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Policy Implications of Truck Platooning and Electrification

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Abstract

Trucks in North America account for more than 23% of the transportation sector's greenhouse gas emissions. Truck platooning and truck electrification are potential technologies for reducing emissions and operating cost. However, adoption uncertainties result in speculations about their potential impact. Traditional modeling techniques to inform policymaking use large datasets, trained professionals to calibrate complex software, and take hours to run a single scenario. This paper provides a closed-form model that rapidly calculates trends of the potential national petroleum consumption reduction for a range of technology adoption scenarios. The primary finding is that truck electrification would have a substantially larger impact on fuel consumption reduction than platooning. The limitations of platoonable miles create an upper bound in benefits. When calibrated for the base year fuel-efficiency, the model shows that petroleum consumption reduction would be less than 4% at full adoption of platooning. The electrification of single unit trucks results in more than a 13-fold reduction of national petroleum consumption relative to platooning. However, without the electrification of combination unit trucks, petroleum consumption will eventually begin to increase again. Therefore, policies to encourage the reduction of greenhouse gas emissions should not overlook incentives to electrify combination unit trucks.

Keywords: Closed-Form Model; Cooperative Adaptive Cruise Control; Fuel Efficiency; Greenhouse Gas Emissions; Platoonable Miles; Technology Adoption

Declaration of Interest: None

1 Introduction

The trucking industry has developed an interest in platooning and electrification technologies because of their potential to reduce petroleum consumption and ultimately cut operating costs. Petroleum is the second highest variable cost behind driver wages and benefits. Petroleum purchases accounts for approximately 25% of operating costs (Bao & Mundy, 2018). Even though only 4% of U.S. vehicles are medium- and heavy-duty vehicles, they account for approximately 20% of the transportation fuel consumed (Union of Concerned Scientists, 2012). In the United States, medium and heavy-duty trucks (HDT) account for 23% of the greenhouse gas (GHG) emitted by the transportation sector (EPA, 2018). In Canada, trucks account for 35% of the GHG emitted by the transportation section (Sharpe, 2019). Hence, governments worldwide have been pushing for heavy vehicle electrification and many cities recently adopted electrification for their entire fleet of public transit buses (Zhou & Rood, 2019).

A combination of truck platooning and truck electrification has the potential to reduce both petroleum consumption and GHG emissions. The next two subsections present a literature review of developments in truck platooning and truck electrification technologies. The third subsection explores theoretical developments to model technology adoption. The fourth section describes the goals and objectives for simulating the impacts on national petroleum consumption based on scenarios that include an interplay between the adoption of truck platooning and truck electrification.

1.1 Developments in Truck Platooning

The earliest initiatives to test truck platooning began in the early 1990's with a proof-of-concept program from the United States Department of Transportation's Automated Highway System (Ferlis, 2007) and the 1996 European CHAUFFER project (Crolla, 2015). Europe extended their efforts into the 2000's by funding the SARTRE (Safe Road Trains for the Environment) project in Sweden and

Spain (Robinson, Chan, & Coelingh, 2010), and the Konvoi project in Germany (Deutschle, et al., 2010). Those initial efforts used a mix of simulations and experiments to quantify the potential reduction in petroleum consumption. A common finding was that the reduction in petroleum consumption depends on the control strategy to reduce air turbulence by managing the distance gaps between trucks. Theoretically, the more streamlined airflow across a convoy reduces the overall drag, thereby increasing energy efficiency for all participating trucks (Vegendla, Sofu, Saha, Kumar, & Hwang, 2015).

Most of the recent studies about truck platooning focus on fluidic modeling or experimentation to determine the achievable drag reduction, and then translate that to an achievable reduction in energy consumption. One of the most recent studies found that a three-truck platoon can reduce fuel consumption by 5% to 13%, depending on the gap distance maintained (McAuliffe, et al., 2018). The recent emergence of vehicle-to-vehicle (V2V) communication standards provide an ability to improve control of the distance gap by synchronizing acceleration and braking (Tsugawa, Jeschke, & Shladover, 2016).

Even with more than one decade of research and development, truck platooning is still in its infancy. An early study by the University of California in 2004 suggested that the industry will apply platooning technology first to trucks. The rationale offered was that trucks already have many of the onboard electronics needed to implement a complete system. Other rationales were that there are fewer safety concerns because professional drivers operate trucks and carriers maintain trucks more regularly than private vehicle owners do (Shladover, 2004).

1.2 Developments in Truck Electrification

In 1997, the Prius sedan became the first mass-produced hybrid electric vehicle in the world [link]. Nine years later, Tesla Motors, a Silicon Valley startup, produced a luxury sports car that could travel 200 miles on a single charge. These two events spurred nearly all major automobile manufacturers to accelerate their electric vehicle initiatives for cars [link]. Truck electrification, however, is still in its infancy and only a few manufactures demonstrated protypes before the year 2020. However, the recent development of electric motors to propel cars more cost efficiently and the economies of scale in battery production will likely accelerate the pace of truck electrification.

Even with battery range extension beyond the average truck travel distance, the rate of adoption will ultimately depend on the availability of adequate infrastructure to charge vehicle batteries quickly. Evolving research investigated the potential for dynamic charging systems to obviate the need for stopping to recharge batteries. Such systems include overhead and in-road electric supply. The overhead system requires a roof mounted pantograph that automatically extends to connect with overhead catenary power lines when power is available and retract where the service is not available. Inroad charging systems are less developed than catenary systems but have the potential to replace overhead lines with hidden power lines. A report by the University of California Institute of Transportation Studies provides an excellent review of both types of systems and their potential costs (Zhao, Wang, Fulton, Jaller, & Burke, 2018). The report pointed out that Sweden tested the world's first inroad charging system in 2016 and opened the service to the public in 2018.

1.3 Technology Adoption Theory

The traditional approach to estimate impacts of technology adoption involve complex software, large datasets, and trained professionals to calibrate data-driven models. The results are overly sensitive to model assumptions such as travel demand, freight movements, route choice, and mode choice (Soteropoulos, Berger, & Ciari, 2019). With such models, the evaluation of a single scenario can take hours.

Everett Rogers developed one of the oldest social science theories of product adoption in 1962, which researchers now call the diffusion of innovation theory (Rogers Everett, 2003). The theory posits that a product or idea spreads over time based on its perception of being new or innovative. Rogers found that the rate of adoption differs among five distinct categories of consumers: Innovators, Early Adopters, Early Majority, Late Majority, and Laggards. Innovators are more willing to try innovations and take risks. Early Adopters embrace change opportunities but need support materials to adopt the product. Early Majority adopt innovations before the average person, but they require evidence that the innovation works. Late Majority are skeptics who adopt innovations after many others have tried them. Laggards are conservatives who adopt innovations after seeing statistics or experiencing pressure from other adopters. Innovators, Early Adopters, Early Majority, Late Majority, and Laggards typically make up 2.5%, 13.5%, 34%, 34%, and 16% of the target market, respectively. The group statistics form a Gaussian distribution such that the cumulative distribution results in an s-shape curve that is typical of a technology adoption curve.

1.4 Goals and Objectives

The main **contribution** of this paper is a closed form model to determine quickly the expected national trends in truck petroleum consumption, fuel cost, and GHG emissions over time for a range of scenarios. The **goal** is to account for anticipated changes in truck fuel efficiency, petroleum prices, and the lag in policy-changes over time. The **objective** is to demonstrate the use of the model by calibrating it to U.S. data for single unit (SU) and combination-unit (CU) trucks. The model accounts for differences in national petroleum consumption reductions between SU and CU trucks as well as differences in their adoption rates for platooning and electrification.

The organization of the remainder of this paper is—Section 2 describes the development of the closed-form model. Section 3 describes the model parameters and the values used for calibration based on data from various sources. Section 4 evaluates the model for different scenarios of technology adoption to explore trends in petroleum consumption, GHG emissions, and savings from the reduced petroleum purchases. Section 5 discusses the results, utility, and limitations of the work. Section 6 provides concluding remarks about the findings, policy-implications, and comments on future work.

2 Methods

This section details the development of the closed-form model. Historical and forecasted vehicle miles traveled (VMT) data for SU and CU trucks calibrate the model for an overall national prediction. Mean statistics for the reduction of petroleum consumption from platooning, and market forecasts for the adoption of platooning and truck electrification provide additional calibration. CU trucks currently account for a greater proportion of the VMT. However, they are likely to lag SU trucks in the adoption of both platooning and electrification because of the more stringent requirements for braking and battery performance. Hence, the model includes this potential lag in technology adoption as a variable.

The model also accounts for the fact that only portions of a route will be suitable for platooning. The National Renewable Energy Laboratory (NREL) classified platoonable miles as those where trucks can travel at least 50 mph for at least 15 consecutive minutes (Lammert, et al., 2018). Based on that requirement, the NREL found that only 63% of truck miles in the U.S. are platoonable. Hence, platoonable miles contribute significantly to the upper bound on fuel consumption reduction from platooning. The model also determines the sensitivity of petroleum consumption reductions to platooning capability in any future year by using fuel efficiency as a variable.

2.1 VMT Growth

The VMT growth model for all SU trucks as a function of year y and follows a compounded growth model where

$$M_{sa}(y) = M_{sY0}(1+\alpha_s)^{(y-y0)}. \tag{1}$$

The parameter M_{sY0} is the VMT in the base year y0 and α_s is the average annual rate of increase. The model for CU trucks is similar but the parameters are M_{cY0} for the base year VMT and α_c is the average annual increase.

2.2 Adoption of Truck Electrification

The electrification of trucks will reduce VMTs traveled by petroleum-powered trucks. Therefore, petroleum consumption will diminish over time. The model does not account for any additional fossil fuels consumed to produce the electricity needed to charge truck batteries. Equation (2) models the proportional increase in truck electrification in future year y by using the logistic model for technology diffusion (Rogers Everett, 2003). The model is

$$\gamma_{ev}(y) = \frac{M_{ev}}{1+e^{-k_{ev}(y-y_m)}} \tag{2}$$

where k_{ev} is the adoption rate, M_{ev} is the maximum proportion of adoption in the horizon year, and y_m is the median year between the horizon and base years. This model produces the typical s-curve of technology adoption. Figure 1 illustrates the difference between the VMT growth model and the technology adoption model. The shifted s-curve simulates a 15-year delay in the adoption of electrification for CU trucks. The model simulates this lag in adoption simply by adding the offset year to y_m. The plot shows a calibration for less than 5% adoption by 2030. The VMT erosion M_s from electrification for petroleum powered SU trucks is

$$M_s(y) = M_{sa}(y)[1-\gamma_{ev}(y, M_{ev}, y_m)]. \tag{3}$$

Similarly, the VMT erosion M_c for diesel CU trucks from electrification is

$$M_c(y) = M_{ca}(y)[1 - \gamma_{ev}(y, M_{ev}, y_m + \Delta y_c)]. \tag{4}$$

The parameter Δy_c is the adoption lag for CU trucks in years.

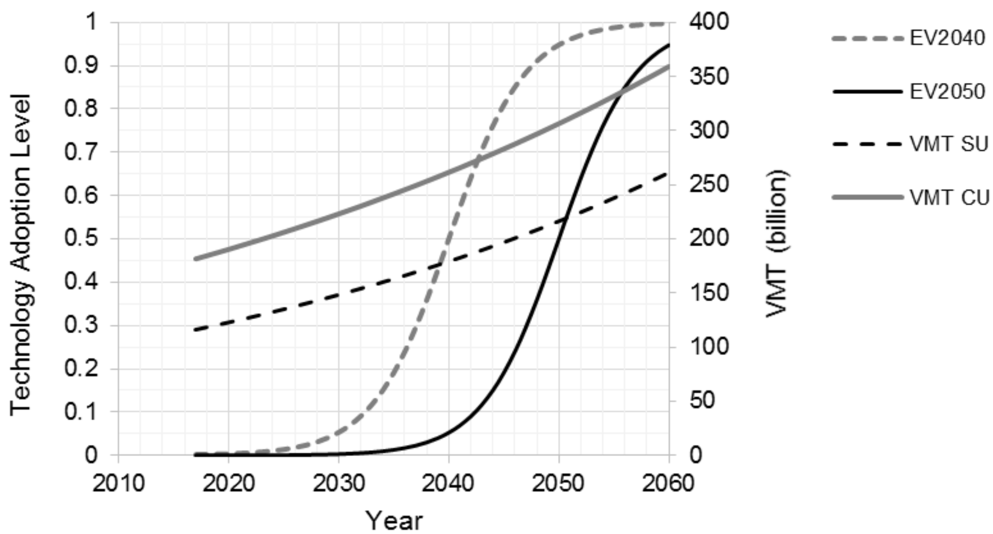

Figure 1 VMT growth and technology adoption as a function of time.

2.3 Platoon Technology Adoption

The adoption of connected vehicle technology and the platoon scheduling system follows a similar technology adoption curve

$$\rho(y) = \frac{\rho_{Tx}}{1 + e^{-k_p(y - y_m)}} \tag{5}$$

where k_p is the adoption rate and ρ_{Tx} is the maximum proportion of trucks that would be enabled.

2.4 Platoonable Miles

The number of platoonable miles depends on the allocation of infrastructure to facilitate truck platooning and the modification of regulations that currently restrict platooning. In general, policy-making and infrastructure preparation lags technology adoption. The technology adoption model accounts for the lag by shifting the median year. The model is

$$\gamma(y) = \frac{M_{Ix}}{1 + e^{-k_\gamma(y - y_m - \Delta y_i)}} \tag{6}$$

where k_γ is the adoption rate, Δy_i is the lag in years, and M_{Ix} is the maximum proportion of VMT that would become available for platooning. Consequently, the miles platooned by SU trucks are

$$M_{ps}(y) = \gamma(y, y_m)\rho(y, y_m)M_s(y, M_{ev}, y_m) \tag{7}$$

and those by CU trucks are

$$M_{pc}(y) = \gamma(y, y_m)\rho(y, y_m)M_c(y, M_{ev}, y_m, \Delta y_c). \tag{8}$$

2.5 Fuel Efficiency

The U.S. Energy Information Administration (EIA) forecasts that fuel economy of HDT SU trucks will increase by 2 MPG from 2018 to 2050 (EIA, 2019). The growth model for an increase in fuel economy for SU trucks is

$$\mu_{ns}(y) = \mu_{nsY0}(1 + \beta_{ns})^{(y - y0)} \tag{9}$$

where μ_{nsYo} is the fuel economy in the base year and β_{ns} is the average annual percentage increase. The model is similar for CU trucks where

$$\mu_{nc}(y) = \mu_{ncY0}(1 + \beta_{nc})^{(y - y0)} \tag{10}$$

The petroleum consumption reduction in gallons with platooning SU trucks is

$$\mu_{ps}(y) = \frac{1}{\mu_{ns}(y)}\left(1 - \eta_{ps}\right) \tag{11}$$

where μ_{ps} is in units of gallons/mile and η_{ps} is the percentage of petroleum consumption reduction per mile. Similarly, the petroleum consumption reduction from platooning CU trucks is

$$\mu_{pc}(y) = \frac{1}{\mu_{nc}(y)}\left(1 - \eta_{pc}\right). \tag{12}$$

The total petroleum consumed when not platooning is

$$F_n(y) = \frac{M_{ns}(y, M_{ev}, y_m)}{\mu_{ns}(y)} + \frac{M_{nc}(y, M_{ev}, y_m, \Delta y_c)}{\mu_{nc}(y)} \tag{13}$$

where M_{ns} and M_{nc} are the miles traveled by SU and CU trucks, respectively, while not platooning. The total petroleum consumed while platooning is

$$F_p(y) = \mu_{ps}(y, \eta_{ps}) M_{ps}(y, M_{ev}, y_m) + \mu_{pc}(y, \eta_{pc}) M_{pc}(y, M_{ev}, y_m, \Delta y_c) \tag{14}$$

Hence, the total petroleum consumed by both truck types throughout their travel is

$$F_T(y) = F_n(y) + F_p(y) \tag{15}$$

Combining equations produces the stand-alone model

$$\begin{aligned}
&F_T\left(y, y_m, \Delta y_c, \eta_{ps}, \eta_{pc}, \rho_{Tx}, M_{Ix}, M_{ev}\right) = \\
&\frac{1 - \eta_{ps} \cdot \frac{\rho_{Tx}}{1 + e^{-k_p(y - y_m)}} \cdot \frac{M_{Ix}}{1 + e^{-k_\gamma(y - y_m - \Delta y_i)}}}{\mu_{nsY0}(1 + \beta_{ns})^{(y - y0)}} \times \\
&M_{sY0}(1 + \alpha_s)^{(y - y0)} \cdot \left[1 - \frac{M_{ev}}{1 + e^{-k_{ev}(y - y_m)}}\right] + \\
&\frac{1 - \eta_{pc} \cdot \frac{\rho_{Tx}}{1 + e^{-k_p(y - y_m)}} \cdot \frac{M_{Ix}}{1 + e^{-k_\gamma(y - y_m - \Delta y_i)}}}{\mu_{ncY0}(1 + \beta_{nc})^{(y - y0)}} \times \\
&M_{\mathrm{cY0}}(1 + \alpha_{\mathrm{c}})^{(y - y0)} \cdot \left[1 - \frac{M_{\mathrm{ev}}}{1 + e^{-k_{\mathrm{ev}}(y - y_{\mathrm{m}} - \Delta y_{\mathrm{c}})}}\right]
\end{aligned} \tag{16}$$

where all parameters can be variables or calibrated constants based on base year data and forecasts. For example, market forecast data for platooning technology, fuel efficiency, and truck electrification determines values for the growth rate parameters k_p, α_s, α_c, and k_{ev}.

A simplified notation of the model provides a more intuitive understanding of how the factors interact to determine petroleum consumption $F_x(y)$ for truck type x as a function of years y as follows:

$$F_x(y) = \left[\frac{1 - \eta_p \cdot \rho(y) \cdot \gamma(y)}{\mu_n(y)}\right] \times M_x(y)[1 - \gamma_{ev}(y)]. \quad (17)$$

The term on the left of the multiplication sign is the fuel efficiency factor and the term on the right is the VMT by petroleum powered truck type x. As the fuel efficiency μ_n grows, the petroleum consumption F_x declines. As the platooning efficiency η_p increases, the numerator decreases and the petroleum consumption F_x declines. Similarly, as the platooning technology proportion ρ and the supporting infrastructure proportion γ increase the petroleum consumption F_x declines. Furthermore, as the truck electrification proportion grows the factor on the right of the multiplication sign diminishes. This makes petroleum consumption less sensitive to the fuel-efficiency factor on the left of the multiplication sign. At 100% adoption of truck electrification, the term on the right becomes zero—reflecting that trucks are no longer consuming petroleum. It is important to note that these parameters change non-linearly with time and reflects different rates of adoption.

2.6 Costs and Emissions

The EIA forecasts nominal, low, and high annual percentage increases in diesel cost at 1.7%, 0%, and 3.5%, respectively (EIA, 2019). The model for petroleum price changes follows the average annual growth model

$$C_f(y, \phi_f) = C_{Y0}(1 + \phi_f)^{(y - y0)} \quad (18)$$

where C_{Y0} is the average price per gallon of diesel in the base year and φ_f is the annual percentage increase.

The model uses the standard EIA emissions coefficient to determine the carbon dioxide (CO_2) release reduction along truck routes (EIA, 2016). The EIA carbon dioxide emissions coefficient per gallon of petroleum consumed provides a direct conversion for CO_2 emissions (EIA, 2016). For diesel, the conversion is 22.4 pounds of CO_2 per gallon consumed.

3 Data

The data needed to evaluate the model is not available in scholarly articles. Hence, this section uses data from available sources such as government reports and websites. Table 1 lists the model parameters, values, and data sources.

Table 1 Model Parameters, Values, and Data Sources

Var	Description	Value	Data Source
$y0$	Analysis base year	2017	Scenario variable
yH	Analysis horizon year	2060	Scenario variable
M_{sY0}	Base year VMT for all SU trucks in the U.S. (million)	116,102	(FHWA, 2019)
M_{cY0}	Base year VMT for all CU trucks in the U.S. (million)	181,490	(FHWA, 2019)
α_s	VMT mean annual growth rate for SU trucks in the U.S. (%)	1.9	(FHWA, 2018)
α_c	VMT mean annual growth rate for CU trucks in the U.S. (%)	1.6	(FHWA, 2018)
M_{ev}	Proportion of SU trucks electrified in the horizon year (%)	100	Scenario variable
k_{ev}	Calibration for 5% of SU fleet electrified by 2030	0.289	(Heid, Hensley, Knupfer, & Tschiesner, 2017)
Δy_c	Lag in electrification for CU trucks (years)	10	Scenario variable
M_{Ix}	Maximum proportion of infrastructure platoonable (%)	56	(Lammert, et al., 2018)
k_p	Calibration for market forecast of 7.4% by 2023	0.149	(Mordor Intelligence, 2019)
k_γ	Calibrate infrastructure to follow truck technology adoption	0.149	(Mordor Intelligence, 2019)
Δy_i	Lag in infrastructure preparation for platooning (years)	5	Scenario variable
μ_{nsY0}	SU truck fuel efficiency in base year (MPG)	7.4	(FHWA, 2019)
μ_{ncY0}	CU truck fuel efficiency in base year (MPG)	6.0	(FHWA, 2019)
β_{ns}	Annual increase in fuel efficiency for SU trucks (%)	0.917	(EIA, 2019)
β_{nc}	Annual increase in fuel efficiency for CU trucks (%)	0.917	(EIA, 2019)
η_{ps}	Petroleum savings per mile from SU truck platooning (%)	13	(McAuliffe, et al., 2018)
η_{ps}	Petroleum savings per mile from CU truck platooning (%)	5	Scenario variable
C_{Y0}	Average price per gallon of diesel in the base year ($)	2.50	(EIA, 2019)
φ_f	Baseline annual increase in diesel price (%)	1.7	(EIA, 2019)
λ_f	Pounds of CO2 released per gallon of diesel consumed	22.4	(EIA, 2016)
P_{Y0}	Base year U.S. population (million)	319	(Colby & Ortman, 2015)
φ_p	Annual increase (%)	0.585	(Colby & Ortman, 2015)

NREL found the total petroleum savings for a three-vehicle SU platoon ranged from 11.5% to 5% for travel separation distances of approximately 6 meters to 58 meters, respectively (McAuliffe, et al., 2018). The savings for a two-vehicle SU platoon ranged from 7% to 3.5% for the same range of travel separation distances. This suggests that total petroleum savings for the SU platooning team can increase further with a greater number of SU trucks participating and traveling more closely. Adding the trailer of the trailing truck as a second trailer to the leading truck to create a CU increased the combined petroleum savings from 7% to 28%. This suggests an upper bound for the petroleum savings as a function of the achievable travel separation distance. It is conceivable that future technologies can reach the upper bound. Evaluation of the model uses the highest NREL petroleum savings of 13% for a three SU truck platoon traveling with 4 meters of separation. Platooning CU trucks will likely achieve a lower fuel efficiency gain because the efficiency gains from hauling additional trailers are already high. Furthermore, the potentially longer stopping distance from the increased load may require a larger travel separation, which decreases platooning fuel efficiency. Hence, the baseline scenario uses a 5% petroleum savings for CUs.

4 Results

The NREL report (Lammert, et al., 2018) stated, "Class 8 combination trucks in the freight sector consumed 29.6 billion gallons of fuel in 2016." Model evaluation for the base year of 2017 showed that CU trucks consumed 30.2 billion gallons of petroleum. This is consistent with the FHWA reported annual VMT increase of 1.6% and validates the model calibration for the base year. The next two sub-sections estimate the petroleum consumption trends and monetary savings from petroleum purchase reductions under several technology adoption scenarios.

4.1 Annual Petroleum Consumption

Table 2 summarizes the petroleum consumption trends for a baseline scenario and four adoption scenarios. The baseline scenario is no adoption of either technology. Scenario 1 is the adoption of truck platooning only. Scenario 2 adds the adoption of electrification for SU trucks with a peak adoption rate beginning in 2040. Scenario 3 advances the scenario 2 peak adoption year to 2030. Scenario 4 adds the adoption of electrification for CU trucks with a 10-year lag behind SU trucks.

Table 2 Observations of Annual Petroleum Consumption for Five Adoption Scenarios

Scenario	Description	Trend Result
Baseline	There is no adoption of platooning or truck electrification.	Diesel consumption increases in direct proportion to heavy truck VMT from approximately 46 billion gallons in the base year to 64 billion gallons in the horizon year, representing a 40% increase.
1	The industry adopts truck platooning but not electrification.	The increase in petroleum consumption slows to an annual volume of approximately 2.5 billion gallons in the horizon year, representing a 3.8% annual reduction from the baseline scenario.
2	Truck platooning and SU truck electrification with peak adoption rate in 2040.	Petroleum consumption begins to slow dramatically by 2030 but then begins to increase again after 2050 when the adoption of truck platooning and SU truck electrification begins to plateau. By the horizon year, SU truck electrification dominates the reduction in annual petroleum consumption by a factor of 8.5 over platooning alone.
3	Truck platooning and SU truck electrification with peak adoption rate in 2030.	The dramatic slowing of petroleum consumption begins earlier as expected but then begins to increase again after the adoption of truck platooning and SU truck electrification plateaus. Earlier adoption increases the total reduction in petroleum consumption but equalizes by the horizon year because there are no additional gains from platooning or SU truck electrification.
4	Truck platooning and SU truck electrification with peak adoption rate in 2030, and CU electrification with a lag of 10 years.	The dramatic slowing of petroleum consumption by 2025 continues until full adoption where trucks no longer consume petroleum. The electrification of CU trucks has a prominent effect because their VMT was 56.3% higher in the base year alone, and their proportional annual increase of VMT is comparable.

Figure 2 shows trends in the annual fuel consumption for the four scenarios relative to the baseline. Without the adoption of either technology, petroleum consumption will increase by 40% from the base year to the horizon year. This includes forecasted improvements in fuel-efficiency and the projected VMT for SU and CU trucks. The national reduction in petroleum consumption from platooning reaches 2.8 billion gallons by the horizon year, which represents a proportional impact of 4.3%. Evaluation of the model with no platooning for the horizon year showed that the electrification of SU trucks alone could reduce petroleum consumption by 36.8 billion gallons. That is a factor of 13.2 larger than the impact of platooning. The limitations on platoonable miles place an upper bound on further reductions of petroleum consumption.

The model reveals that once electrification for SU trucks plateau, the petroleum consumption from CU trucks causes the trend to reverse. Since CU trucks will account for a substantially larger proportion of the truck VMT than SU trucks, it is important that the industry encourage for their electrification even if adoption lags SU trucks.

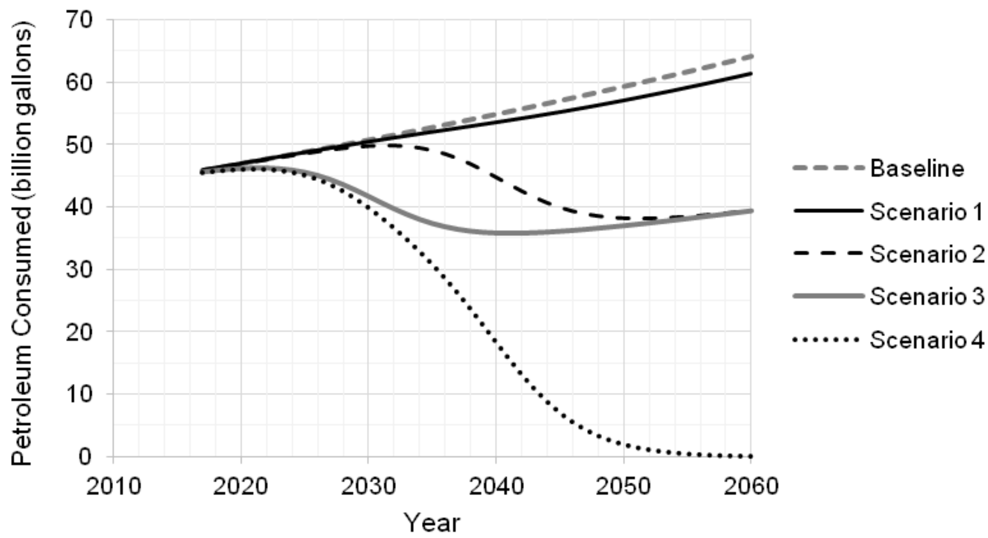

Figure 2 Trends in annual petroleum consumption for different adoption scenarios.

4.2 Annual Savings

Figure 3 shows trends in the annual monetary value of reduced petroleum costs for different scenarios of technology adoption. Table 3 quantifies the achievable annual savings in the horizon year. By the horizon year, the reductions in petroleum costs can range from \$14.3 billion to \$330.8 billion, depending on the technology adoption scenarios, and based on the EIA reference trend for diesel price increases. For perspective, the average selling price of a SU truck in 2018 was \$117,426 (ATD, 2018). Hence, the reduction in petroleum cost annually from the horizon year due to platooning is equivalent to approximately 122 thousand trucks, with a scenario that truck prices remain similar. With the full adoption of truck electrification, the horizon year annual petroleum cost avoided increases to the equivalent of approximately 2.8 million trucks. Although these approximations do not account for inflation or the future price of trucks, the conversion provides perspective on the value of technology adoption to the industry.

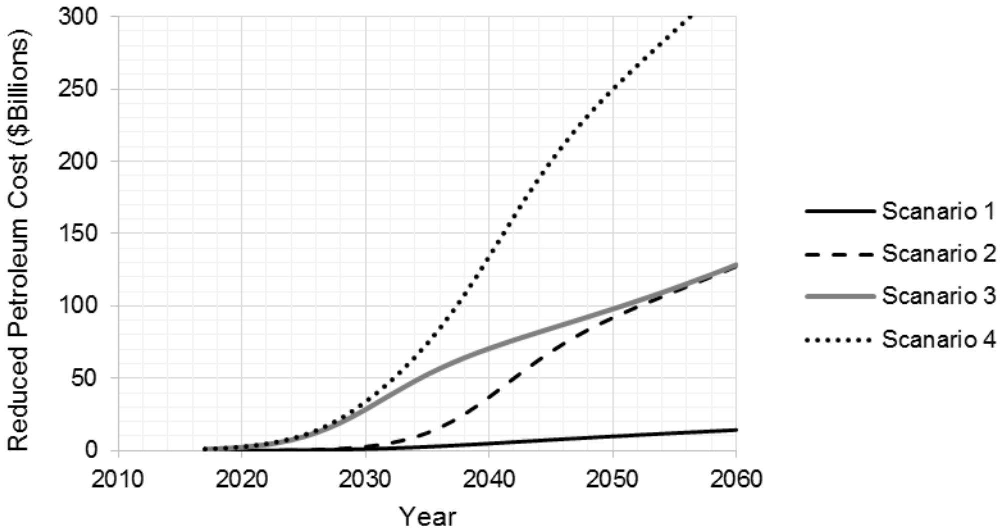

Figure 3 Monetary value of reduced petroleum cost for four technology adoption scenarios.

The petroleum cost reduction resulting from truck platooning at the anticipated maximum team efficiency amounts to 4.3% per mile by the horizon year. This amount increases to 7% if CU trucks realize the same fuel efficiency enhancements from platooning as SU trucks do. The proportion could increase to 13% if platooning can achieve the upper bound in reduced petroleum consumption for both SU and CU trucks. Truck electrification more dramatically affects the national petroleum cost reduction. However, it is important to highlight the model does not reflect any replacement cost for electricity purchase. The amount of CO_2 release prevented by adopting the two technologies is easier to calculate. An estimate of the reduction in release per capita provides more perspective. This calculation uses the forecasted annual population growth (Colby & Ortman, 2015) and the EIA diesel conversion factors (EIA, 2016) mentioned earlier. The result is that by the horizon year, platooning alone could prevent an annual release of 148.5 pounds of CO_2 per person. With the adoption of vehicle electrification, the amount increases to 3.4 thousand pounds per person.

Table 3 Trends in reduced petroleum cost for four technology adoption scenarios.

Scenario	Description	Trend Result
1	The industry adopts truck platooning but not electrification.	By the horizon year, the industry can reduce spending $14.3 billion annually by deploying truck platooning at the maximum expected fuel efficiency. This incorporates the EIA nominal forecast for an average annual increase in diesel price. This avoided cost per mile is equivalent to an average of 4.3%.
2	Truck platooning and SU truck electrification with a peak adoption rate in 2040.	By the horizon year, the industry can avoid spending $113 billion annually on petroleum by adoption electrification for SU trucks. This uses the same diesel price change forecast as scenario 1.
3	Truck platooning and SU truck electrification with a peak adoption rate in 2030.	The earlier adoption of electrification for SU trucks accelerates the avoided petroleum cost. At full adoption, the cost reduction equalizes to $125.5 billion and then continues to increase in line with petroleum price increases.
4	Truck platooning and SU truck electrification with peak adoption rate in 2030, and CU electrification with a lag of 10 years.	Adding electrification of CU trucks with a lag of 10 years from SU trucks accelerates the avoided petroleum cost to $330.8 billion by the horizon year. Avoided petroleum cost continues to increase in line with petroleum price changes.

5 Discussion

The scientific value of the closed-form model is that it provides an aggregate estimate of the potential reduction in national petroleum consumption by adopting truck platooning and vehicle electrification technologies. Accounting for jurisdictional differences in emissions or for differences in the operating profile among trucks such as the time spent accelerating, braking, hoteling, and idling will require a more complex data-driven model (NAS, 2019). The main trade-off is the computational time to achieve a desired geospatial accuracy and precision. The closed-form model uses an annual average VMT growth rate for calibration. Therefore, the model will not provide an accurate prediction for future years if the actual VMT deviates substantially from the forecasted average growth trend.

The main findings from the scenario simulations are that:

1) The number of platoonable miles and the number of trucks available for platooning on any given trip establishes a significant upper bound on the potential benefit of petroleum consumption avoided.
2) Vehicle electrification could produce a more dramatic reduction of national petroleum consumption than platooning could.

The simulation of platooning effects could include additional factors such as the number of participants typically available on a given route, and possible legal restrictions on the number of participants in a platoon. To account for this, the model can restrict the proportion of trucks that participate in platooning by a factor that depends on the proportion of time that platoons form along platoonable routes. It is not possible to determine a value for such a factor until platooning becomes widespread and fully adopted. Model calibration uses the maximum proportion of reduced petroleum consumption currently achievable for a three-truck platoon. It is possible that future technologies could achieve further enhancements in fuel efficiency by enabling longer convoys and achieving a further overall reduction of drag by dynamically optimizing the separation distances among different trucks.

As with all forms of technology, the adoption of truck platooning will evolve over time. Truck platooning offers additional benefits beyond enhanced fuel efficiency. For instance, platooning can improve traffic safety by reducing reaction times, smoothing out traffic flows, improving lane throughput, increasing driver comfort, and removing opportunities for human error (Bhoopalam, Agatz, & Zuidwijk, 2018). The energy savings from reduced drag can increase the range of batteries by 60 to 120 miles (Guttenberg, Sripad, & Viswanathan, 2017).

Today, the industry views platooning as a stepping-stone to autonomous or self-driving trucks because carriers can eliminate back-up drivers in following vehicles (Haas & Friedrich, 2018). The formation of platoons during the early phases of adoption will rely on a service provider to match partners, synchronize departures, and schedule rendezvous (Gerrits, 2019). As adoption increases, trucks will use various algorithms to engage dynamically along their route (Saeednia & Menendez, 2016). The entire platoon formation and disengagement process will likely become fully automated once self-driving trucks become the norm.

The results of this analysis is meaningful because it shows that a dramatic reduction in national petroleum consumption from truck electrification will result in a similarly dramatic reduction of GHG releases along truck routes. We caution, however, that the electrification of all trucks will require a continuous improvement in battery technology, cost reduction, and the widespread availability of dynamic and static charging stations. Furthermore, a net reduction in GHG releases will require the use of alternative fuels to compensate for the additional electricity needed to charge batteries. The model does not account for this net reduction in GHG emissions.

6 Conclusion and Policy Implications

The demand for freight movements by trucks will steadily increase with the growth of population and trade. Currently, combination unit (CU) trucks account for approximately 56% more vehicle-miles-traveled (VMT) than single unit (SU) trucks. Various studies predict this trend will continue. The model indicates that without truck electrification, petroleum consumption will increase in direct proportion to VMT. The electrification of SU trucks is underway, but the electrification of CU trucks is likely to lag because of the additional power needed to haul double or triple the load of SU trucks. Past studies about platooning focus on the achievable fuel efficiency enhancements for SU trucks. However, those studies did not account for potential national impacts from the adoption interplay between truck platooning and truck electrification.

Uncertainties about the timing and levels of adoption have led to a substantial amount of speculation based on various assumptions. Traditional methods of modeling technology adoption and forecasting travel demand require vast amounts of data that could be expensive to obtain. Such methods depend on complex software, trained professionals with experience using the software, and ample time to run and explore various scenarios. There are no alternative closed-form models to assess quickly the coupled effects from adopting truck platooning and electrification technologies. This work contributes a closed form model that considers the interplay of technology adoption, fuel-efficiency changes, petroleum price changes, and freight demand over time.

The scientific value of the closed-form model is that it complements complex data-driven models by enabling rapid first-order exploration of various scenarios for further microscopic analysis. The explicit structure of a closed-form model provides insights, intuition, and a clear understanding of the adoption interplays among the various technologies. The model provides a macroscopic view of the potential national benefits for a wide range of scenarios. Planners and policymakers can apply the model to any country or region by calibrating it with regional VMT data. However, users should be aware of the limitations in predictive accuracy because the model hinges on the accuracy of forecasts for technology adoption, petroleum price changes, and VMT.

It is possible to explore jurisdiction-specific emissions with the closed-form model by calibrating it with local VMT and truck type proportion data for the base year. The model is a non-linear function of time. After calibration with base year data for 2017, the model quantified the potential national fuel consumption reduction for various scenarios of technology adoption. The industry's annual reduction in petroleum consumption from platooning alone approached a ceiling of less than 4% in the horizon year of 2060. Based on the Energy Industry Association nominal forecast for diesel price changes and the U.S. Federal Highway Administration forecast for truck VMT, the horizon year petroleum cost reduction from platooning alone averaged 4.3% per mile. The number of platoonable miles, opportunities to rendezvous, and the minimum achievable travel separation gap limit further gains in platooning fuel efficiency. The model shows that at full adoption, SU truck electrification alone could enable more than a 13-fold reduction in petroleum consumption relative to platooning. However, without adding CU electrification, total petroleum consumption reverses its downward trend after the adoption of platooning and SU electrification plateaus.

The findings of this research suggest that policy making should in general encourage the adoption of both technologies because of their combined benefits beyond GHG reduction and cost reduction. General policy levers should include adoption incentives and the modification of legislation and infrastructure to remove barriers that currently make platooning impractical. In addition to the general policy implications, the scenario simulations suggest the following specific policy considerations:

1) Define and standardize platoonable miles within states and across state boundaries. Definitions should account for bridge loading restrictions that limit the number of trucks in a platoon and underscore any influences on route choice.
2) Modify following-too-closely (FTC) laws that currently prohibit platooning.
3) Emphasize the importance of electrifying combination unit trucks.
4) Incentivize the continuous improvement of battery technology and their cost reduction.
5) Promote infrastructure investments that will lead to the widespread availability of dynamic charging systems and rapid charging stations.
6) Incentivize the use of alternative fuels to feed the battery charging infrastructure.

In future research, the authors will explore ways to modify traditional models using simulation software and big data to determine impacts from a similar range of scenarios. Comparing the blackbox approach of traditional but more accurate methods with the close-form model will provide insights to complement each other.

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