi's framework attempts to determine the optimal number of CAV lanes to maximize mixed traffic throughput at varying demand levels, platooning intensities, and technology scenarios.

Ghiasi's (2017) framework treats time headways between vehicles as stochastic: i.e., "randomly determined; having a random probability distribution or pattern that may be analyzed statistically but may not be predicted precisely" (OED Online, 2022). This differentiates Ghiasi's work from prior capacity analyses for mixed traffic, which assume a constant headway for each vehicle. The framework also accounts for the impact of CAV market penetration—the percentage of CAVs in traffic—on highway capacity. Earlier studies that showed that increased CAV market penetration increases highway capacity were based on models that fail to account for platooning. Even at the same market penetration rate, different degrees of CAV platooning may result in different traffic capacities. When CAVs are better clustered instead of being scattered, highway capacity will increase because of longer CAV platoons with reduced headways.

To capture complex stochastic headway and unify a full spectrum of CAV penetration rates and platooning intensities, Ghiasi (2017) used a Markov chain model. A Markov chain is a model of the random motion of an object in a discrete set of possible locations (Damiani, 2021). Traditional Markov chain models aim to predict an object's status over time. For Ghiasi's model, a stream of vehicles with a given penetration rate of CAVs is processed to determine a clustering strength to establish optimum platoon levels. A mixed traffic capacity is analytically formulated using stochastic and heterogeneous headway settings across the full spectra of CAV market penetration rates and platooning intensities in mixed traffic. Ghiasi claims that this methodology links traditional traffic flow analysis to emerging CAV traffic management; provides an effective and accurate means of quantifying mixed traffic capacity; and will help aid in better management of mixed CAV traffic flow.

Contrary to the assumption that higher CAV penetration rates and platooning intensities always yield greater mixed traffic capacities, Ghiasi's (2017) model indicates that these two factors alone may not always improve highway capacity. Traffic operators should be aware that there is an optimum level for CAV penetration rates.

In "Cybersecurity Challenges in the Uptake of Artificial Intelligence in Autonomous Driving", Dede discusses the need for security awareness in discussions of CAV technology (Dede, 2021). The automotive sector increasing adoption of digital components in vehicles is intended to reduce traffic accidents by automating aspects of vehicular operation, thus reducing opportunities for human drivers, the most common cause of traffic accidents, to make bad decisions. AV technology, however, also creates new opportunities for threats to public safety.

An inadequately secured system or road network can render an AV vulnerable to attack. For example, a bad actor could sabotage an AV's operation by making misleading changes to its operating environment: e.g., by adding paint to a road to mislead its navigation system or adding stickers to road signs to interfere with proper identification.

The European Union Agency for Cybersecurity discusses cybersecurity challenges in autonomous driving and recommends security measures for addressing these threats (Dede, 2021). The agency asserts that the automotive sector must increase preparedness and reinforce incident response capabilities to handle emerging cybersecurity challenges. Artificial intelligence as an enabler for autonomous vehicles further complicates the establishment of cybersecurity as a critical component for ensuring safety and promoting trust.

To mitigate the potential dangers, AV security should be assessed throughout an AV's lifecycle. A security strategy should also analyze the entirety of the supply chain that contributes to a vehicle's design and implementation.

Discussion

These studies indicate the extensive growth of interest in CV technology. The proposed applications of CV technology suggest opportunities to reduce fuel usage and make roads safer. Despite these advances, for the near future, allowing a human driver to surrender control to technology will only be likely in specific driving scenarios. Driving in a platoon on a highway is one of those scenarios.

Due to the continuing growth of HDV transport volumes, the large volume of highway miles, and the centralized control of fleet vehicles, the transportation industry has been an early adopter of platooning: the grouping of vehicles that move in unison, using automatic control and V2V communication to maintain a short distance between vehicles. Platooning improves road throughput and safety and reduces air drag across the platoon, thereby reducing fuel consumption, operating costs, and emissions. Effective platooning results from vehicles driving behind each other with controlled gaps between them. Modern sensor and wireless communication enable automated control of the gaps, reducing risk of accidents due to insufficient gaps and inattentive drivers. One such technology, Adaptive Cruise Control (ACC), relieves the driver of the task of controlling the distance to the vehicle in front. A second, Cooperative Adaptive Cruise Control (CACC), allows vehicles to reduce inter-vehicle gaps compared to human controlled gaps without compromising safety.

Based on his 2016 simulation of truck transport, van de Hoef concluded that "coordinated platooning can yield significant fuel savings and that coordination is crucial in leveraging these savings" (van de Hoef, 2016). For 2000 transport assignments starting over the course of two hours, a number that Van de Hoef cited as reasonable, the simulation found that platooning reduced platoon follower consumption by 15.9% at a speed of 80 km/h and overall fuel consumption by 7.6%. Van de Hoef notes that the total distance traveled in the simulated scenario is in the same order of magnitude as the total distance traveled by domestic road freight transport in Sweden within two hours, assuming that traffic volume is equally spread over the year. The simulated density of road freight traffic in this study was only a fraction of the total road freight traffic in countries with high population density.

In all likelihood, these reductions in fuel consumption could translate directly to reductions in emissions for years to come. As van de Hoef states "another problem is that the great majority of trucks is powered by fossil fuels, and despite various research efforts such as electric highways and alternative fuels, this is not likely to change soon, in particular in the domain of long haulage transport" (van de Hoef, 2016). Van de Hoef also reports that fuel accounts for roughly a third of a heavy truck's operation costs in long haulage transport. The use of fossil fuels leads to problematic emissions, most prominently CO_2. In 2014, the transport sector accounted for 20% of greenhouse gas emissions in the European Union, of which 72% were due to road transport. Van de Hoef reports that experiments motivate that the air drag of a heavy truck in a platoon can be lowered by 40 %, translating into an overall reduction in fuel consumption of over 10%.

This thesis was undertaken to further quantify the potential for platooning to reduce CO_2 emissions generated by long-haul transportation. Chapter 3 presents the research's findings, as published in the Proceedings from the 2022 IEEE GreenTech Conference. The results of the study show that with the implementation of truck platooning 37.9 million metric tons of CO_2 emissions could be eliminated between 2022 and 2026.

The study takes calculations on fuel savings and reductions in emissions and applies them toward known traffic and fuel consumption patterns to predict the benefits that could result with the implementation and growth of truck platooning. RStudio software provides the foundation for the calculations in the study. To apply predictive analytics, the Forecast, MLmetrics, and fpp2 packages were applied. The data containing HDV miles between 2007 and 2019 were obtained from the Bureau of Transportation Statistics (Bureau of Transportation Statistics, n.d.). Because short trips are often not amenable to platooning, platoonable miles are miles during which it is reasonable that a truck could take advantage of platooning opportunities.

Chapter 3. Truck Platooning and Its Impact on Fuel Emissions

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Abstract— Platooning is the use of vehicle-to-vehicle (V2V) technology to form train-like convoys of vehicles. Truck platooning can potentially contribute to safer roadways through the use of inter-vehicle communication to coordinate traffic movement, while increasing fuel economy through reduced wind drag and reducing vehicular emissions. Fuel economy savings described in the literature on truck platooning are applied toward a forecast of heavy-duty vehicle (HDV) traffic through 2026 to predict a potential reduction of CO_2 emissions between 2022 and 2026 of 37.9 million metric tons.

Index Terms—Advanced driver assistance, Connected Vehicles, Intelligent vehicles, Machine-to-machine communications, Mobile communication, Truck platooning, Vehicle platooning, Vehicle routing, Vehicle safety, Vehicular ad hoc networks.

I. INTRODUCTION

Vehicle internal combustion engines produce pollutants that include SO_2, CO_2 emissions, and other pollutants and greenhouse gases. Advances in vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication create opportunities to reduce CO_2 emissions in the transportation sector. By reducing fuel consumption, idling, and vehicle travel miles, connected vehicles (CVs) can reduce pollutants and greenhouse gases. Platooning refers to a group of vehicles forming a road train using electronic coupling between the vehicles. In platooning, automatic control and V2V communication enable vehicles to travel closely together, thereby improving road throughput and safety. The reduced air drag contributes to reduced fuel consumption and emissions. Reduced fuel consumption leads to decreased operating costs, and reduced emissions leads to a cleaner and healthier environment. Increased use of truck platooning in the coming years can reduce CO_2 emissions and contribute to a cleaner environment.

This paper presents a study of the potential environmental and economic benefits of truck platooning. According to the "Overview of Greenhouse Gases and Sources of Emissions" provided by the Environmental Protection Agency (EPA), in 2019, greenhouse gas emissions totaled 6,558 million metric tons of carbon dioxide equivalents, or 5,769 million metric tons of carbon dioxide equivalents after accounting for sequestration from the land sector [1]. According to the Greenhouse Gas Emissions website [1], carbon dioxide makes up 80 percent of overall greenhouse gas emissions, and 29 percent of greenhouse gas emissions come from the transportation industry. Multiple studies in platooning and Heavy-Duty Vehicle (HDV) platooning have shown platooning's potential to reduce emissions while improving vehicular safety and fuel economy.

In summary, the study showed a potential for 4 percent savings in fuel usage that could lead to a savings of nearly 38 million metric tons of CO_2 between 2022 and 2026. Limitations on the results include conservative estimates for future heavy-duty vehicle miles and choosing only MAPE as the guide to test the accuracy of the predictions. This study also did not fully consider multiple heavy-duty vehicle (HDV) platooning or traffic capacity. Future studies can improve upon this study by applying additional predictive analysis techniques and by considering additional vehicles added to the platoon.

II. RELATED WORK

Alam shows the potential for significant fuel reduction using HDV platooning while finding a safe distance between HDVs in a platoon [2]. Alam's study shows a fuel reduction of 3.9 to 6.5% for a heterogeneous platoon of HDVs.

Lakshamanan et al. present the importance of reliable V2V communication in fuel-efficient platooning [3].

McCarthy [4] argues that V2V communication provides the most efficient and safe means of platooning while contributing to significant fuel use reduction. McCarthy points out the SARTRE project, a UN sponsored environmental program, which shared that “platooning could reduce 2.85 tons of CO_2 in a diesel truck every year.

Stegner et al. created experimental fuel consumption results from a heterogeneous four truck platoon. They found benefits of 5 to 11% for following vehicles, and 0 to 4% for the lead vehicle in a platoon relative to their baseline fuel consumption [5]. Compared to the sum of the standalone trucks’ fuel consumption, all platoons in the study cumulatively saved fuel in the range of 6% to 8%.

Van de Hoef et al. used convex optimization techniques to create travel plans for thousands of trucks to show that significant fuel savings can be achieved with truck platoons [6]. Their simulation showed a 7.6% reduction in fuel consumption for 2000 transport assignments starting over the course of two hours. Van de Hoef says that “platoon coordination might be the key to leveraging the full potential of truck platooning”.

Ghiasi et al. references platooning in a broader discussion of connected vehicles [7]. Ghiasi focuses on traffic capacity benefits provided by platooning. Increased traffic capacity also contributes to fuel economy through reduced congestion.

Yao includes platoons operating within a joint optimization framework to reduce congestion with the goal of reducing gasoline consumption [8].

The National Renewable Energy Laboratory (NREL) continually conducts studies to assess the fuel saving potential of truck platooning and pinpoint areas in need for future research.

According to the NREL's Transportation and Mobility Research web site, "platooning reduces aerodynamic drag by grouping vehicles together and safely decreasing the distance between them via electronic coupling, which allows multiple vehicles to accelerate or brake simultaneously" [9]. In an overview of studies conducted with various organizations, NREL reported that lead vehicle savings are up to 10 percent at the closest separation distances, the middle vehicle saves up to 17 percent, and the trailing vehicle saves up to 13 percent [9]. Additional variables assessed with varying results include speed variations, road curvature, unplanned vehicles cutting in and out of the platoon, mismatched vehicles, and the presence of surrounding passenger vehicles.

This paper differs from previous literature by quantifying CO_2 emissions that result from reduced fuel consumption in truck platooning. Alam, Lakshamanan, Stegner et al., Van de Hoef, Ghiasi, Yao, and NREL focus on reduced fuel consumption without discussing CO_2 emissions. McCarthy references CO_2 emissions in the context of a variety of methods for fuel efficiency. This paper's focus is quantifying and forecasting CO_2 emissions that result from implementing truck platooning.

III. METHODS

A. Overall Approach

This study sought to quantify the degree to which truck platooning could improve fuel efficiency, thereby contributing to CO_2 reductions and a cleaner environment. Data sets provided by NREL [10], the EPA [11], and the Bureau of Transportation Statistics (BTS) [12] were used to predict the potential benefits from implementing widespread truck platooning. A dataset named "Combination Truck Fuel Consumption and Travel" from BTS provides the study's core data [13]. The dataset provides data about HDV fuel consumption and highway miles from 2007 to 2019.

Between 2007 and 2019, the average miles per gallon of fuel for heavy-duty vehicles remained steady at 6.0. Average miles traveled per vehicles decreased during that time, but that did not translate into a fuel consumption reduction because there was an increase in registered heavy-duty vehicles. In 2009 there were 2,617,100 registered heavy-duty vehicles, and in 2019 there were 2,925,200. Although average miles traveled per truck had reduced, there were more trucks on the road.

The "Vehicle or Engine Group" selected for the study was referenced as "Long Haul – Combination" and is a Class 8 vehicle. The foundation for the study's predictive model was built in RStudio using the Forecast, MLmetrics and fpp2 packages. A model was trained using data from 2007 to 2014, then validated using data from 2014 to 2019 to obtain a Mean Absolute Percentage Error (MAPE). The MAPE provides realistic guidelines for the study's forecasts into the future.

In addition to calculating the MAPE, a naive method was created to help ensure the forecast model's performance. A simple naive uses a day's worth of data to forecast the next [14]. A seasonal naive uses a longer range of observations such as a week, a month, or a year to provide the forecast for tomorrow. For this data set, the seasonal naive, snaive, was based on observations between 2007 and 2019.

B. Specifics

1. Naive method

Table 2.1 provides details on each element in the command to establish the seasonal naive calculation. A seasonal naive forecast in the Forecast package is calculated as follows:

naive = snaive(training, h=length(validation)) (1)

In the formula, the variable naive is calculated using the snaive function on the training set and the validation set. The goal is to use the "training" set to help predict what should be expected

Table 2.1. Elements of the Command Used to Establish the Seasonal Naive.

naive	the variable that will hold the data
snaive	average prediction for a month, listed as mean, followed by low and high values in the 80th and 95th percentile
training	the variable to be studied
h=length	indicates to read through validation and count the data points
start	row at which to start reading data
validation	the variable used for comparison

in the “validation” set. The result provides a point forecast broken down by month that provides the average prediction for the month, listed as mean, followed by low and high values in the 80th and 95th percentile.

Naive then contains the predicted values for what should be in the validation set. Each row of data is listed in month and year format (Month, Century, Year). The validation set contains the observed values for the time period listed. The naive values can then be compared to the actual values to see how well the prediction performed.

2. Calculating MAPE

To determine the prediction’s accuracy, the Mean Absolute Percentage Error (MAPE) was calculated using the seasonal naive stored in the naive variable:

MAPE(naive$mean, validation) * 100 (2)

The result was used as a guideline for predictions. In a simple naive, what happened in the last year of data is forecast for the entire validation set. When modeling with MAPE, a smaller MAPE results in a better prediction model. For this data set, the Mean Absolute Percentage Error (MAPE) for the data is 4.704094 percent.

3. Forecasting HDV miles per year.

Snaive was used to forecast to 2026 the miles per year traveled by heavy duty vehicles. Because it is a naive forecast, the “Point Forecast” will show the average values for each year.

Using the Hi 80th percentile values, a meaningful prediction can be obtained that is within the 4.70 MAPE that was established. Table 2.2 shows the results of the snaive calculation that were stored in the to2026 variable.

Table 2.3 shows Hi 80th percentile values for HDV yearly miles predicted for 2022 through 2026, and Figure 1 shows the predicted values for 2020 through 2026 next to the observed values for 2007 to 2019 used to establish the predictive model.

4. Determining Platoonable Miles

"Platoonable" miles were determined based on the predicted miles between 2022 and 2026 (Table 2.4). Per NREL, this calculation assumed that trucks would "driv[e] at platoonable speeds of at least 50 miles per hour for at least 15 consecutive minutes" [15], implying that 55 percent of HDV miles are "platoonable" miles (Table 2.5).

Table 2.2. Results of the Snaive Calculation Providing Forecasts of HDV Miles (in Millions) per Year to 2026.

Point	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2015	169830	159263.5	180396.5	153670	185990
2016	169830	154886.8	184773.2	146976.3	192683.7
2017	169830	151528.4	188131.6	141840.1	197819.9
2018	169830	148697.1	190962.9	137510	202150
2019	169830	146202.7	193457.3	133695.2	205964.8
2020	169830	143947.6	195712.4	130246.3	209413.7
2021	169830	141873.8	197786.2	127074.7	212585.3
2022	169830	139943.6	199716.4	124122.6	215537.4
2023	169830	138130.6	201529.4	121350	218310
2024	169830	136415.9	203244.1	118727.6	220932.4
2025	169830	134785	204875	116233.4	223426.6
2026	169830	133226.7	206433.3	113850.1	225809.9

Table 2.3. Hi 80th Percentile Values for HDV Yearly Miles in Millions Predicted for 2022 through 2026.

Year		Predicted
2022		199,716.4
2023		201,529.4
2024		203,244.1
2025		204,875.0
2026		206,433.3

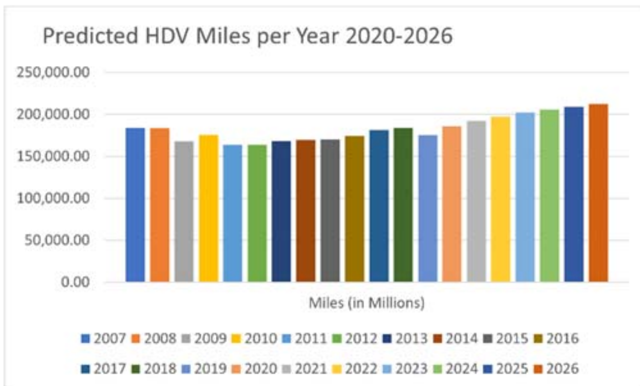

Figure 2.1. U.S Heavy Duty Vehicle Miles Traveled (in Millions), Including 2007 to 2019 Data, with Predictions for 2020 to 2026.

Table 2.4. Potential Platoonable Miles (in Millions) Based on the Hi 80th Percentile Values for HDV Yearly Miles Predicted for 2022 through 2026.

Year	Predicted	Platoonable
2022	199,716.4	109,844.0
2023	201,529.4	110,841.2
2024	203,244.1	111,784.3
2025	204,875.0	112,681.3
2026	206,433.3	113,538.3

Table 2.5. Total Miles (in Millions) Predicted for 2022 through 2026, by Standard and Platoonable miles.

Year		Total	Standard	Platoonable
2022		199,716.4	89,872.3	109,844.0
2023		201,529.4	90,688.2	110,841.2
2024		203,244.1	91,459.9	111,784.3
2025		204,875.0	92,193.8	112,681.3
2026		206,433.3	92,895.0	113,538.3

IV. RESULTS

A. Gallons of Fuel Saved

Table 2.6 shows the results of the calculations and the resulting fuel savings between 2022 and 2026. HDV fuel usage between 2022 and 2026 for non-platooned (i.e., standard) miles was calculated as miles / 6.0, where 6.0 is the Bureau of Transportation Statistics's estimate of HDV fuel efficiency in terms of miles per gallon.

HDV fuel usage for platooned miles was calculated assuming 6.25 miles per gallon, based on Alam's conservative estimate that platooning can save 4 percent in fuel usage.

B. CO_2 Emission Reduction

Table 2.7 shows the CO_2 emissions that could be reduced between 2022 and 2026 with the implementation of platooning. The calculations in Table 2.7 are based on the potential gallons of fuel saved from Table 2.6, and the diesel to CO_2 conversion established in 2010 during a joint rulemaking session between the EPA and the Department of Transportation [16]. The formula for converting diesel fuel used to CO_2 emissions is shown on the EPA's "Greenhouse Gas Equivalencies Calculator" web site [17] and is listed here:

$$10{,}180 \text{ grams of } CO_2/\text{gallon of diesel} = 10.180 \times 10\text{-}3 \text{ metric tons } CO_2/\text{gallon of diesel} \quad (3)$$

Table 2.6. Total Gallons of Fuel Saved (in Millions) Predicted for 2022 through 2026 Assuming Implementation of Platooning.

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Year	Without Platooning	With Platooning	Gallons Saved
2022	33,286.1	32,553.8	732.3
2023	33,588.2	32,849.3	738.9
2024	33,874.0	33,128.8	745.2
2025	34,145.8	33,394.6	751.2
2026	34,405.6	33,648.6	756.9
Total	169,299.70	165,575.10	3,724.50

V. DISCUSSION

This data suggests the extent to which truck platooning could improve fuel efficiency in Class 8 trucks. The reduction in fuel usage reduces costs for operators and CO_2 emissions. Although a conservative approach is taken in this paper by only assuming a 4 percent improvement in fuel economy, the results suggest that even minor improvements can make significant differences. Future studies should consider the savings realized by all trucks in a platoon.

Based on the study, implementing platooning in heavy duty vehicles between 2022 and 2026 could result in a reduction of 37,915,410 metric tons. While this is a modest fraction of the 6.5 billion metric tons released in 2019 [1], it would still contribute to a lowering of greenhouse gas emissions.

For comparison, based on the Greenhouse Gas Equivalencies Calculator available at epa.gov [17], the reduction of nearly 38 million metric tons of CO_2 is comparable to the amount of energy used to provide energy to 4,565,894 houses for a year, or to use 87,782.190 barrels of oil. In addition, as Milner et al. note, "lower carbon emissions can also improve [public] health" [18]. Specific benefits noted by the Health and Environment Alliance are "reduced dementia, cardiovascular disease, diabetes, obesity, breast cancer, colon cancer, and depression" [19].

Table 2.7. Potential CO_2 Emission Reductions in Metric Tons for 2022 through 2026 with Truck Platooning.

Year		Metric Tons of CO_2 Emissions Reduced
2022		7,454,814
2023		7,522,002
2024		7,586,136
2025		7,647,216
2026		7,705,242
Total		37,915,410

REFERENCES

[1] Environmental Protection Agency, "Overview of Greenhouse Gases," 19 November 2021. [Online]. Available: https://www.epa.gov/ghgemissions/overview-greenhouse-gases.

[2] A. Alam, "Fuel-Efficient Heavy-Duty Vehicle Platooning," 2014 .

[3] S. Lakshmanan et al., "Performance of DSRC V2V communication networks in an autonomous semi-truck platoon application," in *American Center for Mobility*, 2021.

[4] J. F. Mccarthy, "Sustainability of Self-Driving Mobility: An Analysis of Carbon Emissions Between Autonomous Vehicles and Conventional Modes of Transportation," 2017.

[5] E. Stegner et al., "Experimental Fuel Consumption Results from a Heterogeneous Four-Truck Platoon," 2021.

[6] S. van de Hoef, Fuel-Efficient Centralized Coordination of Truck Platooning, 2016.

[7] A. Ghiasi et al., "A mixed traffic capacity analysis and lane management model for connected automated vehicles: A Markov chain method," *Transportation Research,* no. 106, pp. 266-292, 2017.

[8] Z. Yao et al., "Reducing gasoline consumption in mixed connected automated vehicles environment: A joint optimization framework for traffic signals and vehicle trajectory," *Journal of Cleaner Production,* no. 265, 2020.

[9] M. Lammert, "The National Renewable Energy Laboratory," [Online]. Available: https://www.nrel.gov/transportation/fleettest-platooning.html.

[10] National Renewable Energy Laboratory, "Data and tools," U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy, [Online]. Available: https://www.nrel.gov/research/data-tools.html.

[11] Environmental Protection Agency , "Open Data," [Online]. Available: https://www.epa.gov/data.

[12] Bureau of Transportation Statistics, "Freight Facts and Figures," [Online]. Available: https://www.bts.gov/product/freight-facts-and-figures?keys=highway+miles&field_topic_target_id=All. [Accessed 30 November 2021].

[13] Bureau of Transportation Statistics and Data, "Combination Truck Fuel Consumption and Travel Dataset," [Online]. Available: https://www.bts.gov/browse-statistical-products-and-data/freight-facts-and-figures/combination-truck-fuel-consumption. .

[14] F. St-Amant, "Time Series Forecasting in R," Towards Data Science, 13 June 2020. [Online]. Available: https://towardsdatascience.com/a-guide-to-forecasting-in-r-6b0c9638c261. [Accessed 19 November 2021].

[15] National Renewable Energy Laboratory, "Transportation and Mobility Research," U.S. Department of Energy , [Online]. Available: https://www.nrel.gov/transportation/fleettest-platooning.html.

[16] United States Environmental Protection Agency , "Greenhouse Gases Equivalencies Calculator - Calculations and References," 28 April 2021. [Online]. Available: https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references.

[17] Environmental Protection Agency, "Greenhouse Gas Equivalencies Calculator," [Online]. Available: https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator.

[18] H. Milner et al., "Health benefits of policies to reduce carbon emissions," *BMJ,* vol. 368, p. l6758, 2020.

[19] Health and Environment Alliance (HEAL), "A Healthy Planet for Healthy People," [Online]. Available: http://www.env-health.org/IMG/pdf/heal_background_paper_climate_co-benefits_en.pdf.

Chapter 4. Conclusion

V2I and V2V communications in combination with VANETs are essential for implementing and advancing CV technology and achieving safer and more efficient vehicles. As shown through the literature review, CV studies share many of the same goals including creating safer roadways, reducing traffic congestion, and reducing energy consumption and CO_2 emissions. Different approaches that can be used to achieve these goals include platooning, optimizing vehicle trajectories, managing traffic crossings at intersections, and reducing headways between vehicles. Malikopoulos (2018) and Yao (2020) discussed signal free intersections that can help reduce stop and go traffic resulting in better fuel efficiency. Ghiasi (2017) also discussed traffic control at intersections with an added focus on reducing headways. Paranjothi (2020) and Wang (2020) discussed network reliability and congestion control in the VANETs that support the infrastructure. Van de Hoef (2016) presented coordinated platooning to yield significant fuel savings. For each approach, improved fuel efficiency results.

In the study, predictive analysis was applied to show measurable reductions in CO_2 emissions when implementing truck platooning. The study showed a potential for 4 percent savings in fuel usage which translates to a savings of nearly 38 million metric tons of CO_2 between 2022 and 2026. Increased use of truck platooning and other connected vehicle enabled approaches to traffic management can lower transportation costs, reduce CO_2 emissions, and improve roadway safety. One challenge in truck platooning that could merit further study is platoon formation by trucks that must adjust their speed to arrive at the start of the common part of their route to form a platoon. Because increased velocities require more fuel, a coordination scheme to help form platoons could contribute to reduced fuel consumption by preventing the need to increase velocity to join an assigned platoon.

References

Alam, A. (2014). Fuel-Efficient Heavy-Duty Vehicle Platooning.

Avedisov, S. (2019). *Effects of Connected Automated Vehicles on Traffic Flow*. ProQuest Dissertations Publishing.

Brummitt, P., & Khan, M. (2022). Truck Platooning and Its Impact on Fuel Emissions. *2022 IEEE Green Technologies Conference (GreenTech)*, (pp. 130-135). https://doi.org/10.1109/GreenTech52845.2022.9772028

Bureau of Transportation Statistics and Data. (n.d.). *Combination Truck Fuel Consumption and Travel Dataset.* Retrieved from https://www.bts.gov/browse-statistical-products-and-data/freight-facts-and-figures/combination-truck-fuel-consumption.

Bureau of Transportation Statistics. (n.d.). *Freight Facts and Figures*. Retrieved November 30, 2021, from https://www.bts.gov/product/freight-facts-and-figures?keys=highway+miles&field_topic_target_id=All

Damiani, E. J. (2021). *Markov Chain*. Retrieved from Science Direct: https://www.sciencedirect.com/topics/computer-science/markov-chain

Dede, G., Hamon, R., Junklewitz, H., Naydenov, R., Malatras, A. and Sanchez Martin, J.I. (2021). *Cybersecurity challenges in the uptake of artificial intelligence in autonomous driving.* Luxembourg: Publications Office of the European Union. doi:10.2760/551271, JRC122440

Environmental Protection Agency. (n.d.). *Open Data*. Retrieved from https://www.epa.gov/data

Environmental Protection Agency. (2021, November 19). *Overview of Greenhouse Gases*. Retrieved from https://www.epa.gov/ghgemissions/overview-greenhouse-gases

Environmental Protection Agency. (n.d.). *Greenhouse Gas Equivalencies Calculator*. Retrieved from https://www.epa.gov/energy/greenhouse-gas-equivalencies-calculator

Fiorini, M., & Lin, J.-C. (2015). *Clean Mobility and Intelligent Transport Systems.* The Institution of Engineering and Technology.

Ghiasi, Hussain, O., Qian, Z. (Sean), & Li, X. (2017). A mixed traffic capacity analysis and lane management model for connected automated vehicles: A Markov chain method. *Transportation Research*, 106, 266-292. https://doi.org/10.1016/j.trb.2017.09.022

Health and Environment Alliance (HEAL). (n.d.). *A Healthy Planet for Healthy People*. Retrieved from http://www.env-health.org/IMG/pdf/heal_background_paper_climate_co-benefits_en.pdf

Lakshmanan, S., Adam, Andres, R., Smyth, B., Kleinow, T., Grenn, K., & Richardson, P. (2021). Performance of DSRC V2V communication networks in an autonomous semi-truck platoon application. *American Center for Mobility.*

Lammert, M. (n.d.). *The National Renewable Energy Laboratory*. Retrieved from Transportation & Mobility Research: https://www.nrel.gov/transportation/fleettest-platooning.html

Malikopoulos, Cassandras, C. G., & Zhang, Y. J. (2018). A decentralized energy-optimal control framework for connected automated vehicles at signal-free intersections. *Automatica (Oxford),* 93, 244–256. https://doi.org/10.1016/j.automatica.2018.03.056

Mccarthy, J. F. (2017). Sustainability of Self-Driving Mobility: An Analysis of Carbon Emissions Between Autonomous Vehicles and Conventional Modes of Transportation.

Milner, Hamilton, I., Woodcock, J., Williams, M., Davies, M., Wilkinson, P., & Haines, A. (2020). Health benefits of policies to reduce carbon emissions. *BMJ*, *368*, l6758. https://doi.org/10.1136/bmj.l6758

Munoz, D. L.-C. (2021). *Mobile Ad Hoc Network*. Retrieved from Science Direct: https://www.sciencedirect.com/topics/computer-science/mobile-ad-hoc-network

National Center for Statistics and Analysis. (2020, December). Overview of motor vehicle crashes in 2019. *Traffic Safety Facts Research Note. Report No. DOT HS 813 060.*

National Renewable Energy Laboratory. (n.d.). *Data and tools*. (U.S. Department of Energy, Office of Energy Efficiency and Renewable Energy). Retrieved from https://www.nrel.gov/research/data-tools.html

National Renewable Energy Laboratory. (n.d.). *Transportation and Mobility Research*. (U.S. Department of Energy). Retrieved from https://www.nrel.gov/transportation/fleettest-platooning.html

OED Online. (2022). Stochastic, Adjective. Oxford University Press. Retrieved from www.oed.com/view/Entry/190593

Osiński, B. a. (2018, July 5). *Reinforcement Learning*. Retrieved from Deepsense Artificial Intelligence: https://deepsense.ai/what-is-reinforcement-learning-the-complete-guide/

Paranjothi, A. K. (2020). A survey on congestion detection and control in connected vehicles. *Ad Hoc Networks*(108). https://doi.org/10.1016/j.adhoc.2020.102277

Schrank, D., Eisele, B., & Lomax, T. (2019). *2019 Urban Mobility Report.* College Station, TX: Texas A&M Transportation Institute.

St-Amant, F. (2020, June 13). *Time Series Forecasting in R*. (Towards Data Science). Retrieved November 19, 2021, from https://towardsdatascience.com/a-guide-to-forecasting-in-r-6b0c9638c261

Stegner, Ward, J., Siefert, J., Hoffman, M., & Bevly, D. M. (2021, April 6). Experimental Fuel Consumption Results from a Heterogeneous Four-Truck Platoon. *SAE Technical Paper 2021-01-0071*. https://doi.org/10.4271/2021-01-0071

United States Environmental Protection Agency . (2021, April 28). *Greenhouse Gases Equivalencies Calculator - Calculations and References*. Retrieved from https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-references

van de Hoef, S. (2016). *Fuel-Efficient Centralized Coordination of Truck Platooning.*

Wang, Y. C. (2020). Cooperative autonomous traffic organization method for connected automated vehicles in multi-intersection road networks. *Transportation Research. Part C, Emerging Technologies*(111), 458-476. https://doi.org/10.1016/j.trc.2019.12.018

Yao, Zhao, B., Yuan, T., Jiang, H., & Jiang, Y. (2020). Reducing gasoline consumption in mixed connected automated vehicles environment: A joint optimization framework for traffic signals and vehicle trajectory. *Journal of Cleaner Production*, 265,121836. https://doi.org/10.1016/j.jclepro.2020.121836

APPENDIX: Glossary

Actuated Signal Control - A type of signal control where time for each phase is at least partially controlled by detector actuations

Actuator - a component of a machine that is responsible for moving and controlling a mechanism or system. An actuator requires a control signal and a source of energy.

ACC – *adaptive cruise control*

adaptive cruise control – a cruise control unit that uses information from the immediate predecessor obtained from its sensors to control longitudinal motion

automated vehicle – a vehicle that relies on an internal computer rather than a human to process information from sensors such as cameras or radars to control their motion

AV – *automated vehicle*

beyond-line-of-sight - distances outside of the normal visible range of a human driver, or outside of the range of sensors in an automated vehicle

BLOS – *beyond line of sight*

C-V2X - *cellular vehicle to everything communication*

CAV – *connected automated vehicle*

CACC - *cooperative adaptive cruise control*

CCC – *connected cruise control*

cellular vehicle to everything communication - a unified connectivity platform designed to offer vehicles low-latency communication

CHV – *connected human-driven vehicle*

connected automated vehicle – an automated vehicle that uses information from V2X communication in addition to sensory information to control its motion

connected cruise control: cruise control augmented with motion signals from vehicles in the line of sight

connected human-driven vehicle – one with some form(s) of V2X connectivity connected vehicle – A vehicle equipped with V2V that can communicate with other CVs in traffic over several hundred meters, beyond the line of site of lidars, cameras, or radars. The received information helps augment its perception of the environment and enhances its ability to respond to cooperative adaptive cruise control - used by all CAVs; uses V2V communication to control CAV motion in a coordinated fashion to achieve certain control objectives

CV - *connected vehicle*

CZ - *control zone*

deep learning - part of a broader family of machine learning methods based on artificial neural networks with representation learning. Learning can be supervised, semi-supervised or unsupervised

DP – *dynamic programming*

dynamic programming - an algorithmic technique for solving an optimization problem by breaking it down into simpler subproblems in a recursive manner

General Pseudospectral Optimal Control Software - MATLAB software intended to solve general nonlinear optimal control problems (problems where it is desired to optimize systems defined by differential-algebraic equations)

GPOPS - *General Pseudospectral Optimal Control Software*

HDV – *human-driven vehicle*

headway – the distance between vehicles measured in time or space. Minimum headway is the shortest such distance or time achievable without a reduction in speed (see also heterogeneous headways and stochastic headways)

Heterogeneous headways – an assumed constant distance between vehicles in traffic studies

human-driven vehicle – a human driven vehicle without connectivity

HV – *human-driven vehicle*

identification - a unique identifier assigned to a network interface controller (NIC) for use as a network address in communications within a network segment iterative algorithm - one that proceeds in discrete steps, with each step operating on the result of the previous step.

I2V – *infrastructure to vehicle communication*

ID – identification

infrastructure to vehicle communication – communication to a vehicle from an infrastructure device

intelligent transportation system – systems that enable traffic and transport networks to behave in an intelligent manner through the application of sensing, analysis, control, and communications technologies to ground transportation to improve safety, mobility, and efficiency management

ITS – *intelligent transportation system*

latitudinal dynamics – an automated driving technique for lane keeping typically, a vision-based system augmented by high precision GPS and high-definition maps

line of sight - the normal visible range of a human driver, or of the range of sensors in an automated vehicle (AV)

longitudinal dynamics – a type of automated driving technique for maintaining speed; includes classical, adaptive, or connected cruise control and maintaining separation from vehicles being followed

machine learning - the study of computer algorithms that improve automatically through experience and the use of data

MANET – *mobile ad hoc wireless network*

(Ghiasi's) Markov Chain Representation– Captures the full spectrum of CAV market penetration rates and all possible values of CAV platooning intensities that largely affect the spatial distribution of different headway types. It accurately quantifies that corresponding mixed traffic capacity at various settings. Allows for examination of the impact of different CAV technology scenarios on mixed traffic capacity.

MATLAB – a proprietary multi-paradigm programming language and numeric computing environment developed by MathWorks that allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages; used for simulation

merging zone – the area at an intersection where vehicles pass and could potentially sustain lateral collisions

mobile ad hoc wireless network – a collection of mobile nodes that act as routers and hosts in an ad hoc wireless network and that dynamically self-organize in a wireless network without pre-established infrastructure

model predictive control - a method of process control used to control a process while satisfying a set of constraints

MPC – *model predictive control*

MZ - *merging zone*

OBU – *on-board unit*

on-board unit – a communication device mounted inside a vehicle

penetration – the percentage of a type of vehicle within a vehicular network or traffic environment.

perception – situational awareness for an automated vehicle; based on data collected via sensors, including GPS, cameras, radars, lidars, and V2X communication from beyond line of sight

proximity sensors - a sensor that detects the presence of nearby objects without any physical contact

reinforcement learning - an area of machine learning concerned with how intelligent agents ought to take actions in an environment to maximize the notion of cumulative reward

roadside unit – a roadside communication device

RSU – *roadside unit*

simultaneous longitudinal and latitudinal dynamics – a combination of longitudinal and latitudinal dynamics; this corresponds to fully autonomous vehicle control; it involves generating a motion plan and using a feedback controller to ensure appropriate behavior

Stochastic headways – an allowance for a randomly determined distance between vehicles in traffic studies

V2C – *vehicle to cloud connectivity*

V2I – *vehicle-to-infrastructure connectivity*

V2V – *vehicle-to-vehicle connectivity*

V2X – *vehicle-to-anything connectivity*

VANET - *vehicular ad hoc network*

vehicle-to-anything connectivity - wireless connectivity from vehicles to other entities

vehicle to cloud connectivity - a form of V2X communication

vehicle-to-infrastructure connectivity - a form of V2X communication

vehicle-to-vehicle connectivity - a form of V2X communication

vehicular ad hoc network – the spontaneous creation of a wireless network of vehicle and roadside infrastructure-based network devices

VISSIM - a microscopic multi-modal traffic flow simulation software package developed by PTV

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