TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Research Article

Transportation Research Record
2021, Vol. 2675(12) 784–796
© National Academy of Sciences:
Transportation Research Board 2021
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/03611981211031231
journals.sagepub.com/home/trr
SAGE

Investigating the Potential of Truck Platooning for Energy Savings: Empirical Study of the U.S. National Highway Freight Network

Xiaotong Sun[1], Haochen Wu[2], Mojtaba Abdolmaleki[3], Yafeng Yin[3], and Bo Zou[4]

Abstract

Truck platooning enabled by connected automated vehicle (CAV) technology has been demonstrated to effectively reduce fuel consumption for trucks in a platoon. However, given the limited number of trucks in the traffic stream, it remains questionable how great an energy saving it may yield for a practical freight system if we only rely on ad-hoc platooning. Assuming the presence of a central platooning coordinator, this paper is offered to substantiate truck platooning benefits in fuel economy produced by exploiting platooning opportunities arising from the United States' domestic truck demands on its highway freight network. An integer programming model is utilized to schedule trucks' itineraries to facilitate the formation of platoons at platoonable locations to maximize energy savings. A simplification of the real freight network and an approximation algorithm are used to solve the model efficiently. By analyzing the numerical results obtained, this study quantifies the importance of scheduled platooning in improving trucks' fuel economy. Furthermore, the allowable platoon size, schedule flexibility, and fuel efficiency all play a crucial role in energy savings. Specifically, by assuming that following vehicles in a platoon obtain a 10% energy reduction, an average energy reduction of 8.48% per truck can be achieved for the overall network if the maximum platoon size is seven, and the schedule flexibility is 30 min. The cost–benefit analysis provided at the end suggests that the energy-saving benefits can offset the investment cost in truck platooning technology.

Truck platooning is likely to be one of the first applications of the burgeoning connected and automated vehicle (CAV) technology. Compared with passenger vehicles, commercial trucks are operated more frequently and the trucking industry is more regulated, making truck platoons comparably easier to form and manage. Truck platooning is promising in yielding significant energy-saving benefits from the aerodynamic drag reduction when trucks are driving closely together. A few pioneer projects have been conducted to test automated truck platooning in closed testing environments (*1*). Experimental studies have shown that fuel savings for the following vehicles in a platoon formation vary from 5% to 13%, depending on speed and intra-platoon headway (*2*). Therefore, truck platooning could lead to a substantial amount of cost savings for the trucking industry, in which fuel consumption dominates at around 30% of the total operating cost (*3*).

Nevertheless, compared with the results obtained in closed test-track experiments, actual energy savings from truck platooning on real highways remain to be seen, as they depend on, among other things, platooning opportunities, which can be scarce if the truck traffic volume and the market penetration of the platooning technology are low. The dissimilarity of trucks' departure time choices and routing decisions limits the availability of platooning partners for individual trucks. It is thus critical to conduct empirical analyses to reveal, when considering practical limitations, how great an energy saving ad-hoc truck platooning can yield and how much

[1]Intelligent Transportation Thrust, Systems Hub, The Hong Kong University of Science and Technology, Guangzhou, China
[2]Department of Mechanical Engineering, University of Michigan, Ann Arbor, MI
[3]Department of Civil and Environmental Engineering, University of Michigan, Ann Arbor, MI
[4]Department of Civil, Materials and Environmental Engineering, University of Illinois at Chicago, Chicago, IL

Corresponding Author:
Yafeng Yin, yafeng@umich.edu

difference coordination or scheduling can make. As early adopters of platooning technology, trucking companies or truck owners will naturally wonder about its energy-saving potential during their operations. For policy-makers, such empirical analyses can help them better understand the key factors that fully reap the potentials of truck platooning, allowing them to form policies that facilitate the deployment of this technology.

Previous studies have investigated the energy-saving potentials of truck platooning in large-scale traffic networks from two perspectives. The first delves into the current truck speed profile or trajectory data to quantify the platooning opportunities (*4–6*). These studies essentially examine the ad-hoc platooning opportunities and fail to consider the potential of platoon planning. The second provides platoon planning schemes that maximize fuel savings through optimization tools (*7*). While many of these studies demonstrate the performance of their proposed mathematical models through numerical examples, they fail to bring practical insights to the overall potential because their examples are not based on empirical data from real systems. This paper is among the first wave of studies incorporating real-world data with a mathematical programming model to offer a holistic understanding of this issue from the planning perspective. Specifically, we examine truck platooning's energy-saving potentials in the U.S. national highway freight system by considering both the nation-wide truck traveling demand and the existing roadway infrastructures' feasibility for platooning. The demand data and network topology are retrieved from the comprehensive database offered in the Freight Analysis Framework version 4 (FAF^4) produced by the Bureau of Transportation Statistics and Federal Highway Administration (*8*). In addition to ad-hoc platooning, we investigate scheduled platooning by adapting a platoon path planning model proposed by Abdolmaleki et al. (*9*), which assumes that a central controller is responsible for scheduling the itineraries of all trucks. With the origin and destination (OD) and the time window of each truck, the model optimizes trucks' itineraries, namely, assigning trucks with proper paths, travel speeds, and departure times, to create more platooning opportunities to maximize the total energy savings, without violating the travel windows of individual trucks.

The challenge of conducting this empirical study lies in solving the platoon path planning model in such a large-scale network with heavy traffic demands. Being a concave minimization problem, its computational time increases exponentially with the size of the network and the number of vehicles in the network. Data processing is first conducted to ease the computational burden by providing the clustered truck demands and a simplified topological representation of the U.S. national roadway network. Trips from 363,570 trucks in 18,891 OD pairs with an average trip distance of 630 mi are considered in the planning model. An approximation algorithm is then implemented to accelerate the computation. A comparative discussion of model results is provided, suggesting that itinerary planning is the pivotal component that improves platooning opportunities and thus increases overall energy savings. We further conduct analysis to identify the impacts on energy savings of a set of controllable variables, including platoon size, schedule flexibility, and trip distance. Finally, a cost–benefit analysis is conducted, which shows that the energy-saving benefits are promising to offset the technology cost.

The remainder is organized as follows. The second section reviews the pertinent literature. The third section, "Data Processing," describes the data processing for generating the network topology and truck OD demands, which are the input data for the platoon path planing model introduced in the fourth section, "The Itinerary Planning Model." The subsequent section introduces the solution algorithms and the tuning of parameters. Results and discussions are provided in the sixth section, and the final section concludes the study and points out future research directions.

Literature Review

Several previous studies have estimated the energy-saving potentials of using a data-driven approach. However, as the estimation method, data source, and study area vary, there is no universal understanding. Muratori et al. utilized the speed profiles of 200 Class 8 vehicles contained in the Fleet DNA Data (*10*) to estimate "platoonable miles" in the U.S., which are defined as the fraction of vehicle miles traveled (VMT) that are amenable for platooning operation (*5*). As the Fleet DNA Data do not contain spatial–temporal information of vehicle journeys, the researchers assumed that if the travel speed is more than 50 mph for more than 15 min, the miles are platoonable. As a result, 65.6% of the total 3,170,079 VMT are platoonable, leading to a 6% reduction in overall energy consumption. Comparatively, Liang et al. used the trajectory data of 1,733 heavy-duty vehicles (HDVs) to examine the platooning possibilities of two HDVs in a region of Europe (*4*). They found that by assuming that the two HDVs are capable of platooning if their distance is no greater than 100 m on the same road, only 1.21% of VMT are platoonable.

Another stream of research has discussed the path planning issue for truck platooning. The planning schemes can be distinguished by whether trucks' travel paths are fixed or flexible. In the former, the planner only changes trucks' speeds and drivers' resting duration to platoon nearby trucks. The latter also allows the planner to alter travel paths to create more platooning opportunities. While some optimization models have been developed (*7*), available empirical studies tend to apply simple criteria when making scheduling decisions, perhaps because of the computational difficulty of implementing these models in large-scale, realistic instances, especially when vehicle trajectory data are used (*4*, *6*, *11*). For instance, Liang et al. showed that when allowing an HDV to coordinate with another partner within 20 km on the same path by changing its departure time, at most 10.76% VMT are platoonable (*4*). A similar study was conducted by Lammert et al., who used the trajectory data from over 57,000 Class 8 HDVs that traveled more than 210 million miles in the U.S. (*6*). The authors assumed that a vehicle is platoonable if it is traveling at at least 50 mph, and there is at least one potential partner within a 15-mi radius and a 15-min travel time window. With this assumption, they concluded that 55.7% of the VMT are platoonable. Though not explicitly discussed in this paper, the consideration of travel radius essentially allows rerouting, generating a much more promising result than that in Liang et al. (*4*).

Trajectory data are usually hard to collect and access. As a result, latent platooning opportunities in the planning horizon may not be explored by the trajectory data collected. Therefore, some other studies perform platoon planning schemes on OD demand data to estimate the energy-saving potentials. These studies usually assign truck demands with fixed paths using traffic assignment models first, then pair nearby trucks to platoons by changing vehicle speed, departure time, and rest duration. The truck OD demand data of several European countries, including Portugal (*11*), Netherlands (*12*), and Germany (*13*), have been utilized. Among them, only Larsen et al. utilized an optimization model (*13*) for the Germany case.

In summary, empirical studies based on itinerary optimization are limited. This implies that the potential of scheduling itineraries to facilitate truck platooning has not been fully explored for realistic networks. Therefore, this paper fills the void by investigating the energy-saving potentials of truck platooning in the U.S. using an optimization approach. Like many other studies, we use the energy-saving percentage as a crucial performance measure of the estimated potential. The concept of platoonable miles is another performance measure that has been frequently used in previous studies. Nevertheless, as our paper considers two or more trucks platooning together, one platoonable mile may be contributed by either a two-vehicle platoon or an n -vehicle platoon with $n \geqslant 3$. As the number of vehicles in the platoon matters to the energy savings achieved, the energy-saving percentage is not a one-to-one correspondence of the platoonable miles. Thus it is excluded as a performance measure in this paper.

Data Processing

For the empirical analysis, we perform two tasks in the data processing. In the first task, we use the geospatial data from the FAF^{4} database to generate an abstract graph representing the U.S. national highway freight system where truck platoons travel. Geospatial data in the FAF^{4} network data are mainly derived from the Highway Performance Monitoring System (HPMS), but also contain state primary and secondary roads, the National Highway System (NHS), the national network (NN), and several intermodal connectors as appropriate for the freight network modeling. The network consists of over 446,142 mi of equivalent road mileage covering the contiguous states plus the District of Columbia, Alaska, and Hawaii (Figure 1*a*). In the abstract graph, each edge or link represents a road, and each node represents an intersection of two roads or the origin/destination of the trucks. Each origin/destination can represent one or more counties. An edge's weight represents trucks' average travel time on the road segment, determined by its capacity, average travel flow, and speed limit.

The second task produces hourly truck OD demands. FAF^{4} is built on Commodity Flow Survey data and incorporates other international trade data from the Census Bureau to provide an overall understanding of U.S. freight movements. It coarsely divides the whole

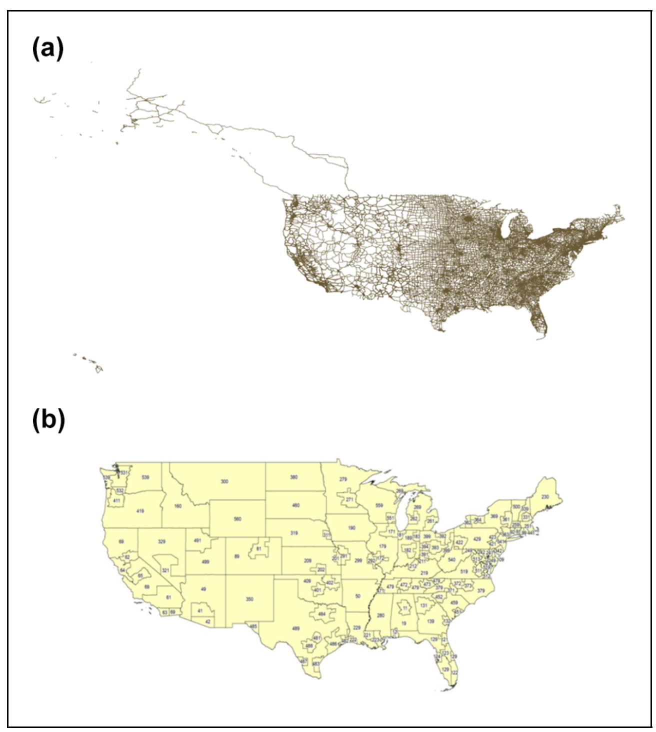

Figure 1. Geospatial data in the Freight Analysis Framework version 4 (FAF^{4}): (*a*) FAF^{4} roadway data and (*b*) FAF^{4} zones.

Table 1. Comparison between the Original Physical Network and the Abstract Graph

	County/region	Nodes	Edges	Mileage
FAF ^{4} network	3,108	na	670,472	446,142
The abstract graph	445	934	1,237	68,981

Note: FAF^4 = Freight Analysis Framework version 4 (*8*); na = not applicable.

country into 132 FAF zones, of which 129 are located in the contigious U.S. (Figure 1*b*). The original data contain the annual truck tonnage, monetary value, and tonmiles by commodities between each pair of zones in the base year 2012, and in forecast years 2020–2045 in 5-year intervals. To obtain the truck flow, we follow the approach used in Noruzoliaee et al. (*14*), which converts the annual truck tonnage to the equivalent annual truck flow by the loaded trucks between FAF zones and further disaggregates it into annual loaded truck trips between counties. The empty truck factor is then introduced to estimate the empty truck flows and the associated total OD truck flows at the county level. To be consistent with the nodes in our abstract graph, we further aggregate OD truck flows at the county level, generating the hourly truck flows from an origin node to a destination node accordingly. These numbers will be used as the truck OD demand for our mathematical program.

Network Topology

The geospatial data in FAF ^{4} are derived from the HPMS over 446,142 mi of roads consisting of 670,427 roadway links, most of which have low speed and are not capable of accommodating platoonable vehicles (Figure 1*a*)(Table 1). Therefore, only the links that belong to higher functional classes, such as those in the Interstate highway system (IHS) and the national freight network, and local principal arterials, are selected. In addition, we focus only on the contiguous states for domestic truck demands and therefore disregard roadways in Hawaii and Alaska. The first round of selection leads to a simplified network with 11,576 roadways, shown in Figure 2*a*, where all counties are marked out as well.

In the simplified network, the east part of the country has a much denser roadway network than the west, and roads in metropolitan areas are much denser than those in the rural areas. Albeit realistic, it creates computational difficulty for solving the platoon path planning problem. A more evenly spaced abstract network of the contiguous states needs to be constructed.

The construction of the final abstract graph mainly repeats the following three steps: county clustering,

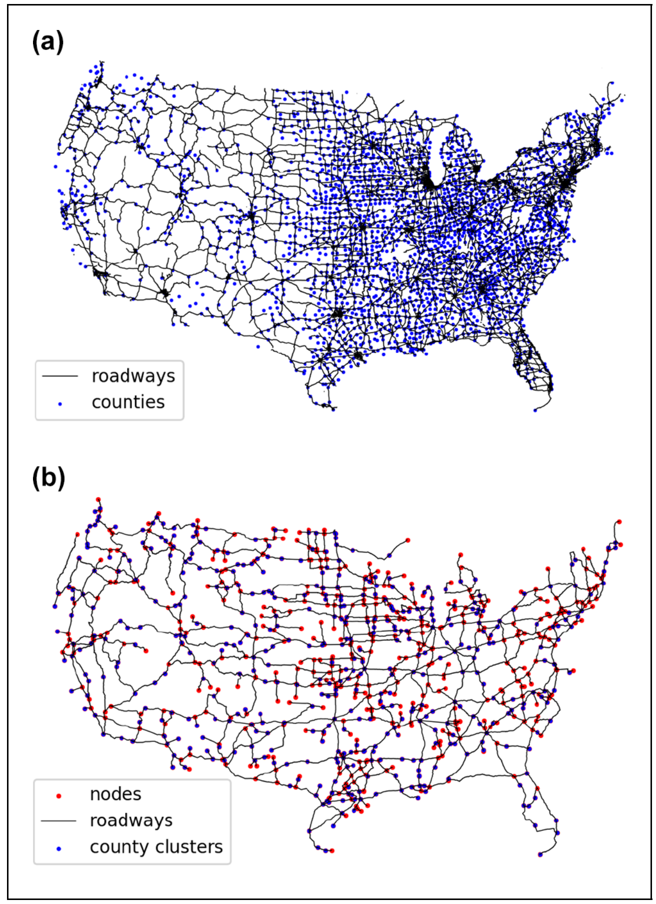

Figure 2. Physical network reconstruction: (*a*) the simplified network after road selection and (b) the abstract graph of the roadway network.

roadway combination, and network cleaning. We implement a clustering algorithm named DENCLUE (*15*) to cluster nearby counties into larger regions. In the 20-mi radius from each cluster center, local roads are removed, and roadways that are close to each other are further combined into artificial roadways with higher capacities to simplify the network topology while maintaining its connectivity (Figure 3). The last step cleans the network by removing geometric data errors from the original data and those isolated, short, and unused roadways, yielding a fully connected graph. For example, in the areas around Los Angeles and San Diego (Figure 4), roadways

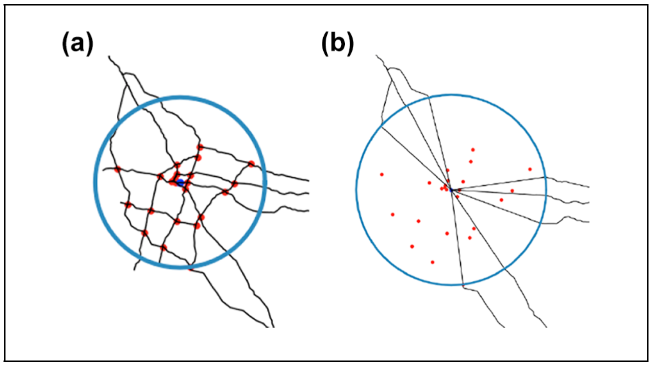

Figure 3. County cluster and roadway combination: (*a*) before and (*b*) after.

that are not on any routes of any OD pairs are disregarded. As a result, the final abstract graph contains 1,237 links and 934 nodes, of which 445 are centers of the county clusters (regions) (Figure 2*b*) (Table 1). The total length of all links is 68,981 mi, while 2.3% of the mileage belongs to artificial roadways.

For each edge e in the abstract graph, we use its average travel time to represent its weight, which is the ratio of the road length $l(e)$ to a prevailing speed $v_f(e)$. The prevailing speed is calculated as per the following equation (*14*):

$$v_f(e) = \begin{cases} 0.88v_p(e) + 14, & \text{if } v_p(e) > 50\text{mph}, \\ 0.79v_p(e) + 12, & \text{if } v_p(e) \leqslant 50\text{mph}. \end{cases}$$

Speed limit $v_p(e)$ is provided in the original data. If the edge is constructed by combining several physical roads, their average speed limit is applied.

Truck Demand Generation

We select five truck classes ("tractor plus semitrailer combination" configuration with types of "dry van," "platform," "reefer," "livestock," and "automobile") out of 45 different truck classes contained in FAF [4] as the platoonable trucks. Their traffic volume is aggregated into platoonable OD truck flow between FAF zones, which occupies 38.1% of total truck flow in the U.S.

We apply the following disaggregation equation to convert the truck demands between FAF zones to those between counties:

$$f_{i,j} = F_{I,J} \times p_i \times a_j \tag{1}$$

The equation follows the proportional weighting method, which has been applied in previous studies that also adopt the FAF database (*14*, *16*, *17*). In this equation, truck flow from FAF zone I to FAF zone J is represented by $F_{I,J}$, and that from county i, located in zone I to county j, located in zone J, is represented by $f_{i,j}$. The production factor p_i is represented by the ratio of the employment number in county i to that in zone I while the attraction factor a_i is the ratio of population in county j to that in zone J.

To be consistent with regions in the abstract graph, we further aggregate the county-level truck OD demands into region-level truck OD demands. Daily truck demands are generated by evenly distributing the annual truck demands into 365 days. To produce hourly truck demands, we assume that a truck only departs during the daytime from 7:00 a.m. to 5:00 p.m. at their origin's local time. We use a K-factor of 0.11 for peak hours

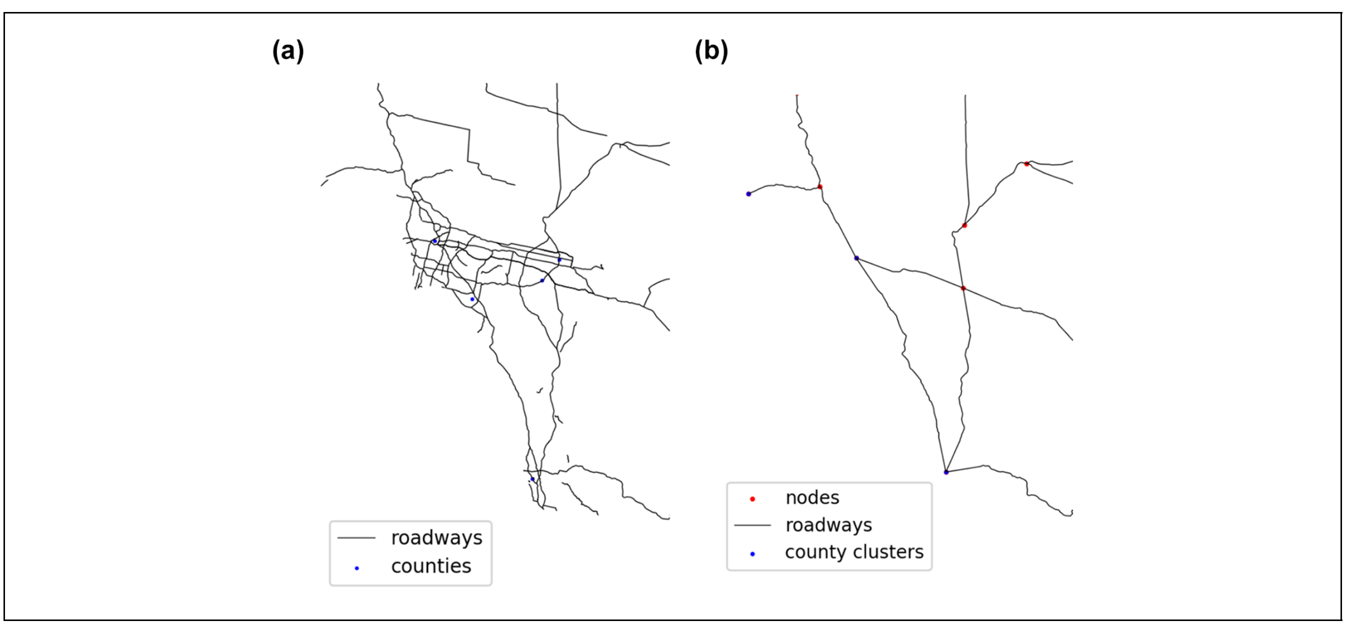

Figure 4. County cluster and network cleaning: (*a*) before and (b) after.

(7:00 a.m.–10:00 a.m., 3:00 p.m. to 5:00 p.m.) and 0.09 for off-peak hours to generate the hourly truck demands. With such a treatment, we essentially assume that the generation of truck demands follows a stationary and recurrent pattern. As a result, 81.3% of all platoonable truck volumes, which include 363,570 trucks in 18,891 OD pairs, are used as the inputs to the platoon path planning model introduced below.

The Itinerary Planning Model

In this model, it is assumed that each truck reports its OD and travel window, specified by its earliest departure and latest arrival time, to a central controller before its departure. Therefore, trucks' trip schedules are known *a priori*. The controller aims to determine the itinerary for each truck to facilitate platooning and minimize the total energy consumption. Each itinerary will specify departure time, route, and speed choices at links along the route. We formulate the itinerary planning problem on a time-expanded network, denoted as $G(N, L)$, constructed based on the original "physical" network and a given planning horizon. In doing so, we discretize the continuous time horizon into time intervals, and create a virtual node at each time interval t for each physical node s. Therefore, a virtual node is represented by a two-tuple (t, s). For each truck, a spatial–temporal link $l \in L$ will be created to connect two virtual nodes, say, (t_i, s_i), $(t_j, s_j) \in N$, if the truck can travel from a physical location s_i at time t_i to another physical location s_j at a later time t_j by using the physical link (s_i, s_j) and following a certain speed, which belongs to a set of discrete feasible speeds at the link (s_i, s_j) (we discretize its speed range into a set of disjoint intervals). In this sense, the time difference $t_j - t_i$ can be more than one time interval and could be longer than the minimum time required to traverse the physical link (s_i, s_j), depending on the speed a truck follows. This procedure yields a time-expanded network that contains all feasible itineraries for each truck to traverse the physical network. A pre-processing procedure is then applied to refine the time-expanded network by eliminating disconnected virtual nodes and infeasible links (i.e., links that would make it impossible for a truck to complete its trip within its travel window).

Note that an itinerary for truck $k \in K$, specifying its departure time, and physical route and speed choices at each physical link, corresponds to a path in the time-expanded network for which the starting node is $n_k^o = (T_k^{\text{ED}}, O(k))$ and the ending node is $n_k^d = (T_k^{\text{LA}}, D(k))$ where T_{k}^{ED} is the earliest departure time of truck k and T_k^{LA} is its latest arrival time; $O(k)$ and $D(k)$ are the origin and destination of truck k respectively. If two trucks appear at the same spatial–temporal link, it means that they travel on the same physical link at the same time with the same speed, thereby becoming platooning partners and saving energy via platooning. Considering the existence of multiple vehicle classes denoted by a set C, we use y_l^c to indicate the number of vehicles in class $c \in C$ on the spatial–temporal link l, and the vector Y_l to denote the number of vehicles in all classes on that link. Therefore, $f_l(Y_l)$ represents the overall fuel consumption on link l, which is an increasing function of the number of vehicles on the link. The model we present below is rather flexible in accommodating various fuel consumption functions and many vehicle classes. However, considering the decreasing trend of marginal energy consumption with an increase in platoon size, we assume the function f_l is a jointly concave function. That is to say, f_l is concave for each of its dependent variable y_l^c, $\forall c \in C$. This concavity assumption of platoon energy consumption is consistent with findings of previous studies and field experiments.

With the above consideration, the itinerary planning problem is equivalent to the problem of finding a path for each individual truck in the time-expanded network such that the summation of link energy consumption f_l over all links $l \in L$, is minimized. The problem can be formulated as follows:

$$\text{Min} \quad z = \sum_{l \in L} f_l(Y_l) \tag{2a}$$

$$s.t. \quad \sum_{l = (t_i, s_i, t, s) \in L} x_l^k - \sum_{l = (t, s, t_j, s_j) \in L} x_l^k = d_{t,s}^k, \tag{2b}$$

$$\forall (t, s) \in N \tag{2c}$$

$$y_l^c = \sum_{k \in K_c} x_l^k, \quad \forall 1 \leqslant c \leqslant C, \forall l \in L \tag{2d}$$

$$x_l^k \in \{0, 1\}, \quad \forall k \in K, \forall l \in L \tag{2e}$$

where

$$d_{t,s}^k = \begin{cases} -1 & \text{If } s = O(k)\,;\, t = T_k^{\text{ED}} \\ 1 & \text{If } s = D(k)\,;\, t = T_k^{\text{LA}} \\ 0 & \text{Otherwise} \end{cases} \tag{2f}$$

In the above, the objective 2a is to minimize the total energy consumption. Constraint 2b ensures flow conservation for each truck k, where the binary decision variable x_l^k is defined to take the value 1 if truck k traverses the spatial–temporal link l and 0 otherwise. Constraint 2d defines y_l^c as the sum of trucks of class c passing through link l. Finally, constraint 2e specifies the decision variable x_l^k to be binary.

The Solution Algorithm

As formulated, the mathematical program 2 belongs to the family of multi-commodity network flow problems

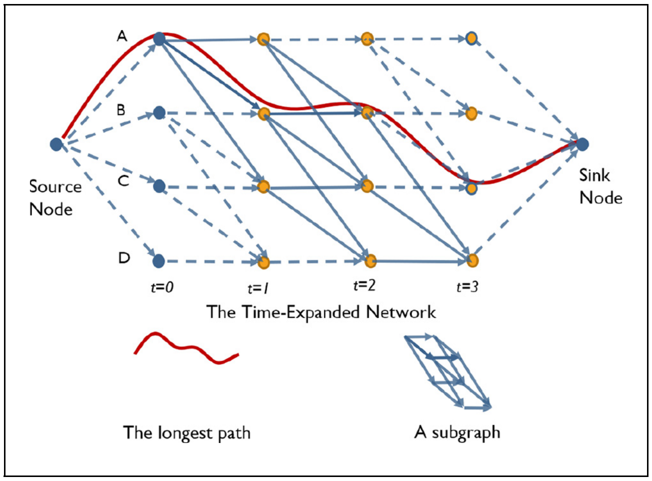

Figure 5. Illustration of the algorithm.

with a concave objective function. For a large-scale network with enormous input demand, it is mathematically intractable to find the exact solution efficiently so that an approximation algorithm is applied. For this empirical study, we simply assume that all trucks are in the same class. Therefore, the fuel consumption under platooning, denoted as f_l, is only a function of the total number of vehicles on that link. Without loss of generality, we can also assume that the amount of energy savings under platooning, denoted as δ_l, increases with the number of vehicles.

There are two stages in the solution algorithm (Figure 5). In the first stage, we generate a subgraph G_k for each vehicle k. Subgraph G_k contains all energy "shortest" paths from node n_k^o to node n_k^d. One can further prove that any path connecting node n_k^o and node n_k^d in G_k is the shortest path. If no planning is performed, truck k would naturally select any of the paths in G_k. Supposing that the itinerary planning only adjusts truck k's path within G_k, truck k's energy consumption will not be increased by the planning if no platoon is formed. In this way, the objective of minimizing the total fuel consumption (**Equation 2a**) is equivalent to another objective of maximizing the total fuel savings:

$$\min \sum_l f_l(Y_l) \Leftrightarrow \max \sum_l \delta_l(Y_l)$$

With this understanding, the second stage initially loads each truck to all its energy "shortest" paths within its travel time window found in the first stage, which contributes to a weighted subgraph of $G(N, L)$ composed of the joint set of all subgraphs G_k, $\forall k \in K$. We denote this weighted subgraph as G' for simplification. Next, we repeat the following two steps. The first step finds the path with the greatest energy savings in G' connecting its source node and its sink node, which we denote as "the longest path." This can be done by finding the shortest path of the graph with the opposite link weights of G', using any shortest-path algorithms. The second step reroutes all vehicles to travel on the intersecting parts of the longest path and their subgraphs. We then simplify the subgraph G' by eliminating links in G_k that are infeasible for vehicle k to travel after the rerouting, and decreasing the weights of the used links by the number of vehicles on it. We repeat these two steps until the longest path has a total weight of zero, resulting in the itineraries for all trucks. The algorithm has a $|K|$ -approx guarantee of optimality. More detailed explanations can be found in Abdolmaleki et al. (*9*).

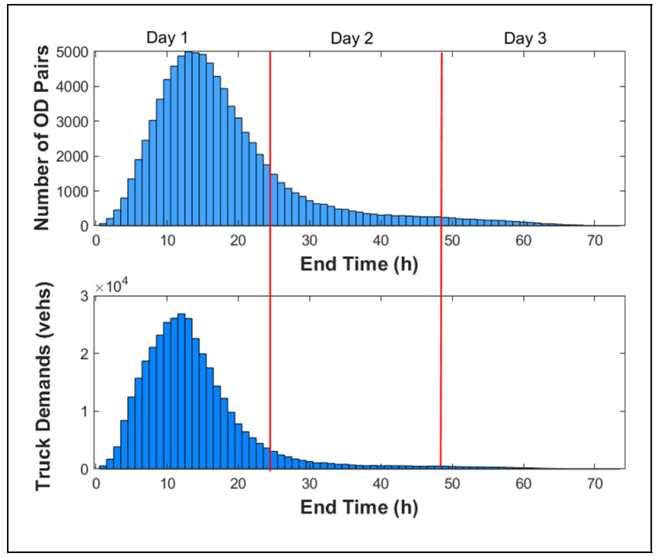

Figure 6. Distribution of freight demands by the trip end time.

The Rolling Horizon Scheme

To construct the time-expanded network, we adopt a 3-day planning horizon as all trips can be finished within 72 h if no rest hours in the middle of the trips are considered. More specifically, if we use 7:00 a.m., the earliest departure time of all trucks, as the initial time in the time-expanded network, 92.0% of the daily trips end on the first day, 6.6% of the trips end on the second day, and 1.4% of them end on the third day (Figure 6). We then use their end time as the latest arrival time to generate the travel windows. We further assume a single time interval in the time-expanded network to be 1 h, resulting in a network with 112,567 links and 85,930 nodes. Because when we explore platooning opportunities in the second day, most trucks have finished their trips in the first day, using only the daily demands as model inputs will lead to an underestimated result. Therefore, a rolling horizon approach is adopted; as shown in Figure 7, a new set of demands will be loaded into the network after

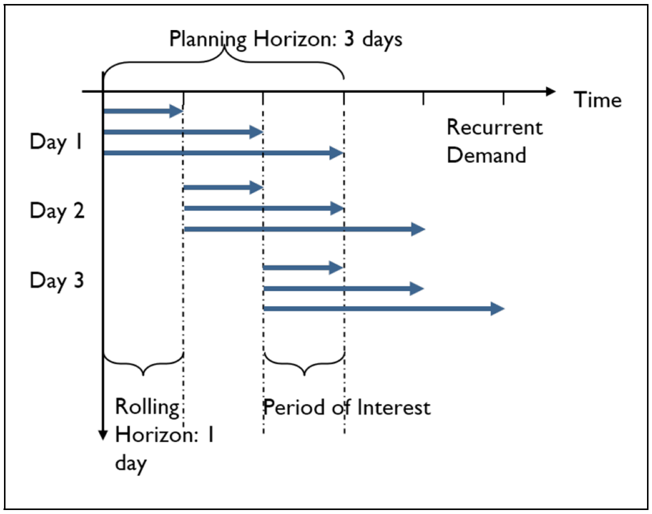

Figure 7. Illustration of the rolling horizon scheme.

a 1-day interval. All the analyses in the "Results and Discussions" section are based on the third day's result, which represents a steady state condition.

Monte-Carlo Simulation

One-hour resolution in the time-expanded network may be too coarse to consolidate truck platoons. It suggests that trucks traveling on a physical link from time 0:00 can platoon with those traveling from time 0:59, leading to an overestimation of energy savings. As a remedy, we apply the Monte-Carlo simulation approach to generate each truck's departure time in minutes by using a uniform distribution and introducing the concept of schedule flexibility, which defines the maximum departure time difference which still allows two trucks to platoon together, when they traverse the same spatial–temporal link. We consider three types of schedule flexibility—10 min, 15 min, and 30 min—in this study. For instance, if the schedule flexibility is 10 min, trucks departing from a link at 0:00 can only platoon with those which depart no later than 0:10.

Other Parameters

We first assume that the fuel consumption is a piece-wise linear function formulated as

$$f_l(m) = (m - \alpha(m-1))f_0, \forall l \in L, m = \min\{\overline{N}, n\}$$

This function indicates that in a platoon with size m, the leading vehicle obtains no energy savings while all the following vehicles receive the same energy consumption reduction. We assume the reduction rate α to be 0.1, a reasonable value that is also used in other studies (*18*). The platoon size is the smaller value of n, the number of vehicles available on the spatial–temporal link l, and $\overline{N}$, the maximum platoon size permitted. Presumably, a platoon cannot be infinitely long. Here, we assume that the maximum platoon size varies from two to seven.

Table 2. Key Parameters in the Empirical Study

Parameter	Value
Fuel efficiency	6.4 mpg
α	0.1
Maximum platoon size	2~7
Fuel price range	\$ 2.152/gal ~ \$3.365/gal
Average fuel price	\$ 2.850/gal
Average annual truck tractor miles until replacement	700,000 mi
Average number of years until replacement	7
Technology cost	\$ 4,000 ~ \$ 12,000

For other parameters listed in Table 2, the average fuel efficiency with the unit of miles per gallon and the average annual truck tractor miles until replacement come from Murray and Glidewell (*3*). The range of fuel prices and the average fuel price can be found from the website of the U.S. Energy Information Administration (*19*). The range of technology cost is estimated by the National Traffic Safety Administration (*20*).

Results and Discussions

To indicate the effectiveness of scheduled platooning from the itinerary planning model, we provide another scenario named ad-hoc platooning as the benchmark. Under the benchmark scenario, each truck randomly selects one of its shortest paths with an equal probability. As no central controller is available to consolidate nearby trucks into platoons, we assume that a truck can only platoon with another if their departure time difference on each spatial–temporal link is no greater than 1 min. As trucks' average speed is around 70 mph, this assumption suggests that the distance between two platoonable trucks is approximately 1 mi, which is optimistic as this distance is beyond the visual range and the communication range of vehicle-to-vehicle communication (*21*). Therefore, our study leads to an overestimation for the ad-hoc platooning compared with the 100-m criterion used in the previous research (*4*).

Network-Level Potentials

With the generated truck itineraries, the spatial distribution of the total daily flow on the U.S. national highway freight network is presented in Figure 8*a*. One can tell that the truck movements in the Great Lakes area, east coast from Boston to Washington D.C., are relatively

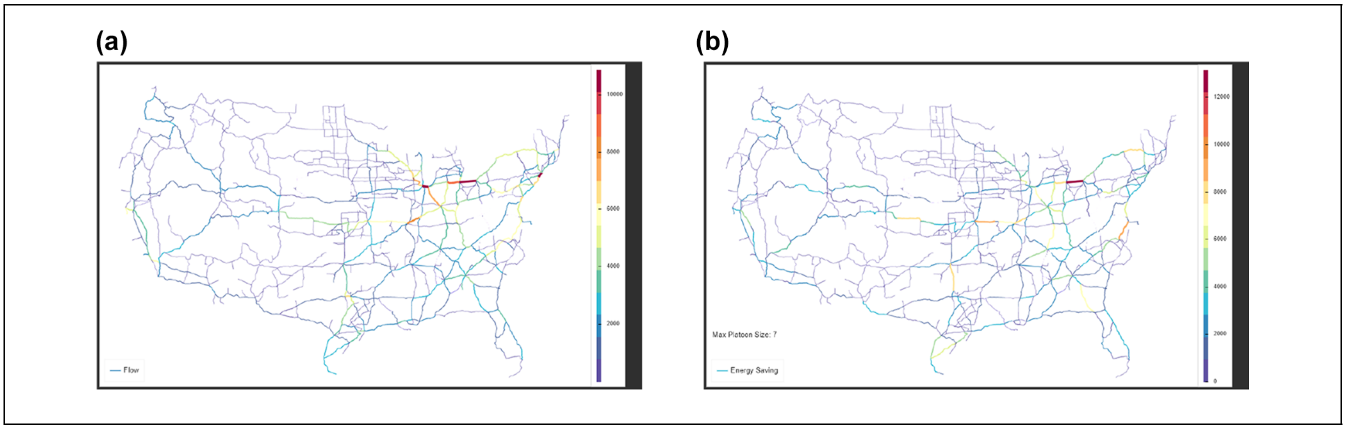

Figure 8. Scheduled truck platooning over the U.S. highway freight network: (*a*) total daily flow under the itinerary planning and (*b*) energy savings with $\overline{N} = 7$ under the itinerary planning.

Table 3. Total Energy-Saving Percentage to Maximum Platoon Size

Max platoon size	2 (%)	3 (%)	4 (%)	5 (%)	6 (%)	7 (%)
Scheduled: 30 min	4.90	6.52	7.34	7.82	8.15	8.38
Scheduled: 15 min	4.80	6.40	7.19	7.67	7.98	8.20
Scheduled: 10 min	4.72	6.29	7.06	7.52	7.82	8.04
Ad-hoc	3.23	4.16	4.54	4.73	4.83	4.89

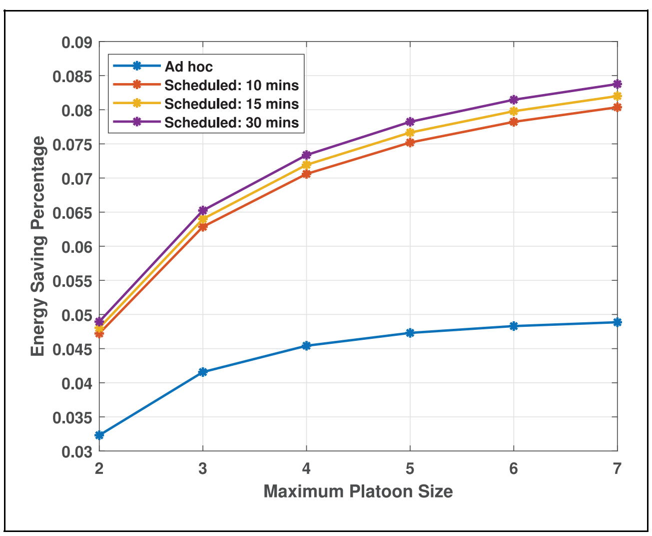

Figure 9. Total energy-saving percentage to maximum platoon size.

busier than other parts of the country. Figure 8*b* presents the daily energy savings per road when the maximum platoon size is seven, showing a similar trend to the spatial distribution of truck flows in Figure 8*a*.

The average energy-saving percentages under different maximum platoon sizes are presented in Figure 9. The percentage increases with the maximum platoon size under both scheduled and ad-hoc platooning scenarios. However, the marginal increase of the former scenario is much larger than that under the latter one. On average, the energy-saving percentage achieved by scheduled platooning is at least one and a half times as large as that in ad-hoc platooning. However, the increment to savings from a greater schedule flexibility is marginal. Table 3 provides the exact values of energy-saving percentages.

Figure 10 illustrates the platoon size distributions over spatial–temporal links and the average platoon size under both scheduled and ad-hoc platooning, with maximum platoon size being two and seven, respectively. Compared with ad-hoc platooning, scheduled platooning has a larger platoon size on average. It shows that the itinerary planning indeed creates more platooning opportunities. Besides, the average platoon size under ad-hoc platooning is only 1.5 when the maximum platoon size is seven. It implies that there is no need to impose a maximum platoon size if no planning is performed, as ad-hoc platooning does not generate long platoons that interrupt the normal traffic flows.

OD-based Performance

Figure 11 plots the relationship between energy-saving potentials and the trip distance per OD pair. The left panel shows the absolute values of energy-saving

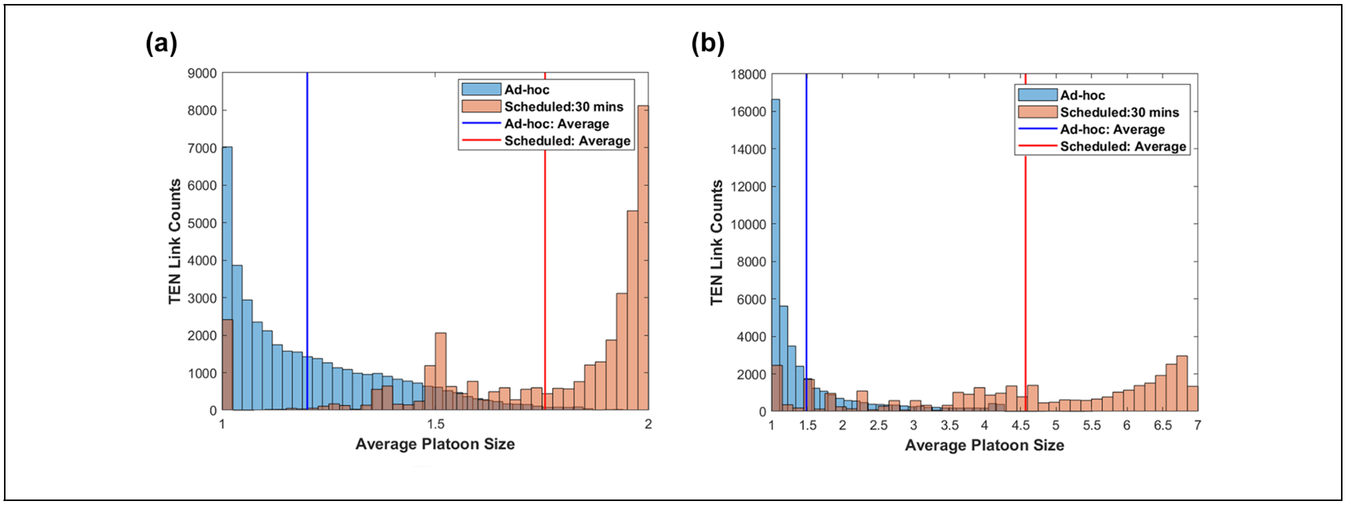

Figure 10. Average platoon length per hour per link: (*a*) $\overline{N} = 2$ and (*b*) $\overline{N} = 7$.

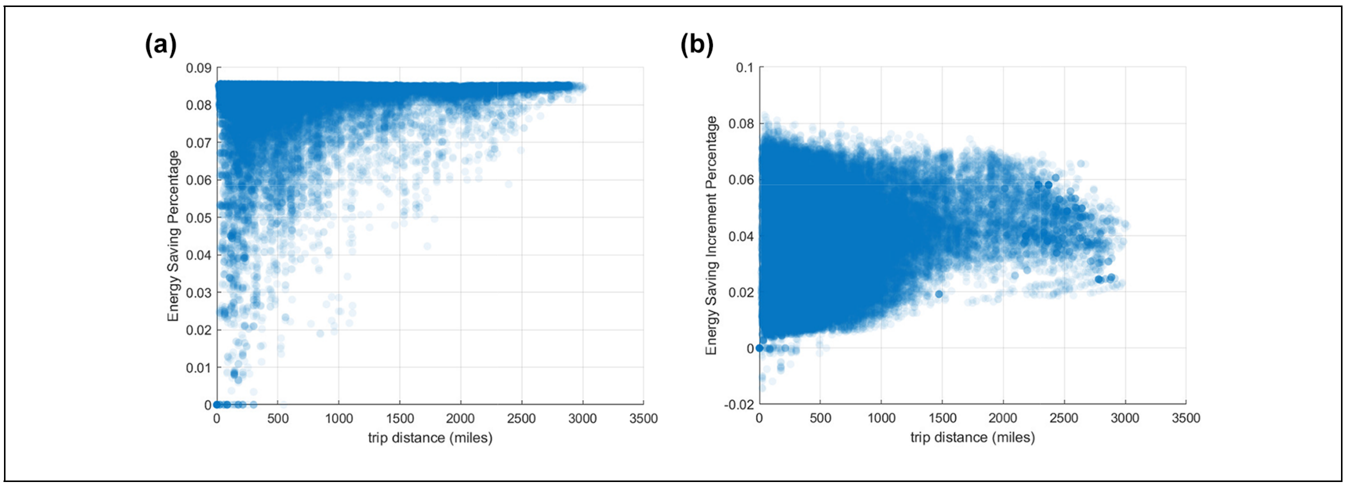

Figure 11. Energy-saving percentage to trip distance, $\overline{N} = 7$: (*a*) absolute energy-saving under scheduled platooning and (*b*) increment from ad-hoc platooning to scheduled platooning.

Table 4. Energy-Saving Percentage to Trip Distance

Miles	(0, 500)	(500, 1000)	(1000, 1500)	(1500, 2000)	(2000, 2500)	(2500, 3000)	(3000, 3500)
Absolute energy-saving percentage							
Mean	8.18	8.28	8.31	8.26	8.36	8.47	8.48
Max	8.57	8.56	8.55	8.54	8.54	8.54	8.48
Min	0	0	2.18	4.23	5.89	7.39	8.48
Std	0.86	0.54	0.41	0.47	0.28	0.10	0
Energy-saving percentage increment							
Mean	3.73	3.74	4.24	4.77	4.65	4.00	4.34
Max	8.29	07.94	7.62	7.44	6.98	6.56	4.34
Min	−1.45	0	0.79	1.37	1.86	1.87	4.34
Std	1.70	1.44	1.27	1.10	0.94	0.85	0

Note: max = maximum; min = minimum; std = standard deviation.

percentage, while the right panel shows the energy-saving percentage increments compared with those under ad-hoc platooning. Based on the trip distance, we further categorize all OD pairs into seven disjoint classes, with each class holding an interval of 500 mi. For each class, the mean value, maximum value, minimum value, and

Table 5. Break-Even Miles of Truck Platooning Technology ($12,000 per Truck)

Max platoon size	2	3	4	5	6	7
Scheduled: 10 min	601,640	452,018	402,434	377,823	363,183	353,506
Ad-hoc	879,321	683,477	625,470	600,586	588,152	581,398

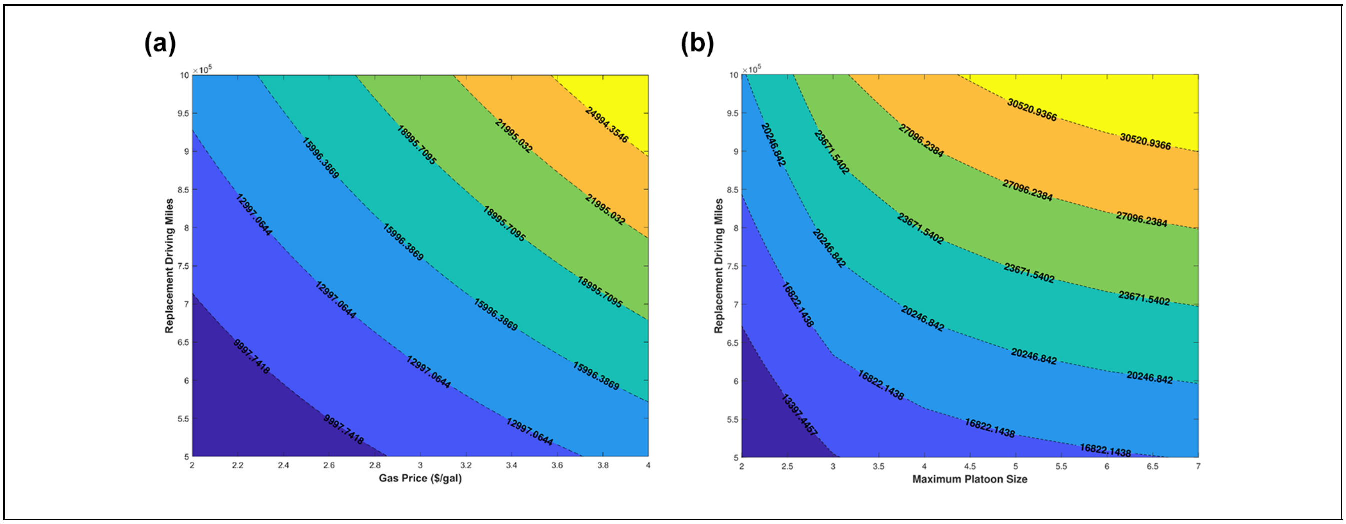

Figure 12. Break-even price for the technology: (*a*) varying gap price and miles and (*b*) varying maximum platoon size and miles.

standard deviation of absolute energy-saving percentages and energy-saving percentage increments are listed in Table 4. It can be seen that all trips benefit from truck platooning regardless of the travel distance. Nevertheless, the longer distance the trip has, the higher the average energy-saving percentage it can receive. Furthermore, shorter trips have larger variances in energy savings than longer trips. In sum, the longer the trip is, the more likely it is that it can benefit from nation-wide planning.

Individual Owner's Perspective

Individual truck owners care about the profits if adopting the technology. Therefore, we conduct a set of cost–benefit analyses in this subsection. We first check break-even mileage, which is the mileage that a truck travels under platooning when the monetary value of energy savings offsets the technology cost. We assume that the technology cost is $12,000, the gas price is $2.850/gal, the driving years before replacement are 7 years (Table 2), and the inflation rate is 1.8% (*22*). Table 5 lists the break-even miles under both scheduled platooning with a 10-min schedule flexibility and ad-hoc platooning, when the maximum platoon sizes varying from two to seven. The results from scheduled platooning are foreseeable, while those from ad-hoc platooning are more promising than expected. One reason is that the U.S. truck demand is very large, so that platooning opportunities appear sufficient if the market penetration of the technology is 100%. Assume that the platooning technology is implemented in the truck tractors whose average driving mileage until the replacement is 700,000 mi (Table 2). If the maximum platoon size is two, a truck owner cannot recover her technology cost by energy savings under ad-hoc platooning. Nevertheless, either by introducing scheduled platooning or by increasing the maximum platoon size, a truck owner can recover her technology cost before vehicle replacement.

However, one can see that the exact values of break-even miles largely depend on the technology cost, which, however, is ambiguous at the technology's infant stage. Thus, we further provide the break-even price, which can be viewed as the net present value of the energy-saving benefits under the given driving miles, gas price, and maximum platoon size. Figure 12*a* shows that when the maximum platoon size is fixed to be two, the break-even price increases with the increase of driving miles and gas price. Here, we assume that the driving miles before the replacement vary from 500,000 mi to 1,000,000 mi, and the gas price changes from $2/gal to $4/gal. Still, the driving years before replacement are 7 years and the inflation rate is 1.8%. The maximum and minimum of the break-even price are $27,994 and $6,998, respectively. Similarly, Figure 12*b* presents the variation of break-even price to the driving miles and the maximum platoon size with gas price $2.85/gal. In this case, the break-even price varies from $9,727 to $33,946. As truck owners will be willing to purchase the platooning technology only if the cost is less than the break-even price, the higher the break-even price (i.e., energy-saving benefits), the more truck owners would like to equip their vehicles with platooning technology. The break-even price then provides a reference for pricing in respect of the technology cost and planning cost.

Conclusion

In this study, we utilize real truck demand data to explore truck platooning opportunities and the associated energy-saving potentials over the U.S. highway freight network. Specifically, scheduled platooning for the recurrent daily truck OD demand is determined by the truck itinerary planning model. An approximation algorithm is applied to efficiently generate a feasible solution with an acceptable degree of optimality.

The numerical results reveal that the energy-saving potentials are promising in general. The exact values are determined by a set of variables, including the reduction rate of energy consumption, platoon size limit, schedule flexibility, fuel efficiency, gas price, and so forth. When using a piece-wise linear function for fuel consumption with a reduction rate of 10%, the average energy savings per truck over the whole network achieve 8.38% if the maximum platoon size is seven. By comparing the result with that from ad-hoc platooning, we can conclude that truck itinerary planning greatly improves the energy-saving figure. Specifically, nation-wide planning benefits longer-distance trips more than shorter-distance trips. The cost–benefit analysis indicates that truck platooning is financially viable for truck owners, even if the energy savings are considered the only economic benefit. It can be expected that with the introduction of labor-cost savings, the truck platooning market will be more promising in the future.

A few extensions can be made to this study. First of all, the fuel consumption model can be further refined by considering road slopes, weather conditions, and traffic conditions, which have been revealed as explanatory variables of fuel efficiency (*23*, *24*). Moreover, the energy consumption during the assembly and disassembly of platoons needs to be considered: previous research has indicated that the energy consumption can largely depend on the position at which a fleet joins or leaves a platoon (*25*). Second, as this study intends to provide an overall insight into energy-saving potentials, the truck itineraries generated may not be appropriate to be directly utilized in truck operations. Other practical limitations, such as truck drivers' rest hour regulations, stochastic truck demand, heterogeneous travel windows, and disassembly and re-assembly processes resulting from traffic congestion and highway on- and off-ramps (*26*), can be included in the optimization model to produce more workable itineraries. Third, as the analysis is conducted based on the current demand and technology level, many of the data and parameters can be revised to consider future developments, such as increased truck demands, fuel efficiency, fuel price, and so forth.

Finally, as this empirical study is conducted on all truck demands of the whole U.S. highway freight system, we would like to emphasize that the result is obtained under the assumptions that the market penetration rate of truck platooning technology is 100%, and a central controller can coordinate all trucking companies to facilitate truck platooning, which are unattainable in reality. For practical consideration, these two critical assumptions can also be addressed. Bridgelall et al. have studied the adoption uncertainty of truck platooning via the logistic model for technology diffusion, which has a closed-form formulation and can be used in a future planning model (*27*). Benefit redistribution mechanisms perform as facilitators that promote inter-organizational cooperation for platoon purposes. These mechanisms have been studied in other papers, for instance (*28*).

Acknowledgments

The authors thank Dr. Mohamadhossein Noruzoliaee at the University of Illinois, Chicago for generously sharing the truck demand data.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Y. Yin; data collection and processing: X. Sun, H. Wu, B. Zou; model and algorithm development: M. Abdolmaleki; analysis and interpretation of results: X. Sun; draft manuscript preparation: X. Sun. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: The work described in this paper was partly supported by research grants from the National Science Foundation (CNS-1837245 and CMMI-1904575).

ORCID iDs

Xiaotong Sun https://orcid.org/0000-0002-3493-8828
Haochen Wu https://orcid.org/0000-0001-5252-6707
Mojitaba Abdolmaleki https://orcid.org/0000-0002-6337-1939
Yafeng Yin https://orcid.org/0000-0003-3117-5463
Bo Zou https://orcid.org/0000-0003-4485-5548

References

1. Tsugawa, S., S. Jeschke, and S. E. Shladover. A Review of Truck Platooning Projects for Energy Savings. *IEEE Transactions on Intelligent Vehicles*, Vol. 1, No. 1, 2016, pp. 68–77.
2. McAuliffe, B., M. Lammert, X. Lu, S. Shladover, et al. *Influences on Energy Savings of Heavy Trucks Using Cooperative Adaptive Cruise Control*. SAE Technical Paper 2018-01-1181. SAE (Society of Automotive Engineers) International Location of the conference, Detroit, MI, USA, 2018, https://doi.org/10.4271/2018-01-1181.
3. Murray, D., and S. Glidewell. *An Analysis of the Operational Costs of Trucking: 2019 Update*. Technical report, American Transportation Research Institute, Arlington, VA, USA, 2019.
4. Liang, K.-Y., J. Martensson, and K. H. Johansson. Fuel-Saving Potentials of Platooning Evaluated through Sparse Heavy-Duty Vehicle Position Data. 2014 IEEE Intelligent Vehicles Symposium Proceedings, IEEE, Ypsilanti, MI, USA, 2014, pp. 1061–1068.
5. Muratori, M., J. Holden, M. Lammert, A. Duran, S. Young, and J. Gonder. Potentials for Platooning in US Highway Freight Transport. *SAE International Journal of Commercial Vehicles*, Vol. 10, 2017, pp. 45–49.
6. Lammert, M., B. Bugbee, Y. Hou, A. Mack, et al. *Exploring Telematics Big Data for Truck Platooning Opportunities*. SAE Technical Paper 2018-01-1083, SAE (Society of Automotive Engineers) InternationalLocation of the conference, Detroit, MI, USA, 2018, https://doi.org/10.4271/2018-01-1083.
7. Bhoopalam, A. K., N. Agatz, and R. Zuidwijk. Planning of Truck Platoons: A Literature Review and Directions for Future Research. *Transportation Research Part B: Methodological*, Vol. 107, No. 18, 2018, pp. 212–228.
8. BTS and FHWA. *Freight Analysis Framework*. https://ops.fhwa.dot.gov/freight/20freight_analysis/faf/, 2016, Accessed August 4, 2019.
9. Abdolmaleki, M., S. Mehrdad, Y. Yafeng, and M. Neda. *Itinerary Planning for Cooperative Truck Platooning*. SSRN. https://ssrn.com/abstract=3481598 Accessed November 6, 2019.
10. National Renewable Energy Laboratory. *Fleet DNA Project Data*. www.nrel.gov/fleetdna, 2019, Accessed January 15, 2019.
11. Reis, V., R. Pereira, and P. Kanwat. Assessing the Potential of Truck Platooning in Short Distances: The Case Study of Portugal. In *Urban Freight Transportation Systems* (Elbert , R., C. Friedrich, M. Boltze, and H.C. Pfohl), Elsevier, Amsterdam, Netherlands, 2020, pp. 203–222.
12. Bakermans, B.. *Truck Platooning: Enablers, Barriers, Potential and Impacts*, Master Thesis. Delft University of Technology, Delft, Netherlands, 2016.
13. Larsen, R., J. Rich, and T. K. Rasmussen. Hub-Based Truck Platooning: Potentials and Profitability. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 127, 2019, pp. 249–264.
14. Noruzoliaee, M., B. Zou, and Y. J. Zhou. Truck Platooning in the US National Road Network: A System-Level Modeling Approach. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 145, 2021, p. 102200.
15. Hinneburg, A., and H.-H. Gabriel. Denclue 2.0: Fast Clustering Based on Kernel Density Estimation. *International Symposium on Intelligent Data Analysis*, Springer, Ljubljana, Slovenia, 2007, pp. 70–80.
16. Fischer, M., J. Ang-Olson, and A. La. External Urban Truck Trips Based on Commodity Flows: A Model. *Transportation Research Record: Journal of the Transportation Research Board*, 2000. 1707(1): 73–80.
17. Opie, K., J. Rowinski, and L. N. Spasovic. Commodity-Specific Disaggregation of 2002 Freight Analysis Framework Data to County Level in New Jersey. *Transportation Research Record: : Journal of the Transportation Research Board*, 2009. 2121(1): 128–134.
18. Larson, J., T. Munson, and V. Sokolov. Coordinated Platoon Routing in a Metropolitan Network. *2016 Proc. Seventh SIAM Workshop on Combinatorial Scientific Computing*, SIAM, Albuquerque, New Mexico, USA, 2016, pp. 73–82.
19. EIA, Gasoline and Diesel Fuel Update, U.S. Energy Information Administration. https://www.eia.gov/petroleum/gasdiesel/. 2020, Accessed March 20, 2020.
20. Kilcarr, S. The Price Tag for Autonomous Trucks Still Unclear. https://www.fleetowner.com/technology/article/21692381/the-price-tag-for-autonomous-trucks-still-unclear. 2019, Accessed December 28, 2015.
21. National Highway Traffic Safety Administration. Vehicle-to-Vehicle Communication. https://www.nhtsa.gov/30technology-innovation/vehicle-vehicle-communication. 2020, Accessed July 25, 2020.
22. Statista, United States: Inflation Rate from 1990 to 2020. https://www.statista.com/statistics/191077/inflation-rate-in-the-usa-since-1990/#professional. 2020, Acessed July 14, 2020.
23. Laxhammar, R. *Cooperative Dynamic Formation of Platoons for Safe and Energy-Optimized Goods Transportation D3.2 Information Model for Platoon Services*, SCANIA CV AB via European Commission, Sodertalje, Sweden. https://cordis.europa.eu/project/id/610990. 2015.
24. Taylor, A. H., M. J. Droege, G. M. Shaver, J. A. Sandoval, S. Erlien, and J. Kuszmaul. Capturing the Impact of Speed, Grade, and Traffic on Class 8 Truck Platooning. *IEEE Transactions on Vehicular Technology*, Vol. 69, No. 10, 2020, pp. 10506–10518.
25. Hao, P., Z. Wang, G. Wu, K. Boriboonsomsin, and M. Barth. Intra-Platoon Vehicle Sequence Optimization for Eco-Cooperative Adaptive Cruise Control. *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)*, IEEE, Yokohama, JAPAN, 2017, pp. 1–6.
26. Calvert, S., W. Schakel, and B. van Arem. Evaluation and Modelling of the Traffic Flow Effects of Truck Platooning. *Transportation Research Part C: Emerging Technologies*, Vol. 105, 2019, pp. 1–22.
27. Bridgelall, R., D. A. Patterson, and D. D. Tolliver. Policy Implications of Truck Platooning and Electrification. *Energy Policy*, Vol. 139, 2020, p. 111313.
28. Sun, X., and Y. Yin. Behaviorally Stable Vehicle Platooning for Energy Savings. *Transportation Research Part C: Emerging Technologies*, Vol. 99, 2019, pp. 37–52.