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Truck platooning technology diffusion: System dynamics with matching platform consideration

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ABSTRACT

Truck platooning pertains to virtually coupling trucks to cut aerodynamic drag. Despite its many benefits, the dynamics of the trucking industry in adopting this technology is not well understood. In this paper, we investigate the dynamics and particularly the impact of the presence of a matching platform on platooning technology diffusion. On the qualitative side, two positive feedback loops and a larger encompassing feedback loop are unveiled. On the quantitative side, tailored system dynamics models (SDMs) are developed to quantify the feedback loops and technology diffusion evolution. We demonstrate use of the SDMs by applying them to the US trucking industry. We find that having a matching platform can significantly accelerate the platooning technology adoption. The fuel and labor savings also substantially differ with a platform. The findings help inform decision- and policy-making towards more coordinated and beneficial truck platooning technology adoption and operations, thereby improving sustainability of freight transportation.

1. Introduction

Truck platooning is an emerging technology that enables virtual coupling of trucks in convoy at an aerodynamically optimized separation, with the primary motivation to reduce truck energy use. While traveling in a platoon, the lead truck is considered to be operated by a human driver in the near- to mid-term future, while the following trucks respond to the lead truck's actions with high automation and limited human intervention (Bhoopalam et al., 2018). The trucking industry has been actively pursuing and pilot testing the technology, anticipating the considerable market potential. The global market value of truck platooning is estimated at $64 billion in 2021 and is projected to grow up to $3.5 trillion by 2030, or a compound growth rate of 56.2% per year (Precedence Research, 2022).

Truck platooning offers a multitude of benefits, including fuel saving, labor saving, emission reduction, enhanced road capacity, and possibly also improved road safety (Song et al., 2021; Al-Qadi et al., 2021; Balador et al., 2022; Barua et al., 2023). Among them, fuel saving benefit has been emphasized the most in the literature, with varying estimates in the range of 4%–12% for a platooning truck, depending on factors such as inter-truck distance and travel speed (Lammert et al., 2014; McAuliffe et al., 2018). Apart from fuel saving, various driver assistance technologies adopted in truck platooning, such as automated vehicle braking, lane departure warnings, and advanced sensors and software, are expected to work in tandem to safely and efficiently maneuver trucks while in a platoon (Council, 2018). These technologies can alleviate truck driver workload and thus offer labor saving benefit, which is less appreciated and quantified than the benefit of fuel saving. These technologies also help enhance traffic safety by reducing human error and enabling quicker response times (Peloton, 2020). For example, automatic braking in platooning can react five times faster than a human driver, which significantly lowers the risk of rear-end collisions (ACEA, 2017). With a smaller inter-truck distance in a platoon, truck platooning further reduces the use of road space compared to trucks traveling individually. This increases the effective road capacity, which in turn helps mitigate traffic congestion and the need for infrastructure investment (Tsugawa et al., 2016; Noruzoliaee et al., 2021). Recent research, such as the European ENSEMBLE project, demonstrated the potential of multi-brand interoperable platooning, which is critical to large-scale deployment of truck platooning (Schmeitz et al., 2023; Willemsen et al., 2023).

While truck platooning has yet to be implemented in the real world, two possibilities of forming platoons have been widely considered. One possibility is "opportunistic platooning", under which a truck spontaneously communicates with another truck when in close proximity. A platoon will be formed if two trucks have a long-enough common path ahead. The other possibility is "planned platooning", which is enabled by a matching platform. Trucks submit their routing and scheduling

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information to the platform, which then creates a platooning plan to achieve a certain system objective, such as maximizing total platooning benefits. Because of the system optimization, a matching platform is expected to allow trucks to travel in platoons to a greater extent than under opportunistic platooning. There also exist varied versions of planned platooning in the literature, for instance, hub-based and event-triggered platoon formation (Johansson et al., 2020, 2023; Bai et al., 2021) and multi-fleet platooning coordination (Johansson et al., 2022; Bai et al., 2023). The need for a matching platform is indeed very relevant to the trucking industry, which is known to be fragmented. Take the US as an example. Among the two million truck carriers, 57% of them just have one truck (FMCSA Federal Motor Carrier Safety Administration, 2022). Understanding the additional benefits brought by a matching platform is therefore important to policy-making, infrastructure investment, system planning, and deployment of truck platooning.

The deployment of truck platooning is a dynamic process. It starts from today's situation that the vast majority of the existing trucks are traditional and do not have the capability of platooning. As drivers see the benefits of platooning, they will consider either purchasing a new truck with platooning capability — which we term as "platoonable truck", or converting their existing traditional trucks to platoonable trucks. Such purchase/conversion decisions are made based on the benefit and cost of doing so. In particular, the benefit stems from the extent to which a driver with a platoonable truck can platoon while traveling, which depends on the percentage of trucks that are platoonable on road and how platoons are formed, i.e., whether opportunistically or centrally planned through a matching platform. In this way, the presence of a matching platform positively affects not only platooning operations, but also the decision on platoonable truck purchase/conversion. As the percentage of platoonable trucks in total trucks and the use of the platform by the platoonable trucks increase, greater platooning benefits are expected, which in turn promotes driver decisions on platoonable truck purchase/conversion. The interactions described above continue over time, constantly driving the evolution of the platooning technology diffusion and performance of the trucking industry.

Despite the promise of platooning to the trucking industry and the potentially sophisticated interactions described above, the literature on truck platooning technology adoption from a system perspective is limited. We are only aware of Aboulkacem and Combes (2023), who design a system dynamic model for the market uptake of truck platooning, but dealing with only one origin–destination pair. No research exists to characterize system dynamics of truck platooning technology diffusion considering the possibility of having a matching platform. This study attempts to fill this research gap, by making three contributions.

- First, we provide a qualitative characterization of the system dynamics in the trucking industry while adopting the platooning technology, both without and with a platooning matching platform. The characterization unveils two positive feedback loops among the different elements in the trucking industry that are inherent in the process of platooning technology adoption, and a larger feedback loop encompassing the two loops when a matching platform is present.
- Second, we develop system dynamics models (SDMs) to explicitly quantify the interactions of the various elements in the trucking industry, feedback loops, and temporal evolution in platooning technology adoption without and with a platform. The model development entails estimating functions about platooning probabilities while trucks are on road. These functions are integral to the SDMs but cannot be straightforwardly derived. To address this challenge, agent-based modeling and optimization are employed for function estimation.
- Third, we demonstrate use of the SDMs by applying them to the US trucking industry. We find that having a matching platform can significantly accelerate adoption of the platooning technology. The chance of traveling in platoons will significantly increase as well, along with much greater fuel and labor savings. It takes much less time for the industry to reach a 50% platooning technology adoption rate with a matching platform. Over a 20-year simulation period, the cumulative fuel and labor savings can amount to $69.5 billion and $403.7 billion, without and with a platform.

It is worth mentioning that this study assumes multi-brand platooning, i.e., a truck can platoon with any another truck regardless of whether they belong to the same trucking company. Also, labor savings from platooning are influenced by the truck automation level. In this study, we consider that platooning is performed under Level 1 or 2 automation, more specifically with Cooperative Adaptive Cruise Control (CACC). At these automation levels, the lead truck in a platoon is operated by a human driver. Each non-lead truck is semi-automated, maintaining a reduced separation from its preceding truck and responding to the lead truck's speed changes with limited human intervention. Drivers in the non-lead trucks remain responsible for system monitoring and will take over control in unexpected situations. In this way, while the reduced workload for non-lead trucks may not be considered as a formal driving break (working time reduction), it can still be viewed as labor savings.

With the above contributions, the value of this research is manifold. First, the research provides freight transportation researchers and practitioners with an overall picture of the system dynamics in the trucking industry facing the platooning technology, especially considering the potential presence of a platooning matching platform. Second, the methodology developed behind the SDMs is easy to implement and can potentially be applied to studying truck platooning system dynamics in other geographical regions in the US and outside. Third, the numerical results from applying the SDMs provide first-of-its-kind projections of truck platooning adoption over time and the associated fuel and labor saving benefits for the US trucking industry. In particular, the different projections without and with a matching platform are helpful to inform future decision- and policy-making towards truck platooning technology adoption and operations that are more coordinated, beneficial, and sustainable.

The remainder of this paper is organized as follows. In Section 2, we qualitatively characterize the dynamics in truck platooning technology adoption, where feedback loops inherent in the adoption are unveiled and highlighted through causal loop diagrams. Building on the qualitative characterization, Section 3 develops SDMs to quantify the system dynamics in the trucking industry when adopting the platooning technology. Section 4 presents the results of applying the SDMs to the US trucking industry and tests sensitivity of the results to key model parameters. Section 5 concludes the paper, discusses the limitations, and suggests directions for further research.

2. Qualitative characterization with causal loop diagrams

The central focus of this study is to characterize the system dynamics that would drive how the trucking industry evolves while adopting the platooning technology, especially with the use of a platooning matching platform. Characterizing the system dynamics requires understanding how different elements in the trucking industry interact with one another. In the dynamics, two aspects are fundamental in truck platooning. First, a driver needs to have a platoonable truck to be able to platoon. A platoonable truck can be acquired either through a new purchase, or by converting a traditional truck to a platoonable one, both incurring some cost. Second, given the number of platoonable trucks, how platoons are formed influences the extent of platooning. In the context of this study, the extent of platoon formation hinges critically on whether a matching platform is present.

Conceptually, when a matching platform is not present, the formation of platoons will be at the hands of individual trucks. As platoonable trucks are expected to have the capability to connect to nearby peer platoonable trucks, it is speculated that a platoonable truck starts communicating with another platoonable truck on possible platooning when the two trucks are in close proximity. Besides location proximity, the decision on whether to form a platoon depends on whether there is a sufficient overlap between the two trucks' routes. When a matching platform is present, platoonable trucks may subscribe to use the platform. The platform collects routing information from the subscribed trucks, based on which a central platooning plan is developed. As such a plan uses many trucks' information towards a system optimum outcome, the extent of platooning is expected to be greater than without a platform, yielding further fuel and labor saving benefits.

The two aspects mentioned above (i.e., the number of platoonable trucks and the extent of platooning) are not independent but intertwined. To depict the intertwining relationships, we propose two causal loop diagrams (CLDs), one without and one with a matching platform as shown in Fig. 1. CLD is particularly suitable for the purpose of the study, given that CLD allows for qualitative characterization and visualization of the complex feedback loops and interactions that are inherent in the adoption of truck platooning technology. Specifically, when a platform is not present, the extent of platooning is represented by the probability of opportunistic platooning, measured as the ratio of platooning miles in total miles driven by a platoonable truck (as defined later in Table 1). The probability determines the benefits from platooning, which consist of fuel and labor savings. The platooning benefits affect driver decisions on whether to have a platoonable truck, through either a new purchase or converting one's traditional truck to a platoonable one, which collectively determine the number of platoonable trucks in the trucking industry. The number of platoonable trucks affects the likelihood of individual platoonable trucks encountering one another on road and forming platoons, thus the probability of opportunistic platooning. It can be seen that these intertwining relationships form a positive feedback loop, as shown in Fig. 1a.

Besides the above positive feedback loop, the presence of a matching platform further promotes platooning, which is represented by the probability of planned platooning. The probability of planned platooning is measured as the ratio of *planned* platooning miles in total miles driven by a platoonable truck (also defined in Table 1). The higher the probability, the greater the benefits of platooning using the platform, which increase the propensity to use the platform. Greater propensity means that more platoonable trucks will use the platform, which in turn enhances the probability of planned platooning. Thus, there is another positive feedback loop associated with the presence of a matching platform. What is more, the benefits of platooning using the platform will be counted when computing the total benefits of platooning for benefit-cost (B/C) analysis, given that a platoonable truck has a propensity to use the platform. Obviously, the number of platoonable trucks using the platform also depends on the number of platoonable trucks. So, on top of the two positive feedback loops, a larger loop is further formed. These feedback loops are shown in Fig. 1b. For reading focus, the parts that are the same as in Fig. 1a are displayed in light color in Fig. 1b.

By mapping out the above-mentioned relationships, the proposed CLDs offer a clear picture of the dynamic nature of truck platooning diffusion, especially how changes in one part of the system will propagate to the other parts and permeate through the entire system. On the other hand, the above CLDs only extract the main dynamics in the trucking industry facing the platooning technology in a qualitative manner. A fuller and more quantitative depiction of the dynamics requires greater details of the feedback loop characterization with additional variables and parameters. This will be enabled by system dynamics modeling, as presented in the next section.

3. System dynamics model development

This section presents the development of the SDMs. Section 3.1 specifies two stock-flow models, which correspond to truck platooning without and with a matching platform. Section 3.2 describes how values of the SDM parameters are determined. Section 3.3 estimates the platooning probability functions as they are used in the SDMs.

3.1. Specifying stock-flow models

System dynamics modeling is a mathematical modeling technique for framing, understanding, and discussing complex issues and problems due to underlying interactions which govern the dynamics (Forrester, 1994). Stocks and flows are the basic building blocks of system dynamics modeling, which represent the accumulation of physical or non-physical quantities (stocks) over time and the flow rates that affect these stocks. The quantities of interest in our SDMs are the number of traditional trucks and platoonable trucks over time. Section 3.1.1 details the stock-flow model without a platform. Building on the stock-flow model, Section 3.1.2 develops a second stock-flow model with a matching platform.

3.1.1. Model without a platform

The SDM in this subsection estimates the number of traditional and platoonable trucks over periods without a matching platform, while keeping the total number of trucks constant. Fig. 2 illustrates the stock-flow model. Part a of the figure shows the interactions among the variables involved, while part b of the figure shows the needed input parameters for computing each variable. In Fig. 2a, the number of traditional trucks in a period is calculated based on the existing number (i.e., stock) of traditional trucks from the previous period, plus the number of traditional truck purchases (Trad_Truck_Purchase), minus the number of traditional trucks converted to platoonable ones (Trad_Truck_Convert), and minus the number of traditional trucks out of the system due to depreciation (Trad_Truck_Depre). For the first period, the existing number (i.e., stock) of traditional trucks is equal to the number of drivers (termed as "Drivers", which is equal to the initial number of trucks) minus the initial number of platoonable trucks (Initial_Plat_Trucks). This is shown by the connections to the stock box "Trad_Trucks". Similarly, the number of platoonable trucks in a period is calculated based on the existing number of platoonable trucks (which is equal to Initial_Plat_Trucks for the first period), plus the number of platoonable truck purchases (Plat_Truck_Purchase), plus the number of trucks converted from traditional to platoonable ones (Trad_Truck_Convert), and minus the number of platoonable trucks out of the system due to depreciation (Plat_Truck_Depre). This is shown by the connections to the stock box "Plat_Trucks".

Building on the two stock variables Trad_Trucks and Plat_Trucks, we proceed to modeling the driver decision-making of adopting the platooning technology, in the form of either purchasing new platoonable trucks or converting traditional trucks to platoonable ones. The platooning technology adoption decision is modeled as a function of the B/C ratio of purchasing a new platoonable truck compared to a traditional truck (B/C in Fig. 2a) in the case of purchase, and a function of the B/C ratio of converting a traditional truck to a platoonable one (Convert_B/C in Fig. 2a) in the case of converting.

For purchasing a platoonable truck, the B/C ratio depends on fuel and labor savings (Fuel_Save_Month and Labor_Save_Month), the price difference between the two types of trucks, the additional operating cost due to platooning capability (Plat_Cost_Month), discount rate, and the time horizon for B/C analysis. Note that Fig. 2a only shows the interactions between variables in the SDM. The prices of platoonable and traditional trucks (Plat_Truck_Price and Trad_Truck_Price), discount rate (Discount_Rate), and the time horizon for B/C analysis (B/C_Time_Horizon) are parameters in the SDM, which are shown separately in Fig. 2b. When a platform is not present, the fuel and

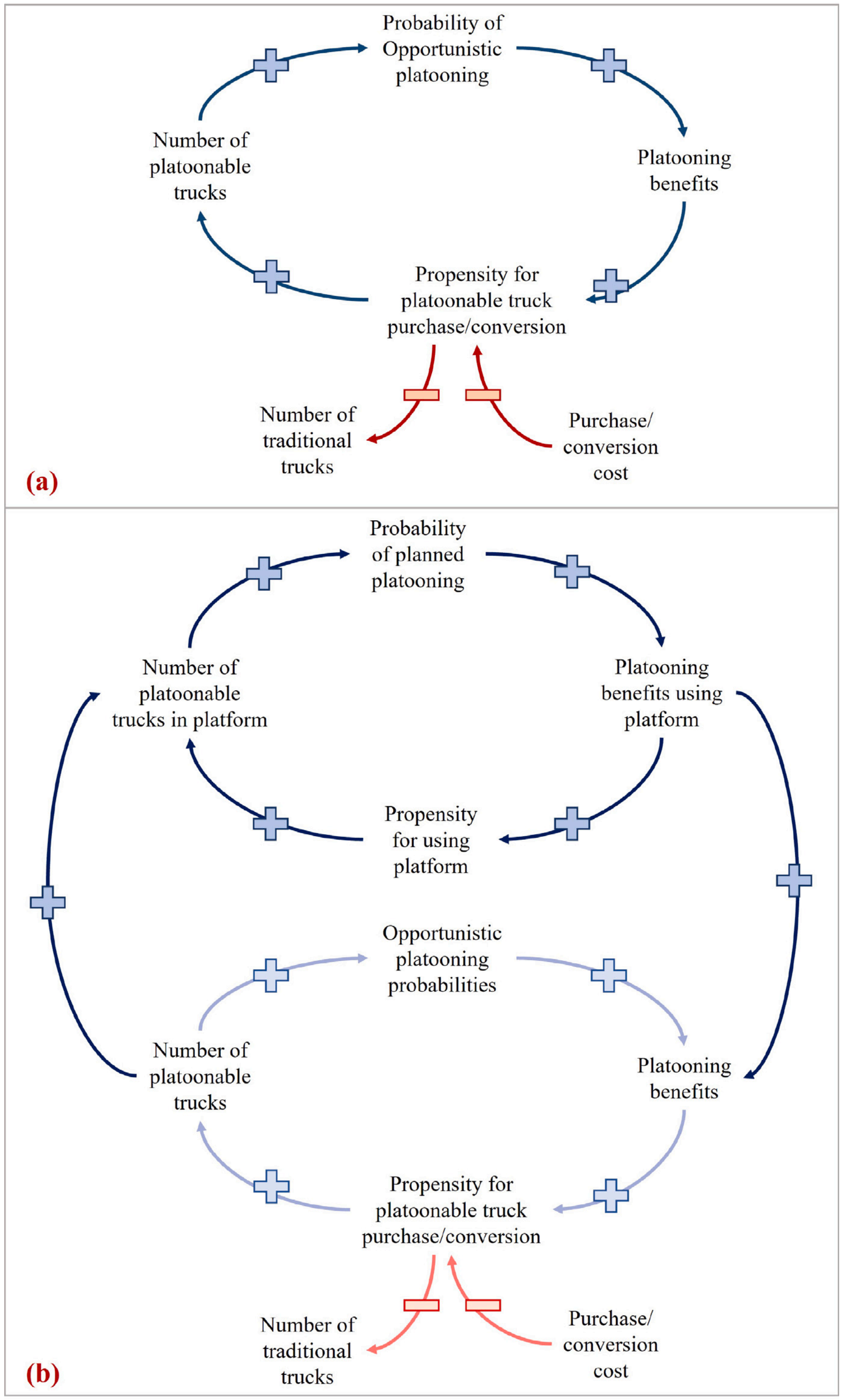

Fig. 1. Truck platooning causal loop diagrams: (a) without a platform, (b) with a platform.

labor savings depend on the probability of opportunistic platooning (Pr_Opp_Plat), which further depends on the probability of finding an adjacent truck as a platoonable truck while on road. The latter probability, termed Pr_Plat_Comp, is measured as the ratio of platoonable trucks in total trucks. For converting a traditional truck to a platoonable one, the B/C ratio is similarly specified. The specific form of the platooning technology adoption functions and its estimation are discussed later in Appendix B.

The complete definitions of the variables and parameters appearing in Fig. 2 (and in Fig. 3) are presented in Tables 1 and 2 respectively. Given that the unit period of the SDM is one month, "per month" is specified for some variables and parameters as needed. To preserve brevity, Fig. 2a only displays the directional connections of the variables. The detailed formulations of all the variables (in total 14) in this figure are given in Eq. (A.1)–(A.14) in Appendix A.

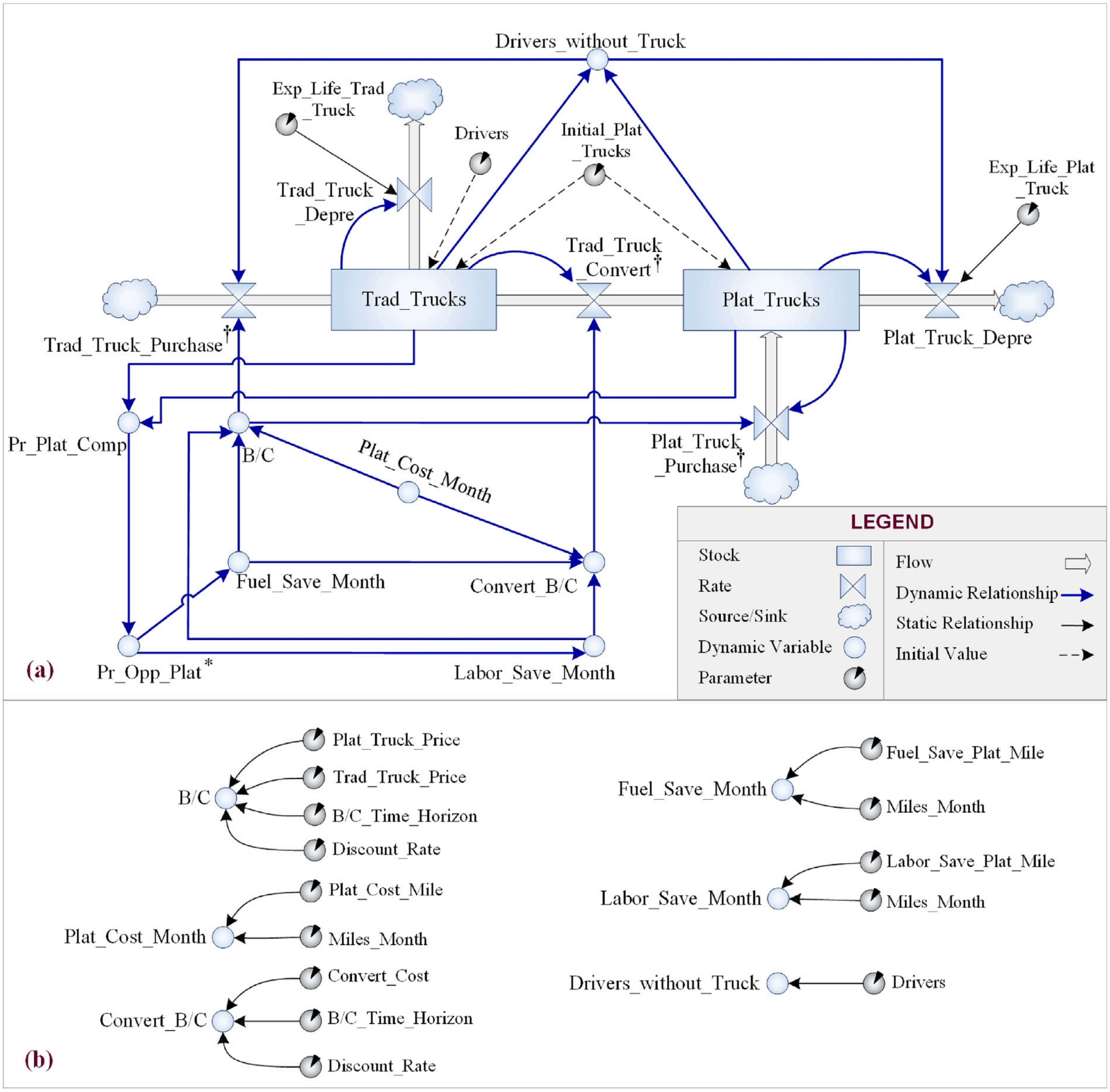

Fig. 2. (a) Stock-flow model without platform. * and † denote interface with agent-based modeling and the adoption rate functions, respectively. (b) Input parameters without a platform.

3.1.2. Model with a platform

Compared to opportunistic platooning without a platform, a matching platform enhances the efficiency of truck platooning by enabling trucks to platoon in a more planned manner. As such, in this paper platooning with a platform is also referred to as planned platooning. With planned platooning, the extent of platooning is expected to increase, leading to further fuel and labor savings. To reflect the benefit changes, two new terms, fuel and labor savings from planned platooning with a platform (Fuel_Save_Platf_Month and Labor_Save_Platf_Month) are added at the bottom right of Fig. 3a, which illustrates the stock-flow model with a matching platform. Fuel_Save_Platf_Month and Labor_Save_Platf_Month, together with the monthly platform use cost Platf_Use_Cost_Month, affect the B/C ratio of using a platform (Platf_B/C). This further affects the number of trucks using the platform (Platf_Trucks) and consequently the probability of planned platooning (Pr_Platf_Plat). In turn, Pr_Platf_Plat influences the amount of fuel and labor savings under planned platooning.

Note that trucks using a platform can still opportunistically platoon. Therefore, the *combined* probability of platooning (a combination of opportunistic and planned platooning), denoted by Pr_Comb_Plat, is also introduced. By comparing Fig. 3 with Fig. 2, we can see that this combined probability Pr_Comb_Plat replaces Pr_Opp_Plat in affecting fuel and labor savings when a platform is present. These added variables and their interactions due to the presence of a platform are highlighted in Fig. 3a. For reading focus, the parts already in Fig. 2a are shaded in Fig. 3a. Similarly to Fig. 2b, Fig. 3b shows the needed input parameters when computing the variables. Again, in Fig. 3b only the new variables and parameters are in black while the remaining are shaded. The detailed formulations of the newly added variables are given in Eq. (A.15)–(A.21) in Appendix A.

3.2. Determining SDM parameter values

This subsection describes how the values of the SDM parameters in Table 2 are determined. For some of the parameters, their values in the context of the US trucking industry are reported in the literature. In this case, the reported values are directly taken. We consider the US context, as it is the context in which our system dynamics simulations are performed. For two parameters, their values are indirectly calculated.

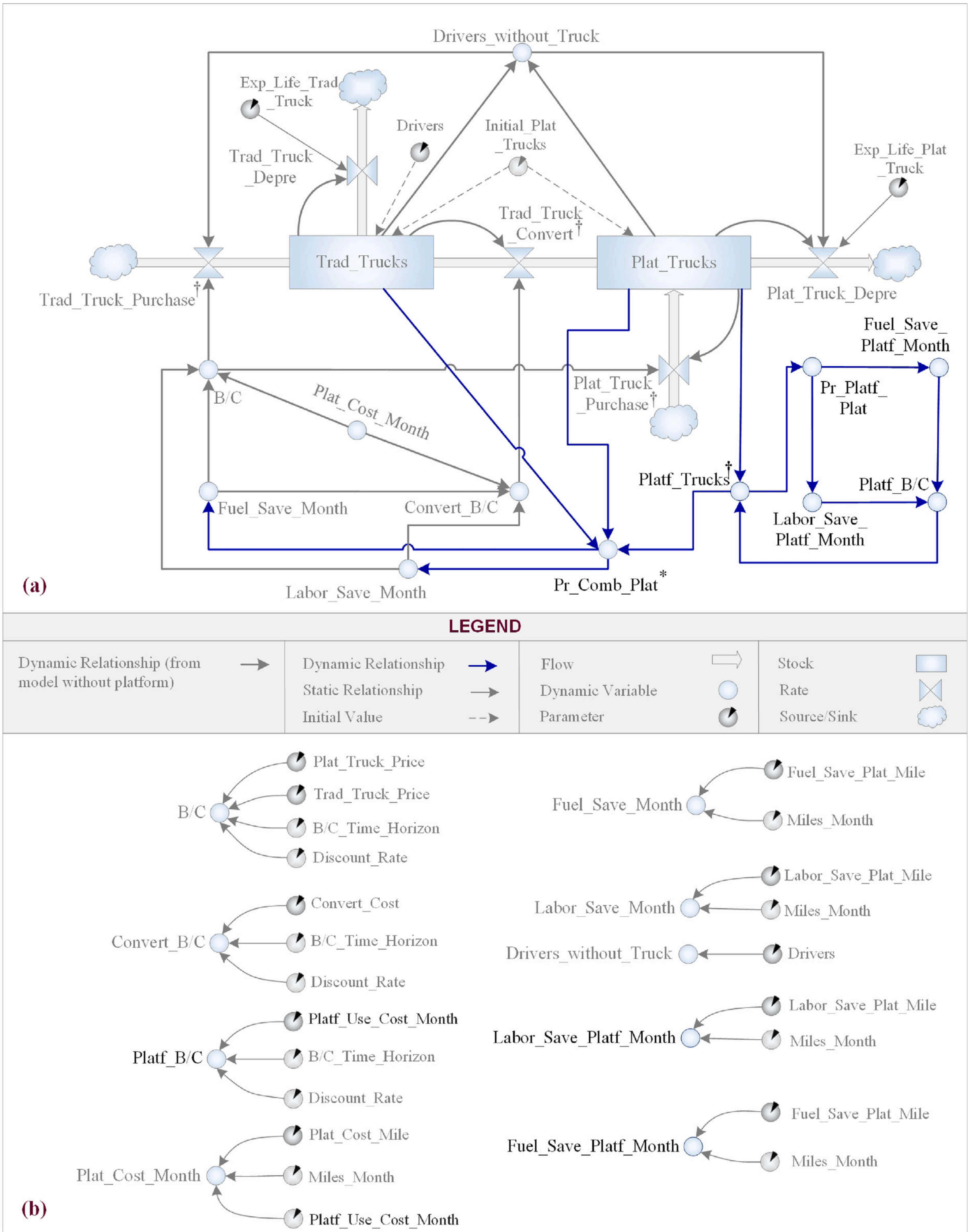

Fig. 3. (a) Stock-flow model with platform. ∗ and † denote interface with agent-based modeling and the adoption rate functions, respectively. (b) Input parameters with platform.

The first is Plat_Cost_Month, the additional operating cost due to platooning capability per truck-month, which is calculated by multiplying the additional operating cost due to platooning capability per truck-mile (Plat_Cost_Mile) by the number of miles traveled per truck-month (Miles_Month). The second is Fuel_Save_Plat_Mile, the fuel saving per platooning truck-mile measured in dollars, which is calculated as the product of fuel price, fuel use per truck-mile, and fuel saving rate with platooning, which take the values of $4/gallon, 0.16 gallons/truck-mile, and 6% respectively (Gas Price, 2023; Elgin, 2023; McAuliffe et al., 2018). When an appropriate value for a parameter cannot be found from the literature, an assumed value is used instead.

The parameter values adopted in our SDMs and their corresponding sources/assumptions are reported in the last two columns of Table 2. Additional information and when possible justifications for the assumptions are provided below.

Table 1
Variable definitions and formulations.

Variable	Definition	Formulation
Trad_Trucks	Number of traditional trucks in the system	Eq. (A.1)
Plat_Trucks	Number of platoonable trucks in the system	Eq. (A.2)
Trad_Truck_Purchase	Number of traditional truck purchases per month	Eq. (A.3)
Trad_Truck_Convert	Number of traditional trucks converted to platoonable trucks per month	Eq. (A.4)
Plat_Truck_Purchase	Number of platoonable truck purchases per month	Eq. (A.5)
Trad_Truck_Depre	Number of traditional trucks out of system due to depreciation per month	Eq. (A.6)
Plat_Truck_Depre	Number of platoonable trucks out of system due to depreciation per month	Eq. (A.7)
B/C	Benefit-cost ratio of purchasing a new platoonable vs. a new traditional truck	Eq. (A.8)
Convert_B/C	Benefit-cost ratio of converting a traditional truck to a platoonable one	Eq. (A.9)
Drivers_without_Truck	Number of drivers without a truck in the system	Eq. (A.10)
Fuel_Save_Month	Fuel saving per platoonable truck-month ($)	Eq. (A.11)
Labor_Save_Month	Labor saving per platoonable truck-month ($)	Eq. (A.12)
Pr_Opp_Plat	Probability of opportunistic platooning, measured as the ratio of platooning miles in total miles driven per platoonable truck-month without platform	Eq. (A.13)
Pr_Plat_Comp	Probability of finding an adjacent truck to be a platoonable truck, measured as the ratio of platoonable trucks in total trucks	Eq. (A.14)
Fuel_Save_Platf_Month	Fuel saving per platoonable truck-month if using platform ($)	Eq. (A.15)
Labor_Save_Platf_Month	Labor saving per platoonable truck-month if using platform ($)	Eq. (A.16)
Platf_B/C	Benefit-cost ratio of a platoonable truck using platform	Eq. (A.17)
Platf_Trucks	Number of platoonable trucks using platform	Eq. (A.18)
Pr_Platf_Plat	Probability of planned platooning using platform, measured as the ratio of planned platooning miles in total miles driven per platoonable truck-month with platform	Eq. (A.19)
Pr_Comb_Plat	Probability of combined platooning, measured as the ratio of total platooning (planned and opportunistic) miles in total miles driven per platoonable truck-month with platform	Eq. (A.20)
Pr_Platf_Comp	Probability of finding a platoonable truck in the platform	Eq. (A.21)

Table 2
Input parameter definitions, values, and sources.

Parameter	Definition	Value	Source
Drivers	Number of drivers in the system (the US)	3,500,000	Elgin (2023)
Initial_Plat_Trucks	Initial number of platoonable trucks	1500	Assumption 1
Trad_Truck_Price	Price of a traditional truck ($)	150,000	Durabak (2021)
Plat_Truck_Price	Price of a platoonable truck ($)	160,000	Assumption 2
Convert_Cost	Cost of converting a traditional truck to a platoonable truck ($)	15,000	Assumption 2
Discount_Rate	Discount rate per year	0.055	Assumption 3
Miles_Month	Miles traveled per truck-month	8000	Free Freight Search (2019)
Plat_Cost_Mile	Additional operating cost due to platooning capability per truck-mile without platform ($)	0.005	Assumption 4
Plat_Cost_Month	Additional operating cost due to platooning capability per truck-month without platform ($)	40	Plat_Cost_Mile × Miles_Month
Platf_Use_Cost_Month	Cost of using platform per truck-month ($)	10	Assumption 4
Fuel_Save_Plat_Mile	Fuel saving per platooning truck-mile ($)	0.038	Gas Price (2023), McAuliffe et al. (2018), Elgin (2023)
Labor_Save_Plat_Mile	Labor saving per platooning truck-mile ($)	0.1	Assumption 5
Exp_Life_Trad_Truck	Expected life of a traditional truck (months)	120	Rydell (2021)
Exp_Life_Plat_Truck	Expected life of a platoonable truck (months)	120	Assumption 6
B/C_Time_Horizon	Time horizon for B/C analysis (months)	120	Assumption 6

- **Assumption 1** (Initial number of platoonable trucks): Since large-scale truck platooning does not yet exist, the initial number of platoonable trucks is set at 1500.
- **Assumption 2** (Platoonable truck price and conversion cost): Given that the price of a traditional truck is $150,000 (Durabak, 2021), the price of a platoonable truck is assumed to be $160,000. We further assume that the cost of installing platooning equipment to convert a traditional truck to a platoonable truck is $15,000.
- **Assumption 3** (Discount rate): Our choice of a discount rate of 5.5% per year is informed by the recent interest rate (Chang, 2023), which is used as a proxy for discount rate.
- **Assumption 4** (Additional cost associated with platooning): The additional operating cost due to platooning capability is assumed to be $0.005 per truck-mile. In addition, using a matching platform is assumed to incur a monthly platform subscription cost of $10 per truck-month.
- **Assumption 5** (Labor saving): Current driver wage is around $0.5 per mile (Melton Truck Lines, 2023). While in a platoon, non-leading truck drivers may be able to take a break, thereby receiving some resting benefit. This benefit is assumed to be on average 20% per driver in platooning, or $0.1 per platooning truck-mile.

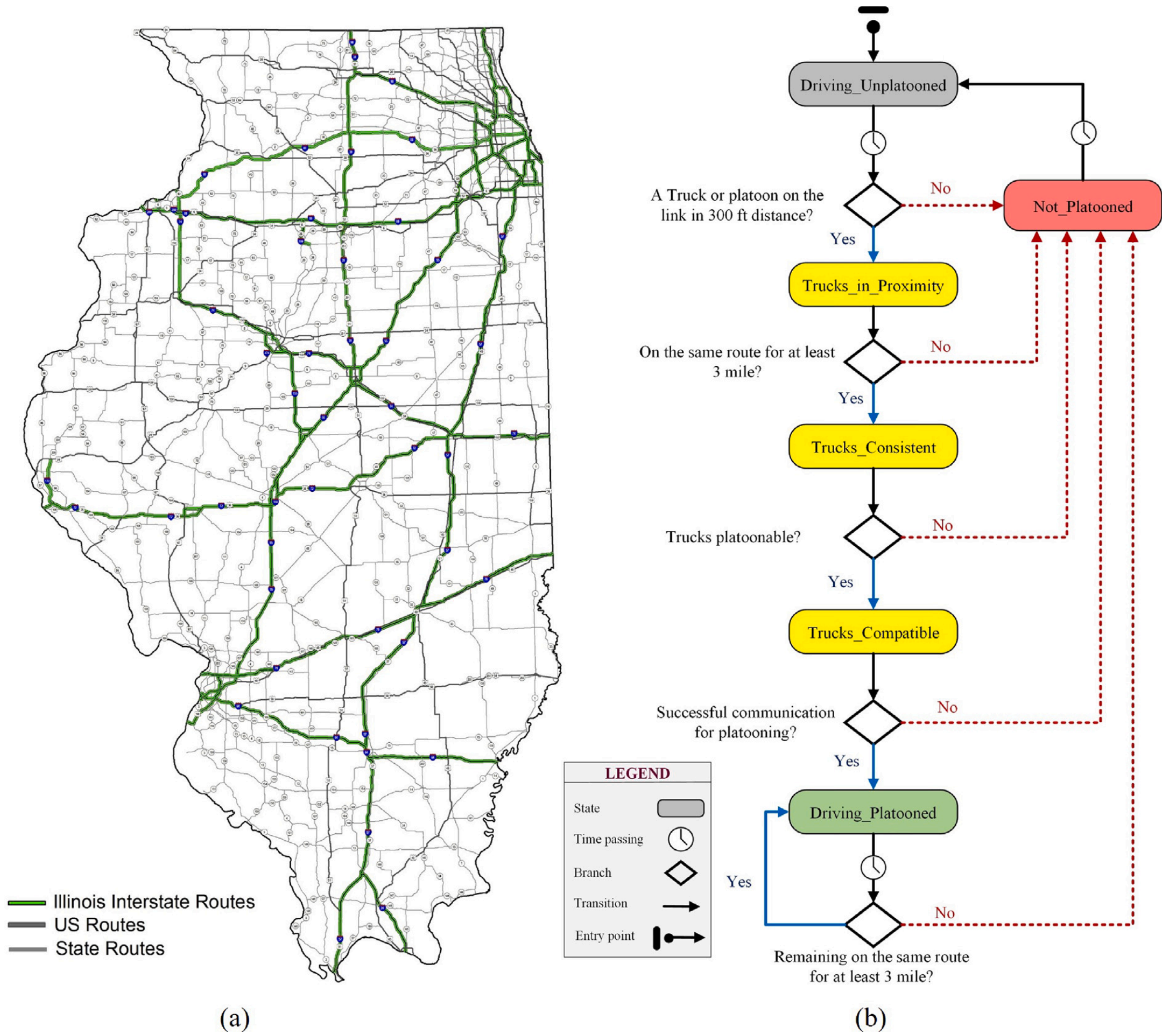

Fig. 4. (a) Interstate highway network in Illinois (adopted from IDOT, 2023); (b) Statechart of platooning among trucks for opportunistic platooning.

- **Assumption 6** (Expected life of a platoonable truck and time horizon for B/C analysis): The expected life of a platoonable truck is assumed 120 months (10 years), same as a traditional truck (Rydell, 2021). Accordingly, the same time horizon is considered for B/C analysis.

3.3. Estimating platooning probability functions

While most of the variables in Table 1 can be straightforwardly expressed as a function of other variables and parameters based on engineering economics and intuition, this is not the case for two groups of variables: (1) those directly connected to a B/C ratio for platooning technology adoption (Trad_Truck_Purchase, Trad_Truck_Convert, Plat_Truck_Purchase, and Platf_Trucks) and (2) those for platooning probabilities (Pr_Opp_Plat, Pr_Platf_Plat, and Pr_Comb_Plat). For the first group of variables, we estimate logistic functions based on a survey of freight researchers, to connect the B/C ratio to the platooning technology adoption rate. Details of the estimation are provided in Appendix B. In this subsection, we focus on estimating platooning probability functions.

Different probability functions are estimated for the second group of variables. For Pr_Opp_Plat, an agent-based model (ABM) is employed to perform simulation runs. Results from the simulation runs are then used to estimate probability functions for opportunistic and combined platooning. For Pr_Platf_Plat, another probability function for planned platooning is estimated based on results from running an optimization model. The estimation of Pr_Comb_Plat will build on both the optimization model and the ABM. Below we provide further descriptions about the estimation processes and results.

For opportunistic platooning, an ABM is first built to simulate platooning. While ideally the ABM should simulate truck platooning in the entire US, given the limited availability of detailed data on truck trips and the road network throughout the US, we resort to a smaller-scale simulation. Specifically, we use the ABM to simulate truck operations on the interstate highway network in the state of Illinois, as shown in Fig. 4a. The network has 2185 miles in length (IDOT, 2023) and serves approximately 77,000 truck drivers (Ganassin, 2022). Given that an average truck driver drives 8000 miles per month and the average length of a trip is 1000 miles (Classadrivers, 2008), 20,000 trips are assumed that traverse the Illinois network in a day. These trips are assigned to different origin–destination pairs among the state's ten major cities, in proportion to the product of population of the origin and destination cities. Trip start times are normally distributed in the 24 h of a day (truncated at the beginning and end of the day), with the peak at 10 AM and the number of trips between 9:30 AM and 10:30 AM being 2659.

We employ a statechart representation to model the opportunistic platooning process, illustrated in Fig. 4b. According to the statechart, when a platoonable truck detects another platoonable truck in close

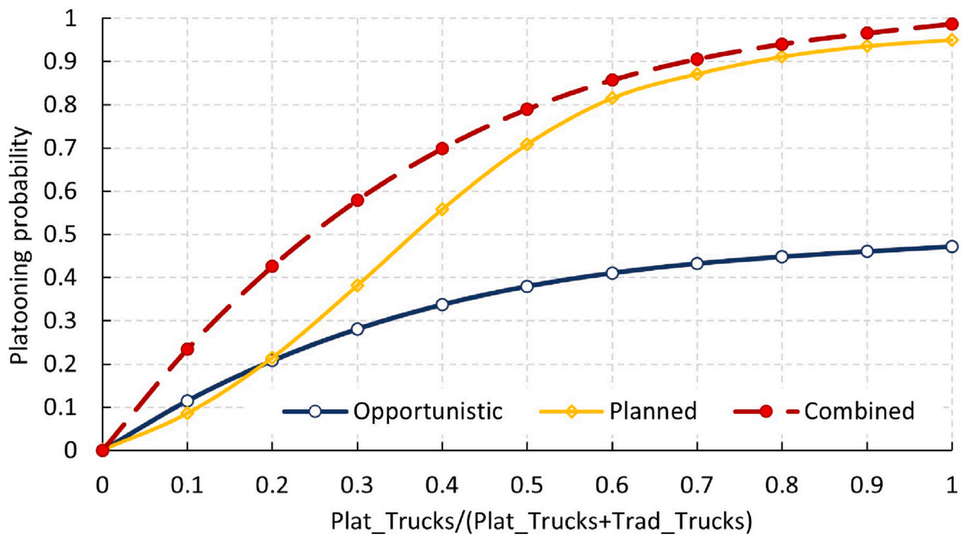

Fig. 5. Platooning probability as a function of the percentage of platoonable trucks in total trucks, under opportunistic, planned, and combined platooning (for planned and combined platooning, it is assumed that all platoonable trucks will use the platform).

proximity (300 ft), the two trucks will start communicating to assess route compatibility and potential for platooning. Two trucks are compatible if they share a common path for at least three miles. Upon forming a platoon, their states will transition from "Driving Unplatooned" to "Driving Platooned" for the duration of the platooning arrangement. Note that a truck may join an existing platoon if the truck and the platoon are close enough and the individual truck and the trailing truck in the platoon have a common path of at least three miles onward. This is possible because in our ABM, a platoon is treated as an agent, same as an individual truck.

It is worth mentioning that the thresholds of 300 ft and three miles used in the ABM above are assumed due to the lack of relevant empirical evidence. Further investigations could be made into how realistic these thresholds are for real-world truck platooning. In addition, the first threshold could be endogenous. The rationale is that as more trucks adopt the platooning technology, the chance and benefits of platooning will increase. Consequently, trucks will look for nearby platooning opportunities more actively, which can be reflected in a larger search distance for other platoonable trucks. This plausible endogeneity of the search distance threshold will, in turn, accelerate the extent of trucks traveling in platoons and the level of platooning technology adoption. Further testing and validation of this endogeneity is reserved for future research.

Using the ABM, three simulation runs are performed for a given level of platooning technology adoption in the network. The level of platooning technology adoption, denoted by Pr_Plat_Comp, is measured as the ratio of platoonable trucks in all trucks (Eq. (A.14) in Appendix A). We consider 10 values for Pr_Plat_Comp: 10%, 20%, …, 100%. Thus in total, 30 simulation runs are performed. For each run, truck trips are randomly generated. Each simulation run is conducted for a duration of one day, using minutes as the time unit. After each simulation run, we compute total platooning truck miles and total truck miles. The ratio gives the probability of opportunistic planning, denoted by Pr_Opp_Plat, per the definition in Table 1. After completing the simulation runs, a polynomial function is fitted to the data with the dependent variable being Pr_Opp_Plat and the independent variable being Pr_Plat_Comp. The fitted polynomial function is shown as Eq. (A.13).

To estimate Pr_Platf_Plat, we use the same truck trip data as for Pr_Opp_Plat. However, instead of using ABM simulation, we resort to an optimization modeling approach, which performs planned platooning with the objective of maximizing system benefit while forming trucks into platoons. The modeling approach starts by computing the *k*th shortest paths for each truck. Then, the platooning opportunities for each truck while taking each of its k paths are identified, using the longest common subsequence algorithm. In identifying the opportunities, we respect the time constraints for each truck in terms of its earliest departure time from origin and the latest arrival time at destination. With the identified platooning opportunities, we calculate the truck utility gain from each opportunity, by accounting for the benefit from fuel and labor savings and the cost due to trucks deviating from their shortest paths while taking the opportunity. Using the utility gains as inputs, an integer programming model is formulated and solved to seek a truck platooning plan that yields the maximum system utility gain. Further details about the model can be found in the first author's PhD dissertation (Choobchian, 2024, chap. 2).

Similar to the case without a platform, the optimization model is solved 30 times with randomly generated truck trips, each time associated with a day of operations and performed before the truck trips start. These 30 optimization runs consider 10 different values for the number of platoonable trucks using the platform (termed as Platf_Trucks). These 10 values correspond to 10%, 20%, …, 100% of the total trucks. Thus, for a given Platf_Trucks value, three optimization runs are performed. Based on the optimization run results, a logistic function is estimated for the probability of planned platooning, denoted by Pr_Platf_Plat, measured as the ratio of planned platooning miles to total truck miles. The independent variable is Platf_Trucks/(Trad_Trucks + Plat_Trucks). The estimated logistic function is shown as Eq. (A.19).

Pr_Comb_Plat further captures the possibility that trucks in a planned platoon form an even larger platoon with an individual truck or another platoon through opportunistic platooning. To determine Pr_Comb_Plat, we use the planned platoons obtained from solving the optimization model above in the ABM simulation, under different platform adoption levels which are defined as the ratio of the number of trucks using the platform to the total number of platoonable trucks and denoted as Pr_Platf_Comp (A.21). We then apply the same statechart as in opportunistic platooning, with a difference that a planned platoon is also considered an agent, same as a truck not in a platoon. We experiment with five Pr_Platf_Comp values (0%, 25%, 50%, 75%, and 100%) and 10 platooning technology adoption levels (i.e., Pr_Plat_Comp) at 10%, 20%, …, 100%. In total, 50 simulations runs are performed. After each run, we compute total platooning truck miles and total truck miles. The ratio of the two mile numbers gives the value for Pr_Comb_Plat. Based on the 50 runs, a polynomial function is fitted with Pr_Comb_Plat as the dependent variable and Pr_Platf_Comp and Pr_Plat_Comp as two independent variables. The fitted function is presented as Eq. (A.20).

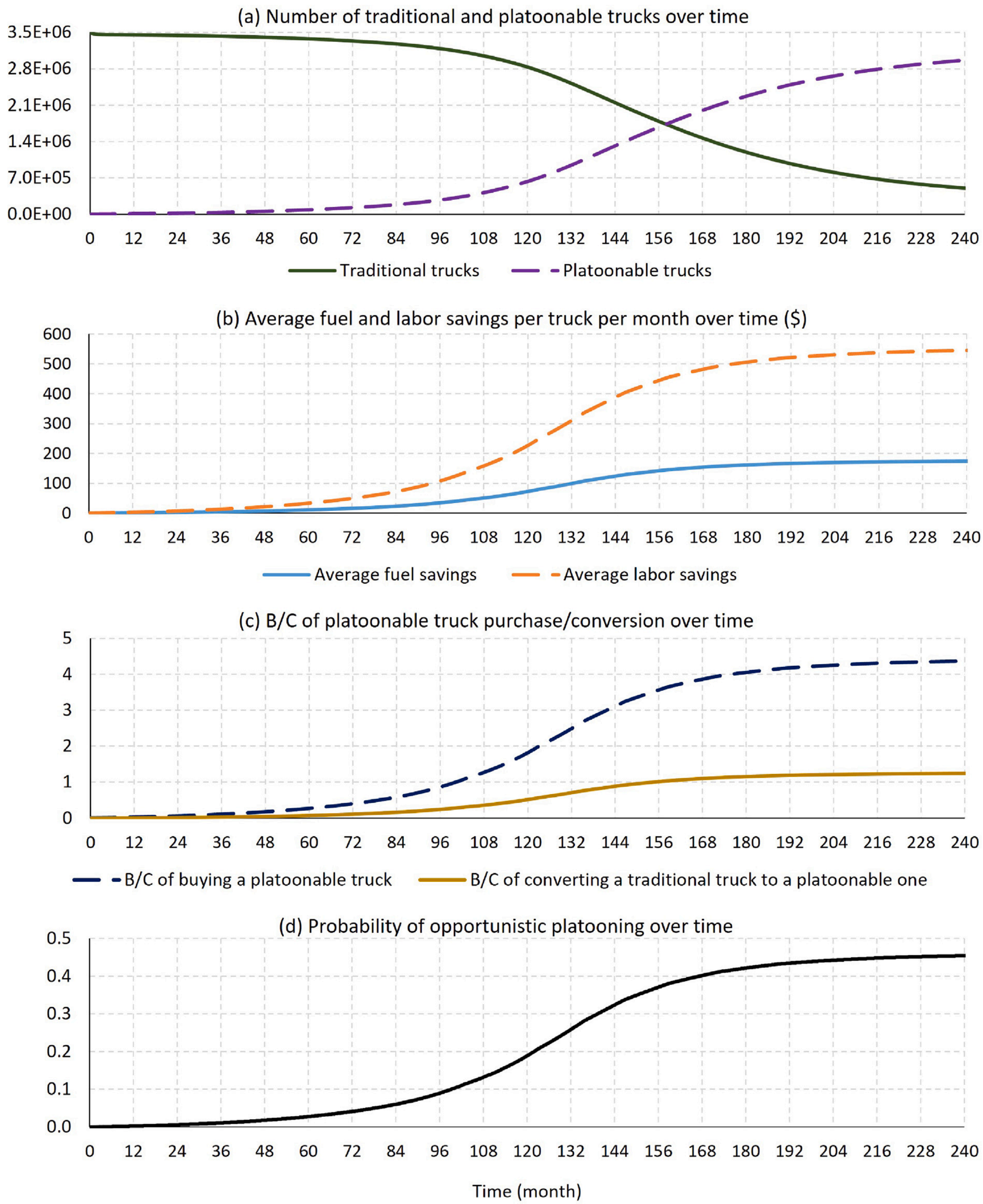

Fig. 6. Simulation results without a matching platform.

Fig. 5 plots the platooning probability curves without and with a platform, as a function of the percentage of platoonable trucks in total trucks (i.e., the product of Pr_Platf_Comp and Pr_Plat_Comp). For the ease of comparison, the plots for the probability with a platform assumes that all platoonable trucks use the platform (in our system dynamics simulations in Section 4, we find that indeed almost all platoonable trucks use the platform). It is not surprising to see that the platooning probability (represented as “Combined” in the figure) will significantly increase when a platform is present. With all the functional relationships specified, an analysis of the validity of the developed SDMs is conducted, as presented in Appendix C.

4. Application to the US trucking industry

This section demonstrates the use of the SDMs by applying them to the US trucking industry. The SDM-based simulations are carried out using the software AnyLogic version 8.8.4. The length of the simulation period is 240 months, or 20 years. In what follows, we first present the simulation results under the two scenarios of without and with

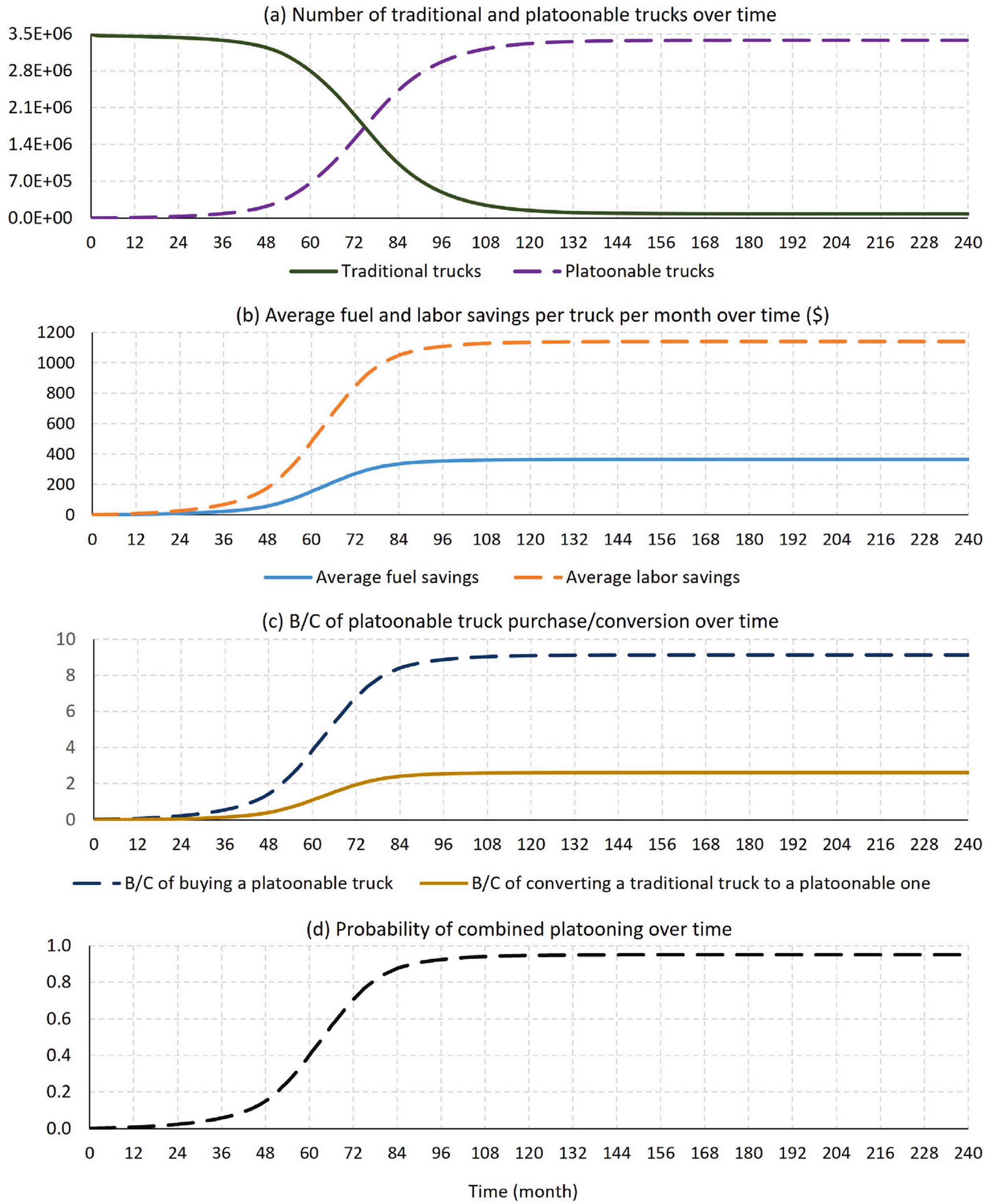

Fig. 7. Simulation results with a matching platform.

a platooning matching platform in Section 4.1.1. Sensitivity analysis is then conducted in Section 4.2 to examine the effects of a few key parameters on performance of the system, which is the US trucking industry in the context of platooning technology diffusion.

4.1. Simulation results

4.1.1. Without a matching platform

We begin by looking at the simulation results without a platooning matching platform. Fig. 6a shows the diffusion curve of the truck platooning technology over a 240-month simulation period. The results indicate that – with the adopted parameter values – an even split point between platoonable and traditional trucks will be reached after approximately thirteen years (159 months). By the end of the 17th year, platoonable trucks will make up about 75% of the total trucks, while traditional trucks account for the remaining 25%. Not surprisingly, the rate of platoonable truck diffusion decreases as time goes by, because the number of drivers who have not adopted platoonable trucks keeps diminishing. This diffusion pattern is consistent with the trends observed in the adoption of similar vehicle technologies, such as

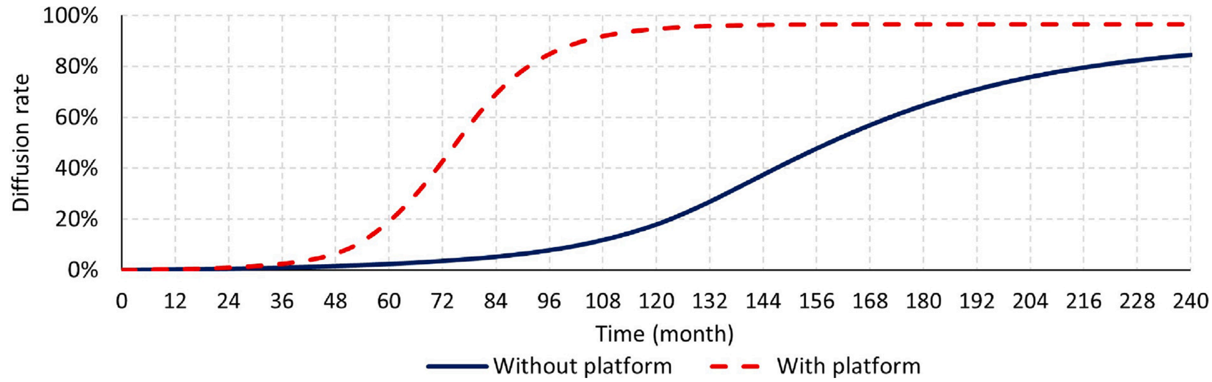

Fig. 8. Diffusion rate of truck platooning with and without platform.

advanced driver assistance systems (ADAS) (Jeffs, 2022). Overall, this diffusion curve suggests that platooning is likely to be significant in the US trucking industry in the foreseeable future.

Fig. 6b shows the evolution of average fuel and labor savings (in dollars) per platoonable truck per month over the simulation period. We observe that both values increase over time but experience saturation near the end of the simulation period. Throughout the simulation, average labor saving remains about three times as large as average fuel saving. For example, after ten years (120 months), drivers using platoonable trucks can save up to $227 per month in labor costs, while the corresponding fuel savings will be about $73. This highlights the importance of considering labor saving benefit in addition to fuel saving benefit when examining diffusion of the truck platooning technology.

Recall that the B/C ratio is the driving force behind platooning technology adoption — no matter it is through purchasing a new platoonable truck or converting an existing traditional truck to a platoonable one. Fig. 6c illustrates the B/C ratios of the two options (purchasing and converting) over time. At the beginning, the B/C ratios for both options are very low, with the values below 0.3 at the end of the fifth year. Note that with the logistic function specification for platooning technology adoption, even with a B/C ratio less than one, some drivers will still purchase a new platoonable truck/converting an existing traditional truck to a platoonable one. After about eight years, the B/C ratio for purchasing a new platoonable truck reaches one. The B/C ratio for buying a new platoonable truck is always much higher than for converting a traditional truck to a platoonable one. However, this does not necessarily mean that most of the added platoonable trucks will be from new purchases. This is because the decision to buy a new platoonable trucks is only relevant to drivers without a truck, while the decision to convert a traditional truck pertains to all drivers with a traditional truck, which can be much larger especially at the beginning of the simulation period.

Fig. 6d illustrates how the probability of opportunistic platooning evolves over time. In the first three years, the probability is very small, only around 1%. However, as time goes by, this probability continues to increase. After 10 years, the probability increases to about 20%. At the end of the simulation period, the probability reaches 45%. This probability, which remains relatively low, suggests a need to improve the efficiency of matching trucks to form platoons, for example, by introducing a matching platform.

4.1.2. With a matching platform

The simulation results with a platooning matching platform are presented in Fig. 7. Fig. 7a shows that with the use of a platform, the diffusion of the platooning technology would be significantly accelerated. Specifically, after 75 months, the number of platoonable and traditional trucks in the system will be almost equal, which is a significant advancement compared to the scenario without a platform (which requires 159 months). At the end of the time horizon (after 20 years), about 96% of the trucks will become platoonable, again a significant increase compared to without a platform (81%). This highlights the prominent role a matching platform can play to boost diffusion of the platooning technology in the US trucking industry.

The platform plays an equally important role in helping truck drivers gain more benefits from platooning. As depicted in Fig. 7b, after five years (60 months), the average fuel and labor savings per platoonable truck per month will reach close to $600 and $200 respectively, which are about 18 times compared to without a platform at the same time point. Moreover, the presence of a platform provides greater incentives for truck drivers to purchase a new platoonable truck and convert their traditional trucks into platoonable ones, as reflected in the B/C ratio. Fig. 7c shows that after seven years (84 months), the B/C ratio for purchasing a new platoonable truck and converting a traditional truck to a platoonable truck will reach 8.4 and 2.3 respectively, much higher than without a platform (0.6 and 0.17). This reaffirms the significance of introducing a matching platform in promoting platooning technology adoption.

Fig. 7d presents the probability of combined (planned and opportunistic) platooning over time with a matching platform. Due to a greater number of platoonable trucks, a larger probability of platooning is observed with a platform than without. For example, at the end of the first year (12 months), the probability for opportunistic platooning without a matching platform is about 0.3%, while the combined platooning probability with a matching platform is around 0.8%. After four years, platoonable trucks would be able to platoon in a trip 20% of the time if a platform is present, while the chance for opportunistic platooning without a platform remains low, at 2%. The stark difference further supports the use of a matching platform in promoting truck platooning.

4.1.3. Further comparison between without and with a platform

Fig. 8 provides a more direct comparison of the platooning technology diffusion rates without and with a matching platform over time. The figure reveals a substantial increase in the diffusion when a platform is introduced, manifested in both the growth rate and the saturation level. By the end of the 10th year, over 95% of trucks will become platoonable if a platform is present, whereas the percentage will reach only 20% without such a platform. Even at the end of the 20-year simulation period, the platooning technology diffusion rate without a platform will be about 83%, which will be achieved in only 92 months (less than eight years) when a platform is present. These results reaffirm the significant role of a matching platform in expediting diffusion of the technology for truck platooning.

Figs. 9 and 10 compare the annual fuel and labor savings without and with a matching platform over the 20-year simulation period. These two figures highlight the substantial impact of a matching platform on the savings from platooning. For instance, for year six, the total fuel saving and the present value of total labor saving will amount to

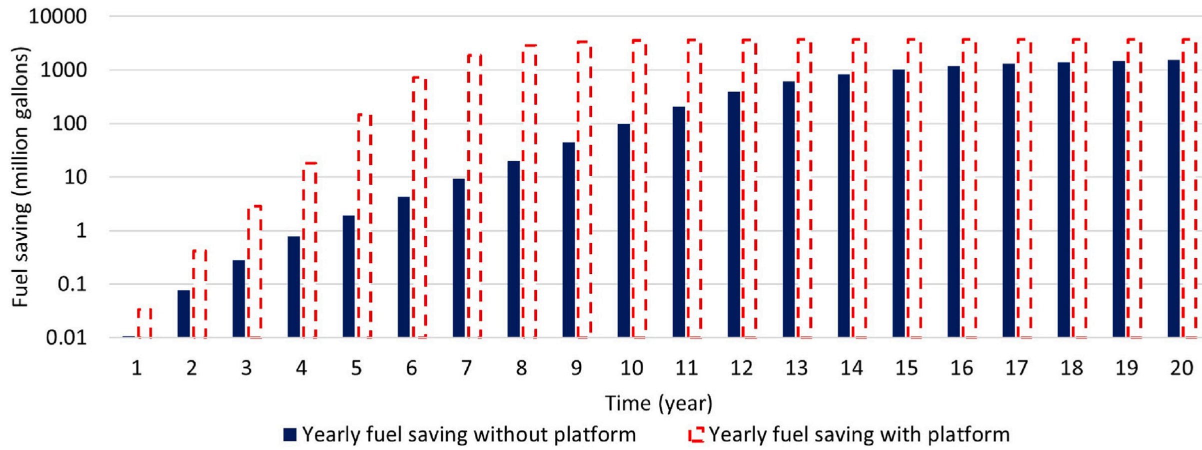

Fig. 9. Annual fuel saving due to platooning with and without platform.

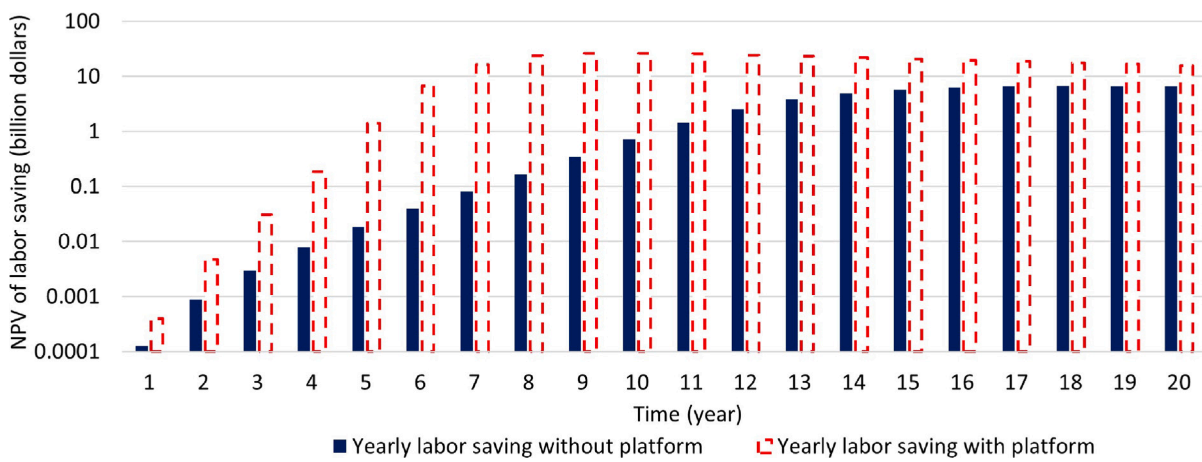

Fig. 10. Annual labor saving (in present value) due to platooning with and without platform.

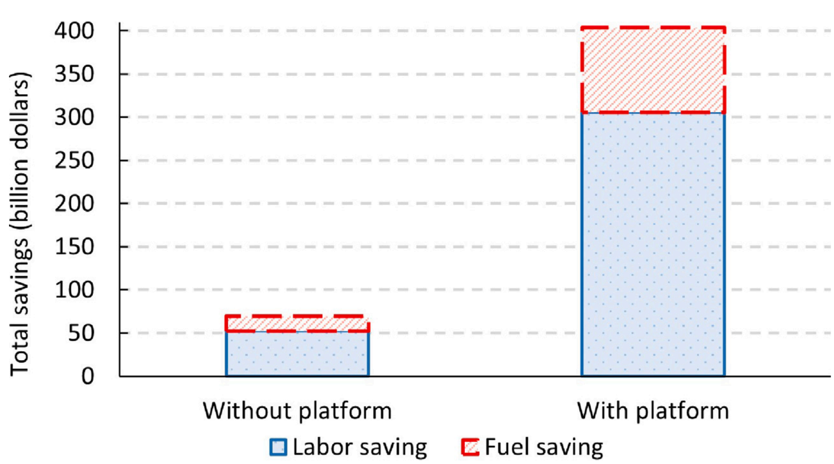

Fig. 11. Comparison of present value of total fuel and labor savings in truck platooning with and without platform.

4.3 million gallons and $39.5 million respectively without a platform. The corresponding values with a platform during the same year are 737 million gallons and $6.75 billion, both more than 170 times increase.

Fig. 11 compares the present value of total fuel and labor savings in truck platooning with and without a platform, over the 20-year simulation period. We find that labor saving is more substantial than fuel saving in terms of dollar values under both scenarios. For instance, without a matching platform, the total fuel saving will be about $16.9 billion, whereas the total labor saving will amount to $52.7 billion, or 3.1 times larger. This shows the importance of accounting for the driver resting benefits when estimating the total benefits of platooning. In total, the labor and fuel savings accumulate to $69.5 billion without a platform over the 20-year simulation period. When a platform is introduced, the corresponding dollar value for the total savings will increase to $403.7 billion, or about a six-fold increase. These findings are consistent with what we observe in Figs. 9 and 10.

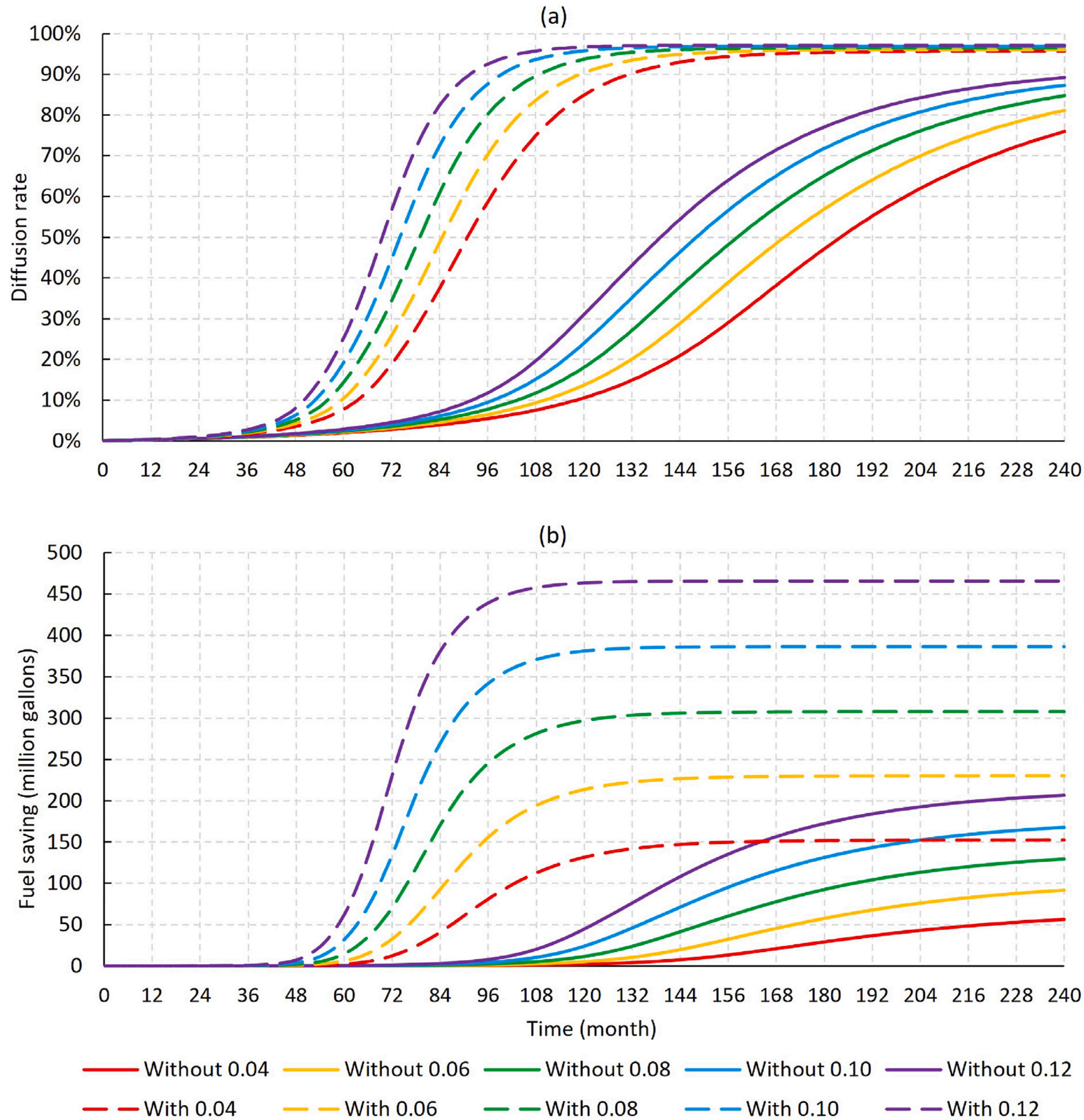

Fig. 12. Sensitivity of platooning technology diffusion rate (percentage of platoonable trucks in the total) and fuel saving amount (million gallons) to fuel saving rate of the technology with and without platform.

4.2. Sensitivity analysis

As the numerical results rely on the SDM parameter values, it is sensible to examine and understand sensitivity of the modeling results to the values of some key parameters. Fig. 12a illustrates sensitivity of the platooning technology diffusion rate (i.e., percentage of platoonable trucks in the total) to fuel saving rate of the technology, without and with a platform. The figure shows notable variations of the diffusion to the fuel saving rate under both scenarios. For instance, to achieve a 50% diffusion rate without a platform, the required time will reduce from 185 months to 140 months if we increase the fuel saving rate from 4% to 12%. Similarly, with a platform, the required time will reduce from 91 months to 70 months.

In Fig. 12b, the sensitivity of the fuel saving amount to the fuel saving rate is further presented. The figure shows that the fuel saving amount is quite sensitive to the fuel saving rate of the platooning technology. For instance, at the end of the eighth year, increasing the technology's fuel saving rate from 4% to 12% will increase the total monthly amount of fuel saving from 81 million gallons to 439 million gallons with a matching platform. The corresponding change without a platform will be even more drastic, from 0.58 million gallons to 7.85 million gallons. These results suggest that, as expected, having an accurate estimate of the fuel saving rate is critical to come up with a reliable estimate of the technology diffusion and fuel saving benefits from platooning.

Fig. 13 presents sensitivity of the diffusion curve and fuel saving amount to the monthly cost of platform use, when a matching platform is present. Recall in Table 2 that the base value for this cost (Platf_Use_Cost_Month) is set to $10. Fig. 13a shows that a decrease in the monthly cost from $30 to $0 (free use of the platform) results in a reduction in the time needed to achieve a 50% diffusion rate, from 84 months to 77 months. Fig. 13b further illustrates that lowering the monthly cost from $30 to $0 leads to a visible increase in the fuel saving amount in the middle of the simulation period. For example,

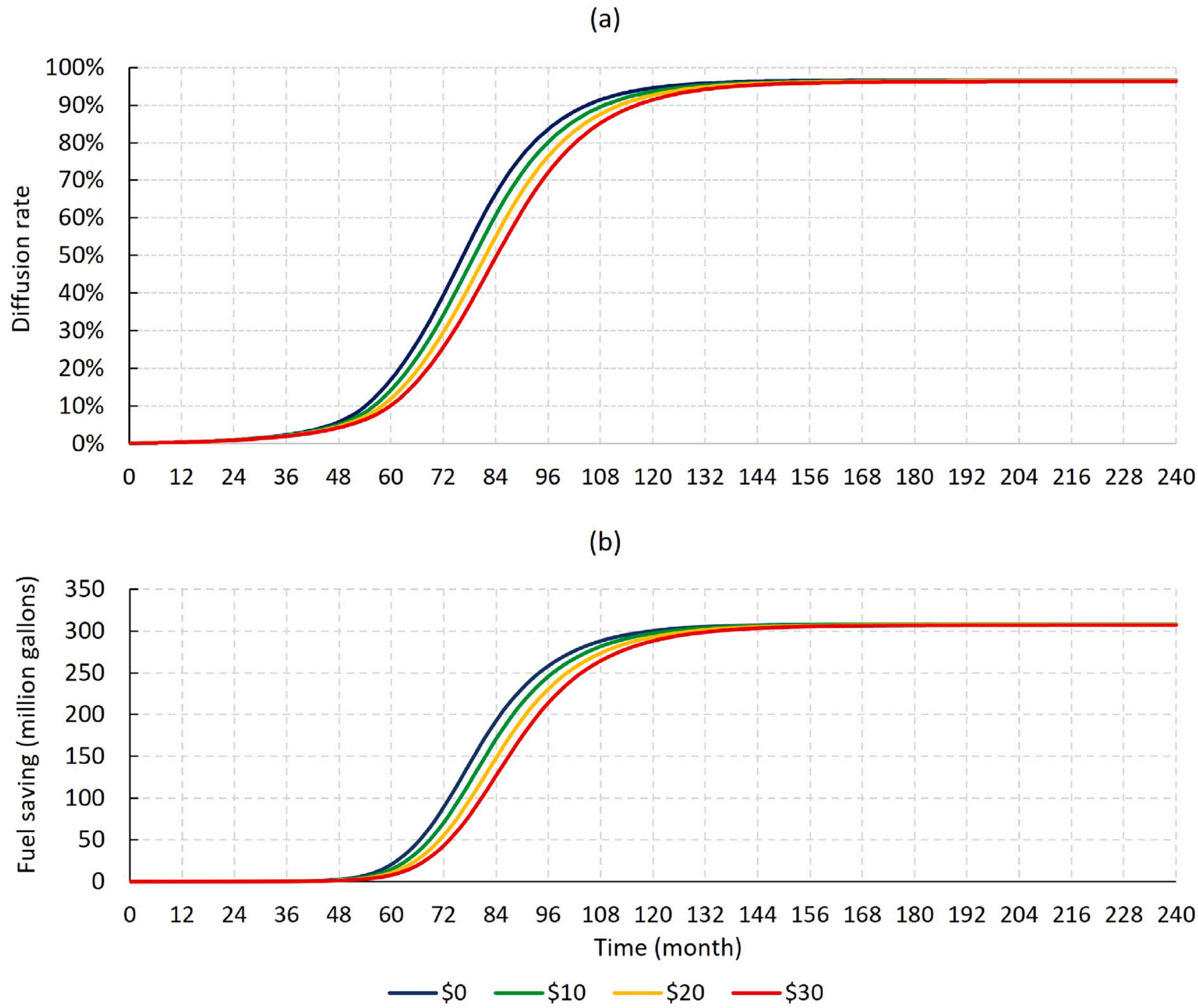

Fig. 13. Sensitivity of platooning technology diffusion rate (percentage of platoonable trucks in the total) and fuel saving amount (million gallons) to monthly cost of platform use.

at the end of the seventh year, the fuel saving amount per month will increase from 127 million gallons to 192 million gallons. Nonetheless, compared to fuel saving rate, the platooning technology diffusion rate and fuel saving are relatively insensitive to the monthly cost of platform use.

Fig. 14 reports the sensitivity results with respect to four additional parameters: fuel price, discount rate, the price difference between a traditional truck and a platoonable truck, and labor saving per platooning truck-mile. Note that fuel price is involved in the SDMs when determining the value for Fuel_Save_Plat_Mile (see Section 3.2). For fuel price, discount rate, and labor saving per platooning truck-mile, a range of possible values that deviate the base values in Table 2 are tested. For truck price difference, we keep the price of a traditional truck fixed while varying the price of a platoonable truck. Rather than showing all the evolution curves throughout the entire simulation period, for the interest of brevity we only report platooning diffusion rate at the end of the sixth year. For other years, the trend of sensitivity is similar, although the diffusion rate numbers are different.

Fig. 14a shows that the diffusion rate increases when fuel price increases, both without and with a matching platform. However, the increase is quite marginal when a platform is not present. Between the lowest and highest fuel prices considered ($2/gallon and $7/gallon), the diffusion rate will change by only 2% without a platform. In contrast, the diffusion rate will increase by 50% (from 20% to 70%) when a platform is present. The result suggests that if fuel prices remain at a high level in the future, it will prompt a more rapid adoption of platooning in the US trucking industry.

Fig. 14b depicts the sensitivity of the diffusion rate to discount rate. Note that the discount rate is used when computing the B/C ratio (see, e.g., Eq. (A.8)). In the base case, a discount rate of 5.5% is used. Here, we vary the discount rate from 1% to 11%. The figure shows that the diffusion rate decreases as the discount rate increases both without and with a platform, although the decrease is more drastic when a platform is present. The diffusion rate will decrease from 48% to around 22% with a platform, while the change without a platform will be only 2% (from 5% to around 3%). Given that the discount rate influences how benefits and costs are discounted to the present values, it is not surprising that the scenario with a platform, which yields significantly higher platooning benefits throughout the simulation period, experiences much greater sensitivity to the value of the discount rate.

Fig. 14c illustrates the sensitivity of the diffusion rate to the price difference between a platoonable and a traditional truck. Intuitively, a larger cost difference will make a platoonable truck less attractive than a traditional truck, consequently lowering the diffusion rate. The changes follow a decreasing trend both without and with a platform, although the shapes of the curves are quite different. If the cost difference increases from $5000 to $20,000, the diffusion rate of platoonable trucks will decrease from 60% to about 13% (or 47% reduction) with a platform, while the decrease is much smaller from 6% to about 2% (or 4% reduction) without a platform. This significant difference highlights

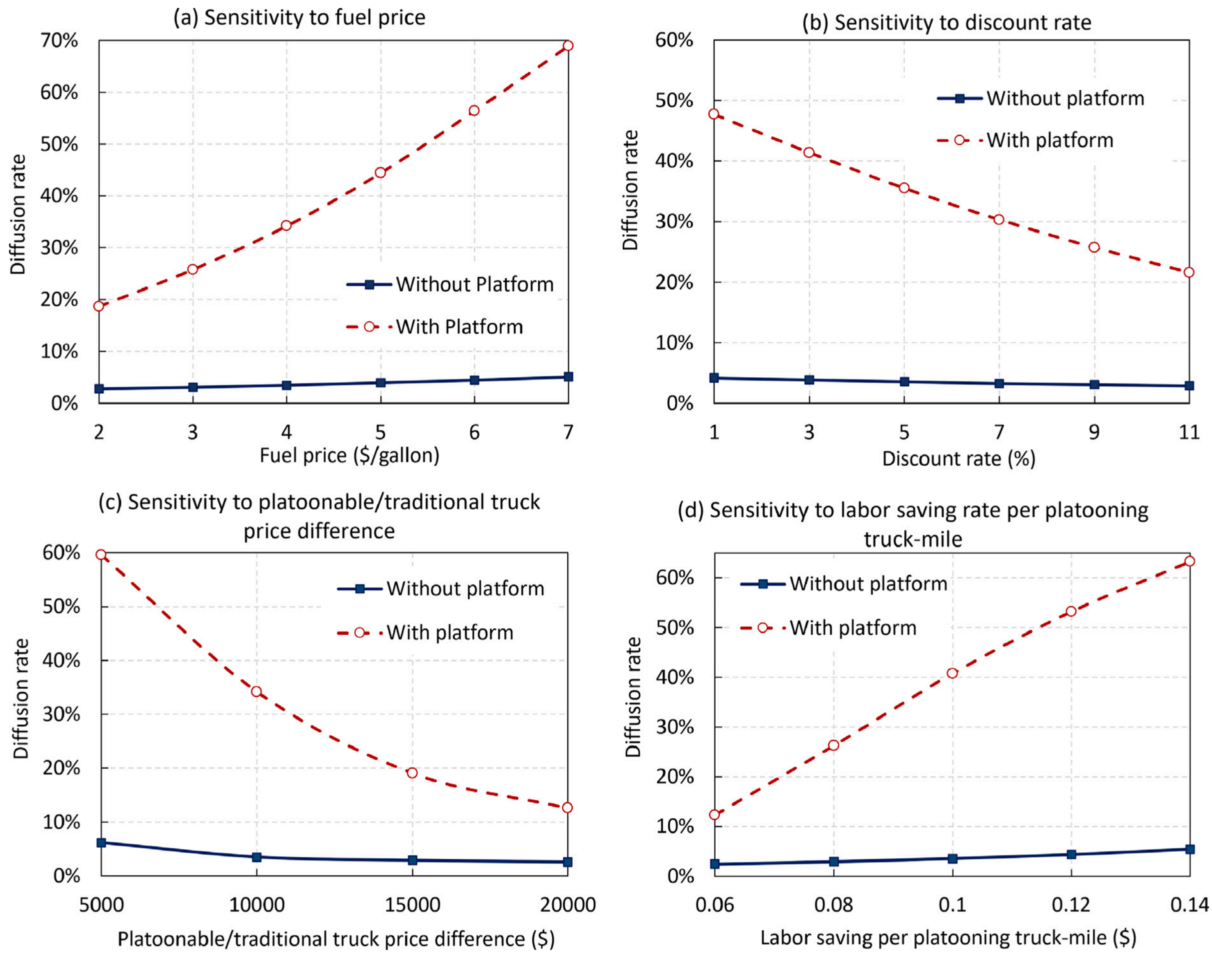

Fig. 14. Sensitivity of platooning technology diffusion rate (percentage of platoonable trucks in the total) at the end of year six to (a) fuel price, (b) discount rate, (c) price difference between a platoonable and a traditional truck, and (d) labor saving per platooning truck-mile.

the amplified effect of initial investment amount on adoption rates when a matching platform is available.

Fig. 14d displays how the diffusion rate responds to variations in labor saving per platooning truck-mile. Conceptually, a higher labor saving per platooning truck-mile is expected to increase the appeal of platooning, thereby boosting the platooning technology diffusion. While an upward trend is observed both without and with a platform, Fig. 14d shows that the diffusion rate is far more sensitive with a platform. For instance, when labor saving per platooning truck-mile increases from $0.06 to $0.14, the diffusion rate would increase from 2% to 5% without a platform. In contrast, with a platform, the discussion rate would jump from 12% to 63%. This reaffirms the greater sensitivity of the platooning technology adoption to the SDM parameter values when a matching platform is introduced.

5. Conclusion

Platooning is expected to bring significant changes to the trucking industry. In this study, an effort is made to understand how the truck industry may respond to the advent of the platooning technology, especially with presence of a matching platform to facilitate platoon formation. We present both a qualitative characterization and a quantitative approach towards understanding the dynamics in the trucking industry while adopting the platooning technology. The qualitative characterization unveils two positive feedback loops and an encompassing bigger feedback loop among the different elements in the trucking industry that are inherent in the technology adoption process, without and with a matching platform. On the quantitative side, SDMs along with tailored methodologies for estimating the technology adoption and platooning probability functions are developed.

The developed SDMs are applied to the US trucking industry. We find that a matching platform can significantly accelerate the platooning technology adoption. With a platform, the time required to achieve a 50% platooning technology adoption is estimated to be 75 months, while the time will increase to 159 months if without a platform. Furthermore, the cumulative fuel and labor savings attributed to platooning is estimated at $69.5 billion over 20 years without a platform, while with a platform, the savings can amount to $403.7 billion. This and the many other numerical results obtained provide useful insights, which can inform future decision- and policy-making towards truck platooning technology adoption and operations that are more coordinated, beneficial, and sustainable. In particular, the insights highlight the potential to redefine the labor roles within the trucking industry, as platooning offers a prospect for drivers to focus more on high-stake truck maneuvering while letting the technology take care of routine driving tasks. This helps reduce the workload of truck drivers and consequently enhance their job satisfaction. Additionally, the implementation of a matching platform can foster a coordination spirit and collaborative work practices among truck drivers within the same and across different companies, leading to greater system efficiency for the entire trucking industry.

The qualitative characterization, quantitative modeling, and application results present a beginning for understanding the system dynamics in the trucking industry as it embraces platooning. The present study does have some limitations, which may warrant further research. First, apart from platooning, other emerging technologies in the trucking industry, particularly electrification and automation, could be jointly considered. Such consideration would require additional efforts for data collection and more elaborate modeling, especially in driver behavior in technology adoption. Second, in this study the platooning probability functions are estimated using the Illinois rather than the national road network. This is mainly to preserve computation efforts, as simulating individual trucks at the national scale would become very challenging. Nonetheless, future research could look into whether and to what extent the estimated functions differ from those using the national road network. Third, location-specific characteristics such as tunnels, bridges, and highway entrances that may impose platooning restrictions are not considered in this study, which is in line with the aggregate-level modeling of the US trucking sector. However, further modeling may include location-specific restrictions and investigate the tradeoff between the added computational efforts and the potential improvement of the characterization accuracy.

CRediT authorship contribution statement

Pooria Choobchian: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Bo Zou:** Writing – review & editing, Writing – original draft, Supervision, Resources, Methodology, Investigation, Funding acquisition, Formal analysis. **Lauryn Spearing:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

None.

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Appendix A. Formulation of the variables in the system dynamics models

This section provides the explicit forms of 21 equations used in the SDMs, to compute the 21 variables in Table 1. Further descriptions of the equations are also given afterwards.

$$\begin{aligned}\text{Trad\_Trucks}(t) &= \text{Trad\_Trucks}(t-1) \\ &+ \text{Trad\_Truck\_Purchase}(t) - \text{Trad\_Truck\_Depre}(t) \\ &- \text{Trad\_Truck\_Convert}(t)\end{aligned} \tag{A.1}$$

$$\begin{aligned}\text{Plat\_Trucks}(t) &= \text{Plat\_Trucks}(t-1) \\ &+ \text{Plat\_Truck\_Purchase}(t) + \text{Trad\_Truck\_Convert}(t) \\ &- \text{Plat\_Truck\_Depre}(t)\end{aligned} \tag{A.2}$$

$$\begin{aligned}\text{Trad\_Truck\_Purchase} &= (1.05 - (0.85/(1+\exp(-1.67\times \text{B/C} - 1.49)))) \\ &\times \text{Drivers\_without\_Truck}\end{aligned} \tag{A.3}$$

$$\begin{aligned}\text{Trad\_Truck\_Convert} &= (-0.005 + (0.92/(1+\exp(-1.03\times \text{Trans\_B/C} - 1.49)))) \\ &\times \text{Trad\_Trucks}\end{aligned} \tag{A.4}$$

$$\begin{aligned}\text{Plat\_Truck\_Purchase} &= (-0.05 + (0.85/(1+\exp(-1.67\times \text{B/C} - 1.49)))) \\ &\times \text{Drivers\_without\_Truck}\end{aligned} \tag{A.5}$$

$$\text{Trad\_Truck\_Depre} = \text{Trad\_Trucks}/\text{Exp\_Life\_Trad\_Truck} \tag{A.6}$$

$$\text{Plat\_Truck\_Depre} = \text{Plat\_Trucks}/\text{Exp\_Life\_Plat\_Truck} \tag{A.7}$$

$$\begin{aligned}\text{B/C} &= (\text{Fuel\_Save\_Month} + \text{Labor\_Save\_Month}) \\ &\times f(\text{Discount\_Rate}/12, \text{B/C\_Time\_Horizon}) \\ &/(\text{Plat\_Truck\_Price} - \text{Trad\_Truck\_Price} + \text{Plat\_Cost\_Month} \\ &\times f(\text{Discount\_Rate}/12, \text{B/C\_Time\_Horizon}))\end{aligned} \tag{A.8}$$

where $f(i,n) = ((1+i)^n - 1)/(i\times(1+i)^n)$

$$\begin{aligned}\text{Trans\_B/C} &= (\text{Fuel\_Save\_Month} + \text{Labor\_Save\_Month}) \\ &\times f(\text{Discount\_Rate}/12, \text{B/C\_Time\_Horizon}) \\ &/(\text{Convert\_Cost} + \text{Plat\_Cost\_Month} \\ &\times f(\text{Discount\_Rate}/12, \text{B/C\_Time\_Horizon}))\end{aligned} \tag{A.9}$$

$$\text{Drivers\_without\_Truck} = \text{Drivers} - \text{Traditional\_Trucks} - \text{Platoonable\_Trucks} \tag{A.10}$$

$$\begin{aligned}\text{Fuel\_Save\_Month} &= \text{Miles\_Month}\times \text{Fuel\_Save\_Plat\_Mile}\times(\text{Pr\_Opp\_Plat} \\ &+ (\text{Pr\_Comb\_Plat} - \text{Pr\_Opp\_Plat})\times 1(\text{Platform}))\end{aligned} \tag{A.11}$$

$$\begin{aligned}\text{Labor\_Save\_Month} &= \text{Miles\_Month}\times \text{Labor\_Save\_Plat\_Mile}\times(\text{Pr\_Opp\_Plat} \\ &+ (\text{Pr\_Comb\_Plat} - \text{Pr\_Opp\_Plat})\times 1(\text{Platform}))\end{aligned} \tag{A.12}$$

$$\begin{aligned}\text{Pr\_Opp\_Plat} &= 0.445\times \text{Pr\_Plat\_Comp}^3 - 1.243\times \text{Pr\_Plat\_Comp}^2 \\ &+ 1.270\times \text{Pr\_Plat\_Comp}\end{aligned} \tag{A.13}$$

$$\text{Pr\_Plat\_Comp} = \text{Plat\_Trucks}/(\text{Plat\_Trucks} + \text{Trad\_Trucks}) \tag{A.14}$$

$$\text{Fuel\_Save\_Platf\_Month} = \text{Miles\_Month}\times \text{Fuel\_Save\_Plat\_Mile}\times \text{Pr\_Platf\_Plat} \tag{A.15}$$

$$\text{Labor\_Save\_Platf\_Month} = \text{Miles\_Month}\times \text{Labor\_Save\_Plat\_Mile}\times \text{Pr\_Platf\_Plat} \tag{A.16}$$

$$\begin{aligned}&\text{Platf\_B/C} = \\ &(\text{Fuel\_Save\_Platf\_Month} + \text{Labor\_Save\_Platf\_Month})/\text{Platf\_Use\_Cost\_Month}\end{aligned} \tag{A.17}$$

$$\text{Platf\_Trucks} = \text{Plat\_Trucks}\times(-0.05 + (0.85/(1+\exp(-1.67\times \text{Platf\_B/C} - 1.49)))) \tag{A.18}$$

$$\begin{aligned}\text{Pr\_Platf\_Plt} &= -0.044 + 0.799/(1+\exp(-6.705 \\ &\times \text{Platf\_Trucks}/(\text{Trad\_Trucks} + \text{Plat\_Trucks}) - 0.425))\end{aligned} \tag{A.19}$$

$$\begin{aligned}\text{Pr\_Comb\_Plat} &= (0.445 + 0.365\times \text{Pr\_Platf\_Comp}) \\ &\times \text{Pr\_Plat\_Comp}^3 - (1.243 + 1.157\times \text{Pr\_Platf\_Comp}) \\ &\times \text{Pr\_Plat\_Comp}^2 + (1.270 + 1.307\times \text{Pr\_Platf\_Comp})\times \text{Pr\_Plat\_Comp}\end{aligned} \tag{A.20}$$

$$\text{Pr\_Platf\_Comp} = \text{Platf\_Trucks}/\text{Plat\_Trucks} \tag{A.21}$$

In Eq. (A.1), the number of traditional trucks in a period is equal to the number of traditional trucks in the previous period plus the number of new purchases, minus the number due to depreciation and conversion to platoonable trucks. Eq. (A.2) is similar, except that the number of trucks to platoonable ones should be added to the stock. Note that compared to the variable notation in Table 1, time is added as these two variables are stock variables whose values in a period need to account for their values in the previous period. Eq. (A.4) calculates the number of traditional trucks that are converted to platoonable trucks, by multiplying the platooning technology convert rate (based on Convert_B/C) by the number of traditional trucks. Eq. (A.5) calculates the number of newly purchased platoonable trucks, by multiplying the platooning technology purchase rate (based on B/C) by the number of drivers without a truck, as the number of these drivers indicates how many trucks need to buy. As such drivers either buy a platoonable or a traditional truck, the number of newly purchased traditional trucks is obtained by multiplying one minus the platooning technology purchase rate (based on B/C) with the number of drivers without a truck, as in Eq. (A.3).

Eq. (A.6)–(A.7) calculates the number of traditional and platoonable trucks out of the system each month due to depreciation, as the total number of traditional/platoonable trucks divided by the expected truck life. Eq. (A.8) computes the B/C ratio of purchasing a new platoonable truck. The benefit is the present value of the sum of fuel and labor savings over the time horizon for B/C analysis, which is also equal to the expected truck life as shown in Table 2. The f function expressed below Eq. (A.8), a standard formula in engineering economics, gives the multiplier of per month benefit (Fuel_Save_Month and Labor_Save_Month) as we accumulate benefits over the B/C analysis time horizon to the present value. On the cost side, we add the price difference of a platoonable and a traditional truck, plus the present value of the additional operating cost due to platooning capability which constantly incurs throughout the B/C analysis time horizon. Eq. (A.9) is similar, except that it is about the B/C ratio for converting a traditional truck to a platoonable one. Thus, instead of using the price difference, the cost of conversion (Convert_Cost) is used. Eq. (A.10) calculates the number of drivers without a truck, as the difference between the number of drivers and the number of trucks.

Eq. (A.11) calculates the fuel saving (in dollars) per platoonable truck-month, as the product of fuel saving per platooning truck-mile and the probability of opportunistic platooning. If a platform is present (as indicated by the 1(Platform) indicator function), the probability of opportunistic platooning is replaced with the probability of combined platooning to also consider the savings due to the use of the platform. Eq. (A.12) follows a similar approach to calculate labor saving (in dollars) per platoonable truck-month. Eq. (A.13) computes the probability of opportunistic platooning using a third-degree polynomial function estimated from the ABM simulations, where the independent variable is the probability of finding an adjacent truck to be a platoonable truck (Pr_Plat_Comp), which is given by Eq. (A.14).

Eq. (A.15)–(A.21) express the variables that pertain to platooning with a platform. Eqs. (A.15) and (A.16) respectively calculate the fuel and labor savings due to planned platooning. The two equations have similar expressions as the first terms in Eq. (A.11)–(A.12), except that the probability of opportunistic platooning without a platform is replaced by the probability of planned platooning with a platform. Eq. (A.17) computes the B/C ratio of a truck when using a platform, calculated as the sum of fuel and labor savings over the cost of using the platform per month. Eq. (A.18) uses the same technology adoption function for purchase as in Appendix B (which characterizes technology adoption as a function of the B/C ratio) and the B/C ratio above to estimate how many trucks will using the platform. Eq. (A.19) computes the probability of planned platooning with a platform, which is further used in Eq. (A.15)–(A.16). Eq. (A.20) calculates the probability of combined platooning (due to both opportunistic and planned platooning), as described in Section 3.3. In this formula, the independent variables are the probability of finding an adjacent truck to be a platoonable truck (Pr_Plat_Comp) and the probability of finding a platoonable truck using the platform (Pr_Platf_Comp), which are given in Eq. (A.14) and (A.21) respectively.

Appendix B. Estimation of platooning technology adoption rate

Technology adoption models are commonly specified to follow a logistic function form (Quan, 2020). In this study, we consider technology adoption rate as a function of the B/C ratio related to the technology:

$$\text{Adoption Rate} = \beta_0 + \frac{\beta_1}{1 + e^{\beta_2(\text{B/C})+\beta_3}}$$

where adoption rate is measured as the probability of adopting the platooning technology. $\beta_0, \beta_1, \beta_2,$ and β_3 are parameters. As no empirical data are available for the estimation, we reach out to 16 researchers in the US with expertise in freight transportation, asking their views about platooning technology adoption rates (both purchasing and conversion) under varying B/C ratios (0.5, 1, 1.5, 2, 3, 4,…, 10). In total, $16 \times 2 \times 12 = 384$ data points are collected. Using the collected data and nonlinear least squares estimation, the logistic function parameters are estimated for purchase and conversion respectively, as shown in Eqs. (A.4) and (A.5) in Appendix A, respectively. Plots of the estimated functions are displayed in Fig. B.15.

It is worth noting that truck drivers who currently own traditional trucks are likely to posses some inertia when deciding on converting their traditional trucks to platoonable ones. This is because such truck drivers have already invested in their existing traditional trucks, and are less receptive of the uncertainties associated with modifying their trucks, especially when they perceive the risk of operational disruptions or financial losses. Thus, it is not surprising to see in Fig. B.15 that at a given B/C ratio, the probability of a new platoonable truck purchase (for a driver without a truck) is greater than that of converting a traditional truck. For a driver without a truck, he/she is expected to purchase either a traditional truck or a platoonable truck. The probability of purchasing a traditional truck is one minus the probability of purchasing a platoonable truck, as reflected in Eq. (A.3).

As a final note for this appendix, while the adoption functions are estimated based on surveying researchers with the relevant expertise, the resulting adoption function remains hypothetic and subject to uncertainties. The uncertainties could impact the prediction accuracy of the platooning technology adoption. For example, the adoption curves in Fig. B.15 could be optimistic or pessimistic compared to the actual situation, resulting in an overestimate or underestimate of the platooning technology adoption. Further research on refining the adoption functions to reduce uncertainties is warranted, for example, by conducting market surveys with stated preference approaches.

Appendix C. Validity analysis

In this appendix, we conduct verification and validation for practicality of the SDMs, using Sargent's framework (Sargent, 1992). As with any model, the verification and validation process uncovers some shortcomings of our SDMs and suggests the need for further research. The detailed analysis findings are presented in Table C.3. Below we highlight two points. First, the operational validity of the SDMs can be limited given the inherent complexity of the trucking industry. For example, there is a lack of information about truck drivers' mental models and attitudes towards platooning, such as how they consider labor saving while being in a platoon. Future research may explore these aspects to enrich the modeling capability. Second, the current SDMs do not account for extreme conditions, such as collisions due to platooning, which can be difficult to accurately model and predict. To enhance reliability and validity of the SDMs, stated preference surveys may be conducted, to gather perspectives of truck drivers and other stakeholders on the safety implications of platooning.

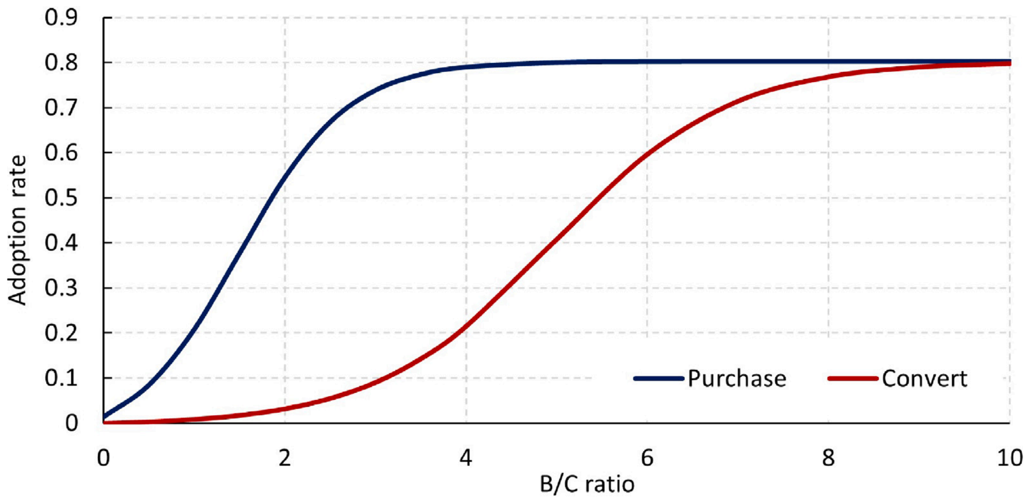

Fig. B.15. Adoption rate of truck platooning technology purchase and conversion based on B/C ratio.

Table C.3
Verification and validation of the simulation for truck platooning technology diffusion.

Component	Rating[a]	Justification
Data Validity: Data are correct, reliable and able to sufficiently represent the system	3	Parameter values are sourced from the literature to the best of our ability. Enhanced data validity could be achieved through further literature review and outreach to the trucking industry.
Conceptual Model Validation: Theories, assumptions, and representations of the studied problem are accurate	3	The conceptual models are the causal loop diagrams, which are grounded in intuitive reasoning of how the trucking industry works when facing the platooning technology. Further enhancement could be made by considering additional elements, such as government influences.
Computerized Model: Quantitative model accurately represents the conceptual model	4	The SDMs align well with the causal loop diagrams. Future improvements could be made by considering additional elements, such as government influences.
Operational Validity: Behavior of computerized model accurately represents the studied system	2	The inherent complexity of the trucking industry poses challenges for operational validity. In particular, understanding driver mental models on platooning (e.g., taking breaks while platooning) will be important to enhance accuracy of the SDMs.
Operational Validity (Degenerate Tests): Computerized model responds appropriately to parameter value change	5	The SDMs effectively respond to parameter variations. The directions of the responses are in line with intuition.
Operational Validity (Extreme Condition Tests): Computerized model behaves appropriately with extreme parameter values	4	The SDMs perform as expected under extreme conditions (e.g., zero fuel and labor savings, significant price difference between platoonable and traditional trucks). More tests under combinations of different extreme conditions could be performed.
Operational Validity (Internal Validation): Multiple model runs replicate the same results.	4	Repeated runs of the SDMs confirms replicability of the results. If the current SDMs are augmented with greater complexity, additional testing would be needed for further validation.

[a] Rating from 5 (highest) to 1 (lowest).

Data availability

Data will be made available on request.

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