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Electric truck routing and platooning problem considering vehicle charging and driver assignment on highway networks

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A R T I C L E I N F O

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A B S T R A C T

Driven by the development of electricity-powered trucks and the connected and autonomous vehicle (CAV) technology, the electric truck (ET) routing and platooning has received considerable attention. To reap the labor cost savings and environmental benefits, this study makes the first attempt to investigate the ET routing and platooning problem considering vehicle charging and flexible assignment of the drivers. The objective is to determine the optimal routes and schedules of the trucks and the drivers that minimize the total operational cost to complete a group of freight transportation tasks while considering the features of the electric trucks, i.e., the limited driving range and charging demands due to limited battery capacity. A mixed-integer linear programming (MILP) model that can effectively determine the itineraries of the trucks and drivers and incorporate specific characteristics of ET platooning is formulated for the proposed problem. By exploring the essential features of the platooning process and its optimal solution structures, a tailor-designed edge set covering algorithm dedicated to platooning-related optimization problem is proposed to address the problem. Numerical experiments are conducted to evaluate the proposed model and solution method against three benchmark methods and quantify the benefits of the ET platooning. Sensitivity analysis is also carried out to explore the impacts of several major influential factors on the system performance and derive managerial insights.

1. Introduction

Trucking plays a critical role in the land-based freight transportation in global supply chains (Ardentx, 2021). However, a series of pressing challenges faced by the trucking sector have been hindering its development in a responsible and sustainable way (Cooperative Logistics Network, 2022). One of the prominent challenges with trucking is huge labor cost, making up about 37 % of the total truck operating cost (Costello and Suarez, 2015; Ji-Hyland and Allen, 2022). Another top concern of the trucking sector is air pollution since most used vehicles for long-haul transportation are heavy-duty trucks with an internal combustion engine. According to European Union Regulation 2017/2400, the greenhouse emissions of the heavy-duty trucks account for about a quarter of the total road transport emissions and will continue to rise (Zacharof et al. 2019). Therefore, the high labor cost and environmental concerns necessitate the transformation of the trucking sector to ensure the supply chains and improve the sustainability of freight

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With the development of autonomous driving and electromobility, one of the most promising solutions is the electric truck (ET) platooning, in which a convoy of autonomous ETs drive closely with small headway. ET platooning will lead to zero tail-pipe greenhouse gas emissions by electrification and achieve great energy savings via lowered air resistance on trucks (Automotive World Ltd., 2021). Notably, since the platoon followers are unmanned, the formation of platoons could dramatically reduce the labor cost and has the potential to mitigate the dependence on truck drivers (Janssen et al., 2015). Despite these environmental and economic benefits, the application of autonomous ET platoons in freight transport services requires non-trivial coordination and planning for both the truck fleet and the drivers, giving the specifics of the electromobility and platooning mode. For example, the charging time of the ETs can be coordinated with the waiting time for platooning partners to facilitate the formation of platoons. Furthermore, since only the leading truck in a platoon requires a driver, the driver assignment plan should be incorporated into the decision-making process regarding ET routing and platooning to save labor costs. Therefore, how to simultaneously determine the routes and schedules of the trucks and drivers that reap the labor cost-saving and energy-saving benefits of autonomous ET platooning is one of the major problems faced by freight transport service providers.

1.1. Literature review

A growing number of studies have been devoted to truck platooning over the past decades (Bhoopalam et al., 2018; Zhang et al., 2020). Previous studies mainly fall into three categories. The first focuses on the technical issues regarding platooning, such as safe driving, automated control and communication technology for platoons (Axelsson, 2016; Faber et al., 2020; Hong et al., 2020; Jia and Ngoduy, 2016). The second concerns field tests and experimental studies to evaluate the platoons' performance in fuel savings and its impact on traffic flow and pavement sustainability, etc. (Bonnet and Fritz, 2000; Guo and Wang, 2018; Ma et al., 2019; She and Ouyang, 2022; Song et al., 2021; Xu et al.,2019). The third optimizes the routing and scheduling of the trucks considering platooning. For example, Larson et al. (2013) were the first to coordinate the vehicles' travelling speeds in a distributed framework using the local controllers to maximize the formation of platoons. Later, some studies additionally considered the route selections of the vehicles to facilitate platooning formulation (Baskar et al. 2013; Liang et al., 2013). Larsson et al. (2015) formally formulated the platooning problem as a mixed-integer linear programming (MILP) model to determine the optimal routes and schedules for the vehicle fleet to minimize the total fuel cost over the entire trips and proved its NP-hardness. After that, the model in Larsson et al. (2015) was extended with new modeling techniques, fast algorithms, and enhanced network-flow formulations (Abdolmaleki et al., 2021; Bhoopalam et al., 2018; Luo and Larson, 2022) and problem-specific characteristics and practical constraints of truck platooning, e.g., drivers' mandatory breaks and uncertain travel speeds (Luo et al. 2018; Xu et al., 2022). There have also been many studies for other interesting problems related to truck platooning. For example, Sun and Yin (2019) investigated optimal platoon formation to maximize the platooning benefit and proposed a benefit-redistribution mechanism to achieve 'behaviorally stable' platooning. Yan et al. (2023) focused on the local container drayage problem using truck platooning technology.

Most of the above-mentioned studies emphasize the common objective that minimizes the system-wide fuel cost. Compared with the fuel-saving effect of truck platooning, the labor cost-saving effect associated with the unmanned platoons' following vehicles has received much less attention. However, labor cost is a substantial factor influencing the feasibility and attractiveness of platooning systems. To the best of our knowledge, only a few studies have ever considered the labor cost-saving effect by platooning in the truck routing and platooning problems. Among the limited studies, Caballero et al. (2022) investigated the labor cost reduction effects by platooning under different driver payments and platoon formation policies. Empirical testing was conducted to explore the impact of different networks on reducing labor costs. You et al. (2020), Xue et al. (2021), and Yan et al. (2023) proposed the truck platooning technology to minimize the labor and fuel costs for the local container drayage problem. MILP models and heuristics were developed to address the problem. Hao et al. (2023) focused on joint operation planning of drivers and trucks for semi-autonomous truck platooning. They formulated a MILP model and developed a tailored Lagrangian relaxation approach to solve the problem. Although the aforementioned studies have already investigated the labor cost-saving effect of truck platooning, they primarily focus on conventional fuel-powered trucks with notable limitations such as higher greenhouse gas emissions and increased fuel costs, which undermine sustainability objectives in transportation networks (Cheng and Lin, 2024). Additionally, the technological integration required for effective platooning, such as truck-to-truck communication and advanced automation systems are often less developed in traditional fuel-powered trucks when compared with the burgeoning electric trucks (WEVOLVER, 2023).

Quite recently, electricity-powered trucks have started to gain increasing attention, which can help to alleviate the dependence on fossil fuels and promote environmental protection (Konstantinou and Gkritza, 2023). Many countries around the world have accelerated the electrification trend of trucks and gradually phased out the sales of diesel trucks (Bibra et al., 2022). Nowadays, much longer driving range and dramatically reduced charging time enabled by advanced battery technologies and tailored super charging infrastructures are emerging to meet the high energy demands of electric long-haul trucks on route (Borlaug et al., 2021). Hence, the adoption of ETs in platooning for the long-distance haulage is viable and highly desired. However, no study of routing and platooning problem has considered ET platooning except Scholl et al. (2023) and Alam and Guo (2023). The former incorporated charging decisions into the scheduling and platooning optimization of ETs, with the aim of minimizing the total energy cost. An adaptive large metaheuristic search framework was developed to optimize the truck platoon formation for long-haul transportation. Alam and Guo (2023) investigated the co-optimization problem of charging scheduling and platooning for long-haul electric freight vehicles. In this work, a MILP model was formulated to minimize the total operation cost by coordinating the platooning and charging strategies of ETs. It is worth mentioning that both two studies considered the truck platooning problem on a single fixed path instead of a general highway network, and they did not consider the route optimization and the effect of labor cost saving by platooning. More specifically, they are limited in addressing the complexities of truck platooning on highway networks where routing options besides scheduling for facilitating platooning are available, and the need for route optimization becomes crucial for further reducing the total operational costs. Additionally, the labor cost-saving effect, which is a significant benefit of truck platooning due to the significantly reduced working time of the drivers, was not thoroughly explored in their frameworks. Such identified gaps necessitate the importance of integrating these considerations into the platooning model to help realize successful applications of truck platooning on the real-world highway networks. Therefore, we are thus motivated to incorporate the consideration of the labor cost-saving effect by platooning alongside the route optimization in a highway network setting in the truck platooning problem, which could potentially further improve the operational efficiency and the economic benefits of the platooning systems. Since only the leading truck in a platoon requires a driver, it is also essential to consider driver assignment and scheduling to maximize the cost-effectiveness of the platooning system. Moreover, the appropriate coordination of the charging decisions with driver scheduling, platoon formation, and truck routing is another research focus for achieving the seamless integration of ETs into platooning systems.

1.2. Objective and contributions

To bridge the above research gaps, this study investigates the ET routing and platooning optimization problem considering driver assignment for the long-haul freight transportation in a general highway network, referred to as ETRP problem thereafter. Trucks are allowed to detour and wait for others to form platoons during the transportation process to save labor costs and energy, in which the leading truck requires a driver for safety concerns to cope with unforeseen events like system malfunctions, harsh weather conditions, or sudden obstacles on the road. This hybrid mode represents the mainstream trend for the platooning systems in the near future. Similar setting has been also considered in previous literature (Hu et al., 2024; Ozkan and Ma, 2022; Marzano et al., 2022). Although autonomous driving technology has made considerable progress, its implementation within platooning systems remains unfeasible in the near future. Having a human driver in the lead vehicle remains a crucial safety measure because the driver can intervene when necessary to handle unexpected situations and ensure the safety of all trucks in the platoon.

We assume that each truck is not necessarily equipped with a driver throughout the whole service process but only requires the assignment of a driver for leading a platoon or traveling alone. Each assigned driver is allowed to be responsible for only parts of the entire trip of the truck and hence each delivery task can be collaboratively completed by several different drivers. Due to limited battery capacity, ETs have limited driving ranges and thereby may need multiple recharges along their routes to continue the haulage. We consider an opportunity charging scheme that the battery of a truck can be charged to a specific level depending on its energy demands. Given the predefined origin, destination, and service time window of each delivery task, the objective of this study is to determine the optimal routes and schedules of the truck fleet and drivers that minimize the total operational cost, including the labor cost, the charging cost, and the penalty cost for late arrivals of deliveries, over the entire trips to complete a group of freight transportation tasks. The main contributions of this study are summarized as follows:

(1) We investigate both the energy-reduction and the labor cost-saving effect by platooning in the truck routing and platooning problem for the electric trucks on highway networks, in which routing, platooning, charging, scheduling plans of both the trucks and the drivers are required to be optimized simultaneously. Such simultaneous considerations including the platoon formation, the assignment of drivers, the battery charging decisions, as well as their intricate interactions will make the first attempt to help cope with the complexities of the real-world long-haul electric freight transportation.
(2) We formulate a novel MILP model that can effectively determine the routes and schedules of the ETs and drivers, while incorporating the ETs' limited driving ranges, opportunity charging, and the energy-saving effect by platooning.
(3) To effectively address the ETRP problem, we design a customized edge set covering algorithm (ESCA) dedicated to platooning-related optimization problems by exploring the characteristics of the platooning process and the optimal solution structures.
(4) An extensive set of numerical experiments are conducted to demonstrate the efficacy of the proposed model and solution method. Sensitivity analysis is also carried out to examine the impacts of several influential factors on the system performance and derive managerial insights.

The remainder of this study is organized as follows. Problem description is elaborated in Section 2, followed by the formulation of a MILP model for the proposed ETRP problem in Section 3. An edge set covering algorithm is developed in Section 4. The efficiency of the proposed model and algorithm and the impacts of three influential factors on the system performance are evaluated in Section 5. Section 6 presents the conclusions and future research directions.

2. Problem description

We define the ETRP problem over a bidirectional highway network $\mathbf{G} = (\mathbf{N}, \mathbf{E})$, where $\mathbf{N}$ is the node set and $\mathbf{E}$ is the edge set. Each edge $(i,j) \in \mathbf{E}$, $\forall i,j \in \mathbf{N}$ represents a road segment in the highway network and is associated with travel time τ_{ij} and electricity consumption d_{ij}. Each node $i \in \mathbf{N}$ corresponds to the intersection of the network and has a limited number h_i of drivers to be assigned to conduct the driving tasks for the trucks in need. The drivers involved in the network are grouped in set $\mathbf{K}$. Let $\mathbf{V}$ denote the set of autonomous ETs with a homogenous battery capacity Q. Each truck $v \in \mathbf{V}$ has one delivery task characterized by the origin node $o_v \in \mathbf{N}$, destination node $d_v \in \mathbf{N}$, and service time window, i.e., the earliest departure time σ_v from the origin node and latest arrival time δ_v at the destination node, beyond which penalty cost per unit time denoted by c_p will incur.

As for ET platooning, the ETs can wait at some nodes or take a deviated path other than the shortest path for platooning opportunities to save labor costs and energy costs. Platoons can only be formed or dissolved at the nodes rather than the edges of the network. Due to technical and safety reasons, we assume that the change of the positions of the trucks in the platoons can only occur at the nodes of the network and they will maintain the fixed intra-platoon vehicle sequence throughout a traveling edge. For safety concerns, the number of trucks traveling together in a platoon on edge (i,j) cannot exceed a prescribed maximum platoon size L_{ij}. Note that a single truck driving individually is also considered a platoon, in which case the size is 1. Regarding the energy-saving benefit of platooning, we assume that the following trucks in the platoons can save energy by a ratio of η, while the leading trucks experience no energy savings. Due to limited battery capacity, each ET may need multiple en-route recharges during the entire trip to continue the haulage. Regarding the charging, each truck $v \in \mathbf{V}$ is assumed to depart from the origin with a partial charge. In addition, for battery health concern, after arriving at a charging station, the trucks are allowed to perform the opportunity charging strategy: each ET can be charged according to its demand, instead of being fully replenished. It should be noticed that the setup time before charging and the time required for post-charging preparation is not consider in this study. The charging stations are located at some nodes of the highway network and are grouped in a set denoted by $\mathbf{C} \subseteq \mathbf{N}$. The charging stations are assumed to be incapacitated. In other words, the capacity of the charging station, i.e., the number of installed chargers, is not considered in this study. Although some queuing behaviors of the ETs caused by insufficient charging capabilities may largely increase the charging/dwelling time of the ETs at charging stations and potentially affect the successful formation of platoons, this assumption allows us to better focus on the optimization of truck routing, platoon formation, and driver assignment without considering the added complexity of limited charging infrastructure. At each charging station, we assume the driver of the leading truck can perform necessary preparatory steps for battery charging. We assume that the charging amount will linearly increase in accordance with the charging time. The charging rate and full charging price are denoted by g and c_r, respectively. Note that the charging process of the ETs should be integrated into their routing, scheduling, and platooning plans. More specifically, the charging time and waiting time at a node can be coordinated for more favorable platooning opportunities as long as the energy demands can be met before having the next recharge.

Truck platoons can reduce the workload of drivers and save the labor cost, while the establishment and dissolution of platoons require careful and flexible driver assignment. Specifically, each truck may not be necessarily equipped with a driver throughout the whole transport process since it does not need a driver when traveling as a platoon follower, which would significantly reduce the working time of the drivers and thus save labor costs. Each assigned driver can drive several different trucks at different times once dispatched and is allowed to be responsible for only parts of the trip for a truck. It is worthwhile to mention that each driver may wait at a node after completing a driving task for a truck until another driving task is assigned to him/her. The driver's service cost comprises two components, i.e., the base cost once being dispatched and the labor cost in accordance with the total working time, i.e., the traveling time over traversed edges and the waiting time at nodes for charging and/or platooning during the trip. Specifically, the base cost and the unit time labor cost for the drivers are denoted by c_b and c_l, respectively.

Given the above information, the objective of ETRP problem is to determine the optimal routes and schedules of the truck fleet and drivers that minimize the total operational cost, including the labor cost, charging cost, and penalty cost for late arrivals of deliveries, over the entire trips to complete a group of freight transportation tasks, such that the platoons can be spatiotemporally coordinated and synchronized, the ETs will not run out of energy en route, and drivers have been assigned to lead the platoons.

3. Model formulation

To fully present the ETRP problem of our interest, we will first elaborate on the formulation for truck platooning and charging, and driver routing and scheduling, and present the model of ETRP problem in the following subsections.

3.1. Truck platooning and charging

For vehicle platooning, trucks should start traversing the same edge at the same time to form or join a platoon. To mathematically formulate truck platooning, we need to define two types of binary decision variables: a route variable x_{ij}^{v}, $\forall(i,j) \in \mathbf{E}, v \in \mathbf{V}$ indicating whether truck v traverses edge (i,j) on its trip, and a platoon variable p_{ij}^{vw}, $\forall(i,j) \in \mathbf{E}$, $v \neq w \in \mathbf{V}$ indicating whether truck v will follow behind truck w in the same platoon over edge (i,j) (Kindly note that trucks v and w are not necessarily adjacent); and a continuous time variable t_i^v, $\forall i \in \mathbf{N}$, $v \in \mathbf{V}$ denoting the time instant truck v starts traversing an edge from node i. Specifically, we shall have the following constraints to ensure the spatial and temporal coordination and synchronization for several trucks if platooned together:

$$-M_1\left(1-p_{ij}^{vw}\right) \leq t_i^v - t_i^w \leq M_1\left(1-p_{ij}^{vw}\right), \ \forall(i,j) \in \mathbf{E}, v \neq w \in \mathbf{V} \tag{1}$$

$$2p_{ij}^{vw} \leq x_{ij}^{v} + x_{ij}^{w}, \ \forall(i,j) \in \mathbf{E}, v \neq w \in \mathbf{V} \tag{2}$$

$$p_{ij}^{vw} + p_{ij}^{wv} \leq 1, \forall(i,j) \in \mathbf{E}, v \neq w \in \mathbf{V} \tag{3}$$

$$\sum\nolimits_{f\in\mathbf{V}} p_{ij}^{vf} - \sum\nolimits_{f\in\mathbf{V}} p_{ij}^{wf} \geq 1 - M_2\left(1-p_{ij}^{vw}\right), \ \forall(i,j) \in \mathbf{E}, v \neq w \in \mathbf{V} \tag{4}$$

$$\sum\nolimits_{w\in\mathbf{V}} p_{ij}^{vw} + 1 \leq L_{ij}, \ \forall(i,j) \in \mathbf{E}, v \neq w \in \mathbf{V} \tag{5}$$

Where M_1 and M_2 are sufficiently large numbers and M_2 satisfies $M_2 \geq |\mathbf{V}|$. Eq. (1) ensures that trucks v and w should depart from the same node at the same time if they platoon together at that node. Eq. (2) is the flow requirement for trucks v and w if they are in the same platoon on an edge. Eq. (3) represents that either truck v travels behind truck w or vice versa. Eq. (4) is used to circumvent the platoon loop by imposing that the number of trucks traveling ahead of truck v must be larger than that of truck w if truck v travel behind truck w in the same platoon. Eq. (5) limits the maximum platoon length on each edge.

To incorporate the energy-saving effect of platooning, we need to define binary decision variables $\alpha_{ij}^v, \forall (i,j) \in \mathbf{E}, v \in \mathbf{V}$ to indicate whether truck $v \in \mathbf{V}$ is a following truck that experience energy savings in the platoon over edge (i,j). It is straightforward to have the following relationship between the route variables x_{ij}^v and the following truck variables α_{ij}^v:

$$\alpha_{ij}^v \leq x_{ij}^v, \forall (i,j) \in \mathbf{E}, v \in \mathbf{V} \tag{6}$$

which suggests that it is impossible for a truck to be a platoon follower on an edge that is not traversed by that truck. We then proceed to have the following constraints to identify the following trucks in the platoons on each edge by establishing the relationship between p_{ij}^{vw} and α_{ij}^v:

$$\alpha_{ij}^v \leq \sum\nolimits_{w \in \mathbf{V}, w \neq v} p_{ij}^{vw}, \forall (i,j) \in \mathbf{E}, v \in \mathbf{V} \tag{7}$$

$$\alpha_{ij}^v \geq \sum\nolimits_{w \in \mathbf{V}, w \neq v} p_{ij}^{vw} \Big/ M_3, \forall (i,j) \in \mathbf{E}, v \in \mathbf{V} \tag{8}$$

where M_3 is a sufficiently large number satisfying $M_3 \geq |\mathbf{V}| - 1$. Eq. (7) imposes that truck v cannot be a following truck on edge (i,j) if there are no trucks traveling ahead of it on that edge. Eq. (8) guarantees that truck v must be a following truck of a platoon on edge (i,j) once there is at least a truck traveling ahead of it on that edge.

To formulate the charging process for the trucks, we define two continuous decision variables $e_i^v, i \in \mathbf{N}, v \in \mathbf{V}$ and $\theta_i^v, i \in \mathbf{N}, v \in \mathbf{V}$ to denote the battery level of truck v upon arrival at node i and the charging time of truck v at node i, respectively. Kindly note that $\theta_i^v = 0$ if node i is not equipped with a charging station, i.e., $i \in \mathbf{N} \backslash \mathbf{C}$. Accordingly, $g \cdot \theta_i^v$ is the amount of energy recharged of truck v at node i. In addition, we define another continuous decision variable $u_i^v, \forall i \in \mathbf{N}, v \in \mathbf{V}$ to denote the dwell time of truck $v \in \mathbf{V}$ at node $i \in \mathbf{N}$. Kindly note that the dwell time of a truck at a node must not be less than its charging time at this node. Hence, we shall have the following constraint:

$$u_i^v \geq \theta_i^v, \forall i \in \mathbf{N}, v \in \mathbf{V} \tag{9}$$

We also have the following constraint to impose that each truck $v \in \mathbf{V}$ departs from the origin with a reasonable initial charge:

$$e_{o_v}^v \leq Q, \forall o_v \in \mathbf{N}, v \in \mathbf{V} \tag{10}$$

Next, we should have the following constraint to guarantee that the battery level of each truck on arrival at each node will never exceed its capacity and make sure it never falls below 0:

$$0 \leq e_i^v \leq Q, \forall i \in \mathbf{N}, v \in \mathbf{V} \tag{11}$$

Moreover, we shall have the following constraint to update the battery level of truck v on arrival at node j after traversing edge (i,j) from node i while considering the energy-saving effect of platooning:

$$e_j^v \leq e_i^v + g \cdot \theta_i^v \Big/ 60 - d_{ij}\left(x_{ij}^v - \eta \alpha_{ij}^v\right) + M_4\left(1 - x_{ij}^v\right), \forall (i,j) \in \mathbf{E}, v \in \mathbf{V}, i \in \mathbf{N}, j \in \mathbf{N} \tag{12}$$

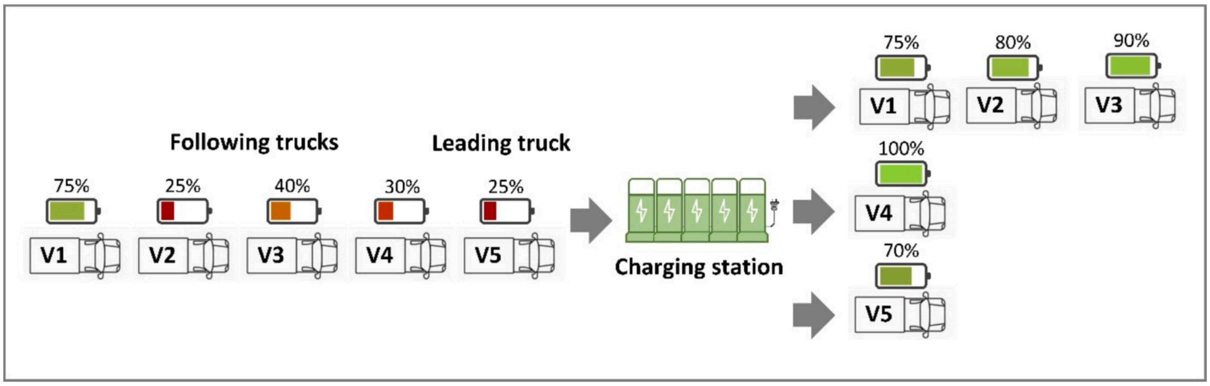


Fig. 1. An example illustrating driver scheduling.

where M_4 is a sufficiently large number satisfying $M_4 \geq Q$.

3.2. Driver routing and scheduling

The routing and scheduling of drivers require non-trivial optimization. For an autonomous ET platoon arriving at a node, the schedule of a driver leading the platoon is dependent on the schedules of all the involved trucks in this platoon. More specifically, the driver's schedule will not only be influenced by the charging decision of each truck in this platoon but also by their respective routing and platooning plans. We provide a simple example in Fig. 1 to illustrate the relationship between the driver schedule and truck schedule, and driver assignment plan. In this example, five trucks (labeled V1 to V5) of an electric platoon with a driver in the leading truck arrive collectively at a charging station but have different recharge demands. Each truck of this platoon has to make decisions regarding the amount of energy recharged, routes, schedules, and platoon plans when departing from this node. We consider a case that trucks V1, V2 and V3 have their batteries recharged according to their respective demands and keep traveling together in a platoon when departing from this node, while truck V4 has a full charge with a long charging time and truck V5 leaves the platoon immediately without any recharge at this node. If this driver is designated to continue to lead the platoon consisting of trucks V1, V2 and V3, the dwell time of the driver at this node should not be less than that of each of these three trucks at this node. Since truck V5 is dissolved from the platoon and leaves immediately, a new driver should be assigned from this node for it. As for truck V4, it has to wait for the completion of the full recharge and may be driven by another new driver assigned from this node or continue to wait for joining another platoon arriving at this node later. The example suggests that the routes and schedules of the drivers need to be carefully modeled.

Kindly note that a truck only requires a driver on a traversed edge when it is a platoon leader on that edge. A truck driving individually can be regarded as the leader of the platoon with length 1. To model driver assignment, we need to define two types of binary decision variables, a driver assignment variable $\chi_{ij}^{vk},\ \forall (i,j) \in \mathbf{E}, v \in \mathbf{V}, k \in \mathbf{K}$ to indicate whether driver $k \in \mathbf{K}$ undertakes the driving task for truck $v \in \mathbf{V}$ on edge (i,j), and a leading truck variable $\beta_{ij}^{v}, \forall (i,j) \in \mathbf{E}, v \in \mathbf{V}$ to indicate whether truck $v \in \mathbf{V}$ is the platoon leader that requires a driver on edge (i,j). Based on the definition of decision variables, we have

$$\beta_{ij}^{v} = x_{ij}^{v} - \alpha_{ij}^{v} \tag{13}$$

Then, we shall have the following constraint to establish the relationship between the driver assignment variables χ_{ij}^{vk} and leading truck variables β_{ij}^{v} and guarantee that each leading truck of a platoon that requires a driver over a traversed edge will be assigned one and only one driver:

$$\beta_{ij}^{v} \leq \sum\nolimits_{k \in \mathbf{K}} \chi_{ij}^{vk} \leq 1, \forall (i,j) \in \mathbf{E}, v \in \mathbf{V} \tag{14}$$

Moreover, to calculate the number of drivers assigned from each node, we introduce an auxiliary node m, specifying that the distance between it and each network node is 0. Then, let $\mathbf{N}'$ and $\mathbf{E}'$ represent the current node set and edge set, respectively, in which $\mathbf{N}' = \mathbf{N} \cup \{m\}$ and $(i,j) \in \mathbf{E}', \forall i,j \in \mathbf{N}'$. We also assume that all the involved drivers must depart from and finally return to the auxiliary node after completing the respective assigned driving tasks. Therefore, we shall have the following constraint to ensure the flow conservation of each driver:

$$\sum\nolimits_{\{j|(i,j) \in \mathbf{E}'\}} \sum\nolimits_{v \in \mathbf{V}} \chi_{ij}^{vk} - \sum\nolimits_{\{j|(i,j) \in \mathbf{E}'\}} \sum\nolimits_{v \in \mathbf{V}} \chi_{ji}^{vk} = 0, \forall i \in \mathbf{N}', \forall k \in \mathbf{K} \tag{15}$$

In addition, by introducing the auxiliary node m, the number of the drivers assigned from each node $i \in \mathbf{N}$ will be the sum of the driver flows out of node m into node $i \in \mathbf{N}$, which can be expressed by $\sum_{v \in \mathbf{V}} \sum_{k \in \mathbf{K}} \chi_{mi}^{vk}, \forall i \in \mathbf{N}$. Then, it is straightforward to have the following constraint to guarantee that the number of the drivers assigned from node $i \in \mathbf{N}$ will not exceed its maximum available number h_i:

$$\sum\nolimits_{v \in \mathbf{V}} \sum\nolimits_{k \in \mathbf{K}} \chi_{mi}^{vk} \leq h_i, \forall i \in \mathbf{N} \tag{16}$$

Regarding driver scheduling, to formulate the schedules for the assigned drivers, we need to define the driver schedule variables $s_i^k, \forall i \in \mathbf{N}, k \in \mathbf{K}$ to denote the time instant that driver $k \in \mathbf{K}$ starts traversing an edge from node i. Specifically, we shall have the following constraint to impose that the time instant the driver $k \in \mathbf{K}$ starts traveling from node j is not earlier than its departure time from node i plus the travel time over edge (i,j).

$$s_j^k \geq s_i^k + \tau_{ij} - M_1 \left(1 - \chi_{ij}^{vk}\right), \forall i,j \in \mathbf{N}, (i,j) \in \mathbf{E}, k \in \mathbf{K}, v \in \mathbf{V} \tag{17}$$

Moreover, it is worthwhile to mention that if driver $k \in \mathbf{K}$ is assigned to be responsible for the driving task for truck $v \in \mathbf{V}$ over edge (i,j), then the time instant that driver $k \in \mathbf{K}$ starts traveling edge (i,j) from node i must be the same as that of truck $v \in \mathbf{V}$ starts traversing the same edge from node i. Therefore, we shall have the following constraint to express the relationship between driver schedule variables s_i^k and truck schedule variables t_i^v:

$$-M_1 \left(1 - \chi_{ij}^{vk}\right) \leq s_i^k - t_i^v \leq M_1 \left(1 - \chi_{ij}^{vk}\right), \forall (i,j) \in \mathbf{E}, i \in \mathbf{N}, v \in \mathbf{V}, k \in \mathbf{K} \tag{18}$$

3.3. Optimization model for ETRP problem

With the notations, the ETRP problem investigated in this study can be formulated as follows:
[ETRP]

$$\min_{x,p,\chi,\alpha,\beta,t,u,s,e,\theta} \sum_{k\in\mathbf{K}}\sum_{i\in\mathbf{N}}\sum_{v\in\mathbf{V}} c_b\chi_{mi}^{vk} + \sum_{(i,j)\in\mathbf{E}}\sum_{k\in\mathbf{K}} c_l\chi_{ij}^{vk}\left(s_j^k - s_i^k\right) + \sum_{i\in\mathbf{N}}\sum_{v\in\mathbf{V}} c_r \Big/ Q\cdot g\cdot\theta_i^v \Big/ 60 + \sum_{v\in\mathbf{V}} c_p\left(t_{d_v}^v - \delta_v\right) \tag{19}$$

subject to Eqs. (1)-(18), and

$$\sum_{\{j|(i,j)\in\mathbf{E}\}} x_{ij}^v \sum_{\{j|(j,i)\in\mathbf{E}\}} x_{ji}^v = \begin{cases} 1, \text{ if } \ i = o_v \\ -1, \text{ if } i = d_v \\ 0, \text{ otherwise} \end{cases}, \forall i\in\mathbf{N}, v\in\mathbf{V} \tag{20}$$

$$t_j^v \geq t_i^v + \tau_{ij} + u_j^v - M_5\left(1 - x_{ij}^v\right), \forall i,j\in\mathbf{N}, (i,j)\in\mathbf{E}, v\in\mathbf{V} \tag{21}$$

$$t_{o_v}^v \geq \sigma_i, \forall v\in\mathbf{V} \tag{22}$$

$$x_{ij}^v, \alpha_{ij}^v, \beta_{ij}^v, p_{ij}^{vw}, \chi_{ij}^{vk} \in \{0,1\}, \forall (i,j)\in\mathbf{E}, v,w\in\mathbf{V}, k\in\mathbf{K} \tag{23}$$

$$e_i^v \geq 0, \theta_i^v \geq 0, t_i^v \geq 0, s_i^k \geq 0, u_i^v \geq 0, \forall i\in\mathbf{N}, v\in\mathbf{V}, k\in\mathbf{K} \tag{24}$$

The objective function in Eq. (19) is the sum of the total operational cost, including the total labor cost comprising of the base cost and the total service time cost, the charging cost, and the penalty cost for late arrivals of deliveries, incurring on all edges by the whole autonomous ET fleet and the drivers to complete a set of freight transportation tasks. Eq. (20) ensures flow conservation for each truck. Eqs. (21) and (22) are the constraints for the truck schedules. Specifically, Eq. (21) ensures that the time instant each truck starts traveling along the edge from node j is not earlier than the departure time from node i plus the travel time over edge (i,j) and the dwell time at node j. Eq. (22) imposes the earliest departure time for each truck. Eqs. (23) and (24) define the domains of the decision variables.

4. Solution method design

The model [ETRP] formulated in Section 3 is a MILP model, which can be solved directly by state-of-the-art solvers like CPLEX. However, our preliminary experiments found that even for a small-sized instance, the model is computationally challenging if solved directly using CPLEX due to problem complexity. Moreover, some well-recognized heuristics, such as the genetic algorithm (GA) and adaptive large neighborhood search algorithm (ALNS), which have already been widely applied in solving various combinatorial problems, may not be efficient for the proposed ETRP problem. One possible reason is that the neighborhood functions in common heuristics, such as the crossover and mutation operations in GA or the random destroy and repair operations in ALNS, would cause cascading effects on subsequent route segments and may end up with low-quality neighboring solutions for our investigated platooning-specific problem, in which case considerable additional time will be required to generate a better solution. This motivates us to develop a customized solution method dedicated to the platooning-related optimization problem by exploring the characteristics of the platooning process and its possible optimal solution structures.

In ETRP problem, for each truck with one freight delivery task, if we consider truck routing only (without platooning), the optimal route for this truck would be the shortest path from its origin to its destination. If we consider truck platooning and driver assignment, the trucks may not take their respective shortest paths but rather make a detour for platooning opportunities to save cost. Nonetheless, each truck can be attracted only by the platooning opportunities along the paths that do not deviate much from its shortest path; otherwise, the achieved labor cost and energy cost savings by platooning could be offset by the additionally incurred cost, e.g., the drivers' service cost and energy cost for a long detour. In other words, the optimal route for a truck in consideration of platooning would not 'spatially' differ too much from its shortest path since the edges that are far away from those in its shortest path between the origin and the destination are unlikely to appear in the optimal solution. This important observation indicates that only a limited number of edges that are involved in the routes on or surrounding the shortest path of each truck can possibly be traversed by the truck fleet. We are thus inspired to confine the search space for each truck to a much smaller but most promising area to better search the optimal routing and platooning plans. Based on the above analysis, we propose a solution method named the edge set covering algorithm (ESCA) to solve the proposed problem.

4.1. An efficient edge set covering approach

The key idea of ESCA is to find the solution to the ETRP problem by optimizing only a subset of decision variables that are related to a subset of edges in the highway network. More specifically, the ESCA will first identify a promising edge set, which includes the promising edges with great potential to contribute to solution improvement, and then optimize the corresponding decision variables related to these edges while fixing the values of the other variables to be zero. In this way, the solution of the original model can be obtained by solving a resultant partial MILP model with most variables fixed. Since only a subset of variables, referred to as unfixed variables, require to be optimized, the solution search space and thus the computation time can be significantly reduced. Notably, the efficacy of ESCA depends on whether we can identify the subset of promising edges and construct the corresponding subset of unfixed variables, the optimization of which can contribute most to achieving good-quality solutions while ensuring satisfactory computational efficiency.

As discussed previously, each truck will only possibly traverse the edges involved in the routes on or near its shortest path from the origin to the destination. Therefore, the ESCA will start from constructing the edge set for each truck by finding its top r^{th} shortest paths and the involved edges will be grouped in set $\Theta_v, \forall v \in \mathbf{V}$. The edge set identified for the whole truck fleet can then be denoted by $\Theta = \bigcup_{v \in \mathbf{V}} \Theta_v$. Note that the top few shortest paths found for each truck should satisfy the following constraint:

$$D^v / d_r^v \geq \varepsilon, \forall v \in \mathbf{V} \tag{25}$$

where D^v and d_r^v denote the travel distance of the shortest path and the top r^{th} shortest path from the origin to the destination for truck $v \in \mathbf{V}$, respectively (Kindly note that $D^v = d_1^v$), and ε is a parameter with the value lying in $(0, 1]$ to control the size of set Θ. In fact, the lower the value of ε, the more the routes for each truck satisfying Constraint (25), and hence the larger the size of set Θ since more edges will be put in.

After the edge set is identified, for each truck $v \in \mathbf{V}$, the values of binary decision variables, including the route variables x_{ij}^v, platoon-related variables p_{ij}^{vw}, β_{ij}^v and λ_{ij}^v, and driver assignment variables χ_{ij}^{vd}, for all edge $(i,j) \in \mathbf{E}$ and trucks $v, w \in \mathbf{V}$ will first be fixed to 0. Then, only a subset of the mentioned decision variables that are related to the edges in the constructed set Θ_v will be unfixed to be optimized for each truck $v \in \mathbf{V}$. It is worth noting that all continuous variables are unfixed and remain optimized. The resultant model can be solved much more efficiently by commercial solvers than the original model without largely comprising solution quality. Kindly note that due to the implementation of a soft time window and the assumption that each node is equipped with a charging station, the feasibility of the solution is guaranteed.

To sum up, the proposed ESCA can find good-quality solutions for the investigated ETRP problem in a very efficient manner according to the following steps:

- **Step 1**: Generate edge set Θ by finding out the top r^{th} shortest paths from the origin to the destination for each truck and construct the set Ω of unfixed binary decision variables accordingly.
- **Step 2**: Fix the values of the binary decision variables, i.e., x_{ij}^v, p_{ij}^{vw}, β_{ij}^v, λ_{ij}^v, and χ_{ij}^{vd}, to be zero for all edge $(i,j) \in \mathbf{E}$ and trucks v, w.
- **Step 3**: Unfix the variables x_{ij}^v, p_{ij}^{vw}, β_{ij}^v, λ_{ij}^v, and χ_{ij}^{vd} for edge $(i,j) \in \Theta_v, v, w \in \mathbf{V}$ for each truck v, that is, unfix the variables in set Ω; Unfix all the continuous variables including $e_i^v, \theta_i^v, t_i^v, s_i^k$ and u_i^v, $\forall i \in \mathbf{N}, v \in \mathbf{V}, k \in \mathbf{K}$.
- **Step 4**: Invoke the MIP solver to optimize the resultant MILP model and return the optimal solution.

The ESCA is outlined in Algorithm 1. As shown in the pseudocode, the algorithm begins with the process to obtain the edge set Θ_v for each truck $v \in \mathbf{V}$ using, e.g., the K-shortest path routing algorithm (see lines 4–13). The binary decision variables, i.e., x_{ij}^v, p_{ij}^{vw}, β_{ij}^v, λ_{ij}^v, and χ_{ij}^{vd} in this study, will then be put into set Ω for all edge $(i,j) \in \Theta_v$ for each truck $v \in \mathbf{V}$ (see line 14). Next, we will fix the values of the variables including x_{ij}^v, p_{ij}^{vw}, β_{ij}^v, λ_{ij}^v, and χ_{ij}^{vd} to be 0 for all edge $(i,j) \in \mathbf{E}$ and trucks $v, w \in \mathbf{V}$ (see line 16). Afterwards, the variables grouped in set Ω will be unfixed for optimization (see line 17). Last, the MIP solver will be invoked to solve the resultant MILP model with most variables fixed (see line 18). The search process will be terminated if the optimal solution S for the resultant model has been found or the computation time is larger than the maximum time limit T_{max}. Finally, the optimal solution S will be returned as the output of the algorithm (see lines 19–21).

Algorithm 1. (*Pseudocode of the edge set covering algorithm*) Pseudocode of the edge set covering algorithm

1	Input: $\varepsilon; T_{max}; \sigma_v; \delta_v; \tau_{ij}; d_{ij}; L_{ij}; h_i; Q; g; c_b; c_l; c_r; c_p; \eta$
2	Output: S
3	Initialization:$\Theta_v \leftarrow \varnothing$; $\Omega \leftarrow \varnothing$; $r \leftarrow 1$
4	For each truck $v \in \mathbf{V}$ do
5	Let $D^v \leftarrow d_1^v$;
6	While $r \geq 1$ do
7	Obtain the r^{th} shortest path from the origin to the destination for truck v by the K-shortest path routing algorithm and calculate its corresponding travel distance d_r^v;
8	If $D^v / d_r^v < \varepsilon$ then
9	Break;
10	Else $r \leftarrow r + 1$;
11	End If
12	Group the edges involved in the obtained r^{th} shortest path for truck v in set Θ_v;
13	End While
14	Group the variables x_{ij}^v, p_{ij}^{vw}, β_{ij}^v, λ_{ij}^v, and χ_{ij}^{vd} in set Ω for truck v, $\forall (i,j) \in \Theta_v, w \in \mathbf{V}$;

(continued on next page)

(*continued*)

End for
Fix the values of the variables x_{ij}^{v}, p_{ij}^{vw}, β_{ij}^{v}, λ_{ij}^{v}, and χ_{ij}^{vd} to be 0, $\forall (i,j) \in \mathbf{E}, v, w \in \mathbf{V}$;
Unfix the variables x_{ij}^{v}, p_{ij}^{vw}, β_{ij}^{v}, λ_{ij}^{v}, and χ_{ij}^{vd} in set Ω; Unfix all the continuous variables including $e_{i}^{v}, \theta_{i}^{v}, t_{i}^{v}, s_{i}^{k}$ and u_{i}^{v}, $\forall i \in \mathbf{N}, v \in \mathbf{V}, k \in \mathbf{K}$;
Invoke the MIP solver to solve the resultant ETRP model with most variables fixed;
If the optimal solution is found or the computation time exceeds T_{max} then
Stop the search process and return the optimal solution S;
End If

4.2. 4.2. Choice of parametere

As aforementioned in Subsection 4.1, the value of the parameter ε is crucial in determining the solution quality and computational efficiency. For a special case of ETRP problem where labor costing saving and recharging demand of ETs are not considered, the parameter ε should be set as follows:

$$\varepsilon \geq 1 - \eta \tag{26}$$

Recall that η is the energy reduction rate of platooning. This is because a truck will never travel on a path longer than $D^{v}/(1-\eta)$ in an optimal solution in this situation; otherwise, the achieved energy savings will be offset by the increased energy cost of the detours for platooning.

For the general case of ETRP problem considering the energy saving, labor cost saving and the recharging demands of ETs, the value of ε can be determined based on an iterative procedure outlined in Algorithm 2. As shown in the pseudocode, the parameter ε is initialized as 1, and the model will be iteratively solved under a gradually decreasing ε with a given step size a, e.g., 0.01. The iteration process will terminate when the relative gap between the objective function values under two adjacent iterations is less than a given non-negative threshold π, e.g., 0.1. Finally, the current value of ε is considered to guarantee good-quality solutions. Intuitively, a higher ε will accelerate the computation but inevitably lead to a low-quality solution, and vice versa. Nonetheless, it should be noted that there may exist a threshold beyond which further reduction of ε may have marginal effects on solution quality. We may choose the values of a and π based on the practical requirements to strike a good balance of solution quality and computation efficiency. In the numerical experiments of Section 5, we will assess the performance of the proposed solution method under different values of ε.

Algorithm 2. (*Pseudocode of the procedure for determining the value of ε*) Pseudocode of the procedure for determining the value of

Input: a; π
Output: ε
Initialization: $\varepsilon \leftarrow 1$
Apply ESCA to solve the problem and obtain solution S;
While $\varepsilon > 0$ do
$\varepsilon \leftarrow 1 - a$;
Apply ESCA to solve the problem and obtain solution S';
If $|S' - S|/S' \leq \pi$ then
Break;
Else $S \leftarrow S'$;
End If
End While
Stop the iteration process and return the value of ε.

5. Numerical experiments

This section presents the results of a comprehensive set of computational experiments on randomly generated instances. First, we will introduce the test instances used for our tests. Then, we will evaluate the performance of the proposed ESCA algorithm for the proposed ETRP problem against CPLEX and two benchmark algorithms. Moreover, we examine the benefits of ET platooning mode and temporal and spatial consistency of platooning and charging behaviors. Finally, sensitivity analysis is conducted to explore the impacts of several major influential factors, i.e., the labor cost, penalty cost, and charging rate, on the system performance. The mathematical model and algorithms are coded in AMPL/MATLAB R2020b, calling CPLEX if applicable. All experiments are executed on a personal computer with Intel (R) Core (TM) i5 1.60 GHz CPU with 8 GB RAM.

5.1. Test instances and parameter settings

Three bidirectional highway networks with different node numbers, i.e., $|\mathbf{N}| \in \{10,30,50\}$ and the same topology complexities measured by the ratio of edge number to node number, i.e., $|\mathbf{E}|/|\boldsymbol{N}| = 1.5$ are randomly generated to test the algorithm. Fig. 2 illustrates two examples of randomly generated networks with 50 nodes. Other than the network node number, the fleet size (i.e., the number employed trucks) is expected to largely influence the computational efficiency of the solution method. Therefore, we consider 4 fleet scenarios with different numbers of ETs, i.e., $|\mathbf{V}| \in \{10, 30, 50, 100\}$, in each of the three networks. The travel time on each edge (i,j), i.e., τ_{ij}, measured in minute, is randomly chosen from the set $\{30, 31, 32, \ldots, 60\}$. The electricity consumption of each edge (i,j), i.e., d_{ij}, measured in kWh, is chosen from the set $\{25, 26, 27, \ldots, 65\}$. The maximum number of available drivers at each node is randomly generated from the set $\{5, 6, \ldots, 20\}$. As for the ET fleet, the battery capacity Q is set to be 540 kWh. The energy-saving ratio of platooning on each edge is set to be 0.2. We set the platoon size (i.e., the maximum number of trucks in a platoon) to 5 to achieve a balance between the benefits of platooning and the practical limitations of road safety and traffic flow. An excessively long platoon will obstruct visibility for other drivers, occupy significant road space, and increase the difficulty of merging and overtaking maneuvers.

The origin and destination of each truck are randomly generated from the node set of the networks. The earliest departure time for each truck is set to 0 and the latest arrival time at the destination, measured in minutes, is uniformly drawn from the set $\{120, 121, \ldots, 360\}$ for each truck. The penalty cost per minute c_p for late arrivals is set to be \$1. As for truck drivers, the base cost and the unit labor cost are set to be \$20 and \$1/min, respectively. In addition, without loss of generality, we assume that there are sufficient homogeneous charging stations with charging rate g and full charging price c_r being 480 kW and \$20, respectively, located at all the nodes of the highway network. Regarding the algorithm-related parameters, we set $\varepsilon = 0.8$ based on our preliminary experiments. The stopping criteria of the ESCA algorithm is set to be $T_{max} = 2$ h. Based on the above parameter settings, the experiments are conducted on multiple groups of random instances with different combinations of network node numbers and fleet sizes. Given the highway network node and truck fleet size, 3 instances with the above randomly generated parameters will be created and the average results will be reported.

5.2. Algorithm performance

5.2.1. Comparison of ESCA and three baselines

To evaluate the performance of the proposed solution method, we will compare the results of ESCA algorithm with those obtained by CPLEX and the other two heuristic algorithms, GA and greedy strategy (GS). CPLEX is a well-recognized commercial optimization solver for a wide range of transportation planning and optimization problems. GA is among the most popular heuristics that can find approximate solutions with less computational effort. GS is a relatively easy-to-implement heuristic for the shortest path-related problems. The ESCA, GA and GS algorithms will be independently run 3 times for each instance and the average results will be reported. Since the ETRP problem is not a real-time optimization task, we set the solving time limit of CPLEX to 24 h so as to provide a more robust assessment of ESCA's performance. The termination condition of GA is that the maximum number of iterations reaches 300. Table 1 presents the results of the proposed ESCA and the other three methods for various test instances. For all methods, we report the objective function values obtained within the time limit (Obj) and the CPU runtimes (Time), as well as the gaps (Gap) of the average objective function values between the ESCA and each of the other three competing methods. The best values of each indicator are highlighted in bold.

We first assess the performance of the proposed algorithm by comparing it with CPLEX. As presented in Table 1, we see that CPLEX can exactly solve the instances with up to 50 trucks in networks with 30 nodes. For the proposed ESCA, the results show that the gap between ESCA and CPLEX remains below 5 % for instances where CPLEX is able to find exact solutions, which demonstrates the superior performance of ESCA in solving the ETRP problem. Additionally, ESCA can still find high-quality solutions for larger instances

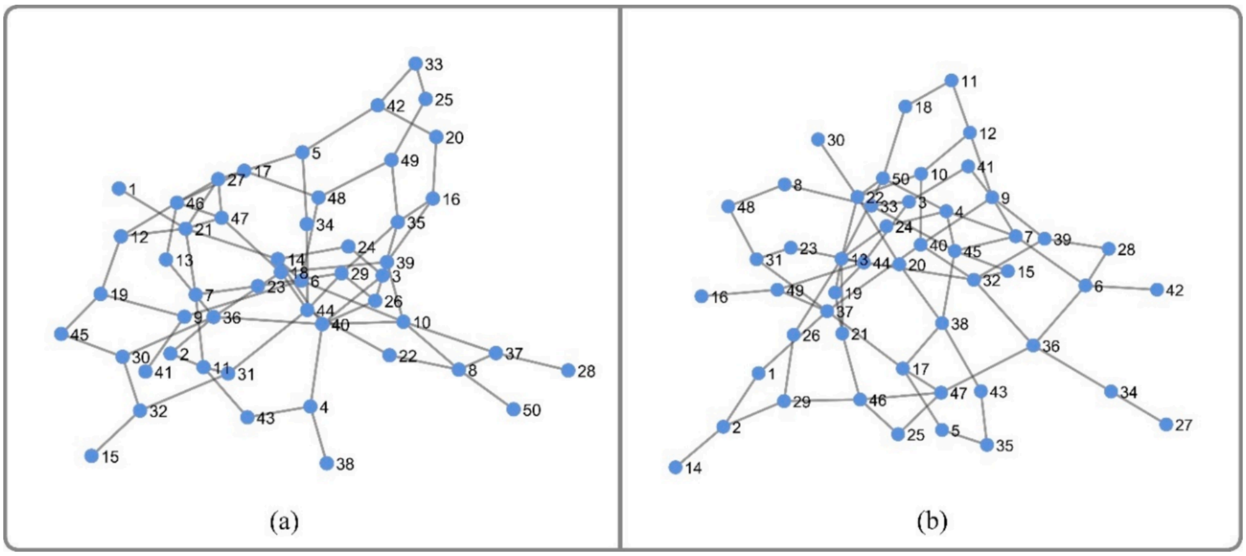


Fig. 2. Examples of randomly generated highway networks with 50 nodes.

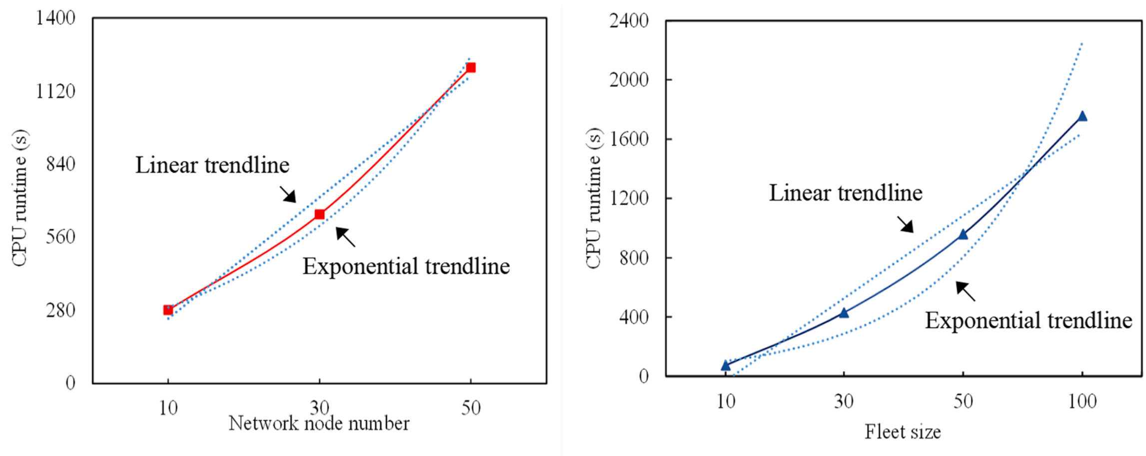
Table 1
Performance comparison of ESCA, GA, GS, and CPLEX.

|N|	|V|	ESCA Obj ($)	Time (s)	GA Obj[1] ($)	Time (s)	GS Obj[2] ($)	Time (s)	CPLEX Obj[3] ($)	Time (s)	Gap[1]	Gap[2]	Gap[3]
10	10	**1,501**	23	1,506	84	1,536	**9**	**1,501**	839	0.32 %	2.32 %	0.00 %
	30	6,332	148	6,990	351	6,830	**24**	**6,226**	9,101	10.40 %	7.87 %	−1.67 %
	50	8,815	293	9,811	1,092	9,363	**52**	**8,610**	16,939	11.30 %	6.22 %	−2.33 %
	100	17,765	662	19,913	2,310	19,662	**113**	**16,993**	71,344	12.09 %	10.69 %	−4.35 %
30	10	**1,757**	**74**	2,198	295	2,555	89	**1,757**	8,297	25.09 %	45.41 %	0.00 %
	30	6,944	423	7,759	702	7,536	**288**	**6,712**	30,699	14.94 %	11.65 %	−3.34 %
	50	**9,587**	556	10,518	1,516	11,108	**513**	9,116	82,512	9.71 %	15.86 %	−4.91 %
	100	**19,907**	1,538	21,708	3,814	22,368	**1,271**	–	86,400	9.05 %	12.36 %	–
50	10	2,170	**126**	2,662	662	2,363	177	**2,114**	10,142	22.70 %	8.90 %	−2.58 %
	30	**7,301**	**717**	8,420	1,438	7,881	789	–	86,400	15.33 %	7.95 %	–
	50	**11,901**	1,529	15,373	2,379	14,279	**1,369**	–	86,400	29.34 %	20.14 %	–
	100	**23,487**	**2,472**	31,213	5,683	29,112	2,693	–	86,400	32.89 %	23.95 %	–
Average		**9,789**	**9,789**	11,506	1,694	11,216	**616**	–	–	–	14.78 %	–

Remarks: Gap^1=(Obj^1-Obj)/Obj; Gap^2=(Obj^2-Obj)/Obj; Gap^3=(Obj^3-Obj)/Obj.

that CPLEX cannot solve within the time limit. More importantly, ESCA achieves an average CPU time of only 11 min, significantly outperforming CPLEX in computational efficiency. For example, both ESCA and CPLEX can find the optimal solution for (30, 10) instances, but ESCA required only 74 s compared to CPLEX's 138 min. In addition, the ESCA can obtain good-quality solutions for instances with up to 100 trucks in the 50-node scenarios within 42 min. The above findings demonstrate the computational challenge of the proposed ETRP problem and the effectiveness and efficiency of the proposed algorithm for solving the underlying problem. To further examine the computational performance of the ESCA, we visualize the variations of the average CPU times of the ESCA algorithm with respect to network node number and fleet size in Fig. 3 (a) and (b), respectively. Kindly note that the blue dotted lines in Fig. 3 are strictly linear and exponential trendlines, which are used to help define the specific changing trend of the CPU time of the proposed ESCA with the increase in the problem size. It can be seen that the CPU runtimes increase in a manner between the linear and exponential trends. This is within our expectation that although the proposed ESCA is an essentially formulation-based algorithm, it can effectively reduce the model size and intensify the search around the most promising area for the proposed ETRP problem, leading to good-quality solutions with a much higher computational efficiency. The proposed ESCA method has good potential to be implemented in real-life applications for platooning-related optimization problems.

We then compare the solutions obtained by the proposed ESCA algorithm with those of GA and GS. As shown in Table 1, we can observe that both ESCA and GA show satisfactory performance for small instances with no more than 10 trucks and 10 nodes. As the number of nodes and trucks increases, the performance of GA decreases rapidly while ESCA still maintains the solution quality and solving efficiency. Specifically, the proposed ESCA can achieve 15.07 % lower objective function values within 52.51 % less CPU runtimes compared with GA, indicating the dominating advantage of ESCA over GA in both solution quality and computational efficiency. As expected, the GA tends to converge to inferior solutions, especially in middle and large instances, which cannot effectively solve the underlying problem. As for GS, we can see that the average CPU runtime of GS has decreased by 13.71 %, whereas the objective function value increased by 14.78 % on average. The CPU runtimes of GS is competitive since GS seeks to find the shortest



(a) Variations of the average CPU time with the increase of network node number

(b) Variations of the average CPU time with the increase of fleet size

Fig. 3. Variations of the average CPU times of the ESCA algorithm.

path for each involved truck without simultaneously considering the formation of platoons and driver assignment. This will, however, result in higher objective function values, i.e., total operational cost. Overall, we can conclude that ESCA outperforms GA, GS, and CPLEX for solving the ETRP problem. The proposed ESCA can obtain good solutions while guaranteeing a relatively high computational efficiency compared with the other three baseline methods and has great potential to be implemented for problems of practical scale.

5.2.2. Comparison of ESCA under different values of ε

For the instances with a given network size and truck fleet size, the performance of the ESCA may vary with the parameter settings. The parameter ε in the proposed ESCA is expected to affect both solution quality and computational efficiency since it determines the size of the set of possibly traversed edges during the trip for each truck, and accordingly, the dimension of the resultant model to be optimized. Therefore, we evaluate the performance of the proposed ESCA for solving the ETR problem under different values of ε in set {0.4, 0.6, 0.8, 1.0}. The results are tabulated in Table 2. Again, we report the objective function values (Obj) and the CPU runtimes (Time) for each group of instances. We further visualize the variations of the average objective function values and CPU runtimes of all groups of instances with respect to ε in Fig. 4.

Overall, it can be seen from Table 2 and Fig. 4 that the value of ε does affect the computational performance of the ESCA for solving the proposed ETRP problem. The objective function values and CPU runtimes show the upward and downward trend performances, respectively, when ε increases. In other words, the ESCA with a lower value of ε finds better solutions, but with a significantly increased computation time. This is because much better routing, platooning and driver assignment plans for both the trucks and drivers can be found in a larger solution space under a low value of ε but at the cost of increased computation time. It is worthwhile to note that the quality of the solutions found by the ESCA with $\varepsilon = 1.0$ is the lowest. When it comes to the ESCA with $\varepsilon = 0.8$, we can see that it can achieve satisfactory performance with respect to both the solution quality and computational efficiency. Specifically, although the average objective function value is increased by 4.99 %, the ESCA with $\varepsilon = 0.8$ can save almost 40 % of the CPU runtimes in comparison with that of $\varepsilon = 0.4$. That's why we set $\varepsilon = 0.8$ in the numerical experiments. Moreover, when ε decreases from 0.6 to 0.4, the objective function values only decrease by 1.45 % on average, yet the average CPU times increase by 21.30 %. On one hand, it suggests there may exist a threshold beyond which a further reduction of ε may have a limited impact on solution quality (see Fig. 4). This can be explained by the fact that the trucks only possibly traverse the edges surrounding their respective shortest paths from the origins to the destinations to form profitable platoons, and further relaxation of the far-away edges does not lead to significant cost savings. In addition, we should be aware that the trade-off between solution quality and computational time should be well balanced by toning the value of ε in real applications.

5.3. Impact of ET platooning

In this subsection, we first explore the impact of the ET platooning on the system performance by comparing the results for the original [ETRP] model and the model without considering truck platooning, referred to as PM and TM, respectively. We present the comparison results of various random instances with different problem sizes under the above-mentioned two models on the cost-related and driver-related indicators, including the total operating cost (TC), the energy cost (EC), the total labor cost (LC), the late arrival penalty cost (PC), the total service time of the drivers (TT), the total detour time of the drivers (RT), the number of the employed drivers (ND), and the gaps between the PM and TM models on the objective values (Gap) in Table 3.

We can see that the platooning mode can effectively reduce the labor cost for all groups of instances. More specifically, the PM, on average, can save the labor cost by 12.05 % compared with TM. This may be explained by the fact that the total working time of the drivers can be significantly reduced since the platoon followers are driverless. Such a great labor cost-saving benefit also demonstrates the great potential of ET platooning to be implemented in real life to cope with huge labor costs. Nonetheless, another notable observation is that the PM will induce an increase in the penalty cost compared with TM. This may be because the trucks tend to wait or detour to form platoons with others with longer transportation times, and thus the deadline of the delivery tasks may be violated. If we

Table 2
Comparison results under different values of ε

|N|	|V|	$\varepsilon = 0.4$ Obj ($)	Time (s)	$\varepsilon = 0.6$ Obj ($)	Time (s)	$\varepsilon = 0.8$ Obj ($)	Time (s)	$\varepsilon = 1.0$ Obj ($)	Time (s)
10	10	1,495	51	1,495	33	1,501	23	1,542	17
	30	6,121	235	6,274	181	6,332	148	6,600	112
	50	8,462	565	8,572	402	8,815	293	9,264	216
	100	17,518	1,011	17,579	801	17,765	662	18,268	499
30	10	1,631	158	1,662	109	1,757	74	2,054	122
	30	6,494	714	6,569	558	6,944	423	7,020	350
	50	9,298	1,606	9,381	1,299	9,587	1,056	10,060	809
	100	18,348	3,102	18,758	2,688	19,907	2,138	20,995	1,656
50	10	1,970	271	2,035	188	2,170	126	2,475	91
	30	7,000	1,382	7,137	1,009	7,301	717	7,705	584
	50	11,366	2,777	11,584	2,036	11,901	1,529	13,617	1,194
	100	21,971	3,883	22,274	3,094	23,487	2,472	27,103	1,888
Average		9,306	1,313	9,443	1,033	9,789	805	10,559	628

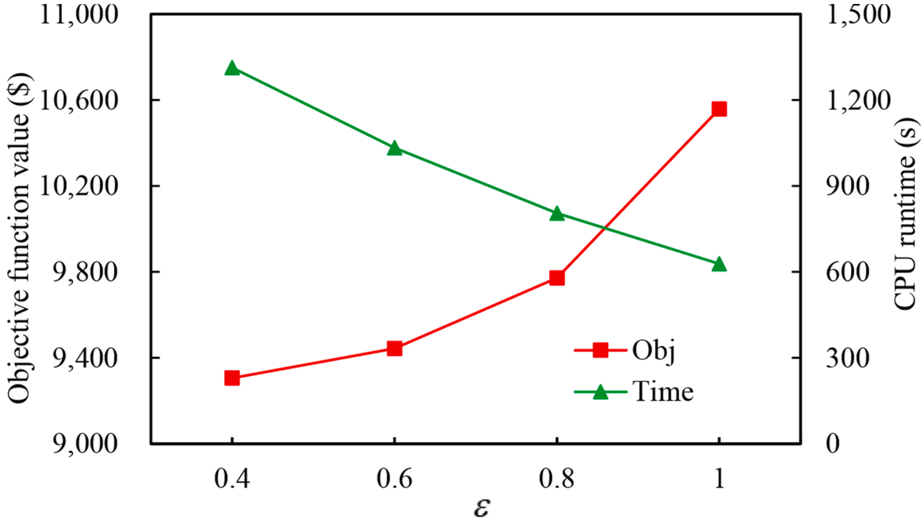


Fig. 4. Variations of the average objective function values and the average CPU runtimes with the increase of..ε

dig deeper, we can find that for a given number of trucks, the penalty cost gradually increases with the increasing number of nodes in the highway network. This is rational as more nodes bring more opportunities for the trucks to stop and wait to form platoons with others on the way.

We can also find that the total energy cost under the model with platooning can be even higher than those of the model without platooning in several groups of instances, in which case the energy-saving effect by platooning cannot outweigh the additional energy consumption on the detours for forming platoons. Despite this, it is encouraging to find that the PM can, on average, save the total operational cost by 12.07 % compared with the TM. This outcome reveals the advantages of the platooning mode over the traditional mode to reduce the total operational cost. It is also worthwhile to mention that the gap values of the total operating cost and the labor cost are much larger for the middle and large instances than those for the small ones, indicating that the PM is more competitive over the TM in relatively large instances. With more nodes and trucks in a highway network, there would be more platoon formation opportunities for labor savings.

As for the driver-related comparison results, we can see that the model with platooning mode can effectively reduce the total working time of the drivers to complete the same number of delivery tasks in comparison with the model without platooning. Specifically, the total working time of the drivers can be saved by 16.20 % on average under the PM, which quantitatively validates the potential of the platooning mode on reducing the driver's working load and saving labor cost. However, we also find that more drivers are engaged under the PM in comparison with that under the TM since the dissolution of the platoons may require additional drivers to be assigned to continue their respective delivery trips. Nonetheless, the total working time of the drivers is reduced, which, to some extent, indicates that the drivers tend to be assigned short-distance delivery tasks. This finding also implies that the PM has the potential to mitigate the dependence on the long-haul drivers for the trucking industry. Regarding the detour time of the drivers, we can find that the detour time of RTs is influenced by multiple interactive factors. For instance, the ET does not necessarily increase with the growth of $|\mathbf{V}|$ in $|\mathbf{N}| = 10$ instances. When $|\mathbf{V}| = 100$, the RT is 0 because the high density of ET distribution results in the formation of all platoons without any detours. For (50,10) instances, the RT increases to 5.9 h, accounting for about 23.6 % of the total working time. The large increase in RT may be attributed to the much longer time required to complete tasks in larger networks. Nevertheless, the results also show that the time cost associated with the increased detours can be outweighed by the reduction in labor costs, which indicates that the long detour for platooning is still cost-effective despite the added travel time under some cases. As for the TM, the detour time is always 0. This is because under the TM mode, all the trucks will just follow their shortest paths to their respective destinations without the consideration of any detours. Moreover, we find that the total working time of the drivers under the TM mode is much higher than that of PM, which further demonstrates the advantage of employing platooning technology to reducing the working time of drivers and improving the overall operational efficiency.

5.4. Mutual impacts between platooning and charging

Furthermore, we also investigate the synergy between truck charging and platooning; for example, whether the waiting time for platoon partners can be used for vehicle charging or vice versa in the context of ETRP. This is to explore the temporal and spatial consistency of the platooning and charging behaviors of ET. First, we examine the temporal consistency by comparing the total charging time (CT) and dwelling time (DT) of the ETs under the PM and TM. The results are reported in Table 4. We can see that the CT and DT of the trucks are equal under the TM since the trucks will not dwell at nodes awaiting platoon partners but for recharging if needed. In the PM, it is observed that the DT of the trucks exceeds the corresponding CT. It is possible that the waiting time for platoon partners is used to charge the trucks. This observation also suggests that the charging decisions can be coordinated with platooning

Table 3
Comparison results of the PM and TM model.

|N|	|V|	PM						TM						Gap^1	Gap^2	Gap^3	Gap^4
		TC^1 ($)	EC^1 ($)	LC^1 ($)	PC^1 ($)	TT (h)	ND	TC^2 ($)	EC^2 ($)	LC^2 ($)	PC^2 ($)	TT (h)	ND				
10	10	1,501	196	1,294	11	18	11	1,560	213	1,346	1	19	10	3.94 %	8.61 %	4.02 %	−88.99 %
	30	6,332	608	5,676	48	84	33	6,686	627	6,036	23	91	30	5.59 %	3.11 %	6.34 %	−52.73 %
	50	8,815	1,017	7,738	60	111	53	9,521	1,104	8,380	37	123	50	8.02 %	8.57 %	8.30 %	−37.79 %
	100	17,765	2,118	15,556	91	225	104	19,104	2,196	16,844	63	247	100	7.54 %	3.73 %	8.28 %	−30.74 %
30	10	1,757	238	1,446	73	20	12	1,844	234	1,562	48	23	10	4.95 %	−2.01 %	8.02 %	−33.33 %
	30	6,944	809	5,992	143	85	43	7,237	796	6,324	117	95	30	7.22 %	−1.50 %	9.07 %	−18.69 %
	50	9,587	1,240	8,030	317	115	58	10,862	1,259	9,370	232	140	50	13.29 %	1.54 %	16.69 %	−26.70 %
	100	19,907	2,333	16,972	602	246	120	22,846	2,505	19,898	443	298	100	14.77 %	7.40 %	17.24 %	−26.40 %
50	10	2,170	305	1,764	101	25	12	2,310	319	1,904	87	28	10	6.44 %	4.63 %	7.94 %	−14.10 %
	30	7,301	759	6,158	384	89	54	8,339	739	7,338	262	112	30	14.22 %	−2.54 %	19.16 %	−31.86 %
	50	11,901	1,481	9,812	608	142	63	13,680	1,398	11,926	355	182	50	15.09 %	−5.52 %	20.34 %	−41.51 %
	100	23,487	2,628	19,738	1,121	285	131	27,429	2,683	24,026	720	367	100	16.78 %	2.09 %	21.72 %	−35.78 %
Average		9789	1,144	8,348	297	120	58	10,951	1,173	9,580	199	144	48	12.07 %	2.34 %	12.05 %	−36.55 %

Remarks: $Gap^1 = (TC^2\text{-}TC^1)/TC^1 \times 100$ %; $Gap^2 = (EC^2\text{-}EC^1)/EC^1 \times 100$ %; $Gap^3 = (LC^2\text{-}LC^1)/LC^1 \times 100$ %; $Gap^4 = (PC^2\text{-}PC^1)/PC^1 \times 100$ %.

plans to avoid dedicated additional time for charging. Another observation is that, for most instances, the charging load at charging stations can be alleviated due to the energy-saving effect by platooning under the PM as reflected by the lower values of CT compared with those under the TM. However, this is not always the case for some instances in which the CT of the trucks under the PM are even larger than that under the TM. The trucks may tend to make long detours to form platoons for labor cost savings, even energy savings obtained by platooning cannot offset the additional energy consumption of such long detours.

Next, we proceed to investigate the spatial consistency of the platooning and charging behaviors under the PM. The number of formed platoons (NP), the average platoon size (APS), the total number of stops of all ETs (NS), the number of stops for both waiting and charging (NWC), the number of stops only for waiting (NW), and the number of stops only for charging (NC) are all tabulated in Table 5. We can see that the increase in the number of ETs in a network of the same scale can lead to more formation of platoons of larger sizes. We also find that given a fixed number of ETs, more platoons can be formed in a larger network, but the size of the platoons may not increase. It is possible that more platooning opportunities exist in the larger network, but, at the same time, the ETs are more dispersed in such a network. Moreover, if we dig deeper into the four indicators in terms of the numbers and the purposes of the stops, i.e., NS, NWC, NW, and NC, we may draw some interesting conclusions about the spatial consistency of the platooning and charging behaviors of the ETs in the PM. Obviously, the total number of stops will increase with the increasing fleet size and network size. It is also worth noting that in most cases, the number of stops for both waiting and charging (NWC) accounts for the largest proportion of the total number of ET stops (NS). In other words, the network nodes where the ETs stop are usually the points where their batteries recharged while waiting for platoon partners. This aligns with our expectation that the ETs tend to charge while waiting for others to facilitate platoon formation and meet their own energy demands at the same time, which is a cost-effective way to save time and reduce the total operating cost. Another observation is that the percentage of the stops for charging only (NC) among all the stops (NS) shows an upward trend as the problem size grows. This may be attributed to the fact that the total charging demands of all the ETs may grow with the increase of the fleet size and the average travel distance in larger networks.

5.5. Sensitivity analysis

In this subsection, we explore the impacts of several influential factors, i.e., the unit labor cost, unit penalty cost, and charging rate, on the system performance in terms of the total operational cost (TC), energy cost (EC), labor cost (LC), penalty cost (PC), drivers' working time (TT), and the number of employed drivers (ND). The sensitivity analysis will be carried out in the instance groups with $\{(|\mathbf{N}|, |\mathbf{V}|)\} = \{(10,10), (30,30), (50,50)\}$.

5.5.1. Impact of labor cost

To explore the impact of the labor cost on the system performance, we compare the solutions to the proposed problem under different labor costs per minute for the drivers by setting $c_l \in \{0.5, 1, 2, 4\}$ while keeping c_b unchanged. The results are tabulated in Table 6. We further visualize the variations of the total penalty cost (PC), the total working time of the drivers (TT), and the number of employed drivers (ND) with the increase of unit labor cost in Fig. 5.

As shown in Table 6 and Fig. 5, we can observe that the increase in the drivers' unit time labor cost will reduce their total working time, but, at the same time, it will cause the number of employed drivers to increase. This may be attributed to the fact that the increase in c_l facilitates the trucks to form as many platoons as possible to save labor costs, whereas, in turn, more drivers are required to continue their respective trips when more platoons are dissolved. In addition, we find that the total penalty cost shows an upward trend as c_l increases. This aligns with our expectation that the trucks tend to form platoons to save labor costs even at the cost of late arrivals owing to long waiting time and detours for establishing the platoons. It is worthwhile to mention that although more platoons are formed, the total labor cost still increases with the increase in c_l, which may not only result from the direct increment of the unit labor cost for the drives but also the comparatively longer time of the drivers used for waiting or detouring for more platooning opportunities. As for the energy cost, it shows no specific changing trend with the increase in c_l. Another notable observation is that the values of PC, TT and ND show no obvious variations with the increase in c_l for the instances with $|\mathbf{N}| = 10$, $|\mathbf{V}| = 10$. This may be explained by the fact that there are only a few potential platooning opportunities in the very small networks with only 10 nodes. Hence, the changes

Table 4
Temporal consistency analysis of platooning and charging.

|N|	|V|	PM CT (h)	PM DT (h)	TM CT (h)	TM DT (h)
10	10	0.00	0.22	0.74	0.74
	30	0.46	1.27	1.52	1.52
	50	0.95	2.63	2.84	2.84
	100	2.31	5.66	4.04	4.04
30	10	2.16	3.91	1.89	1.89
	30	11.73	18.14	11.05	11.05
	50	13.52	23.03	14.59	14.59
	100	18.71	33.65	28.42	28.42
50	10	4.88	5.67	4.67	4.67
	30	8.93	14.15	7.84	7.84
	50	27.05	39.54	22.41	22.41
	100	35.34	51.06	38.43	38.43

Table 5
Spatial consistency analysis of platooning and charging.

|N|	|V|	NP	APS	NS	NWC	NW	NC
10	10	2.2	3.0	3.0	0.0	3.0	0.0
	30	9.0	4.0	27.0	6.3	20.7	0.0
	50	12.7	4.3	53.7	16.7	37.0	0.0
	100	15.3	4.7	87.0	29.7	57.3	0.0
30	10	2.7	2.3	13.3	9.3	2.0	2.0
	30	12.3	3.0	39.3	22.0	10.3	7.0
	50	20.3	4.0	81.7	57.7	11.3	12.7
	100	28.0	4.3	156.3	97.3	33.3	25.7
50	10	4.3	2.0	14.6	7.0	1.3	6.3
	30	16.7	2.7	43.0	17.3	4.7	21.0
	50	31.7	3.0	130.7	70.3	23.7	36.7
	100	55.0	4.0	290.3	198.3	29.0	63.0

Table 6
Impact of the unit labor cost on system performance.

Instance group	c_l($/min)	TC ($)	EC ($)	LC ($)	PC ($)	TT (h)	ND
(10,10)	0.5	998.8	199.7	794.0	5.1	19.6	10.3
	1	1,501.2	196.3	1,294.0	10.9	17.9	11.0
	2	2,458.5	195.2	2,250.0	13.3	16.7	12.3
	4	4,462.3	195.2	4,254.0	13.1	16.7	12.3
	Average	2,355.2	196.6	2,148.0	10.6	17.7	11.5
(30,30)	0.5	4,442.2	817.3	3,492.0	132.9	88.6	41.7
	1	6,943.9	808.5	5,992.0	143.4	85.3	43.7
	2	11,342.2	828.1	10,182.0	332.1	77.3	45.3
	4	20,622.5	899.2	19,384.0	339.3	76.9	46.4
	Average	10,837.7	838.3	9,762.5	236.9	82.0	44.3
(50,50)	0.5	7,899.4	1,519.1	5,791.0	589.3	151.5	62.3
	1	11,900.5	1,480.9	9,812.0	607.6	142.3	63.7
	2	18,944.1	1,601.8	16,346.0	996.3	125.1	66.7
	4	34,118.5	1,708.2	31,412.0	998.3	124.8	73.0
	Average	18,363.1	1,577.5	15,840.3	945.4	135.9	66.4

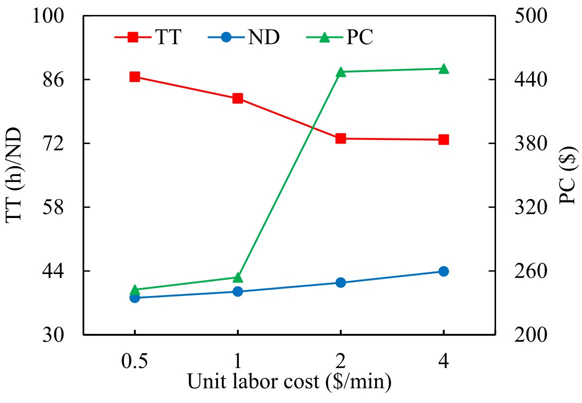


Fig. 5. Variations of the total penalty cost, the total working time of the drivers and the number of employed drivers with the increase of unit labor cost.

in the unit labor cost of the drivers would impose little effect on the routing and platooning plans. Moreover, it should be noted that the values of PC, TT and ND under the model with $c_l = 2$ remain almost the same as those under $c_l = 4$ for all groups of instances, indicating that there exists a threshold for the labor cost beyond which the increase in the unit time labor cost of the drivers would have little impact on facilitating the formation of platoons since the profitable platooning opportunities for a given network and instance are limited.

5.5.2. *Impact of penalty cost*

To investigate the impact of the penalty cost on the system performance, we will compare the solutions to the proposed model under different unit penalty costs by setting $c_p = \{1,3,5,10\}$. The results are summarized in Table 7. We further visualize the variations of the total delay time, i.e., PC/c_p, the total working time of the drivers (TT), and the number of employed drivers (ND) with the increase of the unit penalty cost in Fig. 6.

As shown in Table 7 and Fig. 6, we can observe that the total working time of the drivers increases, yet the number of employed drivers decreases with the increase in c_p. This is within our expectation that a higher unit penalty cost would make trucks harder to find favorable platooning opportunities for cost savings so that fewer platoons can be established, which leads to longer total working time of the drivers but fewer engaged drivers since less dissolution of platoons will be incurred. From Fig. 6, we can easily see that the total delay time follows a downward trend with the increase in the penalty cost. This suggests that the increase in the unit penalty cost can indeed facilitate more delivery tasks to be completed without much delay. However, if we dig deeper, we can find that the comparison results vary little when the penalty cost increases from 5 to 10. In particular, for the instances with $|\mathbf{N}| = 10$, $|\mathbf{V}| = 10$,the concerned values of PC/c_p, TT, and ND under $c_p = 5$ remain almost the same with those under $c_p = 10$, and a similar trend can be found in the instances with $|\mathbf{N}| = 30$, $|\mathbf{V}| = 30$, which suggests that there may exist a threshold beyond which further increase in the unit penalty cost would take little effect on further reducing the total delay time or influencing the routing and platooning plans, especially for the small and middle instances. This, on one hand, may be attributed to that a certain amount of delay time may already exist in nature for the delivery tasks with arbitrarily specified completion time; on the other hand, the profitable platooning opportunities are inherently limited for a given instance. Moreover, it is worthwhile to mention that the total labor cost grows with the increase in the unit penalty cost, which may result from the fact that fewer platoons can be formed under a high penalty cost since some platooning opportunities that require too long waiting time or detour distance would become unacceptable under heavy late arrival punishment. In a word, a high unit time penalty cost poses a negative impact on the formation of platoons, resulting in more labor costs accordingly.

5.5.3. Impact of battery charging parameters

Frequent battery recharging at charging stations is required due to the limited driving range of the ETs. At the same time, the charging time can also be coordinated with the waiting time for forming platoons. As a result, the charging rate of the chargers at the charging stations is regarded to affect the system performance. Therefore, we will analyze the solution results to the proposed ETRP under four different charging rates by setting $g \in \{240,480,720,960\}$ kW. The results are presented in Table 8. We further visualize the variations of the total operational cost (TC), the total labor cost (LC) and the total penalty cost (PC) with the increase in the charging power in Fig. 7.

As shown in Table 8 and Fig. 7, we observe that the solution results of the instances with $|\mathbf{N}| = 10$, $|\mathbf{V}| = 10$ show no variation with the increase in charging power. Since the trip distances for the trucks in a 10-node small network are generally short, the involved trucks may not need to recharge on the way to their respective destinations. Therefore, the changes of the charging rate have no effect on the routing and platooning plans at all for these small instances. For the instances with $|\mathbf{N}| = 30$ and $|\mathbf{V}| = 30$, we can observe that the total penalty cost increases, while the total labor cost decreases as the charging rate decreases from 480 kW to 240 kW. Obviously, the reduction of the charging rate will inevitably result in much longer charging time for the trucks in need. On one hand, the longer charging time will make more trucks fail to complete the delivery tasks on time and thus more penalty costs for the late arrivals would certainly be incurred; on the other hand, the trucks may utilize the longer charging time to form or join more platoons. In addition, we find that the total penalty cost shows an obvious downward trend when the charging rate increases from 480 kW to 960 kW, which is mainly because with the significantly shortened charging time via a high charging power, more tasks can be completed around their respective specified completion time and less penalty cost will be incurred accordingly. However, the total labor cost shows no obvious changing trend as the charging rate grows. This is somehow beyond our expectations. One possible explanation is that even if the required charging time becomes shorter, the trucks tend to continue to wait for platooning if profitable since the time used for charging or waiting is inherently the same from the point of the incurred labor cost. It is also worth noting that the values of all the indicators except PC vary little when the charging rate increases, indicating that the high charging rate has little impact on the routing, platooning, and driver assignment plans. As for the instances with $|\mathbf{N}| = 50$ and $|\mathbf{V}| = 50$, similar trends can be found for all the indicators as those of the instances with $|\mathbf{N}| = 30$ and $|\mathbf{V}| = 30$. In summary, compared to the increased charging rate, the solution results are more

Table 7
Impact of the unit penalty cost on system performance.

Instance group	c_p($/min)	TC ($)	EC ($)	LC ($)	PC ($)	TT (h)	ND
(10,10)	1	1,501.2	196.3	1,294.0	10.9	17.9	11.0
	3	1,623.1	194.1	1,408.0	21.0	19.8	11.0
	5	1,788.0	202.0	1,586.0	0.0	23.1	10.0
	10	1,788.0	202.0	1,586.0	0.0	23.1	10.0
	Average	1,675.1	198.6	1,468.5	8.0	21.0	10.5
(30,30)	1	6,943.9	808.5	5,992.0	143.4	85.3	43.7
	3	7,420.7	786.1	6,280.0	354.6	91.8	38.6
	5	8,876.1	818.0	7,526.0	532.1	114.3	33.4
	10	9,550.5	839.2	7,662.0	1,049.3	116.8	32.7
	Average	8,197.8	813.0	6,865.0	519.9	102.1	37.1
(50,50)	1	11,900.5	1,480.9	9,812.0	607.6	142.3	63.7
	3	13,254.1	1,553.5	10,312.0	1,388.6	153.2	56.0
	5	14,541.8	1,631.8	10,718.0	2,192.0	160.4	54.7
	10	17,215.6	1,708.2	11,190.0	4,317.4	169.3	51.6
	Average	14,228.0	1,593.6	10,508.0	2,126.4	156.3	56.5

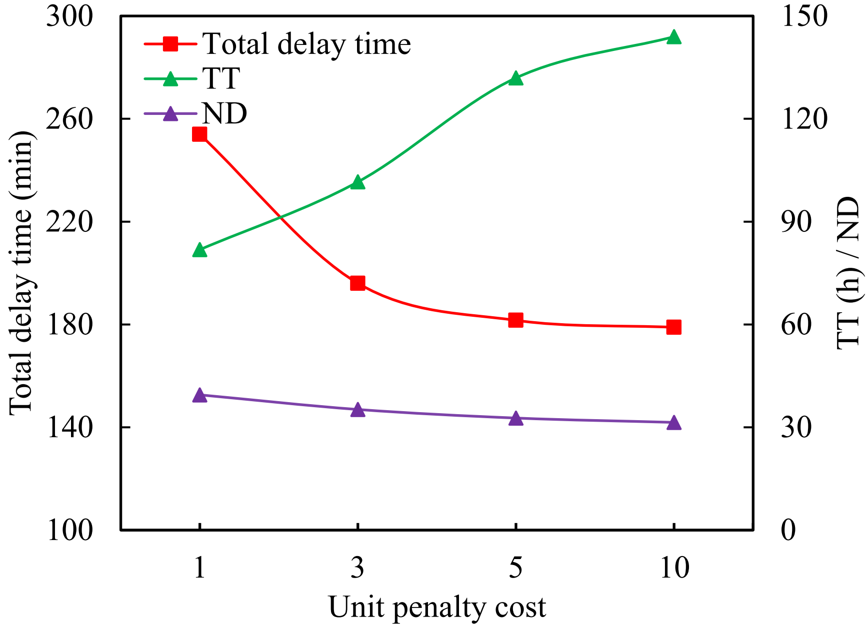


Fig. 6. Variations of the total delay time, the total working time of the drivers and the numbers of employed drivers with the increase in the penalty cost.

Table 8
Impact of the charging rate on system performance.

Instance group	g(kW)	TC ($)	EC ($)	LC ($)	PC ($)	TT (h)	ND
(10,10)	240	1,501.2	196.3	1,294.0	10.9	17.9	11.0
	480	1,501.2	196.3	1,294.0	10.9	17.9	11.0
	720	1,501.2	196.3	1,294.0	10.9	17.9	11.0
	960	1,501.2	196.3	1,294.0	10.9	17.9	11.0
	Average	1501.2	196.3	1,294.0	10.9	17.9	11.0
(30,30)	240	6,828.1	806.8	5,844.0	177.3	82.4	45.0
	480	6,943.9	808.5	5,992.0	143.4	85.3	43.7
	720	6,855.7	810.6	5,918.0	127.1	84.2	43.3
	960	6,794.7	806.3	5,864.0	124.4	83.4	43.0
	Average	6,853.1	808.1	5,904.5	140.6	83.8	43.8
(50,50)	240	12,051.0	1,470.3	9,636.0	944.7	138.5	66.3
	480	11,900.5	1,480.9	9,812.0	607.6	142.3	63.7
	720	11,156.0	1,471.7	9,228.0	456.3	132.9	62.7
	960	11,196.8	1,466.6	9,298.0	432.2	134.3	62.0
	Average	11,576.1	1,472.4	9,493.5	610.2	137.0	63.7

sensitive to the reduced charging rate for all groups of instances. We can also see that the influence of the charging rate on the penalty cost is more significant in larger instances. This may be attributed to the fact that the large-scale instances with more nodes and ETs will have much greater charging demands than those of the smaller instances and are more susceptible to the charging ability.

Another charging parameter that may affect the system performance is the allowable range of the state of charge (SoC). In this study, we assume that the battery SoC of the ETs ranges from 0 % to 100 %. In fact, in real-world operational scenarios, the consideration of a lower and an upper battery SoC limit are necessary to cope with, e.g., traffic/weather uncertainties and to protect battery health, respectively, to ensure more reliable and robust results. Therefore, we further conduct sensitivity analyses to explore the impact of different battery level ranges on the solution results. The results are presented in Table 9. We can observe that the changes of the battery level ranges have no effect on the solution results at all for the small instances with $|\mathbf{N}| = 10$, $|\mathbf{V}| = 10$, which is similar to the impact of the charging rate. For the middle ($|\mathbf{N}| = 30$ and $|\mathbf{V}| = 30$) and large instances ($|\mathbf{N}| = 50$, $|\mathbf{V}| = 50$), we can find that all the considered costs increase, while the number of employed drivers decreases as the SoC range gradually shrinks from (0 %, 100 %) to (30 %, 70 %), indicating that a narrow battery level range would negatively affect the formation of platoons, especially for the large instances. This may be explained by the fact that a narrow battery level range would force the trucks to spend more time and/or stop more times to charge to satisfy the lower and upper SoC requirements, which may make the formation of some profitable platoons unfavorable or unacceptable in penalty costs.

Finally, we also explore the impact of the number of charging stations on system performance. Since an uneven distribution of

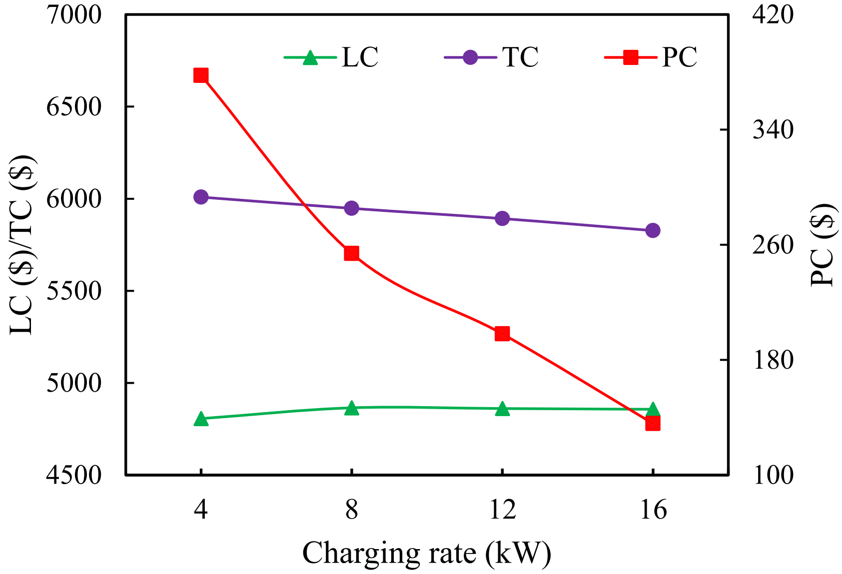


Fig. 7. Variations of the total operational cost, the total labor cost and the total penalty cost with the increase in charging rate.

Table 9
Impact of the SoC range on system performance.

Instance group	SoC range	TC ($)	EC ($)	LC ($)	PC ($)	TT (h)	ND
(10,10)	[0 %, 100 %]	1,501.2	196.3	1,294.0	10.9	17.9	11.0
	[10 %, 90 %]	1,501.2	196.3	1,294.0	10.9	17.9	11.0
	[20 %, 80 %]	1,501.2	196.3	1,294.0	10.9	17.9	11.0
	[30 %, 70 %]	1,501.2	196.3	1,294.0	10.9	17.9	11.0
	Average	1,501.2	196.3	1,294.0	10.9	17.9	11.0
(30,30)	[0 %, 100 %]	6,943.9	808.5	5,992.0	143.4	85.3	43.7
	[10 %, 90 %]	6,943.9	808.5	5,992.0	143.4	85.3	43.7
	[20 %, 80 %]	7,004.0	844.9	6,008.0	151.1	85.7	43.3
	[30 %, 70 %]	7,383.1	908.5	6,306.0	168.6	91.1	42.0
	Average	7,068.7	842.6	6,074.5	151.6	86.9	43.2
(50,50)	[0 %, 100 %]	11,900.5	1,480.9	9,812.0	607.6	142.3	63.7
	[10 %, 90 %]	12,231.7	1,558.4	10,012.0	661.3	146.1	62.3
	[20 %, 80 %]	12,767.5	1,607.4	10,336.0	824.1	151.5	62.3
	[30 %, 70 %]	14,326.5	1,693.2	11,504.0	1,129.3	172.3	58.3
	Average	12,806.6	1,585.0	10,416.0	805.6	153.1	61.7

charging stations may lead to instances where no feasible solution can be found, we set ε to 0.8 for all instances to balance solution efficiency and quality. Hence, a problem instance will be regenerated if no feasible solution can be found with $\varepsilon = 0.8$. For practical scenarios, the solution space can be expanded by reducing ε to identify feasible solutions. However, it is important to note that a larger ε indicates a greater deviation from the shortest route, which suggests that the charging station layout within the highway network is not well-designed. Table 10 shows the solution results with respect to different proportions of nodes equipped with a charging station (PCS). The results indicate that the total operating cost is closely correlated with charging station density. Specifically, the total cost

Table 10
Impact of the number of charging stations on system performance.

Instance group	PCS	TC ($)	EC ($)	LC ($)	PC ($)	TT (h)	ND
(30,30)	100 %	6,943.9	808.5	5,992.0	143.4	85.3	43.7
	80 %	7,304.7	902.1	6,210.0	192.6	88.6	44.7
	60 %	7,940.4	1,067.3	6,586.0	287.1	94.2	46.7
	40 %	9,232.4	1,341.5	7,446.0	444.9	107.0	51.3
	Average	7,855.4	1,029.9	6,558.5	267.0	93.8	46.6
(50,50)	100 %	11,900.5	1,480.9	9,812.0	607.6	142.3	63.7
	80 %	12,832.5	1,777.0	10,276.0	779.5	149.6	65.0
	60 %	13,978.0	2,109.2	10,878.0	990.8	158.4	68.7
	40 %	16,014.1	2,691.1	11,992.0	1,331.0	175.1	74.3
	Average	13,681.3	2,014.6	10,739.5	927.2	156.4	67.9

under PCS = 40 % increases by 26.4 % and 34.6 % for the two sets of instances compared to PCS = 100 %. The increased costs arise from the fact that some ETs would take additional detours to find available charging stations in order to ensure sufficient battery levels to complete their assigned tasks, which leads to a significant rise in both energy costs and penalty costs. As indicated by the increase in the value of ND, it is worthwhile to note that the reduction in the number of charging stations would increase the likelihood of ET choosing the same charging station, which may facilitate the formation of more platoons to some extent. Nevertheless, we also observe that the increase in the total working time of the drivers due to much longer detours for finding charging stations still results in a rise in total labor costs. Therefore, it is crucial to deploy sufficient charging stations in the highway network to ensure a more efficient platoon-based long-haul transportation of ETs.

6. Conclusions

This study investigates the electric truck routing and platooning optimization problem considering the flexible assignment of the drivers in a general highway network. Trucks are allowed to wait and detour to form platoons to save labor and energy costs. Trucks have limited driving range due to battery capacity and thus may need multiple recharges along their routes to continue the haulage. Each truck is not necessarily equipped with a driver throughout the whole service process but rather requires a driver when leading a platoon or traveling alone. The drivers can be flexibly assigned to the trucks in need of further reduction of the labor cost. To solve this problem, a novel MILP model was formulated to determine the optimal solution on routes and schedules of the truck fleet and the drivers that minimizes the total operational cost over the entire trip, while incorporating the electric trucks' limited driving range, opportunity recharging, and energy saving effect by platooning. Due to the complicated structure of the proposed model, a tailored edge set covering algorithm was proposed to obtain good-quality solutions for the underlying problem. Extensive numerical experiments were conducted to validate the efficacy of the proposed model and algorithm. We also demonstrated the benefits of ET platooning mode and the synergy between truck charging and platooning and explored the impacts of several major influential factors on the system performance.

Future research work can be undertaken in several aspects. First, more efficient solution methods that can produce satisfactory solutions for practical instances with less time can be developed in the future. Second, this study considers a single cost-minimization objective function. It is interesting to explore the environmental benefits of truck electrification and autonomation, where multiple objective optimization methods can be employed. Third, it was found in this study that truck platooning has the potential to mitigate the dependence on long-haul drivers for the trucking industry. It could be worthwhile considering different types of drivers, e.g., long-haul and short-haul drivers. The collective efforts of multiple types of drivers could be leveraged to complete the delivery tasks with truck platooning technology. Finally, the proposed model can be extended by incorporating parameter uncertainties and other practical constraints, such as the time-dependent travel speeds and charging congestion due to the limited capacity of the charging station.

CRediT authorship contribution statement

Xiaoyuan Yan: Writing – original draft, Software, Methodology, Conceptualization. **Min Xu:** Writing – original draft, Supervision, Methodology, Conceptualization. **Xiaotong Sun:** Writing – review & editing, Formal analysis, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Notations.

Indices and sets:	
$\mathbf{G} = (\mathbf{N},\mathbf{E})$	Graph with node set $\mathbf{N}$ and edge set $\mathbf{E}$
$\mathbf{N}$	Set of nodes
$\mathbf{E}$	Set of edges
$\mathbf{V}$	Set of trucks
$\mathbf{K}$	Set of drivers

(*continued on next page*)

(*continued*)

$\mathbf{C}$	Set of charging stations,$\mathbf{C} \subseteq \mathbf{N}$
i,j	Indices for nodes
(i,j)	Index for edges
v,w	Indices for trucks
k	Index for drivers
m	Index for the auxiliary node
o_v	Index for origin node of truck $v \in \mathbf{V}$
d_v	Index for destination node of truck $v \in \mathbf{V}$
Known parameters:	
σ_v	Earliest departure time for truck $v \in \mathbf{V}$
δ_v	Latest arrival time for truck $v \in \mathbf{V}$
τ_{ij}	Travel time of edge (i,j)
d_{ij}	Electricity consumption of edge (i,j)
L_{ij}	Maximum platoon size on edge (i,j)
h_i	Number of available drivers at node $i \in \mathbf{N}$
Q	Battery capacity
g	Charging rate (kW)
c_b	Base cost of a driver once being dispatched
c_l	Unit time labor cost for the driver
c_r	Full charging price
c_p	Unit time penalty cost for late arrival of deliveries
η	Fuel reduction rate of the following trucks in a platoon
Decision variables:	
x_{ij}^v	Binary variable indicating whether truck $v \in \mathbf{V}$ will traverse edge (i,j)
p_{ij}^{vw}	Binary variable indicating whether truck $v \in \mathbf{V}$ will follow truck $w \in \mathbf{V}$ over edge (i,j)
α_{ij}^v	Binary variable indicating whether truck $v \in \mathbf{V}$ is a following truck of a platoon on edge (i,j)
β_{ij}^v	Binary variable indicating whether truck $v \in \mathbf{V}$ is a leading truck of a platoon on edge (i,j)
χ_{ij}^{vk}	Binary variable indicating whether driver $k \in \mathbf{K}$ undertakes the driving task for truck $v \in \mathbf{V}$ on edge (i,j)
e_i^v	Continuous decision variable denoting the battery level of truck $v \in \mathbf{V}$ upon arrival at node $i \in \mathbf{N}$
θ_i^v	Continuous decision variable denoting the charging time of truck $v \in \mathbf{V}$ at node $i \in \mathbf{N}$
u_i^v	Continuous decision variable denoting the dwell time of truck $v \in \mathbf{V}$ at node $i \in \mathbf{N}$
t_i^v	Time instant that truck $v \in \mathbf{V}$ starts traversing an edge from node $i \in \mathbf{N}$
s_i^k	Time instant that driver $k \in \mathbf{K}$ starts traversing an edge from node $i \in \mathbf{N}$

Data availability

Data will be made available on request.

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