AUTONOMOUS TRUCK PLATOONING: SCHEDULING, ROUTING AND PERSONNEL

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CERTIFICATE OF ORIGINALITY

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Abstract

Autonomous trucks (ATs) are expected to be an effective solution to reducing the operating costs and carbon footprint in road freight transport. To realize the transition from a human-driving truck (HDT) fleet to a complete unmanned truck fleet, platooning with a driver in the leading vehicle is a practical concept that can be applied in this stage. To fully reap the benefits of cooperative autonomous truck platooning, this thesis proposes a hierarchical modeling framework to explicate the necessitated strategies.

The first work formulates and analyzes an optimal ATs platooning schedule where a detour is possible. Decisions regarding the routing, platoon composition and scheduling are made simultaneously based on the minimal platoon-size dependent costs accounting for labor costs and fuel costs. We also propose a tailored combinatorial Benders decomposition algorithm to solve the model efficiently. Our numerical results show these techniques are effective in reducing computational complexity and time. We discuss the impacts of the number of ATs, the platoon size limit, and the ratio of fuel price and the driver wages on the performance of the AT platooning schedules based on the Hong Kong road network.

The second part of the thesis investigates the potential of AT platooning to fight against driver shortage by considering the coordination between platooning schedules and the driver assignment under the driving hour regulations. The problem is considered in the setting of long-haul freight transport where ATs are deployed to service the mainline haulage. A branch and price algorithm embedded with column generation is developed to find the optimal solution to the formation of AT platoons, trip schedules and driver assignment. Given the transport requests, our model and algorithm can determine the minimal drivers to complete the tasks.

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1 Introduction

Section 1.1 introduces the motivation for this thesis. The outline of this thesis is furnished in Section 1.2.

1.1 Background

The freight transport industry has been promoting and testing the use of autonomous trucks (ATs). Compared to human-driven trucks (HDTs), ATs exhibit several advantages, including labor cost cut, longer daily working time and more flexible working schedules (e.g., night shifts), and better safety (Maurer et al., 2016). Many companies (e.g., Embark, Amazon, UPS, and Suning) have been testing or deploying ATs for commercial trips.

Given the present limitations in technology and legislation, autonomous vehicle platoons traveling in comfortable driving environments (e.g., on highways) is widely believed to be a promising solution before reaching the level of full autonomy (Bhoopalam et al., 2018). An autonomous vehicle platoon consists of multiple autonomous vehicles traveling together with short inter-vehicle distance Zhang et al. (2017). The leader vehicle of a platoon is often operated or overseen by a human driver. In the freight transport sector, using platoons of ATs would have the following major benefits:

i. By letting the leader truck be operated by a human driver, an AT platoon is more capable of handling unexpected complexities in the road environment. This renders higher safety with limited autonomous driving technology.

ii. With the leader truck's driver dealing with the paper-check duties, all the following ATs can be driverless (Bhoopalam et al., 2018). This will save the labor cost significantly compared to individually travelling trucks.

iii. Following trucks in a platoon will suffer less air drag and thus save fuel Zabat et al. (1995); Belzile et al. (2012).

iv. The shorter spacing maintained by autonomous driving technology between ATs will save the road space occupied and thus reduce congestion (Ghiasi et al., 2017).

However, the overall economic benefits of AT platoons are still ambiguous, which is heavily dependent on the AT schedules (Sun and Yin, 2019). To establish a platoon, the departure times, travel speeds, and the routes of the members in the platoon must be synchronized. Unlike HTs, ATs enjoy extra benefits from driverless trips. Intuitively, platoons of ATs have higher tolerance on the detour. That is, an AT may, for instance, deviate from its shortest path to join a platoon without violating its service time windows.

Except the vehicle routing and scheduling, the personnel arrangement also influence the benefits that are reaped from AT platooning. It is more critical as the trucking industry is suffering from the shortage of drivers these days. 70.6% of all freight tonnage is moved on the US highways. According to the American Transportation Research Institute, 43% of trucking's operational costs is driver compensation which is the largest operational cost for a motor carrier (Williams and Murray, 2020). Additionally, as freight volumes increase, the existing driver pool is only more strained. The US has seen a shortage of 20000 in 2005 growing to 50700 by 2017 (Costello and Karickhoff, 2019).

The driver shortfall is expected to rise as freight volumes recover and the industry transitions to the use of electronic logging devices (ELD) to record driver hours-of-service (HOS). Truck drivers have an incentive to violate HOS rules because the industry's widespread use of piece-rate pay (Masten, 2009) can incentivize them to work more hours than legally permitted (Scott and Nyaga, 2019). However, it becomes more difficult to falsify when the paper logbook is replaced by the mandatory ELD in each truck. Consequently, the implementation of ELD under HOS in deed decreases the productivity of a truck driver. This imposes a new challenge for the truck driver scheduling, in particular, confronted with the driver shortage.

From above discussion, we can sense that to what extend those advantages of AT platooning indeed can be realized is heavily dependent on the AT platooning planning and management strategy. Strategies to improve the platooning opportunities on a specific route or over a wide traffic network have been investigated by many recent studies (Larsson et al., 2015; Larson et al., 2016; Sokolov et al., 2017). Nevertheless, few of them focus on the optimization towards the resulted operation cost savings with practical freight transport constraints. The answers, indeed, will testify whether truck platooning is financially reliable in reality, thus plays a crucial factor in the whole truck platoon's adoption process. Therefore, the first research task in this thesis is estimating the cost-saving potentials over a large traffic network from the planning perspective.

More importantly, the coordination between driver shifts and the AT platooning scheduling has gone unnoticed in the previous literature. On the one hand, a fleet manager of a freight transport company aims to facilitate the formation of an minimal-operation-cost platoon, ideally, the one consume least fuel and requires least drivers. This is not difficult if there are no constraints on the capacity of a platoon or availability of drivers. But the fact is that there drivers are in shortage and their service time (travel time of a trip) is confined to the HOS regulations. The mutual influence of HOS regulations and schedules will compromise the opportunity of forming large platoons. The impacts of HOS regulations on given trip time windows has been studied (Goel, 2009; Goel and Irnich, 2017), but has not yet been explored in the context of AT platooning, where the time windows of a platoon is flexible to be decided. Thus, the second research task in this thesis is to answer the potentials of AT platoons to reduce driver shortages in the trucking industry.

1.2 Organization of the thesis

The thesis is organized as follows.

Chapter 2 presents the AT platooning scheduling problem where a detour is possible. Decisions regarding the routing, platoon composition and scheduling are made simultaneously based on the minimal costs accounting for labor costs and fuel costs. We also propose a logic benders decomposition algorithm with some acceleration techniques to solve the model efficiently. Numerical case studies are performed and insights stemming from our models are discussed.

Chapter 3 addresses the coordination problem between AT platooning formation and truck driver assignment. Under the HOS regulations, the travel time on a fixed route is much longer than that of the non-stop driving time. To answer the question, the potential of AT platooning operations in reduce driver shortage, we try to minimize the maximal number of driver needed. The complexity arises exponentially when the driver schedule and the departure times of AT platoons are jointly decided. A branch and price algorithm embedded with column generation is developed to solve it to optimality. Experiments conducted show the validity of our algorithm.

Chapter 4 concludes the thesis by summarizing our contributions, and discussing potential extensions of the present work.

2 The Optimal Autonomous Truck Platooning Scheduling

2.1 Introduction

To facilitate the implementation and operations of AT platoons, this Chapter will develop a model for optimizing the formation and scheduling of AT platoons traveling in a highway network. Specifically, the model will identify the optimal assignment of ATs to platoons, platoon departure times, and routes for minimizing the overall operating cost, including labor and fuel costs.

The truck platooning problems can be classified according to some key operating features. The first feature is whether the trucks to be platooned belong to a single company or not. If platoons are formed by vehicles owned by different companies, the mechanism to incentivize players to join the platoon is a primary research question (Sun and Yin, 2019). In our study, ATs are assumed to belong to a single company, and the platooning decisions are made by a central planner. The second issue is whether the truck trip information is obtained in advance or in real time. Bhoopalam et al. (2018) divided the truck platooning problems into two classes: off-line (or static) planning problems where all trips are known by a central planner in advance, and online planning problems where the trip information is reported to the central planner in real time. Our study falls in the first of the two classes.

Most works in the above realm of literature investigated HDT platooning problems (Zhang et al., 2017). Boysen et al. (2018) explored the complexity of the platoon scheduling problem on an identical path. Liang et al. (2015) studied the fuel efficiency of platoons where each vehicle's route is given. Luo and Larson (2021) designed a routing-then-scheduling heuristic to solve the truck platooning planning problem. Compared to the literature, our study makes three contributions, which are summarized and justified as follows:

i. We formulate the AT platoon scheduling problem which involves the minimization of labor cost in addition to the fuel cost. Most previous studies only considered the minimization of fuel cost (Liang et al., 2014; Van De Hoef et al., 2015; Sokolov et al., 2017) since they focused on the platooning of HDTs.

ii. We develop an exact solution algorithm (a tailored combinatorial Benders decomposition algorithm) for optimal platoon formation considering both routing and scheduling decisions. Many previous works have assumed that platoon routes are fixed (Liang et al., 2015; Boysen et al., 2018). However, route optimization is necessary for truck platoon planning since trucks may take detours to form platoons if the associated cost reduction outweighs the added cost of detours. To our best knowledge, no study has developed exact solutions for jointly optimizing platoon routing and scheduling. The closest work to our study is Luo and Larson (2021). However, only a heuristic solution was developed in that work [1]

iii. We consider a platoon size limit constraint. This constraint is imperative for practical implementation of truck platoons (Aarts and Feddes, 2016), partly due to the present limitation of autonomous driving technologies. A long platoon of trucks will also block the ramps on highways (since trucks usually travel in the shoulder lane) and increase the wear and tear of roads and bridges. However, incorporating this constraint will significantly increase the complexity of the problem (Gijswijt et al., 2007; Correa and Megow, 2015; Boysen et al., 2018). Thus, it would be more challenging to find exact solutions, especially when the nonlinearity of the fuel cost saving function of the platoon size is accounted for

[1]The problem solved in Luo and Larson (2021) can be considered as a more general version of our problem since platoon merges and splits are allowed in that work, but not in our work. Nevertheless, no exact solution was proposed in their work.

Hucho and Sovran (1993); Lammert et al. (2014); Deng (2016); Tsugawa et al. (2016). Previous studies have developed exact solutions to the truck platooning problem considering two-vehicle platoons only (Correa and Megow, 2015) or unlimited platoon size (Boysen et al., 2018). No work has solved the problem with a finite platoon size limit constraint exactly.

The rest of the Chapter is organized as follows. Section 2 describes the AT platoon scheduling problem and key assumptions. A mixed-integer nonlinear program is formulated and linearized in Section 3. A tailored combinatorial Benders cuts (CBC) algorithm is proposed in Section 4. Numerical experiment results and findings are discussed in Section 5. Section 6 presents the conclusions and future work.

2.2 Problem description and assumptions

We denote $G(N, A)$ the graph representing a highway network in an area, where $N = N_{on} \cup N_{off}$ denotes the set of on- and off-ramp nodes; N_{on} the set of on-ramp nodes; N_{off} that of off-ramp nodes; and A the set of highway links connecting these nodes (see Fig. 2.1 for the illustration). Consider a fleet of ATs denoted by $V = \{1, 2, \ldots, |V|\}$. AT $v \in V$ is required to depart its origin o_v no earlier than a time e_v, and arrive at its destination d_v no later than a time l_v. Each origin $o_v(v \in V)$ or destination d_v is connected to one or more on- or off-ramp nodes in G through local roads. The origin and destination nodes and the local road links are excluded from graph G for the simplicity of formulation.

The following key assumptions are made for the simplicity of modeling:

i. Considering the present technological limitations and safety concerns for ATs, an AT can be operated in the driverless mode only when it joins a platoon led by a manned truck (Bhoopalam et al., 2018) traveling on the highways (Albiński et al., 2020). In other words, an AT must be operated by a human driver under one of the following three conditions: if it travels individually; if it is the leader of a platoon; or if it is traveling in local roads where the traffic environment is more complicated and unfriendly to autonomous vehicles.

ii. To ensure safety, a platoon formed at an on-ramp will remain intact until it exits through an off-ramp. In other words, a platoon will not break down into smaller platoons or individual ATs, nor will it merge with other platoons or trucks in the highways. In practice, a group of manned ATs first travel to a sorting yard near an on-ramp, where all but one switch to the driverless mode and form a platoon led by the remaining manned AT. When the platoon exits from an off-ramp, they enter another sorting yard where human drivers board and drive the ATs to their destinations. Different batches of drivers can be used before and after the highway trip.

iii. All ATs are identical in terms of their type, size, age, freight load, engine characteristics, and cruise speed. And they travel at a constant cruise speed throughout their journeys. They also maintain a constant spacing in platoons. This way, the total air drag reduction for an AT platoon only depends on the platoon size. Longer platoons will enjoy greater labor and fuel cost savings.

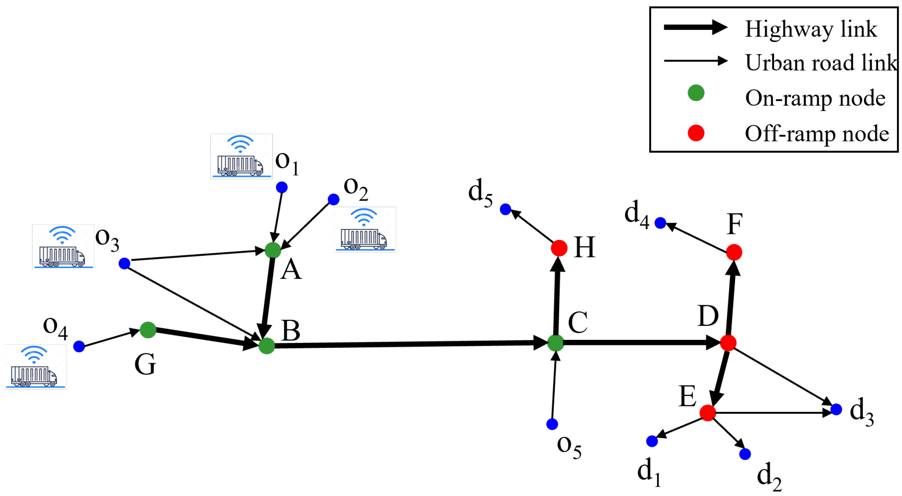


Figure 2.1: Illustration of the AT platoon formation and split

Under the above assumptions, the objective of the AT platoon scheduling problem is to minimize the sum of driver and fuel costs. A fleet manager seeks to determine the optimal departure times, routes, and platoon formation of the $|V|$ ATs under this objective. Note that in order to join a platoon, an AT may choose a non-shortest route from its origin to destination. For example, AT 3 (from o_3 to d_3) in Fig. 2.1 will travel on route $o_3 \to A \to B \to C \to D \to E \to d_3$ instead of the shortest route $o_3 \to B \to C \to D \to d_3$ so that it can join the platoon of ATs 1 and 2 at on-ramp A. Thus, trade-off exists between the labor and fuel cost savings owing to platooning and the increased travel cost due to the detours. In addition, the routing and scheduling of an AT platoon must satisfy the travel time window constraints for all its members. The benefit of optimal platoon scheduling will be assessed via comparison against the scenario where each AT is operated individually by a human driver. In the latter scenario, an AT will always choose the shortest route.

2.3 Model formulation

Section 2.3.1 presents the list of notations used in this chapter. Section 2.3.2 describes the fuel and labor cost functions. Section 2.3.3 furnishes a nonlinear formulation of the optimal AT platoon scheduling problem. Linearization of that formulation is presented in Section 2.3.4

2.3.1 Notation list

Indices and sets

v	Index of an AT
V	Set of ATs
n_{on}	Index of an on-ramp
n_{off}	Index of an off-ramp
N_{on}	Set of on-ramps
N_{off}	Set of off-ramps
k	Index of an AT platoon
K	Set of platoons

r	Index of a candidate platoon path, characterized by an on- and off-ramp pair. It represents the shortest path on the highways connecting the two ramps
R	Set of candidate platoon paths
o_v	Origin of AT $v \in V$
d_v	Destination of AT $v \in V$

Parameters

d_{r,o_v}	Shortest distance between o_v and the on-ramp of path $r \in R$, km
d_{r,o_v}	Shortest distance between d_v and the off-ramp of path $r \in R$ km
d_r	Length of path $r \in R$ km
c	Labor cost rate, \$/h
e_v	Earliest departure time of AT $v \in V$ from its origin, h
l_v	Latest arrival time of AT $v \in V$ to its destination, h
s	ATs' cruise speed, km/h
p	Fuel price, \$/liter
L	Maximum number of ATs allowed in a platoon
$f_{B(s)}$	Fuel consumption rate by an AT traveling individually at speed s, liter/km
$\Phi(n)$	Total air-drag reduction factor of a n-AT platoon
ϕ_m	Air-drag reduction factor for the m-th AT in a platoon
λ_v^r	Ratio of the length of a candidate platoon path $r \in R$ to a whole route of AT $v \in V$, $o_v \rightarrow r \rightarrow d_v$

Decision variables

$x_v^{r,k}$	Binary variable that equals 1 if AT $v \in V$ joins platoon $k \in K$ traveling on path $r \in R$, and 0 otherwise.

$t^{r,k}$	Departure time of platoon $k \in K$ traveling on path $r \in R$ from the associated on-ramp, h
$u^{r,k}$	Binary variable that equals 1 if platoon $k \in K$ on path $r \in R$is nonempty, and 0 otherwise
$S^{r,k}$	Number of reduced drivers of platoon $k \in K$ on path $r \in R$
$T_v^{r,k}$	Departure time of AT $v \in V$ if it joins platoon $k \in K$ traveling on path $r \in R$
$z_m^{r,k}$	Binary variable that equals 1 if the size of platoon $k \in K$ on path $r \in R$is greater than or equal to m, and 0 otherwise.
$\boldsymbol{x}, \boldsymbol{t}, \boldsymbol{u}, \boldsymbol{S}, \boldsymbol{T}, \boldsymbol{z}$	Vector representations of $x_v^{r,k}, t^{r,k}, u^{r,k}, S^{r,k}, T_v^{r,k}, z_m^{r,k}, v \in V,\ r \in R, k \in K, m \in \{1, 2, \ldots, n\}$

2.3.2 Cost functions

The following two subsections describe the fuel and labor cost functions, respectively.

Fuel cost Platoons can save the trucks' fuel cost by reducing the air drag (Zabat et al., 1995; Belzile et al., 2012). We borrow the following vehicle fuel consumption function from Franceschetti et al. (2013) to model an AT's fuel consumption per km:

$$f_B(s) = as^2 (1 - \varphi) + b \tag{2.1}$$

where s denotes the vehicle speed; a and b are constant coefficients related to the AT's shape, size, freight load, and engine characteristics; and $\varphi \in [0,\ 1]$ a factor that captures the air-drag reduction effect. We set $\varphi = 0$ for an individually traveling AT (Abdolmaleki et al., 2019). Denote $x_v^{r,k}$ the binary variable that equals 1 if AT $v \in V$ joins the k-th platoon traveling on the highway path $r \in R$ and 0 otherwise, where r denotes a candidate platoon path and R the set of all candidate platoon paths. For a given pair of on- and -ff-ramps, r is the shortest highway path between them. (We use the term “path” to describe a highway path in G connecting an on-ramp and an off-ramp, and the term “route” to describe a full route from an AT’s origin to its destination.) The fuel cost for AT platoons is formulated as the difference between the fuel cost given that all the ATs travel individually and the fuel saving due to platooning. The former is formulated as follows:

$$FC_I = pf_B(s) \sum_{v\in V} \sum_{r\in R} \sum_{k\in K} \left(d_{r,o_v} + d_r + d_{r,d_v}\right) x_v^{r,k} \tag{2.2}$$

where p denotes the fuel price (\$/liter); s the cruise speed; d_{r,o_v} the distance from o_v to the on-ramp of path r; d_r the travel distance on r; and d_{r,d_v} the distance from the off-ramp of r to d_v. For the fuel saving of platoons, denote $\Phi(n) = \sum_{m=1}^{n} \varphi_m$ the total air-drag reduction factor for a platoon of n ATs, where φ_m ($m \in \{1, 2, \ldots, n\}$) denotes the air-drag reduction factor for the m-th AT in the platoon (the leader truck is numbered the 1st). Values of φ_m can be determined by field experiments. Bergenhem et al. (2012) showed that the leader truck has little air-drag reduction; i.e., $\varphi_1 = 0$. The total fuel saving for all the AT platoons is thus:

$$FC_S = pas^2 \sum_{r\in R} \sum_{k\in K} \Phi\left(\sum_{v\in V} x_v^{r,k}\right) d_r \tag{2.3}$$

Note that $\sum\limits_{v\in V} x_v^{r,k}$ is the size of the k-th platoon traveling on path r. For completeness, we specify that $\varphi_0 = \varphi_1 = 0$. Hence, the total fuel cost is:

$$\begin{aligned} FC &= FC_I - FC_S \\ &= pf_B(s) \sum_{v\in V} \sum_{r\in R} \sum_{k\in K} \left(d_{r,o_v} + d_r + d_{r,d_v}\right) x_v^{r,k} \\ &- pas^2 \sum_{r\in R} \sum_{k\in K} \Phi\left(\sum_{v\in V} x_v^{r,k}\right) d_r \end{aligned} \tag{2.4}$$

Labor cost For simplicity, we assume the labor cost is proportional to the driving time of human drivers. The total labor cost is then formulated as:

$$C = \frac{c}{s} \sum_{v \in V} \sum_{r \in R} \sum_{k \in K} \left(d_{r,o_v} + d_r + d_{r,d_v}\right) \, x_v^{r,k} - \frac{c}{s} \sum_{r \in R} \sum_{k \in K} d_r \left(\sum_{v \in V} x_v^{r,k} - 1 \right)^+ \tag{2.5}$$

where c denotes the labor cost per hour of driving. The first term in the RHS is the total labor cost if all the ATs are operated by human drivers, and the second term is the labor cost saving of AT platoons. We next formulate the optimal AT platoon scheduling model.

2.3.3 Mathematical formulation

The AT platoon scheduling model is formulated as follows:

[M1]

$$\begin{aligned}\min F(\mathbf{x}, \mathbf{t}) = pf_B(s) \sum_{v \in V} \sum_{r \in R} \sum_{k \in K} \left(d_{r,o_v} + d_r + d_{r,d_v}\right) x_v^{r,k} - pas^2 \sum_{r \in R} \sum_{k \in K} \Phi \left(\sum_{v \in V} x_v^{r,k} \right) d_r \\ + \frac{c}{s} \sum_{v \in V} \sum_{r \in R} \sum_{k \in K} \left(d_{r,o_v} + d_r + d_{r,d_v}\right) x_v^{r,k} - \frac{c}{s} \sum_{r \in R} \sum_{k \in K} d_r \left(\sum_{v \in V} x_v^{r,k} - 1 \right)^+\end{aligned} \tag{2.6}$$

$$\sum_{k \in K} \sum_{r \in R} x_v^{r,k} = 1 \qquad \forall v \in V \tag{2.7}$$

$$\sum_{v \in V} x_v^{r,k} \leq L \qquad \forall r \in R, k \in K \tag{2.8}$$

$$x_v^{r,k} \left(t^{r,k} - \frac{d_{r,o_v}}{s} - e_v \right) \geq 0 \qquad \forall v \in V, r \in R, k \in K \tag{2.9}$$

$$x_v^{r,k} \left(l_v - t^{r,k} - \frac{d_{r,d_v} + d_r}{s} \right) \geq 0 \qquad \forall v \in V, r \in R, k \in K \tag{2.10}$$

$$t^{r,k} \geq 0 \qquad \forall r \in R, k \in K \tag{2.11}$$

$$x_v^{r,k} \in \{0, \ 1\} \qquad \forall v \in V, r \in R, k \in K \tag{2.12}$$

where $\mathbf{x}$ and $\mathbf{t}$ are the vector representations of $x_v^{r,k}$ and $t^{r,k}$ ($v \in V, r \in R, k \in K$) respectively; and $t^{r,k}$ the departure time of the k-th platoon on path r from the associated on-ramp. Constraint (2.7) ensure that every AT is assigned to a platoon (here an individually traveling AT is considered as a platoon of size 1). Constraint (2.8) specify that a platoon's size cannot exceed a limit, L, which is determined by the technology level and safety concerns. Constraint (2.9) guarantee that all the ATs in a platoon will arrive at the gathering on-ramp before the platoon departure time. Constraint (2.10) ensure that every AT can arrive at its destination in time. Constraints (2.11)-(2.12) define the ranges of decision variables.

Note that compared to the arc-based model proposed by Luo and Larson (2021) which addressed the routing planning and scheduling problem separately, our route-based model [M1] can simultaneously optimize the decisions on platoon scheduling and route planning.

Model [M1] is a nonlinear program due to the function terms $\Phi\left(\sum_{v\in V} x_v^{r,k}\right)$ and $\left(\sum_{v\in V} x_v^{r,k} - 1\right)^+$ and constraints (2.9)-(2.10). These nonlinear elements are linearized next.

2.3.4 Linearization

Linearization of the objective To linearize the nonlinear function $\Phi\left(\sum_{v\in V} x_v^{r,k}\right)$ we introduce an auxiliary binary variable $z_m^{r,k}$ for each $r \in R, k \in K$ and $m \in \{1, 2, \dots, L\}$ which equals 1 if the size of the k-th platoon on path r is greater than or equal to m, and 0 otherwise. Thus, the size of the k-th platoon on path r, $\sum_{v\in V} x_v^{r,k}$, can be replaced with $\sum_{m=1}^{L} z_m^{r,k}$. Moreover, the platoon's air-drag reduction factor $\Phi\left(\sum_{v\in V} x_v^{r,k}\right)$ can be replaced with a linear term $\sum_{m=1}^{L} \varphi_m z_m^{r,k}$. (Recall that $\Phi(n) = \sum_{m=1}^{n} \varphi_m$.) Accordingly, the following constraints are added to the formulation:

$$\sum_{v\in V} x_v^{r,k} = \sum_{m=1}^{L} z_m^{r,k} \qquad \forall r \in R, k \in K \tag{2.13}$$

$$z_{m-1}^{r,k} - z_m^{r,k} \geq 0 \qquad \forall r \in R, k \in K, m \in \{2, \dots, L\} \tag{2.14}$$

$$z_m^{r,k} \in \{0,1\} \qquad \forall r \in R, k \in K, m \in \{1,2,\ldots,L\} \tag{2.15}$$

In addition, the ceiling function term $(\sum_{v\in V} x_v^{r,k} - 1)^+$ is replaced with an integer auxiliary variable $S^{r,k}$ ($r \in R, k \in K$) that indicates the number of saved drivers in a platoon. Note in the objective function (2.6) that this term has a negative coefficient, meaning that $S^{r,k}$ is the larger the better. Thus, we further introduce an auxiliary binary variable $u^{r,k}$ for each $r \in R, k \in K$ which equals 1 if $\sum_{v\in V} x_v^{r,k} - 1 \geq 0$ and 0 otherwise. The following additional constraints are included in the formulation to ensure the linearized formulation is equivalent to the original one:

$$S^{r,k} \geq 0 \qquad \forall r \in R, k \in K \tag{2.16}$$

$$S^{r,k} \geq \sum_{v\in V} x_v^{r,k} - 1 \qquad \forall r \in R, k \in K \tag{2.17}$$

$$\sum_{v\in V} x_v^{r,k} - 1 \leq M u^{r,k} \qquad \forall r \in R, k \in K \tag{2.18}$$

$$\sum_{v\in V} x_v^{r,k} + 1 \leq M(1 - u^{r,k}) \qquad \forall r \in R, k \in K \tag{2.19}$$

$$S^{r,k} \leq \sum_{v\in V} x_v^{r,k} - 1 + M(1 - u^{r,k}) \qquad \forall r \in R, k \in K \tag{2.20}$$

$$S^{r,k} \leq M u^{r,k} \leq \sum_{v\in V} x_v^{r,k} - 1 + M(1 - u^{r,k}) \qquad \forall r \in R, k \in K \tag{2.21}$$

$$S^{r,k} \in \mathbb{Z} \qquad \forall r \in R, k \in K \tag{2.22}$$

$$u^{r,k} \in \{0,\ 1\} \qquad \forall r \in R, k \in K \tag{2.23}$$

Linearization of constraints (2.9)-(2.10) We introduce auxiliary variables $T_v^{r,k}$ ($v \in V, r \in R, k \in K$) to replace the nonlinear term $x_v^{r,k}\ t^{r,k}$ in constraints (2.9)-(2.10). They are then linearized using the big-M method. Specifically, (2.9)-(2.10) are replaced with the following constraints:

$$T_v^{r,k} - x_v^{r,k}\left(\frac{d_{r,o_v}}{s} + e_v\right) \geq 0 \qquad \forall r \in R, k \in K \tag{2.24}$$

$$-T_v^{r,k} + x_v^{r,k}\left(l_v - \frac{d_{r,d_v} + d_r}{s}\right) \geq 0 \qquad \forall r \in R, k \in K \tag{2.25}$$

$$- M\left(1 - x_v^{r,k}\right) \leq T_v^{r,k} - t^{r,k} \leq M\left(1 - x_v^{r,k}\right) \qquad \forall v \in V, r \in R, k \in K \tag{2.26}$$

In summary, the linearized formulation is presented as follows:

[M2]

$$\begin{aligned} \min \; F(\mathbf{x}, \mathbf{z}, \mathbf{u}, \mathbf{S}, \mathbf{t}, \mathbf{T}) = & \left(pf_B(s) + \frac{c}{s}\right) \sum_{v \in V} \sum_{r \in R} \sum_{k \in K} (d_{r,o_v} + d_r + d_{r,d_v}) x_v^{r,k} \\ & - pas^2 \sum_{r \in R} \sum_{k \in K} \sum_{m=1}^{L} \varphi_m z_m^{r,k} d_r - \frac{c}{s} \sum_{r \in R} \sum_{k \in K} S^{r,k} d_r \end{aligned} \tag{2.27}$$

subject to

Constraints (2.7)-(2.8), (2.11)-(2.12),(2.13)-(2.26).

where $\mathbf{z}, \mathbf{u}, \mathbf{S}, \mathbf{T}$ are the vector representations of $z_m^{r,k}, u^{r,k}, S^{r,k}, T_v^{r,k}$ $(v \in V, r \in R, k \in K, m \in \{1, 2, \ldots$ respectively.

2.4 Solution approach

Although [M2] is solvable by CPLEX, large-scale instances are still difficult to be solved to optimality due to the curse of dimensionality. This section develops a more efficient solution approach by employing the combinatorial Benders cuts (CBC) method. First, we tighten the model by reducing the size of the candidate platoon path set R which significantly affects the solution efficiency. The associated problem-specific cuts are introduced in Section 2.4.1. The CBC algorithm is then presented in Section 2.4.2

2.4.1 Reducing the size of R

Initially, R can be set to include all the $|N_{on}||N_{off}|$ shortest paths in graph G that connect every pair of on- and off-ramps. We then apply the following rules to reduce the size of R.

First, if a path cannot be used by any AT (i.e., if the corresponding on- and off-ramp pair is not connected to any AT's OD), that path should be deleted from R.

Second, if an AT cannot join any other ATs to form a platoon, then this AT will travel individually on the shortest route connecting its OD. Thus, the AT can be removed from set V. The associated on- or off-ramps, if not connected to any other AT, can also be removed from graph G. This rule is elaborated in the following proposition.

Proposition 2.4.1. *If none of the on-ramps connected to o_v is connected to another AT's origin, or, if none of the off-ramps connected to d_v is connected to another AT's destination, then v cannot be platooned with any other ATs. This AT will travel alone on its shortest route connecting o_v and d_v. Thus, it can be removed from set V; i.e., $V \leftarrow V \setminus \{v\}$. The associated on-ramps connecting to o_v or off-ramps connecting to d_v can be removed from set N_{on} or N_{off}, respectively. The paths associated with those removed on- or off-ramps can be deleted from R.*

Proposition 2.4.1 is self-evident. Take the network in Fig. 2.1 for example, AT No. 5 has only one possible route, $o_5 \to C \to H \to d_5$, and it cannot be platooned with any other ATs. Thus, this AT will be deleted from V. Accordingly, on-ramp node C, off-ramp node H, and link CH will be deleted from graph G. Links BC and CD will be combined into a single link BD. Candidate platoon paths associated with node C or H will be deleted from R. Finally, set R can be further trimmed down by pruning some paths that are never optimal. To this end, we define the path dominance as follows. Let r_1 and r_2 be two platoon paths that a specific AT $v \in V$ can take. Denote $dist_i$ the total travel distance for v's route through path r_i, and λ_i

the ratio between the length of highway fragment r_i and $dist_i$. We say r_1 dominates r_2 for AT v if the following two conditions are both satisfied [2] :

$$dist_1 \leq dist_2 \tag{2.28}$$

$$\lambda_2 \leq \frac{\frac{c}{s} + pf_B}{\frac{c}{s} + pas^2\varphi_L}\left(1 - \frac{dist_1}{dist_2}\right) \tag{2.29}$$

We have the following proposition regarding the path dominance: If r_1 dominates r_2 for AT $v \in V$, shifting v from r_1 to r_2 will not reduce the AT's travel cost. The proof of Proposition 2.4.1 is relegated to Appendix A. The following two corollaries can be derived from Proposition 2.4.1.

Corollary 2.4.1.1. *Let R_v^o be the set of all the non-dominated paths for AT $v \in V$. Let $R^p = R \backslash \bigcup_{v \in V} R_v^o$. Platoon paths in R^p can be pruned from R.*

Corollary 2.4.1.2. *Let R_v^d denote the set of all the dominated paths for AT $v \in V$, and $R_v^{'} = R_v^d \backslash \{r_v | r_v \in R^p\}$ denote the set of dominated paths for AT v after path pruning (see Corollary). We have:*

$$x_v^{r,k} = 0, \forall r \in R_v^{'}, k \in K, v \in V \tag{2.30}$$

Corollaries and are also self-evident. Corollary states that, if for each AT that can travel on a path r, r is always dominated by another path, then r should be pruned. Corollary indicates that for any AT, a dominated but not pruned path will never be selected [3]. Eq. 2.30 will be added to [M2] as a cut.

[2] Under rare cases where equalities are held in both conditions, we can arbitrarily choose one of the two paths as the dominating path and the other as the dominated path.

[3] There may exist multiple optima where equalities hold in both (2.28) and (2.29). However, our goal is to obtain one optimal solution. Thus, pruning or deselecting a dominated path will not compromise the optimality of our solution even if multiple optima exist.

Luo and Larson (2021) reported that the ATs will not deviate to a route that is too far from the shortest one to join a platoon. Proposition 2.4.1 and Corollaries and practically rule out the possibility for ATs to take such a "too far" route.

2.4.2 A CBC algorithm

In this section, we develop a CBC algorithm to solve our model in industry scales. Benders decomposition can be applied to separate the platoon size constraint and the truck time window constraints. However, the standard Benders decomposition would perform poorly in our problem due to the many conditional (big-M) constraints in [M2]. These big-M constraints would result in poor bound improvement and slow convergence when cuts are dependent on the dual form. To alleviate the dependency on big-M values, we apply the CBC algorithm here. The CBC algorithm was firstly proposed by Hooker (2011) and extended by Codato and Fischetti (2006) to solve mixed integer programs with special structures. Compared with the classical Benders decomposition, the CBC algorithm tries to derive Benders' cuts from the primal subproblem rather than the dual information. Specifically, the CBC algorithm divides the original problem into a master problem and several sub-problems which are solved iteratively. The master problem assigns the ATs to possible paths and candidate platoons under the size limit. Subsequently, each subproblem verifies whether the proposed plan is time feasible. If an infeasible solution is observed, feasibility cuts are generated, stating that at least one AT should change its path and platoon. The algorithm stops when all the subproblems are feasible (i.e., the optimal solution is obtained) or when a predefined optimality gap ϵ is attained. The master problem and sub-problems are described in Section 2.4.2 Acceleration techniques on the CBC algorithm, including the search for minimal infeasible subsets and the relaxation of subproblems, are presented in Section 2.4.2.

Model reformulation under the CBC framework The original formulation [M2] is decomposed into a master problem [MP] and sub-problems [SP]. The master problem optimizes the assignment of ATs to platoons, which involves decision variables $x_v^{r,k}, z_m^{r,k}, u^{r,k}$, and $S^{r,k}$ $(r \in R, k \in K, v \in V)$. Each subproblem [SP] conducts the time window feasibility check of platoon $k \in K$ on path $r \in R$ involving decision variables $t^{r,k}$ and $T_v^{r,k}$. The subproblems will take the AT assignment generated from the master problem as input. We relax the integer variable $S^{r,k}$ to be continuous since the integrality of $S^{r,k}$ $(r \in R, k \in K)$ is guaranteed if $x_v^{r,k}$ and $u^{r,k}$ $(r \in R, k \in K, v \in V)$ are binary. The formulation of [MP] is therefore given by:

[MP]

$$\begin{aligned} min\ \mathcal{F}(\mathbf{x}, \mathbf{z}, \mathbf{u}, \mathbf{S}) = & \left(pf_B(s) + \frac{c}{s}\right) \sum_{v \in V} \sum_{r \in R} \sum_{k \in K} (d_{r,o_v} + d_r + d_{r,d_v}) x_v^{r,k} \\ & - pas^2 \sum_{r \in R} \sum_{k \in K} \sum_{m=1}^{L} \varphi_m z_m^{r,k} d_r - \frac{c}{s} \sum_{r \in R} \sum_{k \in K} S^{r,k} d_r \end{aligned} \tag{2.31}$$

subject to:

(2.7)-(2.8), (2.12), (2.13)-(2.15), (2.16)-(2.21), (2.23), 2.30, feasibility cuts.

Note that Corollary 2.4.1 is incorporated by adding Eq. (2.30) as a constraint. Denote $\tilde{x}_v^{r,k}$ the optimal solution of $x_v^{r,k}$ $(k \in K, r \in R, v \in V)$ obtained from the [MP]. We define the following subproblem [SP] for each platoon $k \in K$ on path $r \in R$:

[SP]

$$\min 0 \tag{2.32}$$

subject to:

$$T_v^{r,k} \geq \tilde{x}_v^{r,k} \left(\frac{d_{r,o_v}}{s} + e_v \right) \qquad \forall v \in V \tag{2.33}$$

$$T_v^{r,k} - T_v^{r,k} \geq \tilde{x}_v^{r,k} \left(\frac{d_{r,d_v} + d_r}{s} - l_v \right) \qquad \forall v \in V \tag{2.34}$$

$$T_v^{r,k} - t^{r,k} \geq -M \left(1 - \tilde{x}_v^{r,k} \right) \qquad \forall v \in V \tag{2.35}$$

$$t^{r,k} - T_v^{r,k} \geq -M\left(1 - \tilde{x}_v^{r,k}\right) \qquad \forall v \in V \qquad (2.36)$$

Constraint (2.11)

The objective function (2.32) can be set to any constant value since the subproblems only check the feasibility of the [MP] solution. For each pair of r and k, we first check whether $\sum_{v \in V} x_v^{r,k} > 0$ If the answer is no, then platoon k does not exist or does not travel on path r. Thus, the total number of subproblems to be solved is no more than the maximum number of platoons, i.e., $|V|$.

Given $\left\{\tilde{x}_v^{r,k}, r \in R, k \in K, v \in V\right\}$ if there exists a feasible solution to every subproblem, then the solution to [MP] is the optimal solution to [M2]. However, if one subproblem [SP] is infeasible, then at least one of the binary variables $x_v^{r,k}$ associated with a member truck of platoon k on path r must change its value. Mathematically, this can be represented by a linear inequality termed the combinatorial Benders cut:

$$\sum_{v \in C^{r,k} \subseteq V} x_v^{r,k} \leq \left|C^{r,k}\right| - 1, \forall r \in R, k \in K \qquad (2.37)$$

where $C^{r,k}$ is a subset of ATs defined as $C^{r,k} = \left\{v \in V \middle| \tilde{x}_v^{r,k} = 1\right\}$, $r \in R, k \in K$. Namely, $C^{r,k}$ consists of the ATs assigned to platoon k on path r. This cut means not all the ATs in $C^{r,k}$ can be assigned to the same path and platoon. The framework of CBC is summarized in Algorithm 1 in Appendix B. *Accelerating the CBC algorithm* Numerical tests show that the CBC algorithm presented above converges slowly. In what follows, we employ two acceleration techniques to enhance the overall efficiency of CBC.

The first technique involves incorporating relaxed subproblems in the [MP]. Hooker (2007) claimed that this technique can reduce the number of infeasible solutions generated by the [MP]. To this end, we introduce auxiliary variables $y_v^{r,k} \in [0, 1]$,

$v \in V, r \in R, k \in K$ and add the following soft time window constraints to the [MP]:

$$T_v^{r,k} - y_v^{r,k} \left(\frac{d_{r,o_v}}{s} + e_v \right) \geq 0 \qquad \forall k \in K, r \in R, v \in V \tag{2.38}$$

$$T_v^{r,k} \leq \max_{v \in V} \left\{ l_v - \frac{d_{r,d_v} + d_r}{s} \right\} \qquad \forall k \in K, r \in R, v \in V \tag{2.39}$$

$$\frac{x_v^{r,k}}{q} \leq y_v^{r,k} \leq x_v^{r,k} \qquad \forall k \in K, r \in R, v \in V \tag{2.40}$$

$$0 \leq y_v^{r,k} \leq 1 \qquad \forall k \in K, r \in R, v \in V \tag{2.41}$$

Constraints (2.38) are a relaxed version of constraints (2.34) that ensure the earliest departure time constraints, where the binary $\widetilde{x}_v^{r,k}$ is replaced by the continuous $y_v^{r,k}$. The $y_v^{r,k}$ is defined by (2.40)-(2.41), where $q \geq 1$ is a relaxation parameter. Note that a greater q renders tighter time window constraints (2.38), which means the [MP] would be more computationally expensive to solve. Constraints (2.39) are a more relaxed version of constraints (2.40) that enforce the latest arrival time constraints. This form of relaxation is selected to guarantee that the [MP] can be solved in a reasonable time.

Our second accelerating technique employs the so-called minimal infeasible subsets of ATs to strengthen the cuts to the [MP]. Note that cuts (2.37) can be weak if $|C^{r,k}|$ is large, because it only requires one of the $|C^{r,k}|$ ATs to be removed from the platoon. Stronger cuts can be obtained by using smaller subsets of ATs that have conflicting time windows when they are assigned to the same platoon. We define a minimal infeasible subset (MIS) as a set of ATs that cannot be assigned to a single platoon. Since finding all the MISs for a given set of ATs is NP-hard (Amaldi et al., 2003; Verstichel et al., 2015), we choose to search for them in a greedy fashion (Bai and Rubin, 2009; Chen et al., 2012; Côté et al., 2014; Chen et al., 2018).

Specifically, we construct two types of MISs, $C_1^{r,k}$ and $C_2^{r,k}$ $(r \in R, k \in K)$, via the following procedure. For a specific AT $v \in V$ traveling in a non-empty platoon k

on path r, we calculate its earliest departure time, $e_v^{dep,r,k} = \frac{d_{r,o_v}}{s} + e_v$, and latest departure time, $l_v^{dep,r,k} = l_v - \frac{d_{r,d_v}+d_r}{s}$. If $l_v^{dep,r,k} < e_v^{dep,r,k}$, then AT v cannot travel on path r. This AT is then added to set $C_1^{r,k}$.

For a platoon $k \in K$ on path $r \in R$ if there exist two ATs $v_1, v_2 \in V$ satisfying $e_{v_1}^{dep,r,k} > l_{v_2}^{dep,r,k}$ or $e_{v_2}^{dep,r,k} > l_{v_1}^{dep,r,k}$, then the two ATs cannot be assigned to the same platoon. We add the AT pair (v_1, v_2) to set $C_2^{r,k}$. The detailed algorithm for developing $C_1^{r,k}$ and $C_2^{r,k}$ is summarized in Algorithm 2 in Appendix B.

The MIS sets will be developed incrementally within the [MP]-[SP] iterations. In every iteration, we will examine each AT and AT pair in every non-empty platoon of the [MP] solution, and add the newly generated ATs and AT pairs to the original sets of $C_1^{r,k}$ and $C_2^{r,k}$, respectively. Note that the total number of individual ATs checked in an iteration is $|V|$. And the total number of AT pairs checked is no greater than $L(L-1)|V|/4$, since each platoon contains no more than $L(L-1)/2$ AT pairs and there are no more than $|V|/2$ platoons each containing 2 or more ATs. Hence, the solution approach incorporating MISs is not computationally expensive. With the updated $C_1^{r,k}$ and $C_2^{r,k}$ $(r \in R, k \in K)$, the following two types of cuts are included in the [MP] formulation in the next iteration:

$$x_v^{r,k} \leq 0 \qquad \forall v \in C_1^{r,k}, k \in K, r \in R \tag{2.42}$$

$$x_{v_1}^{r,k} + x_{v_2}^{r,k} \leq 1 \qquad \forall v_1, v_2 \in C_2^{r,k}, k \in K, r \in R \tag{2.43}$$

where cuts (2.42) prevent a single AT from being assigned to an infeasible path; and cuts (2.43) ensure that two ATs with conflicting time windows are not assigned to the same platoon.

In addition, one can also stop the solution process of the [MP] before attaining its optimality in the first a few [MP]-[SP] iterations. This will also accelerate the overall solution process.

2.5 Numerical case studies

We conduct numerical case studies to verify the applicability and effectiveness of the proposed AT platoon scheduling model. Comparison against a benchmark scenario where all the trucks are operated by human drivers reveals the platooning strategy's cost benefit and how this benefit is affected by key operating factors, including: i) the number of ATs; ii) the platoon size limit; and iii) the cost parameters. All the numerical experiments are coded in Java calling CPLEX 12.8 on a PC with 4GHz and 8 Gb RAM. Section 2.5.1 describes the case studies. Section 2.5.2 examines the computational performance of our solution procedure. The sensitivity analyses are furnished in Section 2.5.3.

2.5.1 Case description and parameter values

We consider the heavy trucks traveling in the Hong Kong highway network illustrated in Fig. 2.2. There are totally 31 pairs of neighboring on- and off-ramps, i.e., $|N_{on}| = |N_{off}| = 31$. The location of each pair is illustrated by a black dot. Thus, there are totally $|R|$=31×30=930 candidate platoon paths (note that a path should not start and end at the same location). The lengths of these paths (d_r, $r \in R$) are obtained from the Google map.

Truck OD pairs are generated as follows. For a given $|V|$, we assume that all the $|V|$ origins and roughly one third of the $|V|$ destinations are uniformly distributed in the south half of Fig. 2.2; i.e., below the dashed line. This is because most economical activities are conducted in this part of Hong Kong. The remaining destinations are uniformly distributed in the north half of the figure. Euclidean distances are calculated for d_{r,o_v} and d_{r,d_v}, $r \in R, v \in V$. The ratio of the length of a path to an AT's entire route, λ_v^r, can be calculated by $\lambda_v^r = d_r/(d_{r,o_v} + d_r + d_{r,d_v})$. For each AT $v \in V$ we assume $e_v = 1 + \alpha\omega$ (h) and $l_v = e_v + (1+\beta)\, t_v^{min}$ (h), where ω is a random variable uniformly distributed in $[0, 1]$, and t_v^{min} denotes the travel time on

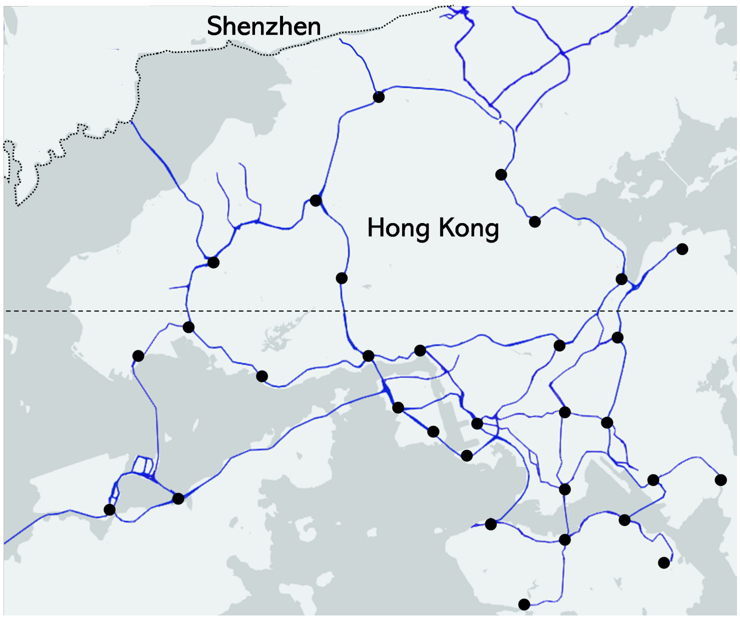


Figure 2.2: The Hong Kong highway network and on-/off-ramp nodes

the shortest route from o_v to d_v. Parameter $\alpha \geq 0$ indicates the dispersion of the earliest departure times. A larger α means that the ATs' time windows are more dispersed over the planning horizon, implying that they are more difficult to form platoons. Parameter $\beta \geq 0$ indicates the tightness of the time windows (Boysen et al., 2018). A smaller β means the ATs have tighter time windows and thus less redundancy to accommodate any detours needed for platoon formation.

We use the type of ATs presented in Zhang et al. (2017) with a 20-ton load, which gives $a = 1.08 \times 10^{-5}$ $(liter \cdot h^2/km^3)$ and $b = 0.22$ (liter/km). We further assume that the AT cruise speed is $s = 70$ km/h. Thus, the fuel consumption rate of an individually traveling truck is $f_B(s) = as^2 + b = 0.27$ liter/km. The diesel price is set to $p = 0.9$ \$/liter. [4] The labor cost rate is set to $c = 15.91$ \$/h (Mayerle et al., 2020). We further set $q = 0.5$, and the optimality gap $\epsilon = 10^{-6}$.

In addition, we assume the following air-drag reduction ratios: $\varphi_2 = 0.30$, and $\varphi_m = 0.40, m \geq 3$. The values of φ_2, and φ_3 are borrowed from Deng (2016) assuming a 20-m bumper-to-bumper spacing between consecutive ATs in a cruising

[4]This value is extracted from *qiyoujiage.com* (in Chinese).

platoon (VanderWerf et al., 2001; Schakel et al., 2010; Tsugawa, 2014). Data for φ_m when $m \geq 4$ are absent in the literature. Thus, we assume $\varphi_m = 0.40$ for all $m \geq 3$. This assumption is conservative since Deng (2016) showed that φ_m should be increasing with m.

2.5.2 Performance of the tailored CBC algorithm

We perform extensive computational experiments to verify the applicability and effectiveness of the tailored CBC algorithm. We set $L = 4$ and $\alpha = 0.86$ h, which is the standard deviation of the shortest travel times t_v^{min}, $v \in V$ We examine nine instances with $|V| \in \{25,\ 45,\ 75\}$ and $\beta \in \{0.05,\ 0.1,\ 0.5\}$. The runtimes and solution quality of the CBC algorithm and CPLEX are summarized in Table 2.2. If CPLEX returns an optimal solution within 1200s, the objective gap is 0. Otherwise, the objective gap reflects the difference of best solutions obtained by CPLEX and CBC in 1200s.

The tailored CBC algorithm could find the optimal solution in all the nine instances. By contrast, CPLEX was unable to find the optimal solution in three of them, although the objective gaps are small in those instances.

Table 2.2: Comparison between the CBC algorithm and CPLEX

Instance		CPLEX		CBC runtime (s)	$\frac{\text{CBC runtime}}{\text{CPLEX runtime}}$
$\lvert V\rvert$	β	Objective gap	Runtime (s)		
25	0.05	10.91%	2.86	0.3	10.49%
25	0.1	1.24%	1200	14.1	<1.18%
25	0.5	0	56.4	1.7	3.01%
50	0.05	11.15%	14.34	1.0	6.97%
50	0.1	1.15%	1200	19.4	<1.62%
50	0.5	0	383.3	7.1	1.85%
75	0.05	12.03%	260	4.4	1.69%
75	0.1	0.83%	1200	148.4	<12.4%
75	0.5	0	870.1	19.7	2.26%

Regarding the computational performance, the CBC algorithm performed exceptionally better for the more realistic instances with $\beta = 0.1$ or 0.5. In these instances, our algorithm could be over 50 times faster than CPLEX. The instances with β=0 (i.e., no redundancy for any detour) are much easier to solve since ATs must choose their shortest routes. Even in those simpler instances, the CBC algorithm performed generally better than CPLEX.

2.5.3 Sensitivity analyses

We examine the cost savings of the optimal AT platoon scheduling as compared to the benchmark scenario where all the ATs travel individually. Three batches of sensitivity analyses are conducted on the cost savings with respect to: (i) the size limit of platoons ; (ii) the ratio between unit labor and fuel cost rates; and (iii) the dispersion and tightness of AT travel time windows, respectively.

Sensitivity to the platoon size limit

For the first batch of analyses, we assume α=0.86, β=0.5, and $|V| \in \{25, 45, 75\}$. An instance is generated with randomly selected AT ODs and time windows for each value of |V|. Each instance is solved with different values of $L \in \{2, 3, 4, 5, 6, 7\}$. Results are plotted in Fig. 2.3. As expected, the percentage cost saving of optimal

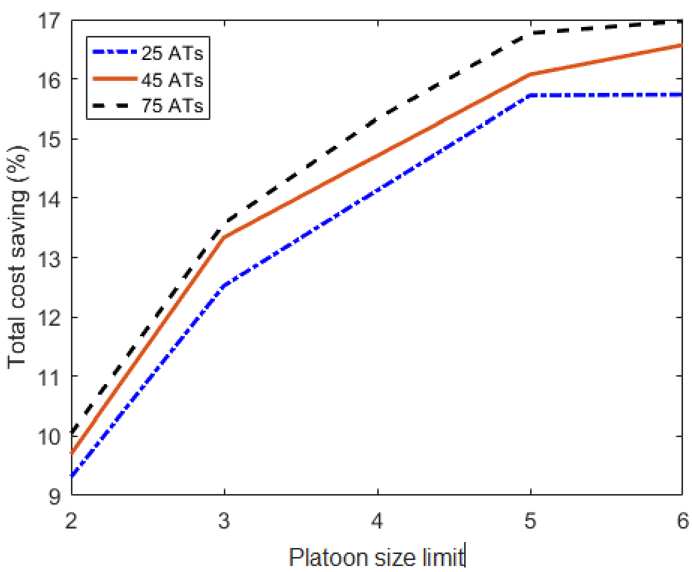
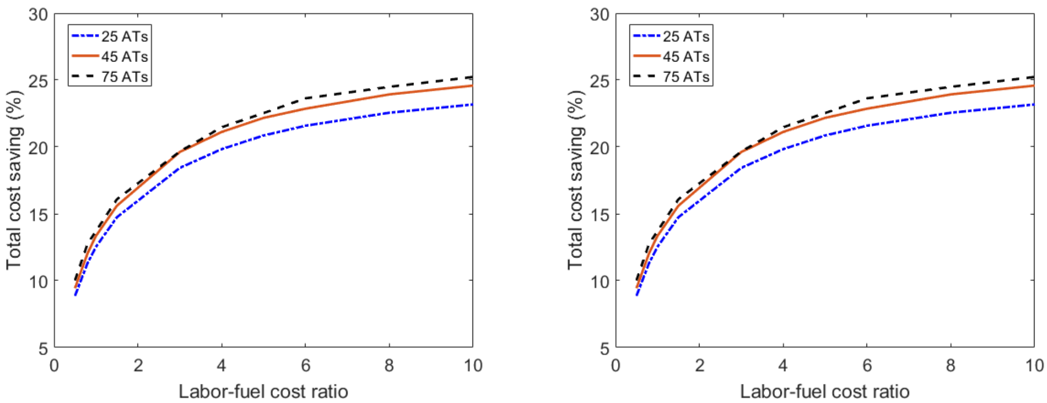


Figure 2.3: Percentage cost saving versus platoon size limit

scheduling of AT platoons increases with L and $|V|$. The improvement by using a larger L is sizeable. For example, when $|V|$=75, allowing 6-AT platoons instead of allowing 2-AT platoons only would bring an additional cost saving of 7%. It is also observed from the figure that the marginal cost saving brought by increasing L by one unit is decreasing with L. When L is sufficiently large (e.g., when L=5 for the instance of 25 ATs), further increasing L would not produce additional cost saving.

Sensitivity to the labor-fuel cost ratio

In this batch of analyses, we use the same three instances as above. The L is fixed at 3. We define the labor-fuel cost ratio as the ratio between the unit labor cost per km, c/s, and the unit fuel cost per km for an individually traveling AT, $p(as^2 + b)$. We let this ratio vary from 0.5 to 10. Fig. 2.4a plots the percentage cost savings of optimal platoon scheduling against that ratio for the three instances.



(a) Percentage cost saving (b) Average platoon size

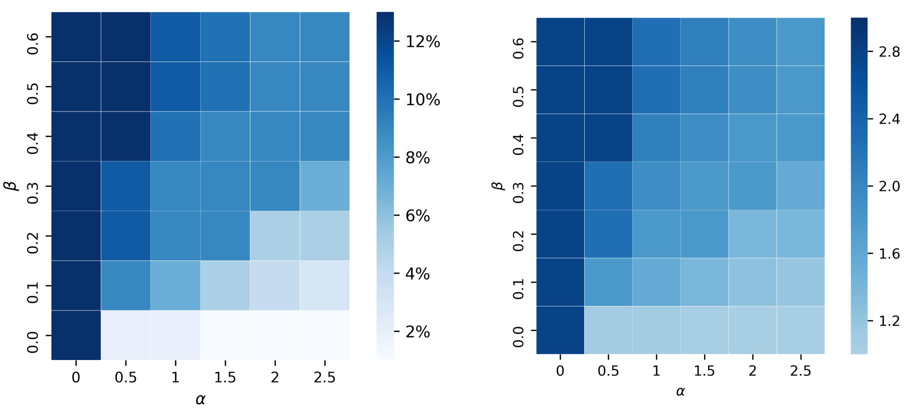
Figure 2.4: Sensitivity to the labor-fuel cost ratio

Results show that the percentage cost saving increases rapidly with the labor-fuel cost ratio. For example, the cost saving increases from 10% to 25% when the ratio increases from 0.5 to 10 in the instance of 75 ATs. (Even greater increases are observed for larger L values.) This finding manifests that the cost saving of AT platooning is mainly contributed by the reduction of drivers. The finding is consistent with the literature (Larsen et al., 2019) and is explainable. Note that the fuel cost saving (if any) would be minor since the AT detours required to form platoons will consume more fuel and erode the fuel saving accrued from air-drag reduction. Fig. 2.4a also shows that the cost saving increases with the cost ratio at a decreasing rate. This is also intuitive because the percentage cost saving has an upper bound when the labor-fuel cost ratio approaches infinity. That upper bound is dictated by the percentage reduction of drivers.

On the other hand, Fig. 2.4b shows that the average platoon size is insensitive to the cost ratio. This indicates that the cost ratio may have little impact on the optimal platoon assignment when the time windows are not tight.

Sensitivity to the AT travel time windows

In the last batch of experiments, we fix L=3 and $|V|$=25, but let the time window dispersion indicator α take values in $\{0, 0.5, 1, 1.5, 2, 2.5\}$ and tightness indicator β take values in $\{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6\}$. The cost parameters take the values specified in Section 2.5.1. Fig. 2.5a and b plot the percentage cost savings and average platoon sizes,respectively, for the $6 \times 7 = 42$ combinations of α and β values. Darker colors indicate larger values.



(a) Percentage cost saving (b) Average platoon size

Figure 2.5: Sensitivity to the time window parameters (α, β)

The figures show that both metrics decrease with α but increase with β. Note that when α=0 and β=0.6 (the upper-left corner), optimal AT platooning can save 26.7% of the total cost with an average platoon size near the upper limit 3. On the other hand, when α=2.5 and β=0 (the bottom-right corner), nearly all the ATs will travel individually, and the cost saving is close to 0. This is expected since a smaller α means different AT's time windows are largely overlapped, and the ATs are more likely to be platooned without violating the time window constraints. Similarly, a greater β means ATs can undergo more detours and adjust their departure times more flexibly to form platoons. Also note that the gradients in these contour plots would be greater when L takes larger values.

2.6 Summary

This chapter studies the optimal scheduling schedule considering the size-dependent costs under hard time window. The proposed model is developed from the perspective of central planners, taking into account the inefficiency in the process of platoon construction. Decisions regarding platoon composition, scheduling and routing are made at the same time. In addition, we propose a customized CBC algorithm to solve the scheduling problem. Numerical experiments provide general conclusions and specific findings. The results show that with the increase of the size limit of the platoon, the profitability of the platoon can be improved.

Future work should be devoted to a large number of ATs, more flexible platooning rules, and more complicated network topologies. Also, it seems necessary to synchronize the driver scheduling and ATs scheduling to accommodate practical regulations.

3 Can Autonomous Trucks Reduce the Driver Shortage: Potentials and Scheduling

3.1 Introduction

Truck is the dominant transportation mode in the freight transportation department, 70.6% of all freight tonnage is moved on the US highways. Despite the economic importance, the trucking industry is suffering from the shortage of drivers these days. The US has seen a shortage of 20000 in 2005 growing to 50700 by 2017 (Costello and Karickhoff, 2019). The driver shortfall is expected to rise as freight volumes recover and the industry transitions to the use of electronic logging devices (ELD) to record driver hours-of-service (HOS) after the COVID-19 pandemic. Previously, truck drivers have an incentive to violate HOS rules because the industry's widespread use of piece-rate pay can incentivize them to work more hours than legally permitted (Masten, 2009; Scott and Nyaga, 2019). However, it becomes more difficult to falsify when the total freight trip is recorded by the mandatory ELD in each truck in 2020. As freight volumes increase, the existing driver pool is only more strained.

This trend imposes new challenges on the sustainability and profitability of freight carriers. The implementation of ELD under HOS in deed stimulates the demand of truck drivers, and thus pushes the labor price. Driver compensation is the largest component of operational costs for a motor carrier (Williams and Murray, 2020), which consists of 43% of trucking's operational costs according to the American Transportation Research Institute.

Wrenn (2017) suggests that autonomous truck (AT) platoons is useful in addressing the driver shortage, especially for long-haul trips. From the profitability perspective, cost savings derived from highly automated vehicles include fuel savings and reduced number of drivers in the following ATs. Lammert et al. (2014) examined more than 57000 vehicles on over 210 million miles in the United States to find that 55.7% vehicle-miles are "platoonable". To what extend those advantages of AT platooning indeed can be realized is heavily dependent on the AT platooning planning and management strategy. Strategies to improve the platooning opportunities on a specific route or over a wide traffic network have been investigated by many recent studies (Larsson et al., 2015; Larson et al., 2016; Sokolov et al., 2017). Stehbeck (2019) develops a mixed integer program to investigate the benefits of platooning on labor-cost saving. Nevertheless, few of them focus on the optimization on fleet operations confined to practical freight transport constraints like driver schedules.

Driver scheduling problems has been studied in various context: for trains veelenturf, buses chen 2013, and for trucks(Goel et al., 2012). At the core, these literature considers the assignment of a series of tasks to drivers and the corresponding order to conduct for drivers (Lin and Hsu, 2016; Ma et al., 2016). To solve the driver scheduling problem without HOS regulations, heuristic algorithms are widely used (Shen and Kwan, 2001; Shen et al., 2013).

On a related note, driver scheduling problems under HOS regulations triggers a heated discussion recently. Most of these work tried to construct a feasible schedule for a given route in conformity with a country legislation (Tilk et al., 2017; Tilk and Goel, 2020). Archetti and Savelsbergh (2009) have considered the problem of determining how a sequence of full truckload transportation requests, each with a dispatch window at the origin, can be executed by a driver in conformity with the HOS regulations. Their algorithm can find a feasible schedule in polynomial time, if one exists. However, the problem gets much more complicated if an optimal schedule towards some objective is desired. Xu et al. (2003) conjecture that the problem of minimizing total costs of all on- and off-duty times for a given tour is NP-hard in the presence of US HOS regulations.

To conclude, the coordination between driver shifts and the AT platooning scheduling has gone unnoticed in the previous literature. More importantly, the problem is more complicated since the decisions on service sequence of transport requests, AT platoon formation and driver assignment are intertwined. In addition, The answers to such problems indeed will testify whether AT platooning is financially reliable in reality and play a crucial role in adoption process of AT platoons. Therefore, it is worth studying the combined scheduling problems of AT platooning and drivers under HOS regulations.

The rest of the chapter is organized as follows. Section 3.2 describes and analyzes the problem of scheduling of drivers and AT platoons under the HOS regulations. A mathematical model is given in section 3.3. A branch and price algorithm embedded with column generation is developed in Section 3.4. Experiments are conducted in Section 3.5 to validate our solution approach.

3.2 Problem statement

Consider a fleet manager who employs ATs and dedicated drivers to complete mainline haulage from a depot to several destinations indexed by $j, j \in J$, (e.g., seaports or regional distribution centers); see Fig. 3.1. We assume that each freight transport request $i \in I$ is a unit demand destined for $j \in J$, i.e., freight of a full truckload. In the freight transportation, a request is typically associated with a time window negotiated by the shipper and the carrier to ensure in-time delivery that also allows for some flexibility regarding preparation, administrative procedures and traffic congestion (Bhoopalam et al., 2018; Johansson et al., 2018). We have binary parameter z_{ij},$i \in I$, $j \in J$ to equal 1 if request i's destination is j and 0 otherwise. We suppose that each request's departure time from the depot is bounded by a time window denoted by $[e_i, l_i]$. A group of drivers denoted by S are assigned to operate AT platoons to serve these requests. At the beginning of the planning horizon, all

ATs and drivers are based at the depot. We assume there are sufficient ATs and our focus is on the assignment of truck drivers.

ATs bound for the same destination can form platoons, each operated by one driver in the leading AT, to reduce fuel consumption and save labors. Longer platoons can achieve greater fuel and labor savings (Liang et al., 2015; Aarts and Feddes, 2016). However, the number of ATs in a platoon is constrained by a predefined size limit, L, to ensure safe driving and alleviate the disruptions to the general traffic. For generality, an independently-driven AT is treated as a single-AT platoon. From the standpoint of drivers, each trip consists of two directions, one from the depot to the destination, (i.e., the outbound direction shown by the solid lines in Fig. 3.1) and the return trip (the inbound direction shown by the dash lines). Let $t_0^j, j \in J$ denote the non-stop driving time in each direction between the depot and destination j. For simplicity, we further assume that the loading and unloading time is factored into t_0^j.

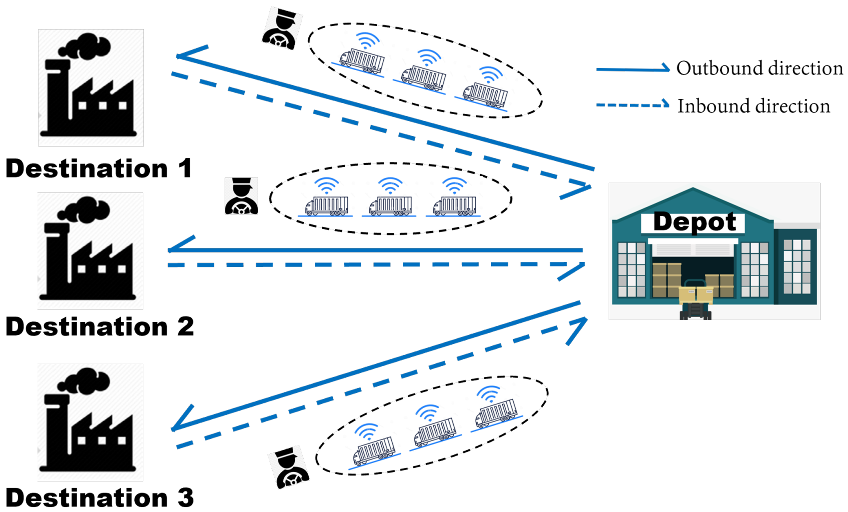


Figure 3.1: Illustration of mainline haulage by AT platoons

A platoon's actual travel time is the sum of the non-stop driving time and necessary break and rest times following the hours of service (HOS) regulations. The fleet manager aims to minimize the driver needed in the planning horizon by determining: (i) the size and dispatch time of each AT platoon; and (ii) the assignment of drivers to the platoons complying with the driver working hour regulations. We describe the HOS and driver states next.

Since it is impossible present a full list of HOS regulations worldwide, this chapter focuses on the regulations enacted in the United States and the European Union. Specifically, we examine the regulations applied to seven consecutive days ($7 \times 24h$) in this chapter. More details can be found in Federal Motor Carrier Saftey Administration (FMCSA) (2020, 2010) and European Union (2014, 2006). Both HOS regulations impose mandatory time constraints on four types of driver activities: *driving time*, *breaks*, *rests*, and *working time*. The driving time refers to the period during which a driver is operating a vehicle. A break refers to a short period exclusively used for recuperation during which a driver must not carry out any work. A rest is a long period during which the driver is off duty and has a free disposal of his time (e.g., for sleeping). Finally, the the working time is all the time a driver is on duty for driving and non-driving jobs (such as paper checking and communication with customers). For simplicity, this chapter ignores the working time constraints because there are many types of non-driving jobs and their durations and correlations are difficult to define (Regan et al., 2011). In addition, most of a driver's working time is spent on his shift driving (Soccolich et al., 2013).

Specifically, we define the following parameters to describe an HOS regulation. Denote τ_B the maximum driving time a driver can perform since his last break or rest before he needs to break again; τ_R the maximum driving time a driver can perform since his last rest before he needs to rest again; ω_B the minimum duration of a break; and ω_R the minimum duration of a rest. Values of these parameters under the US and EU regulations are summarized in Table 3.1. In addition, we stipulate the following:

- A break or a rest must be an uninterrupted period satisfying the minimum duration constraint. Two separate periods, each less than ω_B (ω_R) cannot be paired up to be a break or a rest.

- By having a rest, a driver also fulfills the requirement of having a break. For example, under the US regulation, if a driver drives for 7 hours without a break and then has a rest, he will be able to drive another 8 hours without any break.

- All drivers are fully rested at the beginning of the planning horizon.

Table 3.1: HOS regulations in the US and EU

Parameter	Values in US/EU,h	Description
τ_B	8 / 4.5	the maximum driving time between two consecutive breaks
τ_R	11 / 9	the maximum driving time between two consecutive rests
ω_B	0.5 / 0.75	the minimum duration of a continuous break period
ω_R	10 / 11	the minimum duration of a continuous rest period

A schedule should specify the sequence of trips and the timeline of driving and non-driving activities (e.g., breaks and rests) within a trip for each driver. A typical driver schedule during the planning horizon is illustrated in Fig. 3.2, where trips k and k+1 are two consecutive round trips.The idle time between two consecutive trips can be a rest, a break or a wait if it is shorter than ω_B. A wait has no influence on the driver state. To model the HOS constraints, we define three decision variables to describe the state of drivers: $t^{s,k}_{start}$, $T^{s,k}_B$ and $T^{s,k}_R$, $s \in S, k \in K$. The $t^{s,k}_{start}$ and $t^{s,k}_{end}$ denote the departure and the returning times of the k^{th} trip of driver s, respectively. The $T^{s,k}_B$ and $T^{s,k}_R$ are the remaining driving times at the beginning of the trip k before a break and a rest are needed, respectively. We will elaborate on the relationship between theses driver states variables and driver activities in Section 3.3.2.

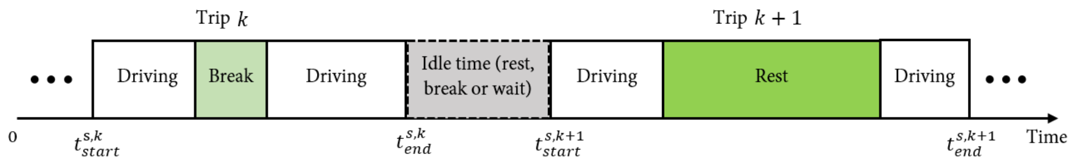


Figure 3.2: An example schedule of a driver

3.3 Mathematical model

We present the model for AT platoon and driver scheduling under the EU and US HOS regulations. But the model can be easily adapted to other HOS regulations.

Section 3.3.1 summarize the notations used in the model. To further reduce the complexity, we first develop an upper bound of a driver's round trip time in Section 3.3.2. Section 3.3.3 presents the constraints for coordinating the AT platoon schedules with the driver schedules. Finally, a mixed integer linear program (MILP) formulation built upon the upper bound of round trip times is furnished in Section 3.3.4.

3.3.1 Notation list

Indices and sets

i	Index of a freight transport requests
s	Index of a driver
k	Index of a trip
n	Index of a platoon
j	Index of a transport request destination
I	Set of freight transport requests
S	Set of drivers
K	Set of round trip indices
N	Set of AT platoons
J	Set of transport request destinations

Parameters

t_0^j	The driving time in a single trip from the depot to the destination j, hour
q^j	The integer number of τ_R in the driving time of a round trip destined for destination j
Δt^j	The time after subtracting an integer multiple of τ_R from the driving time of a round trip destined for destination j, hour
τ_B	The maximum non-stop driving time between two consecutive breaks, hour
τ_R	The maximum total driving time between two consecutive rests or a break and a rest, hour
e_i	The earliest departure time of request i from the depot, hour
l_i	The latest departure time of request i from the depot, hour
$T_B^{s,k}$	The remaining non-stop driving time before a break must be taken at the beginning of the k^{th} trip of driver s, hour
$T_R^{s,k}$	The remaining total driving time before a rest must be taken at the beginning of the k^{th} trip of driver s, hour
$\overline{t}^j$, $\underline{t}^j$	The maximal and minimal travel time to destination j under a given trip plan, respectively, hour
L	The size limit on a platoon
z_{ij}	A binary variable that equals 1 if request i's destination is j and 0 otherwise
ω_B	The duration of a break, hour
ω_R	The duration of a rest, hour

Decision variables

x_{ijn}	A binary variable that equals 1 if request i to destination j is satisfied through platoon n and 0 otherwise
Q_s	A binary variable that equals 1 if the driver s is assigned a trip and 0 otherwise
t_{nj}^{dep}	The departure time of a platoon n at the depot with destination j, hour
$y_{nj}^{s,k}$	A binary variable that equals 1 if platoon n to destination j is assigned to the k^{th} trip of driver s and 0 otherwise
$t_{start}^{s,k}$	The start time from the depot of the k^{th} trip of driver s, hour

3.3.2 An upper bound of the round trip time

We find that the problem is too complicated to find an exact solution. Thus, we formulate our problem to find a tight upper bound of the minimum drivers needed. This formulation relies on an upper bound of a round trip's travel time, which is derived next.

To derive that upper bound, we suppose that the breaks and rests within a trip are arranged in the naive method proposed by Goel (2009),i.e., a break or rest is taken until the respective regulated driving times are used up. In this way, the total driving hour between two consecutive rests is exactly τ_R. Note that this method produces an upper bound of the round trip time. Applying this method to the EU or US HOS regulations, we have the following observation regarding the travel time of a round trip:

- Only one break will occur between two consecutive rests.
- At most one break will be taken before the first rest in the round trip.

- At most one break will be taken between the last rest of the round trip and the returning time to the depot.

- The number of rests during the round trip is and q^j satisfying $2t_0^j = q^j \cdot \tau_R + \Delta t^j$, (the remainder $\Delta t^j < \tau_R$).

Proposition 3.3.1. *The total travel time of the k^{th} round trip, $t_j^{s,k}$, is a function of the driver state $(T_B^{s,k}, T_R^{s,k})$ at the depot before the trip begins. The function can be derived analytically.*

Proof. For simplicity, we leave the index of trip destination j out of this proof. In other words, we use t_0, q, Δt, and $t^{s,k}$ instead of t_0^j, q^j, δ_t^j, and $t_j^{s,k}$.

Since $2t_0 = q \cdot \tau_R + \Delta t$, the total number of rests, $rest^{s,k}$, in this round trip (i.e., the k^{th} trip of driver s),can be given by Eq. (3.1).

$$r^{s,k}\left(T_R^{s,k}\right) = \begin{cases} q, & if\ T_R^{s,k} - \Delta t > 0; \\ q+1, & otherwise. \end{cases} \tag{3.1}$$

Let $b_1^{s,k}$, $b_2^{s,k}$, and $b_3^{s,k}$ denote the numbers of breaks taken before the first rest,after the last rest, and between the first and last rests, respectively. From the first observation above, we know that $b_3^{s,k} = rest^{s,k} - 1$. In addition, $b_1^{s,k}$ and $b_2^{s,k}$ are given as follows:

$$b_1^{s,k}\left(T_R^{s,k}, T_B^{s,k}\right) = \begin{cases} 1, & if\ T_R^{s,k} - T_B^{s,k} > 0; \\ 0, & otherwise. \end{cases} \tag{3.2}$$

$$b_2^{s,k}\left(T_R^{s,k}, T_B^{s,k}\right) = \begin{cases} 1, & if\ 2t_0 - T_R^{s,k} - \tau_R \cdot (r^{s,k} - 1) \geq \tau_B; \\ 0, & otherwise. \end{cases} \tag{3.3}$$

The total number of breaks is $b_1^{s,k} + b_2^{s,k} + b_3^{s,k} = rest^{s,k} - 1 + b_1^{s,k} + b_2^{s,k}$, and the round trip travel time $t^{s,k}$ is

$$t^{s,k} = \omega_B \cdot \left(r^{s,k} - 1 + b_1^{s,k} + b_2^{s,k}\right) + \omega_R \cdot r^{s,k} + 2t_0 \tag{3.4}$$

Table 3.3 lists all the cases for calculating $t^{s,k}$. Proposition 3.3.1 follows directly from Table 3.3. $\square$

Lemma 3.3.1.1. *The maximum and minimum of the round trip travel time denoted by $\overline{t}^j$, $\underline{t}^j$, are $(q+2)\omega_B + (q+1)\omega_R + 2t_0$ and $(q-1)\omega_B + q\omega_R + 2t_0$, respectively. The difference between them is $\omega_R + 3\omega_B$ for all destinations.*

Proof. This follows immediately from the results in Table 3.3 . $\square$

Fig. 3.3 presents a typical case for calculating the round trip time EU HOS regulations when $\Delta t + \tau_R - \tau_B \geq \tau_B$. Areas in same color corresponds to the same round trip time. The number in each area represents the row of $t^{s,k}$ in Table 3.3. A direct application of the above proposition is that by approximating the round

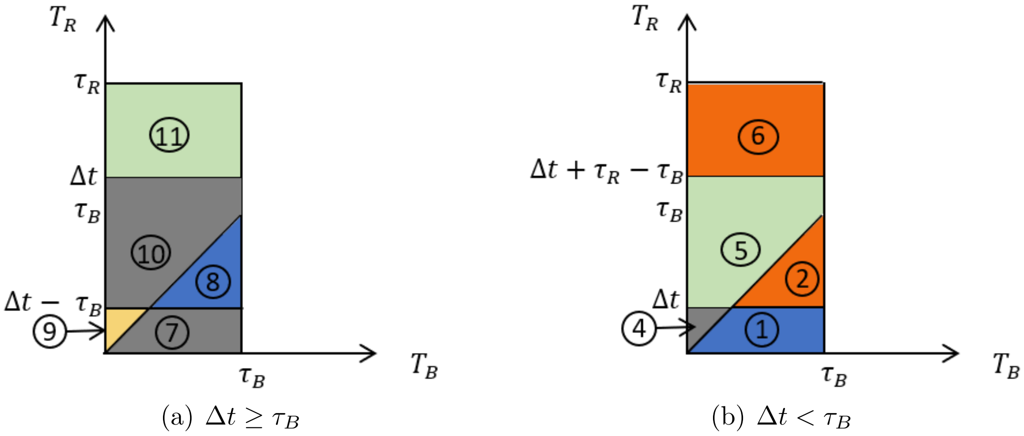


Figure 3.3: Typical cases for the round trip travel time under the EU HOS regulation

trip time at its maximum (given the specific HOS regulations and the non-stoping driving time). Using the upper bound ensures the HOS regulation is satisfied. This will render a conservative estimate of the number of drivers needed.

3.3.3 Coordination between schedules of AT platoons and drivers

This section formulates constraints that link up the schedules of AT platoons and the driver schedules. Denote the departure time of a platoon $n \in N$ with common destination j by t_{nj}^{dep}, which should satisfy all time windows of its members. The following binary variables are defined: x_{ijn}, $i \in I$, $n \in N$, that equals 1 if the request i destined for j is assigned to platoon n and 0 otherwise; and $y_{nj}^{s,k}$, $n \in N, j \in J, s \in S, k \in K$ be 1 if platoon n to destination j is assigned to the k^{th} trip of driver s and 0 otherwise. In addition, denote $t_{start}^{s,k}$ the start time of driver s's k^{th} trip.

$$-M \cdot (1 - y_{nj}^{s,k}) \leq t_{start}^{s,k} - t_{nj}^{dep} \leq M \cdot (1 - y_{nj}^{s,k}) \quad s \in S, k \in K, n \in N, j \in J \tag{3.5}$$

$$t_{start}^{s,k+1} - t_{start}^{s,k} \geq \bar{t}^j \cdot \sum_{n \in N} y_{nj}^{s,k} \quad s \in S, k \in K \backslash \{|K|\}, j \in J \tag{3.6}$$

$$x_{ijn} \cdot e_i \leq t_{nj}^{dep} \leq x_{ijn} \cdot l_i \quad i \in I, n \in N \tag{3.7}$$

$$x_{ijn} \leq z_{ij} \quad i \in I, n \in N, j \in J \tag{3.8}$$

Constraint (3.5) ensures that the start time of a trip equals the departure time of the assigned platoon„ where M is a sufficiently large number. Any value of M greater than or equal to the planning horizon will suffice. Constraint (3.6) states that the interval between two consecutive trips should be larger than the upper bound of the round trip time, $\bar{t}^j$. This constraint guarantees that the next trip of the same driver must start after the previous trip is completed. Constraint (3.7) defines the scope of the departure time of a platoon. Constraint (3.8) guarantees that only the requests with a common destination can be grouped in a platoon.

3.3.4 A MILP formulation

Now we formulate the mathematical program to minimize the maximal number of driver needed. To this end, we introduce an indicator function

$$Q_s = \begin{cases} 1, & \sum_n \sum_k y_n^{s,k} > 0 \\ 0, & \sum_n \sum_k y_n^{s,k} \le 0 \end{cases}, s \in S \tag{3.9}$$

Eq 3.9 states that the binary variable Q_s equals 1 if a driver s is deployed to serve at least one trip and 0 otherwise. To linearize constraint (3.9), we replace it with the following inequalities:

$$-M(1-Q_s) \le \sum_{n\in N}\sum_{k\in K} y_n^{s,k} - 1 \qquad s \in S \tag{3.10}$$

$$\sum_{n\in N}\sum_{k\in K} y_n^{s,k} \le MQ_s \qquad s \in S \tag{3.11}$$

where $M \ge |I|$ is a sufficiently large number.

Now the MILP model for the AT platoon and driver scheduling under an HOS regulations is given below:

[M1]

$$\min \sum_{s\in S} Q_s \tag{3.12}$$

subject to

$$\sum_{n\in N}\sum_{j\in J} x_{ijn} = 1 \qquad i \in I \tag{3.13}$$

$$\sum_{i\in I} x_{ijn} \le L \qquad n \in N, j \in J \tag{3.14}$$

$$\sum_{s\in S}\sum_{k\in K} y_{nj}^{s,k} \le 1 \qquad n \in N, j \in J \tag{3.15}$$

$$\sum_{n\in N}\sum_{j\in J} y_{nj}^{s,k} \le 1 \qquad s \in S, k \in K \tag{3.16}$$

$$0 \leq t^{s,k}_{start} \leq 168 \qquad s \in S, k \in K \tag{3.17}$$

$$0 \leq t^{dep}_{nj} \leq 168 \qquad n \in N, j \in J \tag{3.18}$$

$$x_{ijn} \in \{0,1\} \qquad n \in N, i \in I, j \in J \tag{3.19}$$

$$y^{s,k}_{nj} \in \{0,1\} \qquad n \in N, s \in S, k \in K, j \in J \tag{3.20}$$

$$Q_s \in \{0,1\} \qquad s \in S \tag{3.21}$$

$$Constraints\ (3.5) - (3.8), (3.11).$$

Constraint (3.13) guarantees that each request is served by one platoon. Constraint (3.14) states the size limit on platoons. Constraint (3.15) states that each platoon can only be assigned to one trip of one driver. Constraint (3.16) guarantees that a driver can only serve one platoon in a trip. Constraints (3.17)−(3.20) specify the ranges of decision variables. Note that constraint (3.10) is dropped since the objective (3.12) is in a minimization fashion.

3.4 Solution approach

The [M1] is so complicate to be solved for large scale instances. Thus, in what follows, we solve a simplified case with only one destination. A branch and price algorithm embedding column generation is used.

We reformulate the problem as a set covering model by using the Dantzig-Wolfe decomposition (Vanderbeck, 2000) in Section 3.4.1. The column generation process is described in Section 3.4.2. The corresponding pricing subproblem is solved in Section 3.4.3.

3.4.1 A set covering model

Let $p \in \mathcal{P}$ be a feasible sequence of AT platoons that served by a driver and $\mathcal{P}$ the set of all feasible AT sequences. Here "feasible" means each request is met at most once, and all the time windows constraints, platoon size limit, HOS regulations are satisfied. Define a set of binary decision variables $\{\lambda_p\}$ equals 1 if the sequence $p \in \mathcal{P}$ is chosen in the solution and 0 otherwise , and a set of binary parameters, $\{a_i^p\}$ that equals 1 if AT $i \in I$ is served by the sequence $p \in \mathcal{P}$ and 0 otherwise. Thus, minimizing the total drivers assigned is equivalent to minimizing the number of sequences chosen. The resulting set covering model is formulated as follows:

[M2]

$$\min \quad \sum_{p \in \mathcal{P}} \lambda_p \tag{3.22}$$

subject to

$$\sum_{p \in \mathcal{P}} a_i^p \lambda_p \geq 1 \qquad \forall i \in I \tag{3.23}$$

$$\lambda_p \in \{0, 1\} \qquad \forall p \in \mathcal{P} \tag{3.24}$$

Constraint (3.23) ensures that each request is served at least once. The domain of binary variables are given by constraint (3.24).

3.4.2 Column generation (CG)

If we relax the integrality constraint 3.24 in [M2], the resulting model is referred to as the master problem. This linear relaxation involves an exponential number of columns (variables). Therefore, we apply the column generation scheme which starts by solving a restricted master problem (RMP) defined on a subset of columns, $\mathcal{P}'$. In each iteration, new feasible columns are generated by solving the pricing subproblem to expand the feasible sequence set $\mathcal{P}'$.

The RMP formulation is similar to [M2] except that the integrality constraint is relaxed and $\mathcal{P}$ is replaced by $\mathcal{P}'$. We present it here for readers' convenience:

[M3]

$$\min \quad \sum_{p \in \mathcal{P}'} \lambda_p \tag{3.25}$$

subject to

$$\sum_{p \in \mathcal{P}'} a_i^p \lambda_p \geq 1 \qquad \forall i \in I \tag{3.26}$$

$$\lambda_p \geq 0 \qquad \forall p \in \mathcal{P}' \tag{3.27}$$

We first generate an initial sequence set as $\mathcal{P}'$ by simply assigning each request to one distinct driver; i.e., each driver completes only one trip and each trip serves only one request.

Let π be the dual vectors associated with constraint (3.23). In each CG iteration, the dual vector is used as the input parameters of the pricing subproblem for generating a new feasible sequence (i.e., column) with the lowest reduced cost. The CG procedure terminates when the lowest reduced cost is non-negative, indicating that adding more sequences to $\mathcal{P}'$ will not further decrease the objective of [M3].

3.4.3 The pricing subproblem

The objective of the pricing subproblem is to identify the column associated with the minimal reduced cost. Its feasible region defines a feasible sequence of AT platoons assigned to a driver. The pricing subproblem is essentially a resource constrained elementary shortest path problem (RCESPP), with two types of resource: time and platoon size limit.

Specifically, we define a $\mathcal{G}\left(V \cup \{o, d\}, A\right)$. Each node in subset V_I for represents a request (or equivalently, an AT that serves this request), and each node in V_K represents a platoon. Two dummy vertices, o and d, are also included to represent the origin and destination of each path. Each node $i \in V_I$ is associated with its cost $-\pi_i$, platoon size consumption $h_i = -1$, departure time window $[e_i, l_i]$, and service time $s_i = 0$. And each node $i \in V_K$ is associated with its cost 0, platoon size consumption $h_i = L$, departure time window $[e_i = 0, l_i = 168]$ and service time

$s_i = \bar{t}$ (superscript j is omitted since only one destination is considered). There are three types of arcs in A: (i) from node o to any request node $i \in V_I$; (ii) from node $i \in V$ to node $j \in V$, if $j \neq i$ and $[e_i, l_i] \cap [e_j, l_j] \neq \emptyset$; and (iii) from any platoon node $i \in V_k$ to node d.

Now we present the pricing subproblem formulation with the following additional decision variables:

- a set of binary variables $\{\alpha_i\}$ that equals 1 if a request node $i \in V_I$ is included in the sequence and 0 otherwise;
- a set of binary variables $\{\beta_{ij}\}$ that equals 1 if a node $i \in V$ is the precedent of node $j \in V$ in a sequence and 0 otherwise;
- T_i is the departure time at node $i \in V$;
- T_{ij} denoting the departure time at node $i \in V$ if it is followed by node $j \in V$;
- L_i denoting the remaining platoon capacity at node $i \in V$;
- L_{ij} denoting the remaining platoon capacity at node $i \in V \cup \{o\}$ if it is followed by node $j \in V$.

Note that the subscript p does not apply to the above decision variables since the pricing subproblem is solved for a single sequence. Given an optimal solution of the restricted master problem, the pricing subproblem is formulated as follows:

[M4]

$$\min \quad \bar{c} = 1 - \sum_{i \in I} \pi_i \alpha_i \tag{3.28}$$

subject to

$$\sum_{j \in V_I} \beta_{oj} = 1 \tag{3.29}$$

$$\sum_{i \in V_K} \beta_{id} = 1 \tag{3.30}$$

$$\sum_{j \in V} \beta_{ij} = \sum_{j \in V \cup \{o\}} \beta_{ji} \qquad \forall i \in V \tag{3.31}$$

$$\sum_{j \in V} \beta_{ij} = \alpha_i \qquad \forall i \in V_I \tag{3.32}$$

$$e_i \leq T_i \leq l_i \qquad \forall i \in V \tag{3.33}$$

$$T_{ij} + s_i \beta_{ij} \leq T_j \qquad i \neq j, \forall i, j \in V \tag{3.34}$$

$$-M \cdot (1 - \beta_{ij}) \leq T_{ij} - T_i \leq M \cdot (1 - \beta_{ij}) \qquad i \neq j, \forall i, j \in V \tag{3.35}$$

$$L_i = L \qquad \forall i \in V_K \tag{3.36}$$

$$L_{ij} + h_j \beta_{ij} = L_j \qquad i \neq j, \forall i \in V \cup \{O\}, j \in V_I \tag{3.37}$$

$$L_i \leq 0 \qquad \forall i \in V \tag{3.38}$$

$$-M \cdot (1 - \beta_{ij}) \leq L_{ij} - L_i \leq M \cdot (1 - \beta_{ij}) \qquad i \neq j, \forall i, j \in V \cup \{o\} \tag{3.39}$$

$$\alpha_i \in \{0, 1\} \qquad \forall i \in V \tag{3.40}$$

$$\beta_{ij} \in \{0, 1\} \qquad i \neq j, \forall i, j \in V \tag{3.41}$$

Objective (3.28) minimizes the reduced cost of a feasible sequence. Constraints (3.29)-(3.31) ensure the flow conservation. Variable β_{ij} is linked to α_i in constraint (3.32).Constraints (3.33)-(3.35) define the relationship between the departure times in a sequence. Specifically, if i is a request node, (3.34) stipulates that the departure time of its following node (whether that is a request or platoon node) is no later than node i's departure time. On the other hand, if i in (3.34) is a platoon node, the upper bound trip time $\bar{t}$ will be added between the departure times of node i and its following one (which is a request node or node d). Constraint (3.36)-(3.39) guarantee the platoon size limit constraint. Specifically, (3.36) sets the remaining platoon capacity L_i to L for node o and each platoon node $i \in V_K$. Constraint (3.37) specifies that when an AT node is appended to the current platoon, L_j is subtracted by 1. Constraint (3.38) guarantees that the remaining platoon capacity is always non-negative. Finally, constraints (3.40)-(3.41) define the ranges of binary decision variables.

The pricing subproblem is solved by a label-setting algorithm, which finds a minimum-cost elementary path from o to d within the planning horizon, *168h*. Each node $i \in V$ is encoded by a label of the form (i, C_i, T_i, V_i, L_i) recording a path from o to node $i \in V$, where C_i, T_i, and L_i are the cumulative cost, departure time, and remaining platoon capacity at node i. N_i keeps track of all nodes visited before node i in the sequence. At vertex o, the time label T_o is initialized at 0 and $N_o = \{-1\}$; cost C_o is initialized to 1, which means a new driver is assigned.

The optimal solution is given by the path associated with the minimal cumulative cost at destination node d. The efficiency of the labeling algorithm strongly depends on the effectiveness of dominance rules employed to rule out non-optimal labels. We introduce a dominance rule in the following proposition. Let $I = (i, C_i, T_i, V_i, L_i)$ and $I' = (i, C_i^{'}, T_i^{'}, V_i^{'}, L_i^{'})$ be the two labels of different paths arriving at the same node. We say I dominates I' ($I \succ I'$) if all the following inequalities are satisfied and at least one of them is strictly satisfied:

$$C_i \leq C_i^{'}$$

$$T_i \leq T_i^{'}$$

$$V_i \geq V_i^{'}.$$

where $V_i \geq V_i^{'}$ means the size of the first list is larger than the second. The validity of Proposition 3.4.3 is obvious A detailed proof can be found in Goel and Irnich (2017).

To further improve the efficiency of the label-setting algorithm, we use two acceleration techniques as follows.

Unreachable request nodes. After setting the label at node $i \in V$, we can check whether a neighboring node $j \in V$ has become unreachable with the current resources. A neighboring node is unreachable if extending the label to that node from the current node would violate the platoon size limit or the time window constraint. There is no need to extend the path from the current node to unreachable nodes (Feillet et al., 2004). Then we can reduce the number of feasible labels and accelerate the process of label comparison.

Dual stabilization. CG often experiences slow convergence when the solution is near the optimum. This is called the tailing-off effect (Du Merle et al., 1999; Lübbecke and Desrosiers, 2005). Inspired by Addis et al. (2012), we apply an ad hoc dual stabilization method to fix the problem. Instead of using the dual vectors arising from the RMP directly, a new formula to update the dual vector is adopted:

$$\widetilde{\Phi} = \mu\Phi + (1-\mu)\overline{\Phi}, \tag{3.42}$$

where $0 \leq \mu \leq 1$, and $\overline{\Phi}$ is the incumbent best guess for the optimal dual vector. The same as Wang et al. (2018), we initially set $\mu = 0.5$ and then increase the value of α by 0.05 in each interaction. Then in the following, the best guess $\overline{\Phi}$ is set the value of $\widetilde{\Phi}$ in last iteration. The column generation procedure is repeated until $\mu = 1$ and no columns with negative reduced cost can be found.

The tailored label-setting algorithm is summarized as follows:

3.5 Numerical study

In this section, we run numerical experiments to validate the branch and price algorithm for the AT platooning and driver scheduling problem under US HOS regulations. ALL experiments are run on a PC equipped with a 3.6 GHz Dual Core and an 8 GB RAM. The algorithms are programmed in Java and the RMP is solved by CPLEX 12.8.

Algorithm 1 The tailored label-setting algorithm

Input: π, $\mathcal{G}$

Output: A shortest path from o to d

Step 1 Initialization: set the label of node o, $l(o) = (0, 1, 0, -1, L)$; define the label set of any node $i \in V$, $\mathscr{L}(i) = \emptyset$; define the set of untreated labels, $\mathscr{L}^U = \{l(o)\}$.

Step 2 Find the next label to be treated:

while $\mathscr{L}^U \neq \emptyset$ and $i \neq d$ **do**

  Arrange all the elements in $\mathscr{L}^U$, order them in ascending order, first with respect to time and then cost.(Other orders can also be used). Suppose the first element in the ordered list is the label $l(i) = (i, C_i, T_i, V_i, L_i)$.

  Step 3 Label extension:

  for Node $j \in V$ adjacent to i **do**

    Exclude nodes satisfying the rule of *Unreachable ATs*

    if $j \notin L_i$,$W_i > 0$, $e_j \leq T_i + s_i \leq l_j$ **then**

      Generate a new label $l(j)$ of node j:$C_j = C_i - \pi_i$, $T_j = T_i + s_i$ and $L_j = L_i + h_i$ if j is a request node; $L_j = L$ if j is a platoon node.

      Add $l(j)$ to $\mathscr{L}(j)$, and apply dominance rule in Proposition 3.3.1 to identify the dominated labels. Remove them from both label set $\mathscr{L}(j)$ and $\mathscr{L}^U$.

      $\mathscr{L}^U \leftarrow [\mathscr{L}^U \cup \mathscr{L}(j)]$

    end if

  end for

end while

Find $l(d) \in \mathscr{L}(D)$ with the minimum cost, denoted by $l(d)^*$.

Return The sequence of in permanent label $l(d)^*$.

Numerical instances are created by modifying from the well-known vehicle routing problem benchmark instances developed by Solomon (1987). Smaller instances are generated here by using the only the first 25 nodes in the original data set. For simplicity, we keep the names of instance IDs as it was. Time windows of demand node of Solomon's instances is used as the time windows of a request node. The time windows of the origin, destination, and platoon nodes are set to $[0, 168]$. If a node's earliest departure time larger than $168 - \bar{t}$, we reset it as $168 - \bar{t} - 1$. The size limit of a platoon is set to 3, and the non-stop driving time from the depot to the destination is 10 hours. Thus, the maximum travel time $\bar{t}$ of a round trip is 47 hours according to Eq.(3.4) (note that $\Delta t < \tau_B$).

The initial solution is obtained by assuming that each driver only serves one AT and no platoon is formed. Thus, the initial number of drivers equals the number of request, and each path traverses only the origin, an request node, a platoon node, and the destination.

Table 3.4 shows the optimal number of drivers needed and the runtimes with 25 requests under the US HOS regulations. All the 15 instances were solved within 250 seconds. During the implementation, we found that the acceleration techniques have great influences on the algorithm efficiency.

3.6 Summary

This chapter considers the AT platooning and truck driver assignment problem. Our model jointly optimizes the formation of platoons, the drivers required and the resulting driver schedules under the HOS regulations. A branch and price algorithm with column generation is developed. Numerical experiments validate the efficiency.

Although the problem is considered under the EU and US HOS regulations, our model and algorithm can be adapted to other nation's regulations too. We can replace the driving hour related parameters by that in a new regulation system and calculate the round trip time again. However, our model would fail if the driver scheduling method changes. For example, if rests or breaks are allowed to be split into smaller periods. In doing so, the driver scheduling can be very complicate, which deserves to be considered separately. Our future research will also look into exploring the coordination between AT platoons and driver schedules under different personnel strategies although some simplifications must be made.

Table 3.3: Cases of $t^{s,k}$

			$r^{s,k}$	$b_1^{s,k}$	$b_2^{s,k}$	$t^{s,k}$
$\Delta t < \tau_B$	$T_R \leq T_B$	$T_R \leq \Delta t$	$q+1$	0	0	$q\omega_B + (q+1)\,\omega_R + 2t_0$
		$\Delta t < T_R \leq \Delta t + \tau_R - \tau_B$	q	0	1	$q\omega_B + q\omega_R + 2t_0$
		$T_R > \Delta t + \tau_R - \tau_B$	q	0	0	$(q-1)\omega_B + q\omega_R + 2t_0$
	$T_R > T_B$	$T_R \leq \Delta t$	$q+1$	1	0	$(q+1)\omega_B + (q+1)\omega_R + 2t_0$
		$\Delta t < T_R \leq \Delta t + \tau_R - \tau_B$	q	1	1	$(q+1)\omega_B + q\omega_R + 2t_0$
		$T_R > \Delta t + \tau_R - \tau_B$	q	1	0	$q\omega_B + q\omega_R + 2t_0$
$\Delta t \geq \tau_B$	$T_R \leq T_B$	$T_R \leq \Delta t - \tau_B$	$q+1$	0	1	$(q+1)\omega_B + (q+1)\,\omega_R + 2t_0$
		$\Delta t - \tau_B < T_R \leq \Delta t$	$q+1$	0	0	$q\omega_B + (q+1)\omega_R + 2t_0$
	$T_R > T_B$	$T_R \leq \Delta t - \tau_B$	$q+1$	1	1	$(q+2)\omega_B + (q+1)\omega_R + 2t_0$
		$\Delta t - \tau_B < T_R \leq \Delta t$	$q+1$	1	0	$(q+1)\omega_B + (q+1)\omega_R + 2t_0$
		$T_R > \Delta t$	q	1	1	$(q+1)\omega_B + q\omega_R + 2t_0$

Table 3.4: Results for 25 requests under the US regulation ($t_0 = 10h, \bar{t} = 47h$).

Instance ID	Drivers needed	Runtime (s)
C101	15	11.5
C102	16	40.1
C103	10	248.2
C104	13	7.2
C105	10	0.5
R101	10	0.6
R102	11	2.6
R103	12	0.7
R104	19	12.2
R105	9	1.6
RC101	10	1.2
RC102	9	1.2
RC103	10	1.4
RC104	14	1.0
RC105	11	7.2

4 Conclusions

Section 4.1 summarizes this dissertation's contributions. Section 4.2 discusses possible extensions of the current work.

4.1 Contributions

This thesis first investigates an optimal platooning schedule for ATs considering platoon-size-dependent costs with hard time windows. The proposed model is developed from a central planner's view taking into account the inefficiencies in the platoon building process. Decisions, including platoon composition, scheduling, and routing are made simultaneously. The size for each platoon is not given in advance, and the optimal number of ATs decides it in a platoon in turn. Furthermore, we propose a tailored Combinatorial Benders Cuts algorithm to solve the scheduling problem. Numerical experiments provide general conclusions as well as specific findings. Generally, the proposed algorithm is valid to solve the problem much faster. At a more specific level, the effects of the platooning schedules are influenced by parameters like platoon size limit and the cost ratio between fuel and labors. The results indicate that the profitability of the platoons can be increased as the platoon size limit increase. Under the proposed schedules, more savings come from the reduced drivers even when the driver wage is relatively low.

Meanwhile, to the best of our knowledge, we are the first to consider the coordinated scheduling for AT platooning and truck driver assignment. In particular, the HOS regulations are incorporated. The HOS regulations have been studied in the context of vehicle routing and driver scheduling, but the previous methods are not applicable because the time windows of tasks to be served by drivers are not given when AT platooning is considered. More importantly, the time windows and formation of the

AT platoons are mutually impacted with the schedule of drivers. Our branch and price algorithm embedded with column generation can solve the problem efficiently.

4.2 Future work

Viewing the limitations of this thesis, two future directions are articulated in this section to consolidate the studies on truck platooning management. The first continues the exploitation of endogenous benefits within the truck platooning system by providing a real-time itinerary planning model. The second study will explore the coordination between driver schedules and AT platoons on a more complicated network.

Truck operations are highly disaggregated and stochastic over time and space due to demand uncertainty and huge amount of carriers. To address the more complicated scheduling problem, future work should be devoted to a large number of ATs, more flexible platooning rules, and more complicated network topologies. If another can pick up an existing platoon, dynamic programming is required to be developed to handle the in-time platooning decisions for each group along the trip heading to the destination. An efficient online algorithm can be developed to satisfy practical needs.

Another area of development is to synchronize the driver scheduling and ATs scheduling considering the routing problem. The selection of the merge point which will affect the route of AT platoons, for example. The merge point also serves as a hub terminal where idle drivers leave follower trucks and platoon leaders receive trucks. Then the choice of merge point requires incorporating work shifts of drivers with the platoon routes because otherwise, some truck drivers remain idle for an excessive time span and others may be fatigue driving if assigned to a long journey.

Appendix

A Proof of Proposition 2.4.1

Proof. Suppose that r_1 and r_2 are two platoon paths for AT $v \in V$ with distances $dist_1 \leq dist_2$. Denote λ_i $(i = 1, 2)$ the ratio of the path length d_{r_i} to the route distance from o_v to d_v via path r_i. We further denote δ_{v,r_1} and δ_{v,r_2} the travel costs of v via paths r_1 and r_2, respectively. The former cost is maximized when v travels individually, i.e.,

$$\delta_{v,r_1} \leq \left(\frac{c}{s} + pf_B\right) \cdot dist_1 \tag{A.1}$$

On the other hand, the latter cost is minimized when v travels at the tail of a platoon of L ATs. This way, v incurs no labor cost and enjoys the largest air-drag reduction on the highways. Thus,

$$\delta_{v,r_2} \geq \left(\frac{c}{s} + pf_B\right) \cdot dist_2 - \frac{c}{s}\lambda_2 \cdot dist_2 - p \cdot as^2\varphi_L \cdot \lambda_2 \cdot dist_2 \tag{A.2}$$

From inequalities A.1 and A.2, we have:

$$\delta_{v,r_2} - \delta_{v,r_1} \geq \left\{\left(\frac{c}{s} + pf_B\right) \cdot dist_2 - \frac{c}{s}\lambda_2 \cdot dist_2 - pas^2\varphi_L\lambda_2 \cdot dist_2\right\} - \left(\frac{c}{s} + pf_B\right) \cdot dist_1 \tag{A.3}$$

For AT v, path r_2 is never better than r_1 if $\delta_{v,r_2} \geq \delta_{v,r_1}$ is always true. This condition is satisfied when:

$$\begin{aligned}
&\left(\frac{c}{s} + pf_B\right) \cdot dist_2 - \frac{c}{s}\lambda_2 \cdot dist_2 - pas^2\varphi_L\lambda_2 \cdot dist_2 \geq \left(\frac{c}{s} + pf_B\right) \cdot dist_1 \\
\iff &\lambda_2 \leq \frac{\frac{c}{s} + pf_B}{\frac{c}{s} + pas^2\varphi_L} \cdot \left(1 - \frac{dist_1}{dist_2}\right)
\end{aligned}$$

B Framework of algorithm for the AT platooning

Algorithm 1. The CBC algorithm

Initialization: $iter = 0,\ Set\_of\_cuts = \emptyset,\ UB = \infty,\ LB = -\infty$

While $UB - LB \geq \varepsilon$ or $iter \leq iter\_MAX$ **do**:

  Solve **[MP]** with Set_of_cuts by CPLEX to obtain the optimal solution $\tilde{x}_v^{r,k}$ and objective value $\tilde{\mathcal{F}}$

  Update $LB = \max\{LB, \tilde{\mathcal{F}}\}$

  For $(r,k) \in \left\{(r,k) \middle| \sum_{v \in V} \tilde{x}_v^{r,k} \geq 1, r \in R, k \in K\right\}$:

    Solve **[SP]** given $\tilde{x}_v^{r,k}$

    If [SP] is infeasible:

      Find the minimal infeasible subsets and the cuts using Algorithm 2

      Add the newly generated cuts to Set_of_cuts

    End if

  End for

  If no new cut is added to Set_of_cuts:

    Update $UB = LB$

  Else:

    $iter \leftarrow iter + 1$

  End if

End while

Return the optimal solution to **[MP]**

Algorithm 2. Finding the MISs given the solution of [MP]

Initialization: $t_e = 0,\ t_l =$ end of planning horizon

For $(r,k) \in \left\{(r,k) \middle| \sum_{v \in V} \tilde{x}_v^{r,k} \geq 1, r \in R, k \in K\right\}$:

  For $v' \in V' = \left\{v \in V \middle| \tilde{x}_v^{r,k} = 1\right\}$:

    If $l_{v'} - \frac{d_{r,d_{v'}} + d_r}{s} < \frac{d_{r,o_{v'}}}{s} + e_{v'}$:

      Generate cuts (2.42), $V' \leftarrow V' \backslash \{v'\}$

    End if

  End for

  Sort the departure time windows $\left\{\left[\frac{d_{r,o_{v'}}}{s} + e_{v'}, l_{v'} - \frac{\left(d_{r,d_{v'}} + d_r\right)}{s}\right], v' \in V'\right\}$ in ascending order of the earliest departure time $\frac{d_{r,o_{v'}}}{s} + e_{v'}$

  For $v' \in V'$:

    If $\frac{d_{r,o_{v'}}}{s} + e_{v'} > t_l$:

      Generate cuts (2.43), $t_e \leftarrow \frac{d_{r,o_{v'}}}{s} + e_{v'},\ t_l \leftarrow l_{v'} - \frac{d_{r,d_{v'}} + d_r}{s}$

    Else:

      $t_e \leftarrow \frac{d_{r,o_{v'}}}{s} + e_{v'},\ t_l \leftarrow \min\left\{l_{v'} - \frac{\left(d_{r,d_{v'}} + d_r\right)}{s}, t_l\right\}$

    End if

  End for

End for

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