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Evaluating the Climate Impact of Truck Platooning Adoption: A System Dynamics Approach

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Abstract

Freight transportation is a significant contributor to greenhouse gas (GHG) emissions in the US. As an emerging technology, truck platooning leverages vehicle-to-vehicle communications to enable trucks to travel in convoys with close proximity, which reduces air drag and consequently truck fuel use and GHG emissions. However, uncertainties remain about how this emerging technology may be adopted and its climate impacts. To this end, this paper investigates the role of truck platooning adoption in mitigating the climate impact of trucking from a system perspective. Considering the dynamic nature of truck platooning adoption, System Dynamics (SD) models based on stock and flow diagrams are developed to estimate the potential reduction of fuel use and CO_2 emissions in the US trucking sector when truck platooning technology becomes available. The results show that adopting platooning could save 292 Million Metric Tons of CO_2 emissions in 180 months after the initial introduction of the technology in the US truck sector.

Keywords: truck platooning; CO_2 emissions; system dynamics modeling; technology adoption

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1. Introduction

The US freight transportation system plays a vital role in moving goods and supporting the national economy. As of 2019, the system moved 55.2 million tons of freight per day [1], which is projected to increase by 1.4% annually between 2022 and 2050 [2]. In the freight transportation system, trucks carry the largest portion in terms of both tonnage and value of the freight [3], which continue to grow at a faster rate than other freight transportation modes [4]. The attractiveness of trucking is attributed to the speed, flexibility, and overall capacity that the trucking industry offers to move goods around the country, from dense urban areas and geographically remote regions [5].

The prominent role trucking plays in the US freight transportation system also means a significant negative impact on the environment. In particular, fossil fuel use by trucking resulted in 1060 Million Metric Tons (MMT) of CO_2 equivalent Greenhouse Gas (GHG) emissions in 2021 [6]. It is estimated that in the US truck CO_2 emissions contribute to 60.6% of the total CO_2 emissions from transportation activities [6]. The emissions from medium- and heavy-duty trucks are especially important, accounting for 23% in the total despite accounting for only 4% in the US vehicles [7]. This gives rise to a significant need to innovate and implement new technologies in the trucking industry to reduce its CO_2 emissions.

Truck platooning has recently emerged as such a technology, which is about two or more trucks traveling in convoy maintaining a small headway between them enabled by advanced driver-assisted technologies [8]. Such a convoy is known as a *platoon*. In a platoon, the leading truck is entirely operated by a human driver, while the subsequent trucks automatically respond to certain actions of the lead truck without human intervention. Currently, fully engaged human drivers are still necessary in every truck within a platoon. In the rest of the paper, trucks capable of traveling in platoons will be referred to as *platoonable* trucks.

The small headway between trucks in a platoon reduces the aerodynamic drag and consequently fuel use. The fuel savings from truck platooning, which is directly related to CO_2 emission reduction,

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can be up to 20% has been extensively confirmed through theoretical analyses, simulation studies, and real-world experiments [9–11]. Because of the significant promise to cut fuel use, truck platooning is predicted to become widely adopted in the coming decades, with its market share projected to grow from \$37.6 million in 2021 to \$2.7 billion in 2030 [12].

As an emerging technology, truck platooning also faces many uncertainties about how well truck platooning will perform, how users will adopt, and its impact on transportation, energy, and the environment [13]. While this technology can save truck fuel use and reduce CO_2 emissions, the actual energy and climate impact of truck platooning relies crucially on the extent of the technology adoption over time and the operational conditions of truck platooning as a part of the US dynamic trucking industry [14,15]. Given these uncertainties, there are various potential outcomes in which truck platooning technology may fail to deliver its intended benefits. This means while it has the potential to decrease fuel consumption and CO_2 emissions, it could also carry the risk of the opposite effect. Hence, all positive aspects of truck platooning could be offset by increasing fuel consumption and Vehicle Miles Traveled (VMT). Regarding the former concern, one potential issue is the possibility of increased fuel consumption in certain scenarios. For instance, if trucks are platooning on heavily congested routes, the fuel efficiency gains could be canceled due to additional idling time or longer routes.

As for the latter concern, it is essential to consider the impact on VMT. If truck platooning leads to more trucks on the road, it may result in an overall increase in the total distance covered by vehicles. This could lead to a net rise in fuel consumption and CO_2 emissions, which may offset the initial fuel-saving benefits. According to [16], the perceived convenience of truck platooning could have a negative impact on the usage of alternative transportation modes. This could lead to a mode shift from rail to road transportation, potentially resulting in an increase of 18% in road freight transport [17]. Thus, a system thinking approach is required to understand the behavior of complex systems over time [18].

Motivated by the above, the objective of this research is twofold. First, this research seeks to comprehensively understand the dynamics of the trucking industry as it pertains to adopting truck platooning. We employ a System Dynamics (SD) approach, which is well known for its effectiveness in constructing a stock-and-flow model to comprehensively characterize the structure of complex systems. Two SD models are developed. The first one represents the US trucking system's functioning without platooning, while the second SD model depicts the system's functioning with truck platooning. In the first SD model, we solely consider the trucking system. In this context, the trucking system is defined as a system contains trucking fleets operating on the US road network, their skilled drivers, and their interactions. However, in the second SD model, we analyze a System-of-Systems (SoS) that comprises two components: the trucking system and the truck platooning system, as well as their interaction. The truck platooning system refers to a system that includes platoonable trucks and the associated rules and regulations implemented by relevant entities or authorities. Furthermore, the second SD model incorporates decision-making of truck drivers through the assessment of three technology adoption scenarios based on the technology's benefit-to-cost ratio.

Building on the developed SD models, the second objective of this research is to investigate the potential impact of truck platooning on GHG emissions in the US trucking system. Given that CO_2 emissions account for 96% of total transportation-related GHG emissions [19] and data availability, we focus on quantifying and forecasting CO_2 emissions that result from implementation of truck platooning over time. The modeling results offer valuable insights to freight stakeholders, helping them make informed decisions and develop relevant policies toward a greener and more sustainable trucking system and the overall freight transportation system through the adoption of truck platooning.

2. Literature Review

In this section, we first provide an overview of the existing works on SD modeling, with an emphasis on the applications of SD to analyze CO_2 emissions from road transportation. Then, among

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all benefits of truck platooning, we focus on one which can lead to CO_2 emission reduction and review related studies.

2.1. System Dynamics and Its Application in Sustainable Road Transportation

Many of the challenges we currently face, such as air pollution and climate change, are unforeseen consequences of decisions made in the past. Although decision-makers may have the best intentions to address these issues, a lack of dynamic, system thinking leads to policies not always achieving the intended goals and even inadvertently causing new problems. As such, a system thinking and modeling approach becomes indispensable for understanding the behavior of complex systems over time, especially for emerging technologies [18]. SD is a powerful modeling tool that has been widely employed across various fields over the past three decades [20]. By utilizing SD, transportation researchers can effectively explore and address complex problems, aiding in the formulation of sustainable road transportation strategies.

SD modeling has been widely used to study sustainable road transportation in the past. [21] develops an SD model for highway management to achieve sustainable development for the Commonwealth of Virginia. The urban transportation of Dalian city, China, is modeled by [22]. They propose policies based on the control variable, vehicle ownership, to mitigate NO_2 emission. An SD model is proposed by [23] to predict the future CO_2 emission patterns in the urban development of Malaysia and global warming potential. [24] propose an SD model for analysing the mitigation of CO_2 emissions in the road transportation system in Latvia. Their model aims to predict CO_2 emissions generated from the transportation sub-system by considering changes in social, economic, and technical aspects. [25] applies SD modeling to systematize the interconnections between carsharing and their environmental effects. Using an SD model, [26] investigate how carbon neutrality and carbon peak would be achieved in Beijing's public transportation considering adoption of relevant policies.

2.2. Emissions Reduction Using Truck Platooning

Platooning helps reduce truck emissions in one major way. Platooning reduces fuel use due to the decrease in aerodynamic drag, especially during high speed[1] [14,28]. The extent of air drag reduction during platooning is estimated based mainly on: 1) theoretical studies using computational fluid dynamics [29–33], and 2) experimental wind tunnel and track testing [34–37]. In these estimations, parameters such as truck shape and size, cruising speed, the number of trucks in a platoon, and inter-vehicular spacing within the platoon are considered.

Despite the considerable efforts made within the literature to investigate the environmental impacts of truck platooning diffusion, a significant gap remains in understanding these effects through the lens of a system dynamics framework. The absence of such investigations limits the comprehensive understanding of truck platooning as a dynamic, interconnected system, thereby impeding the identification of critical components and chains of interdependencies influencing its environmental consequences. Addressing this gap is imperative as it can provide decision-makers with a holistic perspective, facilitating the observation of how changes in various system parameters impact CO_2 emissions, and ultimately aiding in the formulation of effective policies to optimize system efficiency and environmental outcomes.

Another gap in the existing literature relates to the lack of assessment regarding the sensitivity of CO_2 emission production to different economic and technological attributes of truck platooning technology. Quantifying the sensitivity of CO_2 emissions of the technology to various technological and economic factors (such as fuel saving efficiency, production cost, fuel price, etc.) holds immense significance for both technology enablers and policy-makers. Through such analysis, it becomes feasible to identify the most influential features of the technology in relation to emissions. Consequently, this knowledge empowers stakeholders to allocate resources strategically, focusing on the most promising

[1] Since the aerodynamic drag is proportional to the second power of speed, platooning can be more effective concerning energy saving at higher speed [27].

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and cost-effective technology enhancement strategies, which can lead to substantial reductions in CO_2 emissions within the trucking system.

2.3. Contributions of This Study

To address the identified gaps in the literature, this study attempts to make two contributions. Firstly, a novel SD model is developed to capture the diffusion of truck platooning technology within the trucking industry. This model investigates the influence of various factors, such as the economic efficiency of the technology, and the rate of return of the economy, on the diffusion of truck platooning and its resulting CO_2 emissions. Given the complex interdependency among these factors, the SD approach proves to be a suitable strategy for comprehending the complexities inherent in the entire diffusion process. Furthermore, an extensive sensitivity analysis is conducted to assess the impacts of different parameters in the model, including fuel price, technology fuel efficiency, and technology price, on CO_2 emissions. The results highlight significant variations in the CO_2 emissions attributed to the various elements of the technology. These findings offer valuable insights to technology enablers, empowering them to devise the most effective technological alignments to curtail CO_2 emissions effectively.

3. System Definition

The truck platooning system will operate as an embedded part of the trucking system. Since truck platooning system has operational and managerial independence from the trucking system, we use the paradigm of SoS [38] for the study. In the next subsection, we define the truck platooning system, the existing trucking system, and the system boundaries through a function-oriented perspective.

3.1. Truck Platooning System

Truck platooning is an innovative system that is revolutionizing the trucking industry in the US. It offers several benefits, including enhanced fuel efficiency and reduced driver wage and shortage [27]. It serves as an excellent illustration of a SoS that aligns precisely with the criteria proposed by [38]. The fundamental building blocks of this SoS are clearly the platoonable trucks themselves, which act as the key constituent systems[2]. These trucks dynamically form platoons, facilitating efficient collaboration and coordination as they operate over time. However, the widespread implementation of truck platooning faces challenges such as regulatory frameworks, infrastructure requirements, and public acceptance. Nonetheless, as technology continues to advance and stakeholders work towards addressing these challenges, truck platooning holds great potential for transforming the US freight market by improving efficiency and reducing overall emissions [27].

3.2. Existing Trucking System

The trucking system is highly favored for its flexibility, swift delivery, and door-to-door service in transporting various commodities. It contains a fleet of trucks, the skilled drivers, and intricate logistic systems. Despite its advantages, the trucking system encounters challenges, including CO_2 emissions, rising operational costs, and driver shortages and aging [40]. The expected driver shortage in the future may expedite the adoption of truck platooning, especially in countries with high labor costs, due to potential health benefits for drivers, improved well-being, and the ability to multitask [27,41–43]. However, the decision between platoonable and traditional trucks remains complex, as it requires careful consideration of various factors.

The decision-making process of truck drivers involves evaluating the quantifiable benefits and drawbacks of adopting truck platooning technology. Two primary decisions arise: comparing platooning benefits when purchasing new trucks and evaluating the advantages and costs of adopting platoonable trucks or retrofitting existing ones with advanced technologies like lidar and sensors [43]. This assessment involves considering factors such as improved fuel efficiency, reduced emissions, and

[2] In the context of a SoS definition, constituent systems refer to the individual systems or components that make up the larger, complex system [39].

potential cost savings from decreased labor requirements [27]. By carefully weighing these considerations, truck drivers can determine the optimal approach to integrate platooning technology while balancing economic viability and operational feasibility.

3.3. System Boundary

SD model should be developed within a closed-system boundary, where all system interactions occur [44]. Although illustrating the boundary of a complex system may present challenges, organizing components within the SoS can be achieved effectively. This study recognizes two main systems that have an impact on the truck platooning industry. In addition to the truck platooning system, the trucking system is a system that contains different truck companies, infrastructure, and drivers. This paper focuses on examining the relationship between the truck platooning system and trucking system. Even though the government system has the ability to influence the truck platooning system by establishing legislation that either permits or restricts platooning [45], further investigation into this system and other interactions is left for future research.

4. Model Development

The problem addressed in this paper, which is often referred to as the reference mode in the SD literature [46], is the increasing trend of GHG emissions resulting from the growing energy consumption, specifically diesel, in the truck freight transportation system. According to EPA [6], the annual CO_2 emissions released from transportation sector have shown an upward trend over the past three decades. As the reference mode changes over time driven by continued growth of freight demand, the reference mode exhibits a dynamic behavior. Additionally, the complexity of the reference mode arises from a multitude of interdependent factors that influence the reference mode. We consider two model scenarios to capture the dynamics of the reference mode: one with truck platooning and the other without.

4.1. Casual Loop Diagram (CLD)

The theoretical framework of platooning model scenario is conceptualized in a qualitative causal loop diagram, which illustrates the interactive relationships among the main factors within the SoS. Figure 1 displays this diagram, which depicts relationship between variables and two feedback loops. A link marked + indicates a positive relation where an increase (decrease) in the causal variable leads to an increase (decrease) in the effect variable. A link marked - indicates a negative relation where an increase (decrease) in the causal variable leads to a decrease (increase) in the effect variable. In addition, the loops are explained as follows:

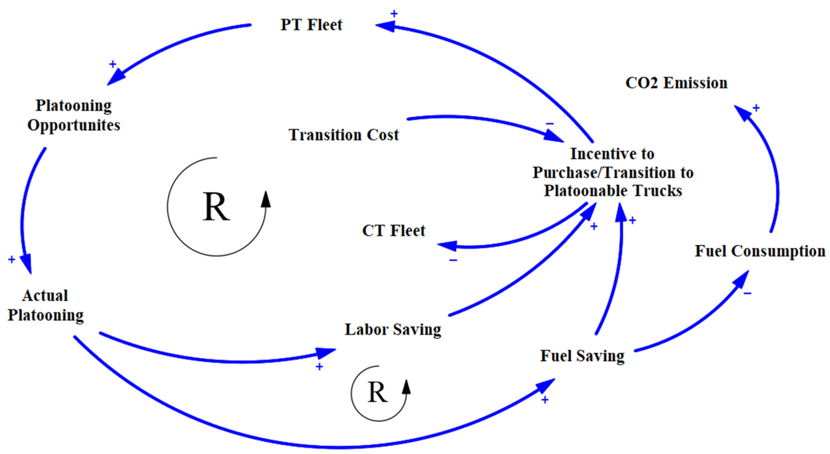

Figure 1. Causal loop diagram of platooning scenario.

1. PT Fleet ⇒ Platooning Opportunities ⇒ Actual Platooning ⇒ Labor Saving ⇒ Incentive to Purchase/ Transition Platoonable Trucks ⇒ PT Fleet (positive feedback loop).

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2. PT Fleet ⇒ Platooning Opportunities ⇒ Actual Platooning ⇒ Fuel Saving ⇒ Incentive to Purchase/ Transition Platoonable Trucks ⇒ PT Fleet (positive feedback loop).

In Figure 1, the "R" signs indicate reinforcing impacts, characterized by a positive feedback loop, meaning that a change in one variable will lead to an amplified change of itself through the feedback loop.

4.2. Stock and Flow Diagram (SFD)

A CLD is transformed into a quantitative SFD, which provides an algebraic representation of models based on causal loops identified [47]. SFDs consist of stocks (levels) and flows (rates), which serve as the fundamental elements of system dynamics models [48]. These components describe the state of system under investigation and serve as the foundation for making decisions and taking actions [18]. Changes in stocks can solely occur through their corresponding flows, which indicate the quantities added to (inflow) or removed from (outflow) a stock as time progresses. Indeed, in an SFD, stocks are fundamental to generating behavior in a system; flows cause stocks to change. Figure 2 shows an SFD for the non-platooning scenario. In the figure, the stock "CT Fleet", which stands for "conventional truck fleet", has a one-stock two-flow structure, in which CT fleet is filled by purchases and drained by retirements. Total CO_2 emissions from the CT fleet is calculated based on the amount of fuel consumed by the CT Fleet and the appropriate emission factor. Table 1 details the employment of variables, and equations in the no platooning SFD. Note that gray variables which are in angle brackets in the SFD, as well as throughout this paper, are referred to as "shadow variables"[3]. On the other hand, Figure 3 shows the SFD for the platooning scenario. This SFD contains three submodels related to: 1) platooning technology adoption, 2) drivers decision, and 3) CO_2 emissions.

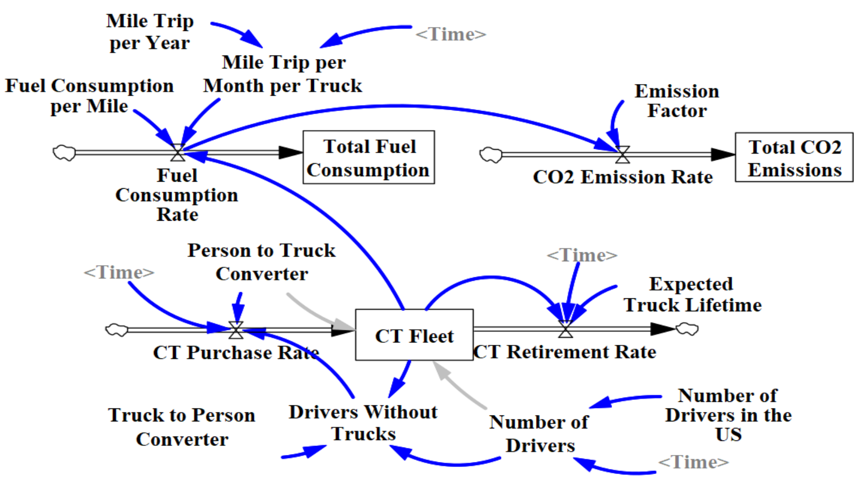

Figure 2. Stock and flow of the no platooning scenario.

Table 1. Variables, units, and definitions of no platooning model scenario.

Variable name	Type	Unit	Definition
CT Fleet	level	vehicle	CT Fleet Initial $+ \sum_{t=0}^{179}$ (CT Purchase(t) $-$ CT Retirement(t))
Number of Drivers	auxiliary	person	Number of Drivers in the US(Time)
CT Purchase	auxiliary	vehicle per month	Drivers Without Trucks $\times$ Person to Truck Converter
Drivers Without Truck	auxiliary	person	Number of Drivers $-$ CT Fleet $\times$ Truck to Person Converter

[3] Shadow variables are valuable in modeling complex systems with interdependencies, enabling modelers to simplify complex equations for better clarity and manageability.

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Table 1. *Cont.*

Variable name	Type	Unit	Definition
CT Retirement	rate	vehicle per month	CT Fleet / Expected Truck Lifetime
Fuel Consumption	rate	gallon per month	CT Fleet × Fuel Consumption per Mile × Mile Trip per Month per Truck
Total Fuel Consumption	level	gallon	$\sum_{t=0}^{179}$ (Fuel Consumption(t))
CO_2 Emission	rate	kilograms of CO_2 per month	Total Fuel Consumption × Emission Factor
Total CO_2 Emissions	level	kilograms	$\sum_{t=0}^{179}$ (CO_2 Emission(t))

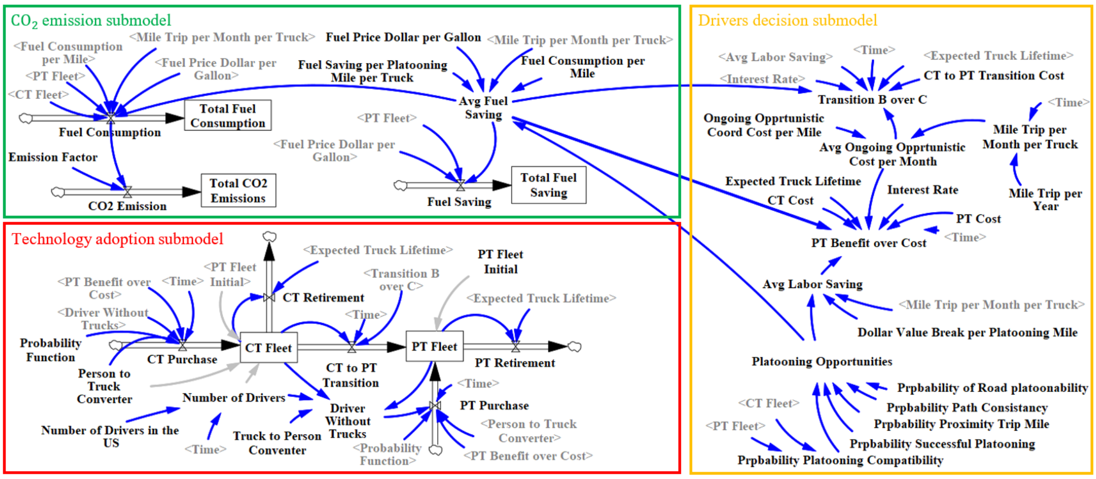

Figure 3. Stock and flow diagram of platooning scenario.

4.2.1. Technology Adoption Submodel

The platooning technology adoption submodel, shown in Figure 3, has two stocks and five flows. In this submodel each CT fleet is filled by purchases and drained by retirements and transition to platoonable truck fleet. Moreover, the stock "PT Fleet", which stands for "platoonable truck fleet" is filled by purchase and transition from conventional fleet and drained by retirements. Indeed, in the technology adoption submodel drivers face two options. Firstly, drivers without a truck may decide to purchase either a conventional truck or a platoonable truck, based on the potential benefits associated with each option. Thus, drivers carefully weigh both the benefits and costs of each type of truck before making their decision. It is worth mentioning that, in this model, a so-called "do-nothing" option has not been considered for drivers.

Secondly, drivers with a conventional truck have the option to transform their vehicles into new platoonable trucks. This can be achieved by retrofitting an existing conventional truck with advanced technologies, such as radar sensors, lidar systems, and communication devices. Despite the cost incurred in transforming to platoonable trucks, owning such a truck can lead to benefits such as labor and fuel savings. Then, by converting potential future benefits and costs values of purchasing a platoonable truck to the present values[4] and dividing this amount by the present investment (cost of transitioning a conventional truck to a platoonable truck) that drivers need to pay currently, they can obtain the benefit over the cost of purchasing a platoonable truck and decide to buy one or stand with their current traditional truck. Table 2 demonstrates variables, units, values, and definitions of adoption submodel.

[4] Calculating present value (P) by using present worth formula: $P = \frac{A(-1+(1+i)^n)}{i(1+i)^n}$, in which A is monthly benefit of having a platoonable truck, i is monthly interest rate, n is the average monthly lifetime of platoonale truck [49].

Table 2. Variables, units, and definitions of platooning model scenario (technology adoption, drivers decision, and CO_2 emission sub-model).

Submodel	Variable name	Type	Unit	Definition
Technology adoption	CT Fleet	level	Vehicle	CT Fleet Initial + $\sum_{t=0}^{179}$ (CT Purchase Rate(t) − CT Retirement Rate(t) − CT Transition to PT(t))
	CT Flee Initial	auxiliary	vehicle	Number of Drivers × Person to Truck Converter − PT Fleet Initial
	CT Purchase Rate	rate	vehicle per month	Drivers without Truck × Person to Truck Converter×(1 – Probability Function(B over C))
	Drivers Without Truck	auxiliary	person	Person Converter − PT Fleet× Truck to Person Converter
	CT Retirement Rate	rate	vehicle per month	CT Fleet / Expected Truck Lifetime
	CT to PT Transition	rate	vehicle per month	exp(Transition B over C − 1)/(1 + exp(Transition B over C − 1)) × CT Fleet
	PT Fleet	level	vehicle	PT Fleet Initial + $\sum_{t=0}^{179}$ PT Purchase(t) + CT Transition to PT Cost(t) − PT Retirement(t))
	PT Purchase Rate	rate	vehicle per month	Drivers Without Truck × Person to Truck Convector× (Probability Function(B over C))
	PT Retirement Rate	rate	vehicle per month	PT Fleet / Expected Truck Lifetime
CO_2 emission	Fuel Saving Rate	rate	gallon per truck per month	Avg Fuel Saving × PT Fleet / Fuel Price Dollar per Gallon
	Total Fuel Saving	level	gallon	$\sum_{t=0}^{179}$ (Fuel Saving Rate(t))
	Fuel Consumption Rate	rate	gallon per month	CT Fleet × Fuel Consumption per Mile × Mile Trip per Month per Truck + (Fuel Consumption per Mile) × Mile Trip per Month per Truck × (PT Fleet) − (Avg Fuel Saving × PT Fleet / Fuel Price Dollar per Gallon)
	Total Fuel Consumption	level	gallon	$\sum_{t=0}^{179}$ (Fuel Consumption Rate(t))
	CO_2 Emission Rate	rate	kilograms of CO_2 released per month	Fuel Consumption Rate × Emission Factor
	Total CO_2 Emissions	level	kilograms	$\sum_{t=0}^{179}$ (CO_2 Emission Rate(t))

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Table 2. *Cont.*

Submodel	Variable name	Type	Unit	Definition
Drivers Decision	Avg Fuel Saving	auxiliary	dollar per truck per month	Fuel Price Dollar per Gallon × Fuel Consumption per Mile × Mile Trip per Month per Truck × Fuel Saving per Platooning Mile per Truck × Platooning Opportunities
	Avg Labor Saving	auxiliary	dollar per truck per month	Mile Trip per Month per Truck × Dollar Value Break per Platooning Mile × Platooning Opportunities
	PT B over C	auxiliary	gallon per truck per month	(Avg Fuel Saving + Avg Labor Saving - Avg Ongoing Opportunistic Cost per Month) × (− 1 + pow (1 + Interest Rate, Expected Truck Lifetime))/Interest Rate × pow(1 + Interest Rate, Expected Truck Lifetime)/ (PT Cost − CT Cost)
	Platooning Opportunities	auxiliary	-	Probability of Proximity Trip Mile × Probability Path Consistency × Probability Successful Platooning × Probability Platooning Compatibility × Proportion of Road platoonability
	Probability Platooning Compatibility	auxiliary	-	PT Fleet / (PT Fleet + CT Fleet)
	Avg Ongoing Opportunistic Cost per Month	auxiliary	dollar per month per vehicle	Ongoing Opportunistic Coordination Cost per Mile× Mile Trip per Month per Truck
	Transition B over C	auxiliary	-	(Avg Fuel Saving + Avg Labor Saving – Avg Ongoing Opportunistic Cost per Month) × (− 1 + pow(1 + Interest Rate, Expected Truck Lifetime))/ Interest Rate × pow(1 + Interest Rate, Expected Truck Lifetime)/ (CT to PT Transition Cost)

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4.2.2. Drivers Decision Submodel

The truck drivers decision submodel, which can be seen in Figure 3, involves evaluating the benefit-over-cost ratio of either transition their current truck into a platoonable truck ("B over C Transition") or persisting with their conventional truck. Furthermore, drivers who do not currently own trucks assess the benefit-over-cost ratio of purchasing a platoonable truck ("PT B over C"). These decisions are based on the potential benefits they may receive and the associated costs they may incur. There are two sources of benefit generated by platooning: fuel savings and labor savings for the follower trucks in the platoon. These savings are determined by the fuel price, labor wage, and the platooning opportunities available. The platooning opportunity is determined by the number of platooning trucks in the system and the network characteristics, which include the probability of path consistency among trucks, proximity to other trucks on the road, and the probability of being on a platoonable road in the network. Additionally, adopting a platoonable truck incurs two types of costs : the initial fixed cost associated with adoption (installation costs or the price difference between a platoonable truck and a conventional one) and the ongoing costs of platooning operations (assumed to be a constant portion of each trip). Table 2 shows variables, units, values, and definitions of driver decision process sub-model.

4.2.3. CO_2 Emission Submodel

Figure 3 demonstrates the CO_2 emission submodel. In this submodel, the total CO_2 emissions stock represents the amount of emissions released into the air, taking into account the interactions between the CV Fleet and PT Fleet stocks and reflecting the influence of the drivers' decision-making process on this stock. The factors that affect this stock include the number of platoonable trucks and the percentage of fuel saving that each truck can achieve through platooning. The percentage of fuel saving resulting from platooning has been reported by various studies to range from 3% to 15% [50–53]. However, To maintain a conservative approach, we adopt a 5% fuel-saving assumption for trucks in a platoon within our model. It is worth noting that we assume emission factor equal to 10.19 kg per gallon of diesel consumed in our models [54]. Table 2 shows further details on Variables, units, values, and definitions of the emission submodel.

4.3. Parameter Identification

In this section we present the input parameters are obtained based on data from the US road network, since our research focuses on the entire US road freight transportation network. We describe the numerical values given to the model's parameters, based on data in journal publications [55,56] and information from additional sources such as leading trucking companies like [57–59]. Additionally, the authors' engineering estimations have also been taken into account. The parameters values that are used in the no platooning model and platooning submodels can be seen in the Table 3. Furthermore, in another part of the platooning model, we require data for VMT and number of single and combination unit trucks for the next 180 month. As the data we aim to obtain is time-based, employing time series data prediction methods is essential to forecast the values until 2035. We use historical data of VMT and number of SU and CU trucks in the US road network from 1970 to 2021 [60,61]. To generate the forecasts, we employ the AutoRegressive Integrated Moving Average (ARIMA) model which is a widely used method for time series forecasting [62]. Figures 4 and 5 depicts both historical and forcasted values of VMT and number of SU and CU trucks in the period of 1970 to 2035.

To characterize the adoption function of truck platooning as a function of economic efficiency, we generate three scenarios of truck platooning adoption with respect to the benefit-over-cost of the technology, named as optimistic, expected, and pessimistic scenarios. The generated scenarios assign an adoption rate to different levels of benefit-over-cost ratios of buying a platoonable truck over the alternative case, i.e., buying a conventional truck. The tables of adoption rates for different benefit-over-costs are used in the model to calculate the rate of purchasing platoonable trucks over time. Note that the scenarios are synthetic, and further tuning of the scenarios needs a survey. The

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adoption rate of different scenarios with regard to the benefit-over-cost ratios of the technology is depicted in Figure 6. Furthermore, to address the behavior of conventional truck owners when faced with the decision to either stick with their conventional truck or transition to a platoonable truck, we assume a standard logistic function [5]. This assumption allows us to better model and understand the decision-making process of these truck owners.

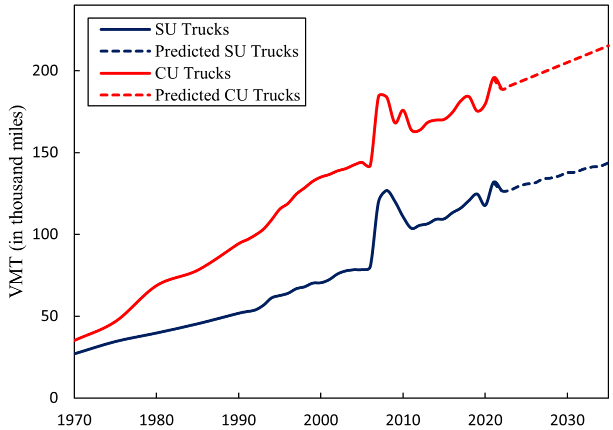

Figure 4. Historical and forecast VMT based on the designed ARIMA model.

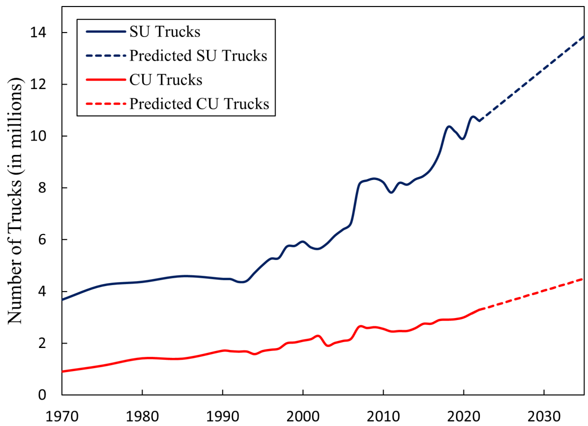

Figure 5. Historical and forecast number of trucks based on the designed ARIMA model.

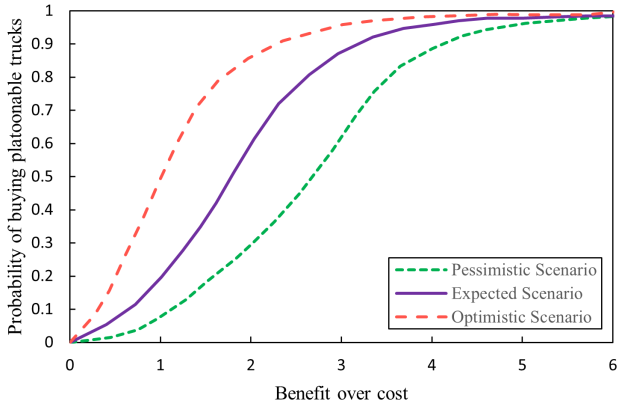

Figure 6. Probability function of buying platoonable trucks.

[5] The standard logistic function is represnted by $F(x) = \frac{e^x}{1+e^x}$, where x denotes the decision-making factor.

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Table 3. Parameters of platooning model scenario.

Parameter name	Type	Unit	Value	Reference
Platoonable Truck Price	constant	dollar per vehicle	150000	Assumption
Conventional Truck Price	constant	dollar per vehicle	135000	[57–59]
PT Fleet Initial	constant	vehicle	1000	Assumption
CT Fleet Initial (summation of SU and CU trucks for base year 2021)	constant	vehicle	13,859,181	[60,61]
Interest Rate (%)	constant	per year	5	[63]
CT to PT Transition Cost	constant	dollar per vehicle	11000	Assumption
Fuel Price	constant	dollar per gallon	4	[64]
Fuel Saving per Platooning Mile per Truck (%)	constant	–	5	[50]
Probability Proximity Trip Mile	constant	–	0.5	Assumption
Probability Path Consistency	constant	–	0.5	Assumption
Probability Road Platoonability	constant	–	0.6	[65]
Probability Successful Platooning	constant	–	0.75	Assumption
Fuel Consumption per Truck	constant	gallon per mile	0.05	[66]
Ongoing Opportunity Coordinating Cost	constant	dollar	0.007	Assumption
Model time scale	constant	month	180	Assumption
Hour Cost of Trucking	constant	dollar	10	[67]
Average Truck Speed	constant	mile per hour	50	[68]
Expected Truck Lifetime	constant	months	120	[69]
Emission Factor	constant	kilograms of CO_2 released per gallon of diesel consumed	10.19	[54]

[a] This parameter represents the probability of two platoonable trucks being in close proximity to each other. [b] This parameter shows the probability of two platoonable trucks having consistent paths while encountering each other during a trip. [c] This parameter indicates the probability of two platoonable trucks meeting on a road with platooning capabilities; approximately 60% of roads are deemed platoonable [53,65]. This determines the proportion of miles where trucks can sustain a speed of 50 mph or higher for more than 15 minutes (criterion for identifying platooning). [d] This parameter explains the probability of successful platooning by considering two platoonable trucks that are in close proximity, have a consistent path, and are on a platoonable road.

5. Model Implementation and Results

The results present the general output and findings of the models for two considered scenarios: the no platooning scenario and the platooning scenario. The study compares their outcomes by conducting sensitivity analysis on the main parameters of the model to see the variation of CO_2 reduces. The results of the presented models in this paper are obtained by using VENSIM PLE Version 9.4.2. All experiments are conducted on a personal computer with Intel Core (TM) i7 3630QM 2.40 GHz CPU, 8 GB RAM, and Windows 10 operating system.

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The simulation results indicate that the adoption of truck platooning technology over 180 months (15 years) for three different scenarios (optimistic, expected, and Pessimistic) is projected to follow the patterns illustrated in Figure 7. This figure demonstrates that the time required to achieve almost 50% market penetration of a platoonable truck fleet is approximately 100, 135, and 168 months for the optimistic, expected, and pessimistic scenarios, respectively. In these points, there will be an equilibrium between the number of platoonable and conventional trucks in the system. This implies that as time progresses and the truck platooning fleet increases, the number of conventional trucks will decrease. This finding suggests that platooning technology is likely to play a crucial role in the trucking industry in the near future and has the potential to capture a significant market share from traditional trucks.

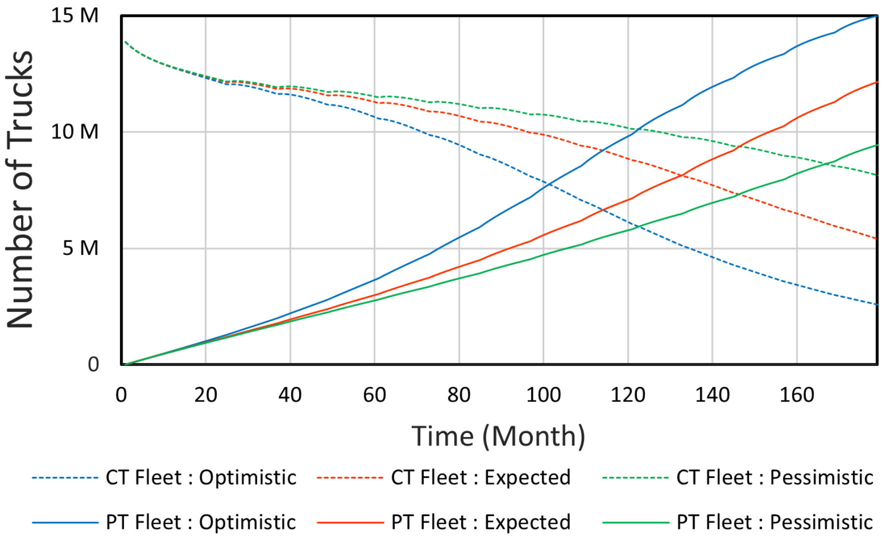

Figure 7. Diffusion of platoonable trucks during 180 months.

Additionally, the average labor-saving for these three scenarios is \$25, \$22, and \$20 per month per truck at the end of the model timescale (180 months), respectively (Figure 8). However, as evident from Figure 9, the fuel-saving values for each scenario are relatively modest, amounting to \$3, \$2.6, and \$2.4 per month per truck, respectively. Moreover, the main factors driving truck drivers' decisions to invest in platoonable trucks or platooning devices is the benefit-over-cost ratio and transition benefit-over-cost of the decision. Figure 10 illustrates that the benefit-over-cost ratio of purchasing a platoonable truck after 180 months is nearly equal to 3, 1.9, and 1 for optimistic, expected, and pessimistic scenarios, respectively. This indicates that as time progresses, platoonable trucks offer a more advantageous decision compared to conventional trucks in both optimistic and expected scenarios. However, in the pessimistic scenario, no clear preference can be observed since the benefit-over-cost ratio of purchasing a platoonable truck is equal to one after 15 years. That is to say, drivers are indifferent between buying a platoonable truck and conventional trucks based on the pessimistic scenario. Furthermore, the transition benefit-over-cost is equal to 1.8, 1.2, and 0.8 at the end of the model timescale (Figure 11). In other words as time moves forward, the benefit of purchasing a platoonable truck outweighs the cost of transforming a conventional truck into a platoonable one in optimistic and expected scenario.

Figure 12 shows that as the model's timescale increases, the total fuel saving stock shows an upward trend in all scenarios. Additionally, by considering no platooning as a base line model scenario with no fuel saving (zero emission reduction), Figure 13 illustrates the total emission reduction based on three platooning scenarios which follows a growing trend as time progresses. Furthermore, as a main finding of this paper, Figure 14 shows a comparison of total CO_2 emission stock in the platooning and no platooning scenarios. Despite our conservative assumption that only 5% fuel savings will result from platooning, Figure 14 indicates a substantial difference in CO_2 emissions: nearly 292 Million Metric Tons (MMT) after 180 months. To put this into context, the CO_2 reduction achieved through

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truck platooning is equivalent to the GHG emissions from 64,978,841 gasoline-powered passenger vehicles[6]. Moreover, a significant portion of the energy consumed in homes is derived from the combustion of fossil fuels such as natural gas, propane, and oil. When these fuels are burned for electricity generation or to provide heating for homes, they release GHG, primarily CO_2, into the atmosphere. As a result, for further comparison, the amount of CO_2 reduction achieved by truck platooning can be expressed as equivalent energy saved, which would be required to power 36,801,817 houses for a year[7].

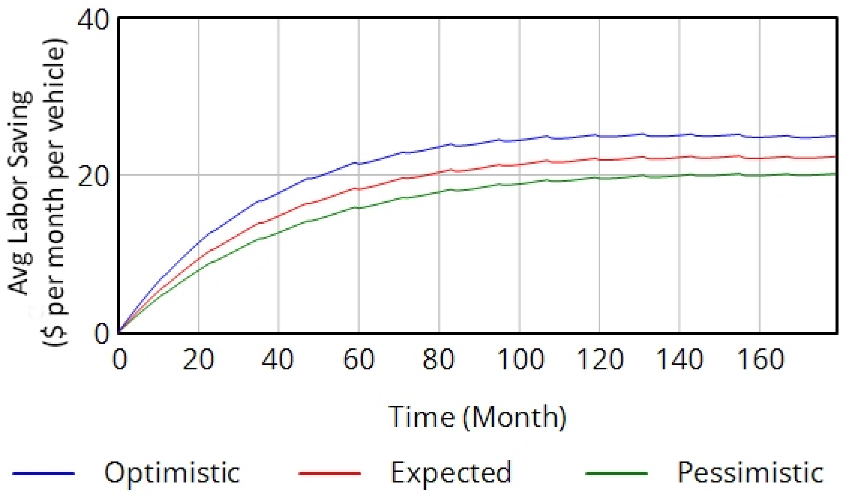

Figure 8. Average labor saving for optimistic, expected, and pessimistic scenarios.

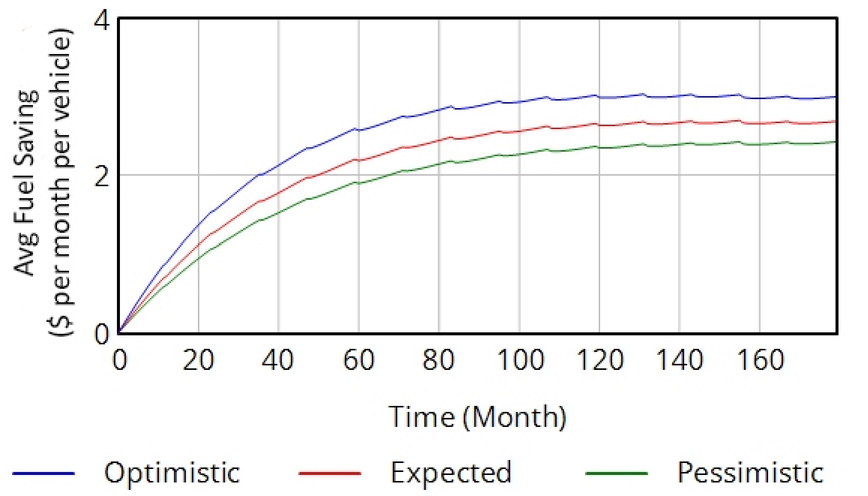

Figure 9. Average fuel saving for optimistic, expected, and pessimistic scenarios.

6 Passenger vehicles refer to two-axle four-tire vehicles, including passenger cars, vans, pickup trucks, and sport/utility vehicles. Additionally, the average VMT and fuel efficiency of vehicles are approximately 11,520 miles per year and 22.9 miles per gallon[70]. Furthermore, the amount of carbon dioxide emitted per gallon of motor gasoline burned is 8.89 × 10-3 metric tons [71],

7 This calculation assumes that each home in the US emits 7.93 metric tons of CO_2 annually, comprising 5.139 metric tons of CO_2 from electricity, 2.29 metric tons from natural gas, 0.23 metric tons from propane, and 0.27 metric tons from fuel oil [72]. These values are based on the [72] report in which each home consumes almost 11,880 kWh of delivered electricity, 41,590 cubic feet of natural gas, 42 gallons of propane, and 25.6 gallons of oil. To convert electricity, natural gas, propane, and oil to equivalent released CO_2 emission, we use the following converters: 884.2 lbs of CO_2 per megawatt-hour [73], 0.0550 kg of CO_2 per cubic foot [74], 235.0 kg of CO_2 per barrel [75], and 426.1 kg of CO_2 per barrel [75], respectively.

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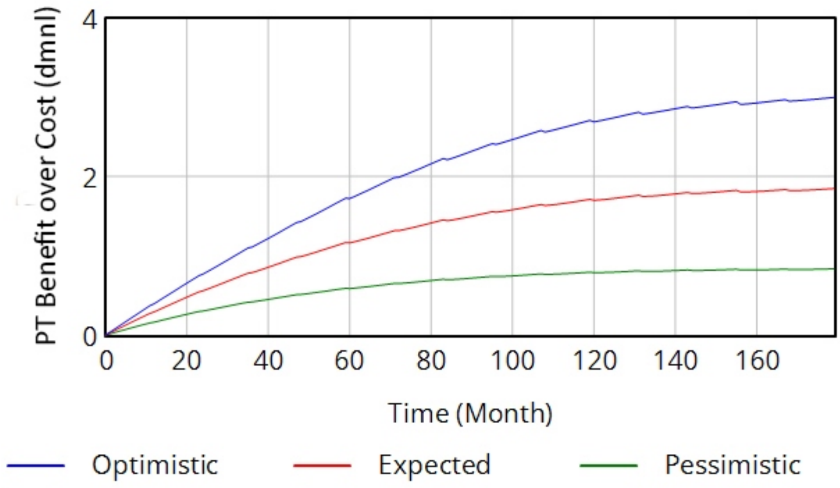

Figure 10. Platoonable truck benefit over cost ratio for optimistic, expected, and pessimistic scenarios.

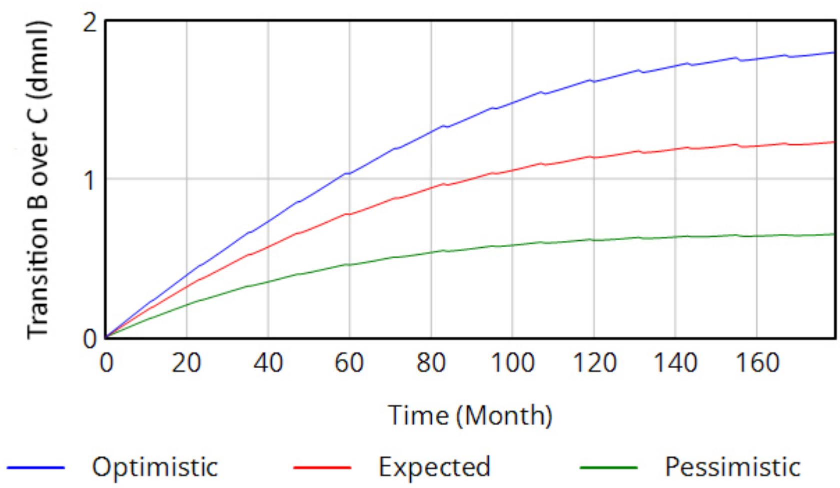

Figure 11. Platoonable truck transition benefit over cost ratio for optimistic, expected, and pessimistic scenarios.

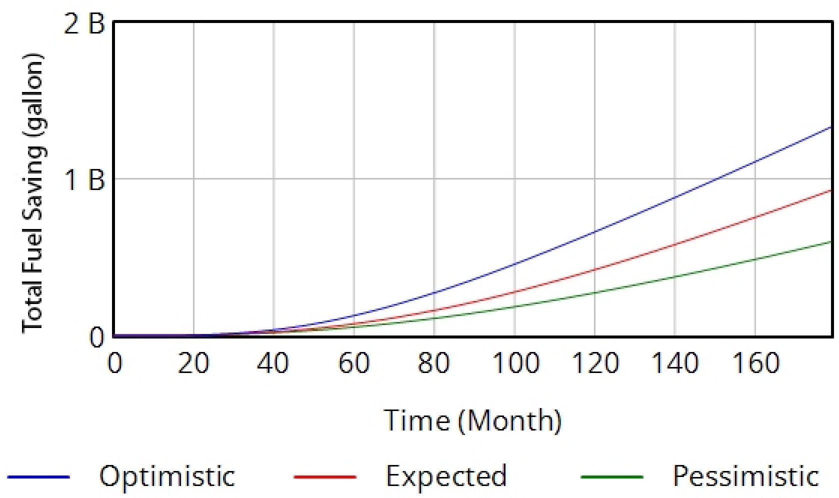

Figure 12. Total fuel saving for optimistic, expected, and pessimistic scenarios.

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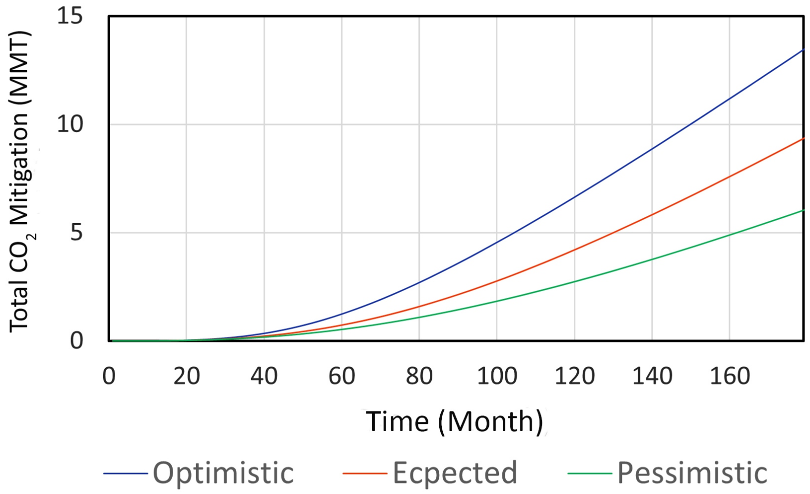

Figure 13. Total CO_2 mitigation for optimistic, expected, and pessimistic scenarios.

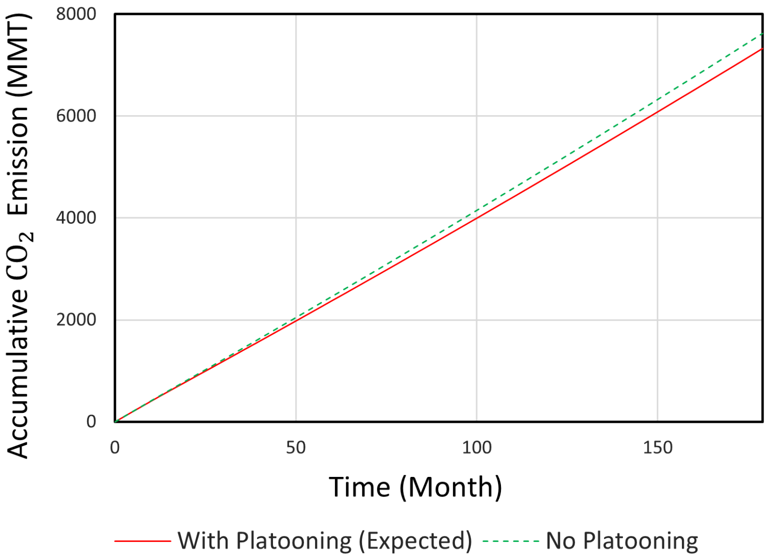

Figure 14. Accumulative CO_2 emission for platooning and no platooning models.

5.1. Sensitivity Analysis

In this subsection, we investigate the sensitivity of CO_2 emission to several parameters of the model during the diffusion of truck platooning technology. First, Figure 15 reports the sensitivity of the CO_2 emission reduction to fuel price for three scenarios of technology adoption. The vertical axis in the figure is equal to the amount of CO_2 savings after 15 years. As shown in the figure, the changes in the amount of CO_2 saving is more significant with higher fuel price for all the mentioned scenarios. For instance, when the fuel price is equal to \$10 per gallon, the CO_2 savings after 15 years amount to 13.4, 12.7, and 12.6 MMT for the optimistic, expected, and pessimistic scenarios, respectively. Interestingly, even when the fuel price tends towards zero, the amount of CO_2 emission reduction due to truck platooning remains substantial, exceeding 10.5 MMT for all scenarios. This is attributed to the additional benefits of the technology for truck drivers beyond fuel savings, like labor savings. Furthermore, the amount of CO_2 emission reduction follows an almost linear pattern with increasing fuel price per gallon. This finding suggests that raising fuel prices in the trucking industry can significantly contribute to reducing CO_2 emissions by encouraging a more rapid diffusion of truck platooning technology.

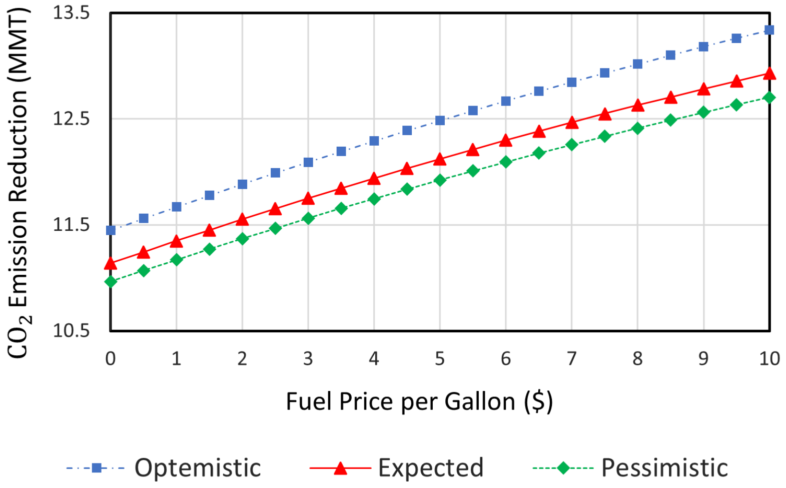

Figure 15. Sensitivity of CO_2 emission reduction to fuel cost.

Figure 16 illustrates the sensitivity of CO_2 emission reduction to the transition cost from a conventional fleet to a platoonable fleet. The results indicate a rapid decrease in CO_2 emission reduction, declining from approximately 12 MMT to around 5 MMT, as the transition cost increases from $1500 to $10,000 for all optimistic, expected, and pessimistic scenarios of technology adoption. Furthermore, the figure shows that the changes in CO_2 emission reduction within the range of transition costs from $10,000 to $25,000 are not significantly impactful. Observing the trend of change, it becomes evident that the decrease in CO_2 emission reduction follows an exponential pattern in response to the transition costs. This behavior can be attributed to the influence of the economy's interest rate. Figure 17 shows the sensitivity of the CO_2 emission reduction to fuel efficiency of the platooning technology. Note that with the current technology, the fuel saving is around 5% for the leading truck and around 10% for the following trucks [76]. The figure suggests that with one increasing the fuel saving of the technology, the CO_2 emission reduction would be increased by around 3 MMT for the investigated technology adoption scenarios. Finally, Figure 18 shows the sensitivity of CO_2 emission reduction to the interest rate of the economy. It shows an almost linear pattern of decreasing the CO_2 emission reduction with increasing the annual interest rate of the economy.

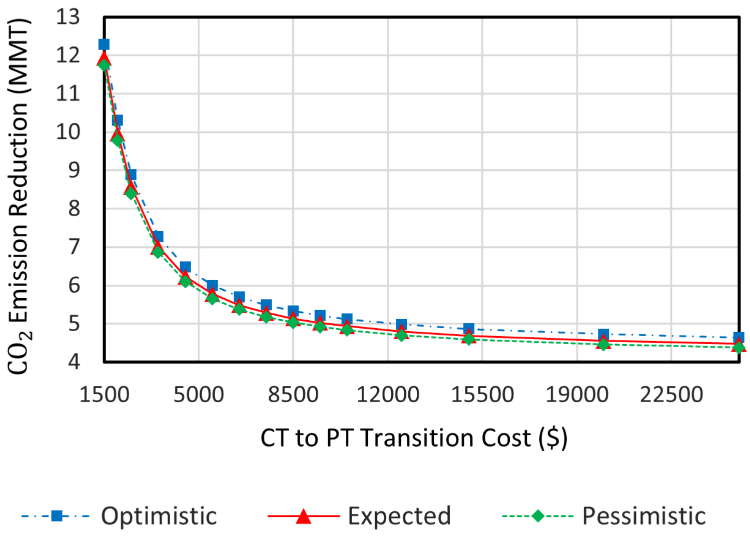

Figure 16. Sensitivity of CO_2 emission reduction to CT to PT transition cost.

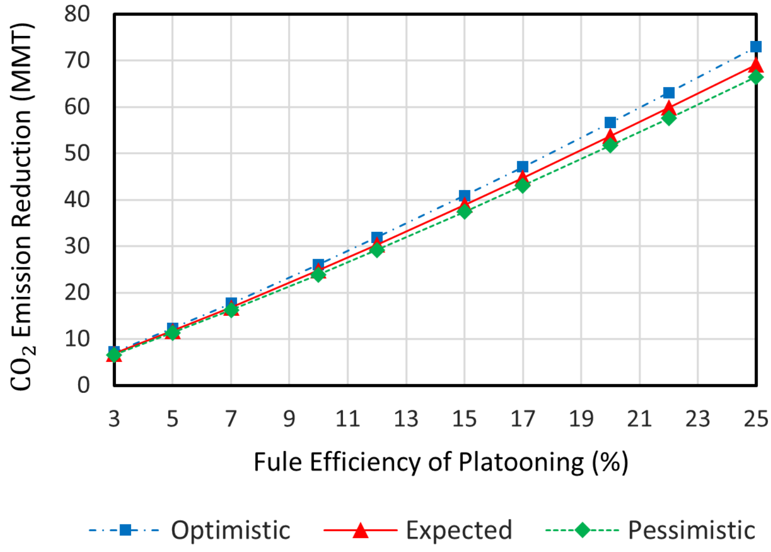

Figure 17. Sensitivity of CO_2 emission reduction to fuel efficiency.

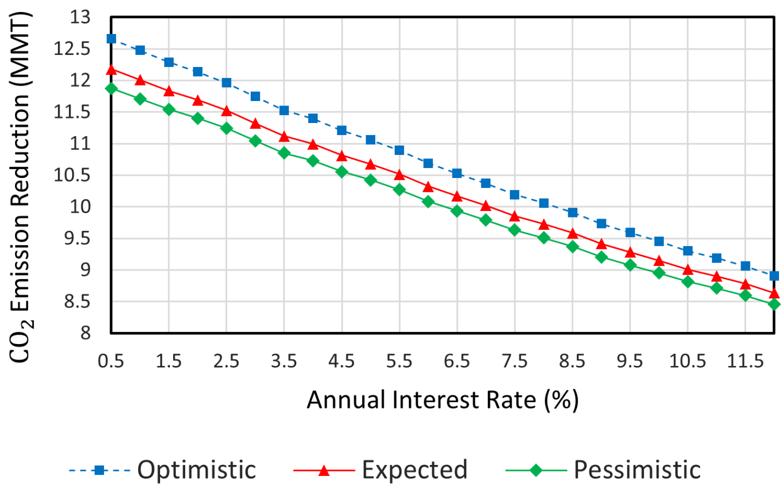

Figure 18. Sensitivity of CO_2 emission reduction to interest rate.

6. Conclusion

The imminent adoption of the platooning technology in the trucking industry prompts the need to understand its climate impact compared to without such a technology. Leveraging the system dynamics framework, we employ a causal loop diagram to model the dynamics of the trucking system with and without truck platooning. Our modeling results reveal substantial reductions in CO_2 emissions across optimistic, expected, and pessimistic scenarios characterized by different technology adoption rates. Sensitivity analysis reveals a positive linear correlation between fuel price and the efficiency of truck platooning with emission reduction. This finding suggests that raising fuel prices in the trucking industry can significantly contribute to reducing CO_2 emissions by encouraging a more rapid diffusion of truck platooning technology. The modeling results demonstrate that increasing fuel efficiency has a significant impact on CO_2 emission reduction as well. Furthermore, the transition cost of a conventional truck to a platoonable truck to $10,000, a rapid drop in CO_2 emissions is observed. However, for costs exceeding $10,000, the decrease in CO_2 emissions becomes more gradual. Finally, by increasing annual interest rate a slow decrease can be seen in CO_2 emissions for all scenarios. These findings have important implications for decision-makers, underscoring the importance of critical influencing factors for adoption of platooning technology in the trucking industry.

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We acknowledge that the present study presents just a beginning for understanding the climate impact of truck platooning. There exist some limitations which may warrant further investigations. First, the analysis pertains to a generalized network system, with no differentiation of the nuances across local and interstate road segments, as well as truck speed variations on these segments. Future studies may consider an integration of some agent-based simulations to better reflect route and traffic details on the road network studied. Second, our current work does not explore the impact of truck spacing while platooning and platoon size on fuel saving. These aspects warrant further investigation to comprehensively understand their contributions to the overall fuel efficiency of truck platooning. Third, the study does not consider the role of truck platooning in emission reduction through the potential increase in road capacity. Future investigations could address this aspect, offering insights into the broader environmental benefits of truck platooning. Fourth, the analysis focuses solely on diesel trucks capable of platooning. As a constructive step forward, future research could explore scenarios involving electric platoonable trucks, which may yield even more significant reductions in CO_2 emissions.

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