Freight Focus

TRR
JOURNAL OF THE TRANSPORTATION RESEARCH BOARD

Transportation Research Record
2023, Vol. 2677(2) 78–97

DOI: 10.1177/03611981221101890
journals.sagepub.com/home/trr
SAGE

Evaluating Cost Savings from Truck Caravanning

Vasileios Liatsos[1], Dimitrios Giampouranis[1], Mihalis Golias[1], Sabyasachee Mishra[1], John Hourdos[2], Razi Nalim[3], Mark T. Frohlich[4], and Clayton Nicholas[5]

Abstract

Truck platooning and related autonomous vehicle coordination concepts have been proposed as sustainable ways to increase profits and improve service quality. Recently the concept of truck caravanning, a hybrid truck platooning with only one truck driver required per platoon, has been proposed in the literature. This paper describes the research effort in developing a model that can estimate the cost savings of truck caravanning. The motivation of the proposed model is to investigate if substantial monetary savings exist to justify the initial capital investment (both in equipment and infrastructure) required for the implementation of the truck caravanning concept. A linear programming model is developed and used to evaluate different size networks. Results from numerical experiments indicate that a caravan size of four trucks or greater is needed for significant cost savings to be achieved and that driver compensation is the most critical factor dictating profitability.

Keywords

freight systems, truck platooning/caravanning, vehicle routing/scheduling, trucking industry research, vehicle-highway automation

The freight transportation system in the United States is one of the cornerstones of economic prosperity and relies heavily on efficient transport by road. Long-term economic growth, as well as the nation's dramatic shift to e-commerce, is expected to result in even greater demand for truck-based freight transportation. In 2019, trucks moved 11.84 billion tons of freight or 71.4% of the nation's tonnage, with trucking revenues accounting for 80.4% of the nation's freight bill (*1*). The latest version of the Freight Analysis Framework projects that, by 2045, truck traffic in the U.S. will increase 30% by tonnage and 60% by value. Transportation in the U.S. accounted for the largest portion (29%) of total greenhouse gas emissions in 2017 with light, medium, and heavy duty trucks contributing 82% of this portion (*2*).

In recent years, the concept of truck platooning (*3–5*) has gained interest among researchers and practitioners as an approach that can reduce fuel consumption and emissions while increasing safety and driver retention (among other benefits such as traffic flow stability). A truck platoon is a set of trucks that travel in the same direction within sufficient proximity to reduce aerodynamic drag and discourage other (passenger) vehicles from interrupting the platoon. This means that only the leading truck is responsible for the navigation of the platoon. All following trucks are connected to the leader and receive information automatically about steering, acceleration, and deceleration.

The concept of truck platooning has been around since the late 1990s. However, there are issues with realizing the true savings envisioned, along with the potential issue of trailing driver inattention which is just as dangerous as driver distraction. Preliminary research results on

[1]Department of Civil Engineering, University of Memphis, Memphis, TN
[2]Department of Civil, Environmental, and Geo-Engineering, Minneapolis, MN
[3]Department of Mechanical and Energy Engineering, Indiana University–Purdue University, Indianapolis, IN
[4]Kelley School of Business, Indiana University, Indianapolis, IN
[5]Purdue School of Engineering and Technology, Indiana University, Indianapolis, IN

Corresponding Author:
Mihalis Golias, mgkolias@memphis.edu

truck platooning suggest aerodynamic drag reductions of approximately 10% (*6*) for the trailing vehicles, which translates into a reduction of fuel consumption (with estimates ranging from 3% to 21%) (*7–10*) depending on spacing, vehicle speed, vehicle position, and vehicle mass. These fuel savings have been debated, as revealed by an extensive literature review by Zhang et al. (*11*), as they do not take into consideration a variety of factors that affect the final fuel consumption.

As Bhoopalam et al. (*12*) observed, "truck platooning constitutes a first step toward automated freight transportation." Based on the rapid advances in autonomous vehicle technology, the development of hybrid truck platoons or truck caravans where either only the lead truck has a driver, or no driver is required (*13–15*) could constitute the second step in this direction. In the U.S. for example, the State of Georgia is moving forward with a truck only highway (known as a dedicated truck corridor) that would support safe implementation of the truck caravanning concept (*16*). In addition to automation, truck caravanning may have significant monetary savings stemming largely from reductions in driver compensation costs. To the best of the authors' knowledge, no study exists that quantifies these benefits. Although not considered in this paper, the concept of a Caravanning Autonomous Vehicle System (CAVS) could also result in fuel savings as it includes the concept of energy storage within each unit of the CAVS, with the possibility of the lead truck generating power from fuel and sharing it with other trucks.

In this research, we propose a mathematical model to quantify the monetary benefits of truck caravanning from the need for fewer truck drivers (i.e., only the leading truck requires a driver) under the assumption that technological advances will allow implementation. In the problem studied here, trucks start from different origins, couple in caravans at pre-designated locations, travel in convoys to decoupling stations, and then traverse to their destination individually. The goal of this paper is not to support or validate the technological feasibility of truck caravanning or hybrid truck platooning but rather to propose a model that can estimate cost savings if such a concept is technologically feasible. The rational for establishing this model is to identify if substantial monetary savings exist to justify the high capital investment (both in equipment and infrastructure) that would be required for the truck caravanning concept to be implemented. In this paper, and unlike research published on truck platooning to date, the cost savings considered are easily verifiable as they only consider driver compensation savings (i.e., a reduction of drivers needed for the caravans). Any cost savings from fuel or emissions reductions are not considered, though they could be easily incorporated into the proposed model if reliable data or models became available. The rest of the paper is structured as follows: the next section provides a summary of the related literature followed by a section on the model description and mathematical formulation. The subsequent section presents results from numerical experiments followed by conclusions.

Literature Review

In this section, we will review research on simulations of truck platooning coordination, with one operator for each truck. The fundamental classification of operational research studies for truck platooning coordination is based on the availability of trip announcements (*12*) and is divided into three different categories: (i) scheduled platoon planning, where a centralized authority knows in advance the departure time of trucks; (ii) real-time platooning, where all the trip information is announced just before or during the trip; and (iii) opportunistic (i.e., spontaneous or on-the-fly) planning where trucks in the vicinity of a locality act opportunistically to reap the benefits from existing traveling convoys. Most research published to date has focused on the first two platooning categories. Next, we present a brief discussion of the published literature in each one of the three categories.

Scheduled Platoon Planning

Larsson et al. (*17*), proved that scheduled truck platooning routing problems without deadlines at the destination points and with similar starting points in a planar network graph is NP-hard. An integer linear formulation was proposed that resulted in a maximum of 9% in fuel savings for the instance of a system of 200 trucks. This work was extended by Larson et al. (*18*) who proposed a mixed-integer problem that produced an optimal solution for routing and platoon scheduling with up to 25 trucks. Fuel savings up to 8% were obtained when trucks were willing to wait at coupling points. Larson et al. (*19*, *20*) proposed a formulation where a local controller, based on a road network junction, determines whether fuel costs from speed adjustments of trucks to merge in a platoon was profitable when compared with the conventional individual truck routing. Results from simulation-based analysis showed fuel reductions close to 9% with problem instances of more than 7,000 trucks. Larsen et al. (*21*) studied a hub-based platooning schedule with fixed hub locations and truck routes. Results showed that total profits fluctuated between 4% and 5% for instances up to 500 trucks, when the ability of drivers to rest when they participate in platoons, fuel reduction, and waiting costs are the objectives.

Adler et al. (*22*) formulated the platooning schedule problem between two fixed hubs. The main purpose of their model was the evaluation of the energy-delay trade-offs between idle time and energy savings in platooning policy. They concluded that efficient platoon sizes vary between five and seven trucks, but the consideration of only one origination point and one destination point limits the generalization of their results to real world applications.

Boysen et al. (*23*) considered an identical-path truck platooning problem to evaluate the impacts of: (i) platooning technology dissemination; (ii) maximum number of trucks in every platoon; and (iii) willingness of trucks to wait to merge in platoons. Results showed that 91% of total cost savings (i.e., energy and reduced wage savings) were derived from unmanned follower trucks and that platoons with more than six trucks are not cost beneficial because of high truck waiting times to form the platoon. This was the first published study to quantify cost savings from truck drivers' compensation and proved that it could be substantial enough to justify investment costs. Nourmohammadzadeh and Hartmann (*24*), proposed a genetic algorithm-based heuristic to solve the platoon scheduling problem. Results showed a 5% fuel reduction for instances of 50 trucks. An extension of this work was presented by the same authors (*25*) with the implementation of a metaheuristic algorithm, inspired by an ant colony optimization (ACO). The proposed metaheuristic could handle problem instances of up to 500 trucks with fuel savings around 7%.

Meisen and Seidl (*26*) proposed an algorithm to detect beneficial platooning throughout a database of routes. They used random departure times from zip codes that showed an exponential increase of platoon formation as the number of routes increased, with a maximum of 5,000 routes. A game theoretic framework based on the Nash equilibrium was proposed by Farokhi and Johansson (*27*) to explore the trade-off between road traffic congestion and truck platooning incentives. They introduced an atomic congestion game with two types of agents. The first agent type consists of trucks and cars without platooning equipment, and the second of trucks motivated to participate in platooning to decrease fuel consumption. A joint strategy fictitious play to derive a pure strategy Nash equilibrium game was applied. A linear relationship between the velocity of commuting and the number of trucks which travel on the road at the same time was observed. Luo and Larson (*28*) proposed a repeated route-then-schedule heuristic method to deal with the complexity of truck platoon scheduling. The results indicated fuel reductions of 4.5% for a problem instance with 150 trucks. Abdolmaleki et al. (*29*) formulated the itinerary truck platoon planning as a network flow problem with time discretization. Fuel consumption savings fluctuated between 2% and 8% depending on the number of trucks. Sun et al. (*30*) provided a robust insight into the energy saving potential of truck platooning, using real truck demand data for 363,570 trucks over a simplified U.S. highway freight network. They formulated the itinerary planning problem to minimize the total energy consumption. The results of the approximation algorithm indicate gas consumption savings between 5% and 8% depending mainly on platoon size and scheduling flexibility.

Real-time Platooning

Hoef et al. (*31*) proposed a pairwise catch-up platooning formulation (i.e., acceleration of following truck to merge into a platoon). The leading truck of each platoon was selected by a clustering method based on pairwise fuel-optimal speed profiles. After the leaders have been selected, all pairs were composed into an overall coordination. As an alternative to catch-up (i.e., acceleration of following trucks), the leading trucks can decelerate to allow merging with following trucks. In either case, the existence of extra cost is inevitable, as there exists an increase in fuel consumption during acceleration and penalties for late arrival during deceleration. Fuel reductions between 6% and 8% were estimated. To avoid the use of a central authority decision maker, Saeednia et al. (*32*) proposed a consensus-based algorithm for real-time platooning. In every iteration of the algorithm, trucks try to reach a consensus on the common characteristic of speed, which allows all the members to participate in beneficial platoons. Trucks with intervehicle distance up to 3 km require approximately 14 min to merge in a platoon. However, a real-life implementation of any platooning formation may differ from theoretical models.

The dynamic nature of road traffic with a platoon structure has been described by Li (*33*, *34*). In the former, a stochastic dynamic model for truck platooning was proposed. They used a Markov regime-switching method to deal with the dynamic nature of platoon-to-platoon transition and a space-state model to detect the dynamic motions of individual trucks in platoons. The latter took into consideration platoon size, within-platoon headway, between-platoon headway, and platoon speed. Under this coordination scheme, the optimal platoon size was 1.08 and 1.58 trucks for lower and higher velocity models respectively. This appears to contradict most of the literature on optimal platoon size (i.e., from two to 10 trucks). However, studies about aerodynamic evaluation of truck platooning (already mentioned in the introduction) dissented about the fuel reduction, it was a common observation that the first truck in a convoy has almost no or the least benefit. If only a single truck benefits, the platooning concept cannot be profitable. The uncertainty of travel time was taken into consideration by van de Hoef et al. (*35*) in a stochastic dynamic problem formulated to maximize the probability of two different trucks being in the vicinity to merge in a platoon. Notably, the merging probability using optimal control under reliable type segments was 52%.

Opportunistic Planning

Liang et al. (*36*) compared the results of opportunistic platooning coordination and real-time coordination where a vehicle's departure can be adjusted. The fuel savings from the latter were almost three times greater compared with the opportunistic case and platooning rate increased substantially when trucks were willing to adjust their departure time. Liang et al. (*37*) extended their research (*29*) by formulating the optimal fuel-speed problem for two trucks. Fuel savings from this opportunistic planning were less than 5% and depended on the vehicles' weight. Under opportunistic planning, platooning is fuel-beneficial if the distance to the destination of the following truck is 16.5 times longer than the intervehicle distance the following truck must cover to catch the leading truck (*38*). The potential of opportunistic platooning scheduling was studied by Noruzoliaee et al. (*39*) through a system-level equilibrium model. This constitutes one of the very few examples of large-scale network research into truck platooning. A multiclass network equilibrium model integrates the relationship between platoon formation time, fuel saving, and increase in effective road capacity. Despite the substantial—almost 8%—fuel savings, platooning could lead to an increase in road capacity of up to 60% on rural interstate road networks.

Literature Review Summary

Table 1 summarizes the examined literature on truck platooning. Most of the objectives considered focused on fuel savings and delays. Despite the plethora of publications on truck platoon scheduling, to the best of the authors' knowledge, no published research exists that deals with the truck caravanning problem, as was defined above by the authors, and is discussed in more detail below.

Problem Description and Mathematical Models

The problem studied in this paper is the typical transportation problem with intermediate nodes where truck caravans are (de)coupled. An example caravanning network (CN) is shown in Figure 1. In the model proposed here, trucks start from several predefined origins at different times to cover demand at various destinations. Drivers release trucks at coupling points (i.e., node set K_1), where a truck caravanning provider is responsible for the coupling operations. All trucks travel in caravans between coupling and decoupling points (i.e., node set K_2), where a truck caravanning provider is responsible for the decoupling operations. In this paper we assume that candidate locations to serve as possible (de)coupling nodes have already been selected based on network connectivity and proximity to the origin and destination nodes. The proposed mathematical model (presented next) will decide which nodes should be used. In our formulation we do not consider costs associated with creating the facility as these would be a one-time expense and should not be considered when calculating long-term benefits from the proposed concept.

We likewise assume that drivers at the decoupling nodes are available to drive the individual trucks to their destinations. The objective of the proposed model is to minimize labor usage and the total costs for the entire network. Labor savings are derived from using fewer drivers while costs can increase as a result of late delivery times caused by delays at the coupling nodes and longer paths to accommodate the formation of caravans. Driver compensation from/to the coupling/decoupling nodes (either bobtail or deadheading which depends heavily on the continent) is also considered and set equal to the regular truck driver compensation rate. In this paper we do not consider the cases of reverse logistics where a load is available at nodes K_1 or where a truck driver delivers a load at node K_2 destined to be returned to the origin, since both will reduce the total cost of the proposed concept. Travel times between every node in the network are known and deterministic and the maximum internode travel time is limited to time allowed by the U.S. hours of service (HOS) regulation (*40*). Each truck departs from its origin at a predetermined release time, can join any available caravan at any coupling node, and can satisfy the demand at any destination point. Consequently, supply and demand are expressed in whole truck fractions. Finally, the caravan size is predetermined, and each demand point has a delivery deadline. Next, we present the nomenclature used throughout the paper, followed by the mathematical model (from now on referred to as the Caravanning Network Model [CNM]).

In this paper we also introduce a second model (from now on referred to as the base network [BN] problem) where trucks traverse directly from the origins to the destinations following the shortest (in time) possible route. The Base Network Model (BNM) interprets the traditional transportation way, and it is used comparative with the proposed concept (CNM) for the cost savings calculation. Next, we present additional nomenclature and the BN model formulation (BNM).

Nomenclature

For the numerical experiments in the paper, we assumed that the total supply is equal to the total demand (i.e.,

Table 1. Overview of Examined Literature

Author	Platooning planning	Objective	Formulation	Solution algorithm	Results	Remarks
Larsson et al. (*17*)	**S**	Min. fuel consumption	ILP	Branch and bound	9% fuel reduction for 200 trucks (same starting point for all trucks)	Heuristic and local search improvement heuristic algorithm for large-scale instances
Larson et al. (*18*)	**S**	Min. fuel consumption and delays	MIP	Branch and bound	8% fuel reduction for 25 trucks when they are willing to wait to merge in platoons	Auxiliary parameter and constraint introduction for large-scale instances
Larson et al. (*19*, *20*)	**S**	Min. fuel consumption	Distributed method	Local search controllers	Less than 2% fuel reduction for 300 trucks and 9% fuel savings for less than 9,000 trucks	Large-scale simulation
Larsen et al. (*21*)	**S**	Max. profits of driving in platoon	MIP	Simulation and Heuristic	4% to 5% fuel reduction for 100 to 500 trucks	Local search heuristic implementation (delays are taken into consideration as cost)
Adler et al. (*22*)	**S**	Min. energy consumption and delays	Queueing theory	Pareto-optimal boundary	Efficient platoon size between 5 and 7 trucks	Policies: i) open loop (timetable); and ii) feedback. Pareto-optimal policies and the optimal energy-delay curves are explored for each case
Boysen et al. (*23*)	**S**	Min. platooning cost	LP-MIP	Heuristic	Saving only from reduced number of drivers from 80% to 95% depending on drivers' wages and diesel price	The costs are fuel costs, driver wages, and early or late delivery costs
Nourmohammadzadeh and Hartmann (*24*)	**S**	Min. fuel cost	MIP	Genetic algorithm	5% fuel reduction for 50 trucks by GA	For instances of more than 20 trucks only the GA implemented
Nourmohammadzadeh and Hartmann (*25*)	**S**	Min. fuel cost	MIP	Genetic algorithm	3.26% fuel savings by exact solution (optimality gap is not mentioned as the termination condition is 30 min) and 7.26% by metaheuristic solution for 500 trucks	Metaheuristic solution method inspired by ant colony optimization

(continued)

Table 1. (continued)

Author	Platooning planning	Objective	Formulation	Solution algorithm	Results	Remarks
Meisen and Seidl (*26*)	**S**	Max. profits of driving in platoon	Mining frequent sequences	Truck platoon sequential pattern	Profit up to €4.5 per truck	Platoons are increased exponentially with increase in number of trucks
Farokhi and Johansson (*27*)	**S**	Car traffic and truck platooning incentives interaction	Non-cooperative Nash Equilibrium	Simulation	Linear relationship between the velocity of commuting and the number of trucks which are travel on the road at the same time	Trade-off between road traffic congestion and platooning incentives
Lue and Larson (*28*)	**S**	Max. fuel savings	MILP	Branch and bound	4.5% fuel reduction for 150 trucks	Route-then-schedule heuristic method and valid inequalities implementation
Abdolmaleki et al. (*29*)	**S**	Max. fuel savings	MINLP	Outer approximation cuts and local search	Less than 9% fuel reduction for 10,000 trucks by heuristic	Dynamic-programming heuristic implemented for large-scale networks
Xiaotong Sun and Yafeng Yin (*30*)	**S**	Max. utility of the platoon (optimal platoon speed and vehicle sequence)	MINLP	Exact	Average energy reduction of 8.48% per truck (platoon size seven trucks and 30 min schedule flexibility)	The introduction of labor-cost savings could make platooning very promising
Hoef et al. (*31*)	**R**	Max. fuel savings	MIP	Leader selection clustering based on speed	6% to 8% fuel reduction for 7,000 trucks	Monte Carlos simulations
Saeednia et al. (*32*)	**R**	Min. fuel consumption and delays	MIP	Exact	Superiority of consensus-based algorithm under changing traffic conditions	Comparison between optimization-based and consensus-based algorithms
Li (*33*, *34*)	**R**	Speed and travel time	State space model	Kalman and Hamilton filters	At the lower velocity model trucks tend to travel alone and not to form platoons (average platoon size 1.08 at optimum)	More statistical distribution models to evaluate crucial platoon characteristics (*28*)
Hoef et al. (*35*)	**R**	Max. probability of successful platoons	Integer dynamic programming	Backward recursion	Merging probability 52% using optimal control under reliable type segments	Model's evaluation through simulation

(continued)

Table 1. (continued)

Author	Platooning planning	Objective	Formulation	Solution algorithm	Results	Remarks
Liang et al. (*36*)	O	Max. fuel savings	Simulation	Map-matching and path-inference	0.60% fuel reduction with departure coordination and 0.22% fuel reduction with catch-up coordination (20 km coordination horizon)	Flexibility of departure time shows promising fuel saving
Liang et al. (*37*)	O	Max. fuel savings	MINLP	Interior point (fmincon in MatLab)	1.7% to 3.8% fuel reduction depending on truck weight	Model's evaluation through simulation
Liang et al. (*38*)	O	Max. fuel savings	Simulation	Scenario based analysis	Up to 7% fuel reduction with catch-up coordination strategy	Platooning incentive factor is introduced to evaluate catch-up attempts
Noruzoliaee et al. (*39*)	O	Interlocking relationship between, platoon formation time, fuel saving, and increase in effective road capacity	NLP	Dial's bush-based algorithm	Platooning could reach fuel saving up to 7.9%	Fuel saving is increased by increasing platoon size and is decreased by decreasing inter-truck distance

Note: S = scheduled; R = real-time; O = opportunistic; Min. = minimum; Max. = maximum ILP = Integer Linear Programming; MIP = Mixed-Integer Programming; MILP = Mixed-Integer Linear Programming; MINLP = Mixed-Integer Nonlinear Programming.

Sets

I:	Set of all nodes
O:	Set of origins
D:	Set of destinations
K_1:	Set of coupling nodes
K_2:	Set of decoupling nodes
P:	Set of caravans from K_1 to K_2
C:	Set of trucks

Note that: $O \cap K_1 = \emptyset$, $O \cap K_2 = \emptyset$, $O \cap D = \emptyset$, $K_1 \cap K_2 = \emptyset$, $K_1 \cap D = \emptyset$, $K_2 \cap D = \emptyset$, $O \cup K_1 \cup K_2 \cup D = I$

Input parameters

$t_{ij} \in \mathbb{R}$:	travel time (in hours) between nodes $i, j \in I$
$dm_m \in \mathbb{N}$:	demand at destination $m \in D$, $\sum_m dm_{m \in D} = C$
$cs \in \{2, 4, 5, 10\}$:	fixed number of trucks needed to form a caravan, i.e., caravan size
$O_{ic} \in \{0, 1\}$:	1 if truck $c \in C$ is located at origin $i \in O$
$ad_{mc} \in \mathbb{R}$:	arrival deadline at destination $m \in D$ for truck $c \in C$
$rt_c \in \mathbb{R}$:	release time of truck $c \in C$
$R^p_{jk} \in \{0, 1\}$:	1 if caravan $p \in P$ can be formed between nodes $j \in K_1$ and $k \in K_2$, $\sum_{j,k} R^p_{jk} = 1$, $\forall p \in P$
$DC_1 \in \{25\}$:	regular truck driver compensation (\$/hour)
$DC_2 \in \{50, 75\}$:	caravan truck driver compensation (\$/hour)
$DAP = \$500$:	delayed arrival penalty (\$/day)

$\sum_{m \in D} \mathrm{dm_m} = \sum_{i \in \mathrm{O}, c \in \mathrm{C}} \mathrm{O_{ic}} = C$). Supply and demand are allocated with a uniform distribution along all origin (i.e., node set O) and destination (i.e., node set D) points respectively. The departure time of every truck from the origin ($\mathrm{rt_c}$) is chosen by a uniform distribution U [2, 9]. This reflects that all trucks are released between 2 a.m. and 9 a.m. The regular truck driver compensation is defined as 25 \$/h. The caravan truck driver will be compensated by the double and the triple of the regular truck driver wages. The rationale behind those two case selections, as the selection of travel time and arrival deadline, is explicitly described in the next section. If any truck reaches its destination after the deadline, it will be penalized by 500 \$/day or 20.8 \$/h.

Caravanning Network Model (CNM)

The caravanning problem can be formulated as follows (Equations 1 through 14):

CNM :

$$min \sum_{\substack{i \in O, j \in K_1,\ k \in K_2, \\ m \in\ D. c \in C}} 2DC_1(x^c_{ij}\, t_{ij} + z^c_{km} t_{km}) + \sum_{\substack{j \in K_1,\ k \in K_2, \\ p \in P}} (DC_1 + DC_2) f^p_{jk}\, t_{jk} + \sum_{c \in C} dh_c DAP \tag{1}$$

CNM Decision variables

$x^c_{ij} \in \{0,1\}$	1 if truck $c \in C$ traverses from origin node $i \in \mathrm{O}$ to coupling node $j \in K_1$ and zero otherwise
$y^{cp}_{jk} \in \{0,1\}$	1 if truck $c \in C$ is assigned to caravan $p \in P$ from coupling node $j \in K_1$ to decoupling node $k \in K_2$ and zero otherwise
$z^c_{km} \in \{0,1\}$	1 if truck $c \in C$ traverses from decoupling node $k \in K_2$ to destinationnode $m \in D$ and zero otherwise
$f^p_{jk} \in \{0,1\}$	1 if caravan $p \in P$ is formed from node $j \in \mathrm{K_1}$ to $k \in K_2$ and zero otherwise
$dt_p \in \mathbb{R}$	departure time of caravan p $\in$ P from coupling node $\mathrm{K_1}$
$at_c \in \mathbb{R}$	arrival time of truck $c \in C$ at its destination
$tt_c \in \mathbb{R}$	total travel time of truck $c \in C$
$dh_c \in \mathbb{R}$	hours of delayed arrival at destination for truck $c \in C$

Subject to:

Supply/demand constraints

$$\sum_{j\in K_1} x_{ij}^c \leq O_{ic}, \forall i \in O,\ c \in C \tag{2}$$

$$\sum_{k\in K_2, c\in C} z_{km}^c = dm_m,\ \forall\ m \in D \tag{3}$$

Conservation of flow constraints

$$\sum_{i\in O, c\in C} x_{ij}^c = \sum_{k\in K_2, p\in P, c\in C} y_{jk}^{cp}, \forall\ j \in K_1 \tag{4}$$

$$\sum_{j\in K_1, p\in P, c\in C} y_{jk}^{cp} = \sum_{m\in D, c\in C} z_{km}^c,\ \forall\ k \in K_2 \tag{5}$$

$$\sum_{k\in K_2 m\in D,} z_{km}^c = 1, \forall\ c \in C \tag{6}$$

Caravan size constraint

$$\sum_{c\in C} y_{jk}^{cp} = f_{jk}^p cs, \forall\ j \in K_1,\ k \in K_2, p \in P \tag{7}$$

A truck can be assigned to only one caravan

$$\sum_{j\in K_1, k\in K_2, p\in P} y_{jk}^{cp} = 1, \forall\ c \in C \tag{8}$$

Caravan departure time estimation

$$dt_p \geq rt_c + \sum_{i\in O, j\in K_1,\ k\in K_2} x_{ij}^c\, t_{ij} R_{jk}^p - M\Big(1 - \sum_{j\in K_1,\ k\in K_2} y_{jk}^{cp}\Big), \forall\ c \in C,\ p \in \mathrm{P} \tag{9}$$

Arrival time of trucks at destination estimation

$$at_c \geq dt_p + \sum_{j\in K_1,\ k\in K_2} t_{jk} y_{jk}^{cp} + \sum_{k\in K_2,\ m\in D} z_{km}^c t_{km} - M\left(1 - \sum_{j\in K_1,\ k\in K_2} y_{jk}^{cp}\right),\ \forall\ c \in C,\ p \in P \tag{10}$$

Truck travel time estimation (from origin to destination)

$$tt_c = at_c - rt_c, \forall\ c \in C \tag{11}$$

Hours of late arrival estimation

$$dh_c = at_c - \sum_{k\in K_2, m\in D} z_{km}^c ad_{mc}, \forall\ \mathrm{c} \in \mathrm{C} \tag{12}$$

Waiting time at coupling points estimation

$$\mathrm{wt_c} = \mathrm{tt_c} - \Big(\sum_{i\in O j\in K_1} x_{ij}^c\, t_{ij} + \sum_{j\in K_1, k\in K_2,\ p\in P} y_{jk}^{cp} t_{jk} + \sum_{k\in K_2,\ m\in D} z_{km}^c t_{km}\Big), \forall\ c \in C \tag{13}$$

Caravan formation constraints

$$f_{jk}^p \leq R_{jk}^p,\ \forall\ j \in K_1,\ k \in K_2,\ p \in P \tag{14}$$

$$\mathrm{y_{jk}^{cp}} \leq R_{jk}^p,\ \forall\ j \in K_1,\ k \in K_2, c \in C,\ p \in P \tag{15}$$

To better understand the mathematical model for the CNM we underline the importance of the binary decision variable f_{jk}^p along with parameter R_{jk}^p. The latter is equal to 1 if a caravan can be formed between a coupling and a decoupling node. We chose to include this parameter to reduce the models' complexity. The alternative would be the introduction of a decision variable to assign caravans between the coupling and decoupling nodes which would significantly increase the columns of the constraint matrix. For instance, if the total demand is 100 trucks and the caravan size is 5 then a maximum of 20 caravans can be formed between each K_1 and K_2 node pair (i.e., $\sum_{\mathrm{p}\in \mathrm{P}} R_{jk}^p = 20,\ \forall\ j \in K_1,\ k \in K_2$). Consequently, at this case the total member of available caravans will be $\sum_{\mathrm{j}\in \mathrm{K_1},\ \mathrm{k}\in \mathrm{K_2}, \mathrm{p}\in \mathrm{P}} R_{jk}^p = 20*|\mathrm{K_1}|*|\mathrm{K_2}|$. The decision variable f_{jk}^p decides which of these available caravans will be used. Note that future research could introduce a decision variable that assigns caravans between the (de)coupling nodes, a formulation that would support the development of a column generation-based heuristic (or Bender's decomposition for the dual) to solve the resulting model.

The first two components of the objective function (Equation 1) calculate the total driver cost (bobtail/deadheading driver compensation is included by doubling the one-way driver cost) while the third component calculates the cost from delayed arrivals at the destinations. Constraints sets 2 through 6 are the supply and demand constraints, and conservation of flow constraints at the (de)coupling nodes respectively. Constraints set 7, sets the number of trucks that join a caravan (if that caravan is formed) equal to a predetermined number. Constraints set 8 assigns each truck to only one caravan. Constraints set 9 estimates the departure time of a caravan, while constraints set 10 estimates the arrival time of a truck at the destination. Constraints set 11 estimates the travel time of a truck while constraints set 12 estimates the hours of late arrival. Constraints set 13 calculates the individual truck waiting (idle) time at the coupling points. Constraints sets 14 and 15 set the values of variables y and f equal to 0 for the (de)coupling nodes where a caravan is not defined.

The Base Network Model (BNM)

The Base Network Model (BNM) Decision Variables

$x_{im}^c \in \{0, 1\}$	1 if truck $c \in C$ traverses from node $i \in O$ to node m $\in D$ and zero otherwise
$at_c \in \mathbb{R}$	arrival time of truck $c \in C$ at its destination
$tt_c \in \mathbb{R}$	total travel time of truck $c \in C$
$dh_c \in \mathbb{R}$	hours of delayed arrival at destination *for truck* $c \in C$

BNM:

$$\min \sum_{c \in C} 2tt_c DC_1 + \sum_{c \in C} dh_c DAP \tag{16}$$

Subject to:

Supply/demand constraints

$$\sum_{m \in D} x_{im}^c \leqslant O_{ic}, \forall\ i \in O,\ c \in C \tag{17}$$

$$\sum_{i \in O,\ c \in C} x_{im}^c = dm_m,\ \forall\ m \in D \tag{18}$$

Estimation of truck arrival time at destination

$$at_c \geqslant rt_c + \sum_{i \in\ O, m \in D} x_{im}^c t_{im}, \forall\ \mathrm{c} \in \mathrm{C} \tag{19}$$

Truck travel time estimation (from origin to destination)

$$tt_c = at_c - rt_c, \forall\ c \in C \tag{20}$$

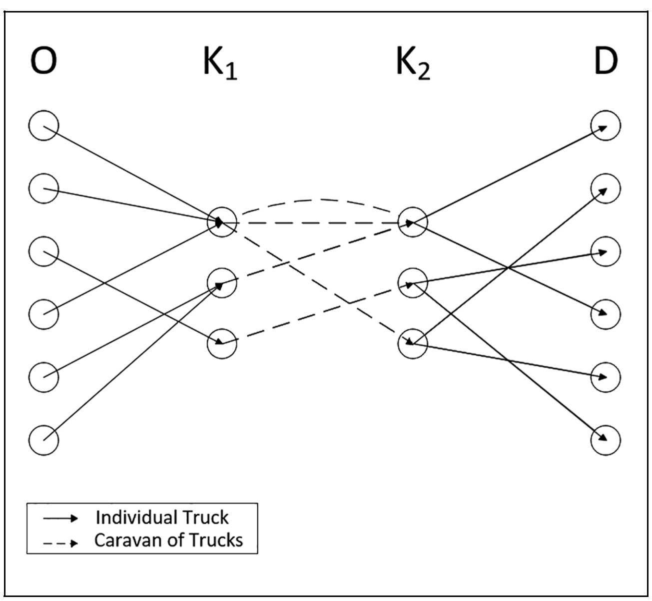

Figure 1. Caravanning network (CN).

Estimation of truck late arrivals (in hours)

$$dh_c \geqslant at_c - \sum_{i \in\ O, m \in D} x_{im}^c ad_{mc}, \forall\ \mathrm{c} \in \mathrm{C} \tag{21}$$

The objective function of the BNM (Equation 16) contains two components: the driver cost (bobtail driver compensation is included by doubling the one-way driver cost) and the cost of late arrivals at the destination. Constraints sets 17 and 18 are the supply and demand constraints. Constraints set 19 estimates the arrival time of a truck at the destination point while constraints set 20 and 21 calculate the truck travel time and hours of delayed arrival.

Numerical Experiments

Various numbers of origin, destination, and (de)coupling nodes, and demand were used to develop 36 test networks to explore the potential cost savings from the proposed truck caravanning freight operations concept. From problem instances 1 to 18 and 9 to 36 the demand is 100 and 200 trucks respectively. In this paper we assume that the supply is equal to the demand (truck units). Table 2 summarizes these data for each problem instance. Next, we discuss the selection for the values of the CNM and BNM parameters (i.e., travel times, driver compensation, caravan size, and arrival time deadlines at the destination nodes).

Travel Times

Travel times between all possible origin–destination pairs in the CN were generated using two uniform probability distributions. For the CN links that connect the origins to the coupling nodes and the decoupling to the destination nodes, travel times were generated based on a uniform distribution of U [2,3] in hours while travel times between caravanning nodes (K_1 and K_2) were based on a uniform distribution of U [9,11] in hours. The uniform distribution ranges between caravanning nodes were selected to comply with the HOS regulations (*40*). These predetermined travel time ranges result in trucks engaging in caravans between 60% and 73% of their total travel time (excluding any delays at the (de)coupling nodes). The BN travel times between an origin–destination (O-D) pair were calculated as a percentage of the shortest path travel time in the CN. For each problem instance in Table 2 we considered two cases, where travel times between the O-D pairs in the BN, are reduced by 20% and 40% respectively, as compared with the shortest paths in the CN.

For example, if the shortest path between origin node 1 and destination node 2 in the CN is 14 h then the travel time in the BN between origin node 1 and destination

Table 2. Test Network Instances

Network instance	Demand (trucks)	Origin nodes (O)	Coupling nodes (K_1)	Decoupling nodes (K_2)	Destination nodes (D)
1/19	100/200	4	2	2	4
2/20	100/200	6	2	2	6
3/10	100/200	8	2	2	8
4/22	100/200	4	3	3	4
5/23	100/200	6	3	3	6
6/24	100/200	8	3	3	8
7/25	100/200	2	2	2	4
8/26	100/200	2	2	2	6
9/27	100/200	2	2	2	8
10/28	100/200	2	3	3	4
11/29	100/200	2	3	3	6
12/30	100/200	2	3	3	8
13/31	100/200	4	2	2	2
14/32	100/200	6	2	2	2
15/33	100/200	8	2	2	2
16/34	100/200	4	3	3	2
17/35	100/200	6	3	3	2
18/36	100/200	8	3	3	2

node 2 would be 11.2 and 8.4 h for case 1 and 2, respectively. We also considered three different Arrival Time Deadlines (ATD) for the trucks at their destinations. For each O-D pair we calculated the shortest path in the BNM network. We then set the ATD to be a multiple of that shortest path travel time based on three uniform distributions of U [1, 1.5], U [1.5, 2], U [2, 2.5]. For example, assume that the shortest path travel time between an origin and a destination is 12 h. We consider three ATD cases where in the first case the deadline at this specific destination would be between 12 h and 18 h; in the second case between 18 h and 24 h; and in the third case between 24 h and 30 h, respectively.

Truck Driver Compensation

The caravanning concept is based on the idea that trained caravan drivers will take responsibility for a convoy of trucks between nodes K_1 and K_2. In this paper we consider two cases with respect to the truck caravan driver compensation where the hourly compensation is set to two ($^{DC_2}/_{DC_1} = 2$) and three times ($^{DC_2}/_{DC_1} = 3$) higher than that of a truck driver (from now on referred to as the Driver Compensation Ratio or DCR).

Caravanning Size

Another parameter that will affect the profitability of the proposed concept is the number of trucks that participate in a caravan (i.e., cs parameter value in the CNM). In this paper we considered four different caravan sizes of 2, 4, 5, and 10 trucks with the rational that cs values of 2 and 10 represent the extreme cases (worst- and best-case scenarios) while values for cs of 4 and 5 are more realistic. This assumption is in line with what has been presented in the literature (*22*, *23*, *41*). Additionally, big caravan sizes could create issues of traffic disruption (e.g., at on-ramp/off-ramp areas), traffic safety (e.g., moving bottleneck), and pavement damage especially if the vehicles do not have a lateral offset between them (*42*, *43*). At this point we underline the importance of truck allocation in every caravan/platoon. Sun and Yin (*44*) proposed a cooperative platooning game theory model to identify behavioral instability and reallocate the benefit among platoon members to incentivize drivers to form and maintain the optimal platoon formation. Future research should focus on developing a mathematical model with variable caravan sizes (with a preset upper bound).

Input Data Summary

In total, 1,728 different network instances (i.e., different combination of network size, travel times, arrival deadlines, cs, and DCR values) were evaluated. We grouped the various networks into six sets based on the arrival deadline, BN to CN travel times, network size and demand, caravan size, and DCR values. Table 3 summarizes the values and ranges of these parameters for every one of the six sets. CPLEX/GAMS (version 25.1.3) state of the art dual simplex algorithm (*45*) was used to solve all optimization problems on an Intel(R) Core (TM) i7-8700 CPU @ 3.20 GHz and 16 GB of memory, with CPU times averaging 33 min for the CNM and 1 s

Table 3. Test Network Instances

	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6
Arrival time deadline (ATD)	[1–1.5]	[1.5–2]	[2–2.5]	[1–1.5]	[1.5–2]	[2–2.5]
Travel time reduction (BN versus CN) (%)		20			40	
Network instance			1–36			
Caravan size (cs)			[2,4,5,10]			
Driver compensation ratio (DCR)			[2,3]			

Note: BN = base network; CN = caravanning network.

for the BNM. Both models are solved with an optimality gap of less than 1%. Next, we present and discuss the results from the numerical experiments. The CNM requires significantly higher CPU times mainly as a result of the introduction of variables y_{jk}^{cp} and f_{jk}^{p} and the additional constraints required to form the caravans and estimate the hours of delayed arrivals.

Overall Cost Savings. In this subsection we present and discuss the results (summarized in Table 4) on the mean, median, and standard deviation of cost savings between the CN and BN. As expected, cost savings reduce with the increase of the DCR and the shortest path travel times difference between the CN and BN. In the case where the BN shortest path travel time is 40% less than the CN (Sets 4, 5, and 6), a caravan of 10 trucks is required to achieve any substantial cost saving. We observe significant losses for the CN when the caravan size is limited to two trucks (cs = 2) which is to be expected given the delays at (de)coupling nodes. However, for the more realistic cases where the cs values are either 4 or 5, the DCR value is 2, and the travel time reduction between the BN and CN is 20%, the average cost savings, when using the CN, range between 9% and 33%.

When the caravan size is 10, average cost savings range between 24% and 46%. As a sidenote, it is unlikely that caravan sizes larger than 5 will be feasible (as a result of safety and operational efficiency of the highways) unless dedicated truck corridors are in place. In North America, standard lengths of semi-trailers range from 28 ft to 53 ft which means that a caravan of 10 trucks could stretch back from the lead tractor by between 280 ft and 530 ft. Additionally, as the caravan size increases over five trucks there is a diminishing trend of cost savings because of the increased waiting time at coupling points. Median and mean cost values are relatively similar with a low standard deviation (that also decreases with the increase of cost savings) across all sets which points to a low dispersion and more robust savings as the caravan size increases. More specifically, no problem instance of any set differs more than 18% from the mean value which renders a clear tendency of clustered cost savings around central values (mean and median). Consequently, the results are robust whatever the network size and parameter values (e.g., demand, travel time, ATD, etc.).

Cost Savings and Arrival Time Deadlines

ATD is a crucial parameter as it affects the profitability of the caravan concept and has significant implications on the models' complexity (i.e., when ATD is increased computational times reduce significantly). Results in Table 4 highlighted the importance of ATD to cost savings being realized by the CN as sets with higher ATDs showed improved cost saving between sets (i.e., sets 1, 2, and 3, and sets 4, 5, and 6) ranging from 2% to 17% for the mean and 0% to 17% for the median. For the standard deviation, we observe the same patterns to the overall cost savings (discussed in the previous subsection) albeit with a smaller range between 0% and 6%.

Cost Savings and Travel Time

In this subsection, we discuss the effects of travel time to cost savings based on the results from the numerical experiments. Table 5 reports the average, median, and standard deviation cost savings difference for each one of the two shortest path travel time cases where we compare cost savings between sets 1 and 4, 2 and 5, and 3 and 6. For these pairs of sets the only difference is the shortest path travel time (i.e., the BN shortest path travel time is 20% lower for sets 1, 2, and 3, and 40% lower for sets 4, 5, and 6 for the CN). Results for all cases illustrate that although higher travel times (in the CN when compared with the BN) reduce cost savings (as expected), the CN still provides significant savings ranging between 25% and 64%. As in previous results, average and median cost savings are similar, and the standard deviation is low, which provides confidence that the results are not affected by the parameter values.

Table 4. Caravanning Network (CN) Average, Median, and Standard Deviation of Cost Savings

Sets	Average cost difference							
	DCR = 2				DCR = 3			
	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)
1	−22	9	16	30	−41	−1	8	24
2	−12	21	27	42	−33	9	19	38
3	−8	26	33	46	−30	15	24	42
4	−73	−35	−27	−9	−99	−49	−38	−14
5	−69	−24	−13	4	−97	−37	−25	−1
6	−52	−8	1	21	−81	−22	−12	16
	Median cost difference							
	DCR = 2				DCR = 3			
	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)
1	−16	12	20	30	−37	4	12	27
2	−9	22	29	42	−31	12	20	38
3	−7	27	33	47	−29	15	24	42
4	−65	−27	−20	−6	−91	−39	−29	−10
5	−62	−19	−10	5	−91	−33	−22	1
6	−49	−5	4	22	−77	−21	−9	17
	Standard deviation cost difference							
	DCR = 2				DCR = 3			
	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)
1	12	10	9	4	12	11	11	7
2	7	4	5	2	9	8	6	2
3	5	3	3	2	5	3	3	2
4	16	15	14	10	18	15	15	11
5	16	12	9	7	16	12	11	6
6	11	10	8	5	11	7	9	2

Note: DCR = driver compensation ratio; cs = cost saving.

Table 5. Travel Time Effects: Average, Median, and Standard Deviation of Cost Savings

	DCR = 2				DCR = 3			
	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)
Set 1 versus 4								
Average	50	44	44	38	58	48	46	39
Median	48	41	41	36	53	44	42	37
SD	10	10	10	8	15	11	11	9
Set 2 versus 5								
Average	57	45	41	38	64	46	45	38
Median	50	41	39	37	58	44	42	38
SD	15	12	9	7	16	12	13	6
Set 3 versus 6								
Average	44	35	32	25	51	37	35	26
Median	44	33	31	24	51	37	35	26
SD	11	11	9	5	12	8	11	2

Note: DCR = driver compensation ratio; SD = standard deviation; cs = cost saving.

Table 6. Demand Effects (200 versus 100 Trucks): Average, Median, and Standard Deviation of Cost Savings

Sets	DCR = 2				DCR = 3			
	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)
Average savings: 200 versus 100 trucks								
1	18	13	10	4	16	13	12	8
2	5	3	3	1	5	5	2	1
3	−1	−1	0	0	0	0	0	0
4	24	22	20	11	25	24	23	12
5	19	17	12	8	22	16	12	7
6	10	7	7	3	5	5	7	1
Median savings: 200 versus 100 trucks								
1	16	9	5	4	12	6	4	5
2	3	0	1	0	3	1	1	0
3	0	0	1	0	0	0	−1	1
4	23	22	25	8	20	27	26	7
5	15	14	10	5	17	12	8	6
6	6	4	4	2	−1	2	3	1
Savings standard deviation: 200 versus 100 trucks								
1	11	10	11	5	12	13	13	8
2	7	6	6	2	11	11	8	3
3	8	3	4	4	4	3	4	3
4	14	13	12	10	17	13	13	13
5	18	11	9	7	16	12	11	7
6	14	13	11	7	15	9	12	3

Note: DCR = driver compensation ratio; cs = cost saving.

Cost Savings and Demand. In this subsection, we analyze the impact on demand to cost savings with results reported in Table 6. Increasing the number of trucks should reduce arrival time delays at the destination as it increases the opportunity for caravan formation (and in turn reduces waiting times at the coupling nodes K_I). One would thus expect higher cost savings as demand increases. However, as Nourmohammadzadeh and Hartmann (*25*) observed, "when a larger number of trucks are released on the road network, the platooning potential has already been used, and as a result, the positive influence of more trucks is reduced." This positive influence could be translated as fuel cost reduction but, in this case, it is labor cost reduction.

The results shown in Table 6 do not support either assumption (i.e., both statements are partially true). The parameter which emerges to affect cost savings the most is the ATD at the destination. When the ATD value is high, the caravanning scheduling is more flexible as the cost from arrival time deadline violations is minimized. In these cases (sets 3 and 6) the increase in demand (from 100 to 200 trucks) does not result in significant cost savings and, in some cases, results in a cost increase (set 3, cs of 2 and 4, DCR of 2). On the other hand, when the ATD value is small (i.e., sets 1 and 4) demand plays a key role to profitability with cost savings differences ranging from 4% (for a caravan size of 10) to 25% (for a caravan size of 2). Based on the latter observation, the authors suggest that networks with higher demand be tested to provide more robust insight into a possible connection between demand and cost savings. To perform this analysis a heuristic or hybrid solution algorithm would need to be developed since the CNM cannot be solved efficiently for a demand of 300 trucks and above.

Cost Savings, Caravan Size, and Driver Compensation

In this subsection, the analysis is focused on the effects of caravan size to cost savings and results are summarized in Tables 7 to 9. We observe significant cost saving

Table 7. Cost Savings Differences Between Caravan Sizes

Set	Cost savings difference DCR: 2					
	cs: 2 versus 4 (%)	cs: 2 versus 5 (%)	cs: 4 versus 5 (%)	cs: 2 versus 10 (%)	cs: 4 versus 10 (%)	cs: 5 versus 10 (%)
1	31	39	8	52	21	13
2	38	45	8	64	26	19
3	33	39	6	54	21	15
4	45	56	11	73	28	17
5	34	41	7	54	20	14
6	44	54	9	73	29	20
	Cost savings difference DCR: 3					
Set	cs: 2 versus 4 (%)	cs: 2 versus 5 (%)	cs: 4 versus 5 (%)	cs: 2 versus 10 (%)	cs: 4 versus 10 (%)	cs: 5 versus 10 (%)
1	41	49	8	66	25	17
2	42	52	10	71	29	19
3	45	54	9	72	27	18
4	51	61	10	85	34	24
5	60	72	12	96	36	25
6	59	69	10	97	38	28

Note: DCR = driver compensation ratio; cs = cost saving.

Table 8. DCR Effects: Average, Median, and Standard Deviation of Cost Savings Differences

Sets	Average cost difference				Median cost difference			
	DCR = 2 versus 3				DCR = 2 versus 3			
	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)
1	16	11	11	8	17	11	11	7
2	15	10	9	5	15	10	8	5
3	20	16	12	8	19	14	12	8
4	17	11	11	5	18	12	10	5
5	21	15	14	9	20	15	13	8
6	19	13	13	7	18	14	13	8

Sets	Standard deviation cost difference			
	DCR = 2 versus 3			
	cs = 2 (%)	cs = 4 (%)	cs = 5 (%)	cs = 10 (%)
1	0	0	1	0
2	0	0	0	0
3	1	2	1	0
4	1	1	0	0
5	0	0	0	0
6	0	0	0	0

Note: DCR = driver compensation ratio; cs = cost saving.

differences between or within each set when we vary the values of DCR, with the highest cost savings between caravans of size 2 and 10 (as expected), and declining cost saving differences as caravan size increases (e.g., from 4 to 5 trucks) (Table 7). For example, when the caravan size doubles from 5 to 10 (100% increase in caravan size) the cost savings increase ranges from 14% to 28%. We also observe a significant reduction in profits when DCR increases from 2 to 3 (Table 8) but an insignificant change in the average hours of delayed arrivals per truck between and within each set when we vary either cs or DCR (Table 9). The combined results from Tables 7–9

Table 9. Average, Median, and Standard Deviation of Delayed Arrivals (in Hours Per Truck)

	Average delayed arrivals								
	DCR = 2				DCR = 3				
Sets	cs = 2	cs = 4	cs = 5	cs = 10	cs = 2	cs = 4	cs = 5	cs = 10	BN
1	6.07	6.15	5.85	5.71	5.94	6.00	5.96	5.96	2.69
2	1.54	1.69	1.73	1.43	1.53	1.85	1.66	1.46	0.05
3	0.05	0.04	0.05	0.05	0.06	0.05	0.05	0.05	0.00
4	9.84	10.21	10.32	10.02	9.86	10.27	10.38	10.05	3.70
5	5.56	5.51	5.34	5.37	5.53	5.36	5.38	5.21	0.48
6	2.10	2.20	2.02	2.55	2.13	2.20	2.29	1.61	0.00
	Median delayed arrivals								
	DCR = 2				DCR = 3				
Sets	cs = 2	cs = 4	cs = 5	cs = 10	cs = 2	cs = 4	cs = 5	cs = 10	BN
1	5.38	5.66	5.39	5.54	5.70	5.35	5.18	5.58	2.58
2	1.47	1.63	1.65	1.45	1.49	1.51	1.50	1.51	0.02
3	0.02	0.02	0.02	0.03	0.02	0.02	0.02	0.03	0.00
4	9.23	9.48	9.73	9.64	9.56	9.66	9.67	9.63	3.41
5	5.20	4.91	4.82	5.18	5.25	4.83	5.06	4.83	0.45
6	2.02	1.94	1.82	2.22	2.00	2.11	2.06	1.58	0.00
	Standard deviation delayed arrivals								
	DCR = 2				DCR = 3				
Sets	cs = 2	cs = 4	cs = 5	cs = 10	cs = 2	cs = 4	cs = 5	cs = 10	BN
1	1.78	1.77	1.76	1.00	1.61	1.90	1.92	1.42	1.10
2	0.74	0.62	0.62	0.25	0.87	1.07	0.73	0.24	0.06
3	0.10	0.06	0.07	0.05	0.06	0.06	0.07	0.06	0.00
4	1.63	1.90	1.88	1.37	1.62	1.93	1.98	1.56	1.31
5	1.60	1.52	1.37	1.06	1.49	1.53	1.42	1.03	0.30
6	0.83	0.93	0.87	1.47	0.78	0.66	0.89	0.17	0.00

Note: DCR = driver compensation ratio; SD = standard deviation; BN = base network; cs = cost saving.

lead to the conclusion that driver compensation is the most critical component affecting profitably of the caravanning concept although its influence decreases significantly with the caravan size.

Truck Travel Times

In this subsection, we present results and discuss the truck travel times between the two networks for the various sets. Table 10 reports the average, median, and standard deviation truck travel time (in hours) between the origin and the destination for both the CN and BN. Table 11 provides the average, median, and standard deviation of waiting time (in hours) at the coupling nodes K_I. The average total travel time (Table 10) fluctuated between 15 h and 18 h depending on the case for the CN. This means an increase in truck travel times (when compared with the shortest path in the BN) anywhere between 4 h and 9 h (Table 10). For sets 1, 2, and 3, the mean or median truck travel time in the CN increases by between 38% and 66% when compared with the BN. For sets 4, 5, and 6, the mean or median truck travel time in the CN increases by between 85% and 104% when compared with the BN. These data can be used in the selection of commodities/shippers that can be shipped using the caravan network, as some commodities/shippers may not be able to accept such travel time increases.

Depending on the case, trucks wait to form a caravan, on average, anywhere between 1 h and 4 h (Table 11). The waiting times at the coupling nodes are between 6% and 22% of the total travel times in the CN. This means that better coordination to form caravans and reduce wait times may not result in significant increase of savings.

Conclusions and Future Research

In supply chain management, we typically categorize companies based on their roles as suppliers, manufacturers, wholesalers, distributors, or retailers. This study investigates

Table 10. Average, Median, and Standard Deviation of Total Travel Time from Origin to Destination (in hours per truck)

	Average total travel time								
	DCR = 2				DCR = 3				
Sets	cs = 2	cs = 4	cs = 5	cs = 10	cs = 2	cs = 4	cs = 5	cs = 10	BN
1	15.61	15.86	15.77	15.67	15.67	15.91	15.82	15.61	11.30
2	15.83	16.37	16.47	17.11	15.85	16.37	16.62	17.04	11.06
3	16.29	17.04	17.38	17.82	16.29	17.27	17.30	17.97	11.12
4	15.46	15.98	16.15	16.26	15.34	15.90	15.92	16.26	8.30
5	15.37	15.42	15.33	15.34	15.43	15.76	15.41	15.34	8.25
6	15.99	16.37	16.64	16.92	15.96	16.47	16.61	17.03	8.34
	Median total travel time								
	DCR = 2				DCR = 3				
	cs = 2	cs = 4	cs = 5	cs = 10	cs = 2	cs = 4	cs = 5	cs = 10	BN
1	15.38	15.58	15.48	15.48	15.43	15.83	15.41	15.31	10.98
2	15.74	16.27	16.51	17.10	15.74	16.37	16.59	17.02	11.02
3	16.40	17.32	17.67	18.27	16.40	17.43	17.67	18.27	11.00
4	15.38	15.72	15.73	16.34	15.23	15.57	15.65	15.88	8.27
5	15.12	15.16	15.12	15.05	15.20	15.64	15.05	15.17	8.16
6	16.27	16.26	16.51	16.74	16.25	16.21	16.38	16.85	8.25
	Standard deviation total travel time								
	DCR = 2				DCR = 3				
	cs = 2	cs = 4	cs = 5	cs = 10	cs = 2	cs = 4	cs = 5	cs = 10	BN
1	0.88	1.02	0.94	0.90	0.95	0.99	1.04	0.87	0.72
2	0.94	0.94	0.81	0.81	0.92	1.02	0.94	0.84	0.50
3	0.78	1.05	0.95	1.18	0.78	0.81	1.15	0.99	0.53
4	1.15	1.39	1.42	1.26	1.09	1.40	1.37	1.40	0.37
5	0.85	0.96	0.89	0.74	0.81	0.97	0.99	0.79	0.35
6	0.94	0.84	0.90	0.84	0.91	0.92	0.90	0.83	0.40

Note: DCR = driver compensation ratio; BN = base network; cs = cost saving.

the equally important role of transporters. Among its theoretical contributions, this research investigated an important gap in our transportation knowledge and proposed an alternative to truck platooning known as truck caravanning where only a single driver is needed for each platoon (or caravan) of trucks. The motivation for introducing and evaluating the concept came from claims in the literature that truck platooning does not provide significant enough fuel savings to justify its relatively costly application. Truck caravanning on the other hand, as showcased by this research, potentially produces significant cost savings (stemming from less labor needs), especially in networks where the (de)coupling nodes are strategically placed so that they do not increase travel time significantly when compared with the base network (i.e., network with direct connections from the origins to the destinations). Results from this research also show that caravans with two trucks provide negative cost savings and that as the caravan size increases a diminishing rate of cost saving is observed. Results indicate that truck caravan driver compensation and arrival time deadlines are the most critical parameters affecting the concept's profitability.

Future Research Directions

In this research, fuel savings from the formation of caravans or costs and savings from the introduction of electric trucks were not considered. The proposed model is capturing the operational aspects of trucking, (de)coupling nodes are predetermined, and opening/maintaining/operating costs of these facilities are not considered. The rationale is that the model proposed in this manuscript can be used to quantify monetary benefits from truck caravanning that can be used in a cost benefit analysis for the selection of the number and location of the facilities. As a next step, the development of a bilevel network design model (Stackelberg or hierarchical) is warranted to capture both the tactical and operational levels.

Table 11. Waiting Time at Coupling Points K1(in hours per truck)

Sets	Average waiting time							
	DCR = 2				DCR = 3			
	cs = 2	cs = 4	cs = 5	cs = 10	cs = 2	cs = 4	cs = 5	cs = 10
1	1.14	1.45	1.26	1.34	1.16	1.50	1.30	1.28
2	1.29	2.18	2.41	3.04	1.30	2.16	2.44	3.02
3	3.06	3.42	3.62	3.86	3.06	3.51	3.54	3.93
4	0.96	1.52	1.72	1.98	0.99	1.46	1.57	1.82
5	1.08	1.32	1.31	1.38	1.21	1.65	1.39	1.35
6	1.30	2.17	2.43	2.96	1.30	2.22	2.40	3.00
	Median waiting time							
	DCR = 2				DCR = 3			
	cs = 2	cs = 4	cs = 5	cs = 10	cs = 2	cs = 4	cs = 5	cs = 10
1	1.22	1.44	1.23	1.23	1.27	1.52	1.25	1.09
2	1.30	2.17	2.44	3.07	1.31	2.28	2.47	3.02
3	3.02	3.52	3.64	3.92	3.02	3.53	3.64	3.95
4	0.98	1.43	1.57	1.55	1.03	1.52	1.38	1.54
5	1.14	1.14	1.17	1.12	1.24	1.52	1.23	1.19
6	1.32	2.22	2.53	3.03	1.33	2.23	2.45	3.08
	Standard deviation waiting time							
	DCR = 2				DCR = 3			
	cs = 2	cs = 4	cs = 5	cs = 10	cs = 2	cs = 4	cs = 5	cs = 10
1	0.30	0.68	0.84	0.90	0.30	0.65	0.82	0.91
2	0.13	0.26	0.27	0.30	0.12	0.38	0.27	0.34
3	0.22	0.38	0.25	0.35	0.22	0.18	0.46	0.23
4	0.38	0.72	0.88	0.96	0.35	0.75	0.79	0.87
5	0.27	0.48	0.63	0.63	0.19	0.43	0.53	0.56
6	0.17	0.28	0.34	0.32	0.19	0.27	0.35	0.39

Note: DCR = driver compensation ratio; cs = cost saving.

The tactical level (upper) would consider costs for opening/maintaining/operating the facilities at the (de)coupling nodes and the cost of purchasing electric trucks while the operational level (lower) would capture the vehicle routing costs (similar to the model proposed in this manuscript).

Another research direction that would provide more insight into the feasibility of the caravan concept would be variations of the empty backhaul trips. In this paper, we did not consider the cases of reverse logistics and the model assumes that all return trips (i.e., backhauls) are empty (both for the CNM and BNM) and the drivers are compensated. A study completed by Florida Department of Transportation (*46*) found that empty backhaul trips varied by origin–destination and by route from approximately 11% to 67%. Future research should introduce various levels of full to empty backhaul trip ratios (in both models) to estimate cost savings.

Future research should also focus on evaluating more complex networks (e.g., the size of each caravan can be variable, higher supply and demand, larger networks, etc.), relax some assumptions (e.g., a subset of trucks may be able to travel directly to the destination without joining a caravan), introduce longer caravan travel times with two or more alternating drivers (to comply with HOS regulations), fully autonomous trucks (SAE Level 5), and development of hybrid solution algorithms to handle large problem instances within acceptable computational times and optimality gaps.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: V. Liatsos, D. Giampouranis, M. Golias, S. Mishra, J. Hourdos, R. Nalim, M. T. Frohlich, C. Nicholas; data collection: V. Liatsos, D. Giampouranis, Golias M.; analysis and interpretation of results: V. Liatsos, D. Giampouranis, M. Golias, S. Mishra, J. Hourdos, R. Nalim,

M. T. Frohlich, C. Nicholas; draft manuscript preparation: V. Liatsos, D. Giampouranis, M. Golias, S. Mishra, J. Hourdos, R. Nalim, M. T. Frohlich, C. Nicholas. 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: This research has been partially supported by the Freight Mobility Research Institute (FMRI) U.S. DOT University Transportation Center at the University of Florida, and the Center for Transportation Innovations in Education and Research (C-TIER) at the University of Memphis.

ORCID iDs

Vasileios Liatsos https://orcid.org/0000-0001-9849-6988
Dimitrios Giampouranis https://orcid.org/0000-0002-7908-9217
Mihalis Golias https://orcid.org/0000-0001-9402-2996
Sabyasachee Mishra https://orcid.org/0000-0002-7198-3548
John Hourdos https://orcid.org/0000-0001-9888-0445
Razi Nalim https://orcid.org/0000-0002-7586-6357
Clayton Nicholas https://orcid.org/0000-0003-0012-0195

References

1. American Trucking Associations (ATA). *American Trucking Trends 2020*. ATA, Arlington, VA, 2020.
2. United States Environmental Protection Agency. *Fast Facts US Transportation Greenhouse Gas Emissions 1990–2017*. EPA, 2019.
3. Volvo. Volvo Autonomous Solutions Reveals Prototype Long-Haul Autonomous Truck for North America Application. *AB Volvo*, 2021. https://www.volvogroup.com/en/news-and-media/news/2021/sep/news-4075850.html.
4. Fleet Owner. Volvo Trucks Tests On-highway Three-truck Platooning. *Fleet Owner*, 2017. https://www.fleetowner.com/technology/article/21695605/volvo-trucks-tests-onhighway-threetruck-platooning.
5. Bishop, R. U.S. States are Allowing Automated Follower Truck Platooning While the Swedes May Lead in Europe. *Forbes*, 2020. https://www.forbes.com/sites/richardbishop1/2020/05/02/us-states-are-allowing-automated-follower-truck-platooning-while-the-swedes-may-lead-in-europe/?sh=3fb3ad9cd7e8.
6. Patten, J., B. Mcauliffe, W. Mayda, and B. Tanguay. *Review of Aerodynamic Drag Reduction Devices for Heavy Trucks and Buses*. Technical Report CSTT_ HVC_TR-205. National Research Council of Canada, Ottawa, ON, 2012.
7. Lammert, M. P., A. Duran, J. Diez, K. Burton, and A. Nicholson. Effect of Platooning on Fuel Consumption of Class 8 Vehicles Over a Range of Speeds, Following Distances, and Mass. *SAE International Journal of Commercial Vehicles*, Vol. 7, No. 2, 2014, pp. 7–9.
8. Lammert, M., K. Kelly, and J. Yanowitz. *Correlations of Platooning Track Test and Wind Tunnel Data*. NREL, US, 2018. www.nrel.gov/publications.
9. California Department of Transportation. *Truck Platoon Testing Allowed Under SB 719*. California Department of Transportation, Sacramento, CA, 2017.
10. Bonnet, C., and H. Fritz. *Fuel Consumption Reduction in a Platoon: Experimental Results With Two Electronically Coupled Trucks at Close Spacing*. SAE Technical Paper 2000-01-3056. Society of Automotive Engineers, Detroit, 2000.
11. Zhang, L., F. Chen, X. Ma, and X. Pan. Fuel Economy in Truck Platooning: A Literature Overview and Directions for Future Research. *Journal of Advanced Transportation*, Vol. 2020, 2020, p. 2604012.
12. 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, 2018, pp. 212–228. https://doi.org/10.1016/j.trb.2017.10.016.
13. Steve, L. Musk's Strategy may be Self-driving, Electric Semi-truck Caravans, 2017. https://www.axios.com/musks-strategy-may-be-self-driving-electric-semi-truck-caravans-1513304750-8dfa5dc7-8184-40a4-8f0a-60c3b36eea17.html.
14. Adler, A. TuSimple will Haul 'Driver Out' Intermodal Freight Loads for Union Pacific, 2022. https://www.freightwaves.com/news/tusimple-will-haul-driver-out-intermodal-freight-loads-for-union-pacific.
15. Zachary, S. New Driverless Semi Truck Demo, 2021. https://cleantechnica.com/2021/08/12/new-driverless-semi-truck-demo/.
16. Georgia Department of Transportation GDOT. I-75 Commercial Vehicle Lanes, 2020. https://0014203-gdot.hub.arcgis.com/.
17. Larsson, E., G. Sennton, and J. Larson. The Vehicle Platooning Problem: Computational Complexity and Heuristics. *Transportation Research Part C: Emerging Technologies*, Vol. 60, 2015, pp. 258–277. https://doi.org/10.1016/j.trc.2015.08.019.
18. Larson, J., T. Munson, and V. Sokolov. Coordinated Platoon Routing in a Metropolitan Network. *Proc., 7th SIAM Workshop on Combinatorial Scientific Computing*, Albuquerque, New Mexico, 2016, pp. 73–82.
19. Larson, J., C. Kammer, K. Y. Liang, and K. H. Johansson. Coordinated Route Optimization for Heavy-duty Vehicle Platoons. *Proc., 16th International IEEE Conference on Intelligent Transportation Systems*, Kurhaus, The Hague, The Netherlands, 2013, pp. 1196–202.
20. Larson, J., K. Y. Liang, and K. H. Johansson. A Distributed Framework for Coordinated Heavy-Duty Vehicle Platooning. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 16, No. 1, 2015, pp. 419–429.
21. 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.

22. Adler, A., D. Miculescu, and S. Karaman. Optimal Policies for Platooning and Ride Sharing in Autonomy-Enabled Transportation. In Goldberg, K., Abbeel, P., Bekris, K., Miller, L. (eds) *Algorithmic Foundations of Robotics XII*, Springer, Cham, 2020, pp. 848–863.
23. Boysen, N., D. Briskorn, and S. Schwerdfeger. The Identical-Path Truck Platooning Problem. *Transportation Research Part B: Methodological*, Vol. 109, 2018, pp. 26–39. https://doi.org/10.1016/j.trb.2018.01.006.
24. Nourmohammadzadeh, A., and S. Hartmann. The Fuel-Efficient Platooning of Heavy Duty Vehicles by Mathematical Programming and Genetic Algorithm. *Theory and Practice of Natural Computing*, Vol. 30, 2016, pp. 46–47.
25. Nourmohammadzadeh, A., and S. Hartmann. Fuel-efficient Truck Platooning by a Novel Meta-Heuristic Inspired From Ant Colony Optimisation. *Soft Computing*, Vol. 23, No. 5, 2019, pp. 1439–1452. https://doi.org/10.1007/s00500-018-3518-x.
26. Meisen, P., and T. Seidl. A Data-Mining Technique for the Planning and Organization of Truck Platoons. *Proc., International Conference on Heavy Vehicles*, Paris, 2008, pp. 389–402.
27. Farokhi, F., and K. H. Johansson. A Game-theoretic Framework for Studying Truck Platooning Incentives. *Proc., 16th IEEE Conference on Intelligent Transportation Systems*, Kurhaus, The Hague, The Netherlands, IEEE, Piscataway, NJ, 2013, pp. 1253–1260.
28. Luo, F., and J. Larson. A Repeated Route-then-Schedule Approach to Coordinated Vehicle Platooning: Algorithms, Valid Inequalities and Computation. *Operations Research*, 2021. https://doi.org/10.1287/opre.2021.2126.
29. Abdolmaleki, M., M. Shahabi, Y. Yin, and N. Masoud. Itinerary Planning for Cooperative Truck Platooning. *SSRN Electronic Journal*, 2019. https://papers.ssrn.com/sol3/papers.cfm?abstract_id = 3481598#references-widget.
30. Sun, X., H. Wu, M. Abdolmaleki, Y. Yin, and B. Zou. Investigating the Potential of Truck Platooning for Energy Savings: Empirical Study of the U.S. National Highway Freight Network. *Transportation Research Record: Journal of the Transportation Research Board*, 2021. 2675: 784–796.
31. van de Hoef S., K. H. Johansson, and D. V. Dimarogonas. Coordinating Truck Platooning by Clustering Pairwise Fuel-Optimal Plans. *Proc., 18th IEEE International Conference on Intelligent Transportation Systems*, Gran Canaria, Spain, 2015, pp. 408–415.
32. Saeednia, M., and M. Menendez. A Consensus-based Algorithm for Truck Platooning. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 18, No. 2, 2017, pp. 404–415.
33. Li, B. Stochastic Modeling for Vehicle Platoons (I): Dynamic Grouping Behavior and Online Platoon Recognition. *Transportation Research Part B: Methodological*, Vol. 95, 2017, pp. 364–377. https://doi.org/10.1016/j.trb.2016.07.019.
34. Li, B. Stochastic Modeling for Vehicle Platoons (II): Statistical Characteristics. *Transportation Research Part B: Methodological*, Vol. 95, 2017, pp. 378–393. https://doi.org/10.1016/j.trb.2016.07.017.
35. van de Hoef S., K. H. Johansson, and D. V. Dimarogonas. Efficient Dynamic Programming Solution to a Platoon Coordination Merge Problem With Stochastic Travel Times. *IFAC-PapersOnLine*, Vol. 50, No. 1, 2017, pp. 4228–4233. https://doi.org/10.1016/j.ifacol.2017.08.822.
36. Liang, K. Y., J. Martensson, and K. H. Johansson. Fuel-saving Potentials of Platooning Evaluated Through Sparse Heavy-duty Vehicle Position Data. *Proc., 2014 IEEE Intelligent Vehicles Symposium*, Dearborn, MI, 2014, pp. 1061–1068.
37. Liang, K. Y., J. Mårtensson, and K. H. Johansson. Heavy-Duty Vehicle Platoon Formation for Fuel Efficiency. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 17, No. 4, 2016, pp. 1051–1061.
38. Liang, K. Y., J. Martensson, and K. H. Johansson. When is it Fuel Efficient for a Heavy Duty Vehicle to Catch up With a Platoon? *IFAC Proceedings Volumes*, Vol. 46, No. 21, 2013, pp. 738–743.
39. Noruzoliaee, M., B. Zou, and Y. Zhou (Joann). Truck Platooning in the U.S. National Road Network: A System-level Modeling Approach. *Transportation Research Part E: Logistics and Transportation Review*, Vol. 145, 2021, p. 102200. https://doi.org/10.1016/j.tre.2020.102200.
40. Olson, R. L., J. Bocanegra, J. Hanowski, and J. S. Hickman. *Federal Motor Carrier Safety, Administration*. Hours Report No. FMCSA-RRR-09-042, 2020. https://www.fmcsa.dot.gov/sites/fmcsa.dot.gov/files/docs/DriverDistractionStudy.pdf.
41. Minnesota Statute. *169.881 Vehicle Platoons*. Minnesota, 2020, pp. 1–2. https://www.revisor.mn.gov/statutes/cite/169.881
42. Gungor, O. E., and I. L. Al-Qadi. All for One: Centralized Optimization of Truck Platoons to Improve Roadway Infrastructure Sustainability. *Transportation Research Part C: Emerging Technologies*, Vol. 114, 2020, pp. 84–98. https:// doi.org/10.1016/j.trc.2020.02.002.
43. Song, M., F. Chen, and X. Ma. Organization of Autonomous Truck Platoon Considering Energy Saving and Pavement Fatigue. *Transportation Research Part D: Transport and Environment*, Vol. 90,2021, p. 102667. https://doi.org/10.1016/j.trd.2020.102667.
44. Sun, X., and Y. Yin. Behaviorally Stable Vehicle Platooning for Energy Savings. *Transportation Research Part C: Emerging Technologies*, Vol. 99,2019, pp. 37–52. https://doi.org/10.1016/j.trc.2018.12.017.
45. GAMS. https://www.gams.com/25.1/docs/S_CPLEX.html.
46. Florida Department of Transportation. *Truck Empty Backhaul*. FDOT, Tallahassee, FL, 2018.

Any findings and opinions expressed in this paper are those of the authors and do not necessarily reflect the view of the FMRI or C-TIER.