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Autonomous Truck Scheduling and Platooning Considering Cargo Consolidation

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Abstract: Thanks to advancements in automated driving technology, autonomous trucks (ATs) can form platoons with minimal inter-vehicle distances on highways, significantly reducing air drag and fuel consumption for fleets. Given the dispersed distribution and small quantities of cargo, fleet operators should manage ATs to enable cargo consolidation during platooning. In this way, fleet operators can enhance operational efficiency and reduce fuel consumption. This study addresses the AT scheduling and platooning problem considering cargo consolidation. The problem is the scheduling of ATs to transport cargo while consolidating cargo and forming platoons between two terminals, all while minimizing operational costs. A mixed-integer linear programming (MILP) model is formulated for the proposed problem. In addition, we conduct extensive numerical experiments to evaluate the proposed model. The results show that Gurobi can solve instances with different sizes to optimality or near-optimality. Impact analysis is also conducted to explore the influences of several factors, such as maximal platoon size and the load capacity of AT, on the system performance and to provide managerial insights.

Keywords: autonomous truck; scheduling and platooning; cargo consolidation; MILP model

MSC: 90B06

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1. Introduction

The trucking industry is a cornerstone of the national economy, facilitating cargo transportation on highways. Emerging autonomous trucks (ATs) promise to revolutionize the industry by improving cargo transportation efficiency and reducing operational costs through the maintenance of optimal speeds, as well as controlled acceleration and deceleration. Estimates suggest that ATs could lower transportation costs by 25% and increase truck flow efficiency by 11% [1]. Additionally, advanced automated driving technology enables ATs to form platoons, traveling closely together to reduce fuel consumption due to diminished aerodynamic drag. Advanced control systems, real-time communication, and adaptive mechanisms play a pivotal role in maintaining stability within a platoon of autonomous trucks. These technologies enable precise coordination, ensuring consistent spacing, smooth acceleration, and braking. By addressing external disturbances and dynamic maneuvers, such as merging or speed changes, they ensure safe and efficient platoon operations. Figure 1 presents a truck platoon, where each truck maintains a short inter-vehicle distance to save fuel consumption. Pilot truck platooning field tests have shown that, in a two-truck platoon, the follower truck experiences the most fuel savings, while the lead truck benefits less [2–4]. Ref. [5] demonstrated that 65.6% of the total miles driven by ATs in the U.S. were platoonable, leading to an annual fuel consumption saving of 2.7%. With the rapid development of global trade and increasing transport demand, effectively managing AT fleets to leverage platooning technology is a crucial challenge for the trucking industry.

Figure 1. The truck platoon [6].

1.1. Literature Review

Over the past decade, many studies have explored how fleets can manage their ATs to perform cargo transportation using platooning technology. Ref. [7] was the first to propose a platoon planning problem aimed at maximizing the platoon opportunities for trucks. Ref. [8] investigated a general truck scheduling and platooning problem (TSPP) to optimize a truck fleet's schedules on a fixed path, minimizing total operational costs given each truck's departure time window. Departing earlier than the earliest departure time and departing later than the latest departure time were not permitted. Each truck was assumed to be homogenous, consuming the same amount of fuel and benefiting from fuel savings as either a leading or following truck when traveling along the road link. The truck speed was assumed constant such that they only optimized the truck departure times at the start point of the fixed path. They formulated a mixed integer programming (MIP) model and developed efficient algorithms to address the TSPP. A computational study examined the effects of platooning, maximum platoon length, and time window tightness on platooning efficiency from the start to the destination of a fixed path. Ref. [9] addressed the TSPP with travel time uncertainty, aiming to minimize total costs. They proposed a model and conducted numerical experiments to evaluate the benefits of truck platooning, providing valuable insights for transport planners and logistics managers. Additionally, the TSPP has been extended to a network level, incorporating the truck routing problem. Related studies have formulated various mathematical models and developed efficient algorithms [10–14]. Additionally, truck platooning has been explored in the container drayage problem, where carriers use platooning strategies for container pickup and delivery services for shippers and consignees [15–17].

Although various studies on truck platooning have been conducted, none of them have considered cargo consolidation. Cargo consolidation by trucks is a strategic move that can achieve various benefits, especially for long-haul transportation, such as improved operational efficiency, enhanced service offerings, and cost savings [18]. This process allows for the consolidation of cargo from various sources, enabling the more efficient use of truck capacities and reducing the number of trips required. In addition, cargo consolidation facilitates the better synchronization of vehicle departures, naturally creating opportunities for platooning as ATs wait to accumulate sufficient cargo. Therefore, fleet operators should incorporate cargo consolidation into AT scheduling for platooning on highways.

In fact, cargo consolidation has been considered in the classic pickup and delivery problem (PDP). The problem is to determine the service route and schedule for vehicles to pick up less-than-truckload cargos from origin locations and deliver them to destination locations. Various mathematic models have been formulated for the PDP [19–22]. For example, ref. [22] formulated a multi-objective mixed integer programming model based on a time-space network and developed a novel algorithm integrating K-means clustering, Genetic Algorithm, forward dynamic programming, and an improved Shapley value method to solve a PDP. However, none of these studies have considered the potential of vehicle platooning, which requires the temporal and special synchronization of participant vehicles. As the schedules of different vehicles are interdependent with one another, the TSPP with cargo consolidation is a nontrivial extension of the PDP for model formulation.

1.2. Objective and Contributions

To address the identified research gap, this study explores the AT scheduling and platooning problem considering cargo consolidation, thereafter referred to as the TSPP-C. ATs are required to transport less-than-truckload cargo between two terminals. During the transportation process, ATs can form platoons with one another by waiting at the origin terminal. Additionally, ATs can perform cargo consolidation at the origin terminal. We also assume that truckload change caused by cargo consolidation affects the fuel consumption of ATs. Given the information of ATs, i.e., self-weight, load capacity, the origin terminals, destination terminals, and the time windows of the departure times at origin terminals, and the information of cargo, i.e., quantity, the supplier terminals, customer terminals, and the time windows for cargo pickup, an optimal schedule and platoon plan of ATs and a consolidation plan of cargos are determined to minimize the total fuel cost in this study.

To achieve our objective, we develop an MILP model to formulate the TSPP-C. The contributions of this study are summarized as follows. First, we introduce a new problem that considers cargo consolidation in the TSPP, which has not been explored in the existing literature. Second, we propose an effective MILP model to formulate the TSPP-C. Third, extensive numerical experiments have been carried out to evaluate the effectiveness of the proposed model, investigate the impacts of several key factors on system performance, and provide managerial insights.

The remainder of this study is structured as follows. Section 2 outlines the problem description with assumptions and notations for the TSPP-C. The MILP model is presented in Section 3. Section 4 analyzes the efficacy of the proposed model and examines the impacts of two key factors on system performance. Finally, conclusions and future research directions are discussed in Section 5.

2. Assumptions, Notations, and Problem Description

We consider a fleet operator to manage several ATs providing a cargo transportation service on a highway between terminal A and terminal B, which is illustrated in Figure 2, for suppliers and customers. During transportation, ATs can form platoons on the highway and perform cargo consolidation. We focus on solving the TSPP-C from terminal A to terminal B since the TSPP-C from terminal B to terminal A can be solved in the same way. To further describe the TSPP-C, we first present the details of AT and cargo. Afterward, we will introduce AT platooning.

Figure 2. The terminals and highway.

2.1. AT and Cargo Consolidation

The set of ATs, denoted as $\boldsymbol{V}$, comprises fully autonomous vehicles that are homogeneous in specification and configuration. As we focus on solving the TSPP-C from terminal A to terminal B, each AT $v \in \boldsymbol{V}$ should transport cargo from terminal A to terminal B if it has cargo to transport. Each AT $v \in \boldsymbol{V}$ has self-weight m_v, load capacity u_v, and a time window for AT departing from terminal A $[\tau_v, \tau_v']$. AT $v \in \boldsymbol{V}$ has to start transporting cargo from terminal A no earlier than τ_v and no later than τ'_v if it has cargo to transport, otherwise the AT should not be put into operation. The ATs are assumed to travel at a free-flow speed on the highway. The set of cargos is represented as $\boldsymbol{R}$. Each cargo $r \in \boldsymbol{R}$ has a quantity q_r and a time window for cargo pickup at terminal A $[a_r, b_r]$. All cargos are less-than-truckload, implying that $q_r, \forall r \in \boldsymbol{R}$ is always smaller than $u_v, \forall v \in \boldsymbol{V}$.

Cargo consolidation refers to the process of aggregating cargos from multiple suppliers into fewer vehicles to optimize vehicle capacity utilization, reducing the number of trips and operation costs. As the time window for cargo pickup may conflict with the schedules of ATs when considering cargo consolidation, the feasibility and flexibility of the AT schedules may be affected. Therefore, cargo consolidation requires careful coordination with platooning and scheduling by fleet operators. Furthermore, the natural waiting time for cargo consolidation allows for the better synchronization of vehicle departures, creating opportunities for platooning. In addition, cargo should be consolidated at terminal A and delivered to terminal B by ATs, which satisfies the pickup time windows at terminal A. Based on the stated information, we can formulate spatial and temporal itineraries of ATs and cargo. The binary variable x_v is defined as 1 if AT $v \in \boldsymbol{V}$ departs from terminal A, and 0 otherwise. The continuous time variable t_v indicates the time instant at which the AT v starts transport from terminal A. The binary variable y_{vr} is equal to 1 if cargo $r \in \boldsymbol{R}$ is loaded in AT $v \in \boldsymbol{V}$ from terminal A to terminal B, and 0 otherwise. Specifically, if there is cargo transported by an AT on an arc, this AT must traverse the arc synchronously:

$$y_{vr} \leq x_v, \quad \forall v \in \boldsymbol{V}, r \in \boldsymbol{R}. \tag{1}$$

In addition, the following constraint restricts that the load capacity of ATs should not be exceeded:

$$\sum_{r \in \boldsymbol{R}} q_r y_{vr} \leq u_v x_v, \quad \forall v \in \boldsymbol{V}. \tag{2}$$

2.2. AT Platooning

To maximize fuel savings from platooning, we assume that ATs can wait at terminal A for an indefinite period to join or form a platoon. As the travel speed of ATs is assumed to be a constant free-flow speed on the highway, indicating there is no disturbance from other vehicles during transportation, platoons can be formed by synchronizing the departure times of ATs at terminal A and the formation of platoons can only occur at terminal A as AT cannot accelerate or decelerate. In addition, once a platoon is formed, its formation remains fixed; therefore, ATs in the platoon cannot merge with other vehicles. When ATs form a platoon, the lead AT will experience a lower rate of fuel savings, whereas all follower ATs will benefit from a uniform, higher rate of fuel savings. Besides the AT position in a platoon, many factors like truckload affect the fuel consumption in the TSPP-C. Based on the fuel consumption model proposed by [23], ref. [24] provided a fuel consumption rate equation of trucks, which included various parameters such as total vehicle weight, travel speed, vehicle structure, etc. Later, considering truck platooning, ref. [9] introduced a reduction factor of air resistance σ in the fuel consumption rate equation as follows:

$$F_r = \frac{\zeta}{\kappa\eta}\left(kN_eV + \frac{0.5c_d\rho A\nu^3(1-\sigma) + M\nu(g\sin\alpha + gc_r\cos\alpha)}{1000\varepsilon\varpi}\right), \tag{3}$$

where ζ represents the fuel-to-air mass ratio, κ is the heating value of the fuel, η is a conversion factor from grams to liters, k is the engine friction factor, N_e is the engine speed, V is the engine displacement, ρ is the air density, A is the vehicle front area, ν is speed, M is the total vehicle weight, g is the gravitational constant, α is the road gradient, c_d is the coefficient of aerodynamic drag, c_r is coefficient of rolling resistance, ε is vehicle drivetrain efficiency, and ϖ is the engine efficiency parameter.

Next, we develop the fuel consumption equation (unit: liter) as $F = F_r \cdot \frac{D}{v}$ where D is the length of the highway:

$$F(M, \sigma) = f_1 - f_2\sigma + f_3 M, \tag{4}$$

where σ is the reduction factor of air resistance, $f_1 = \zeta DkN_e V/\kappa\eta\nu$, $f_2 = 0.5\zeta Dc_d\rho A\nu^2 (1-\sigma)/(1000\kappa\eta\varepsilon\varpi)$, and $f_3 = \zeta DM(g\sin\alpha + gc_r\cos\alpha)/(1000\kappa\eta\varepsilon\varpi)$ are composite coefficients for the convenience of presentation.

To formulate AT platooning, we propose additional decision variables. We define that the binary decision variable p_{vw} is equal to 1 if AT $v \in \boldsymbol{V}$ travels somewhere behind AT $w \in \boldsymbol{V}$ in the same platoon on the highway, and 0 otherwise. To further present ATs with different positions in a platoon, we define two more binary decision variables. We define binary variable α_v as equal to 1 if AT $v \in \boldsymbol{V}$ leads a platoon on the highway, and 0 otherwise. Let binary variable β_v equal 1 if AT $v \in \boldsymbol{V}$ trails behind some truck(s) in a platoon on the highway, and 0 otherwise. Let σ_l and σ_f denote the reduction parameters of air resistance for lead and follower AT. Given that fuel weight constitutes a marginal portion of the total vehicle weight, especially for heavy-duty trucks, we assume that the variations in fuel weight will not influence the fuel consumption of ATs. Therefore, the transportation cost TC_v of AT $v \in \boldsymbol{V}$ on the highway can be presented as follows:

$$TC_v = \pi f_1 x_v - \pi f_2(\sigma_l \alpha_v + \sigma_f \beta_v) + \pi f_3(\sum_{r \in \boldsymbol{R}} q_r y_{vr} + m_v x_v), \tag{5}$$

where π represents the USD price for fuel per liter.

Therefore, to form a platoon, ATs v and w should simultaneously depart from terminal A:

$$2p_{vw} \leq x_v + x_w, \quad \forall v, w \in \boldsymbol{V}, v \neq w, \tag{6}$$

$$-M_1(1 - p_{vw}) \leq t_v - t_w \leq M_1(1 - p_{vw}), \quad \forall v, w \in \boldsymbol{V}, v \neq w, \tag{7}$$

where M_1 is a sufficiently large parameter satisfying $M_1 \geq \max\{\tau'_v | v \in \boldsymbol{V}\} - \min\{\tau_v | v \in \boldsymbol{V}\}$. In addition, to further define the relative position relationship between AT v and AT w when they are platooned, the following constraints must be satisfied:

$$p_{vw} + p_{wv} \leq 1, \quad \forall v, w \in \boldsymbol{V}, v \neq w, \tag{8}$$

$$\sum_{k \in \boldsymbol{V}, k \neq v} p_{vk} - \sum_{k \in \boldsymbol{V}, k \neq w} p_{wk} \geq 1 - M_2(1 - p_{vw}), \quad \forall v, w \in \boldsymbol{V}, v \neq w, \tag{9}$$

where M_2 is a sufficiently large parameter satisfying $M_2 \geq |\boldsymbol{V}|$. Moreover, the size of a platoon cannot exceed the maximum limit:

$$\sum_{w \in \boldsymbol{V}, w \neq v} p_{vw} + 1 \leq s, \quad \forall v \in \boldsymbol{V}, \tag{10}$$

where s is the maximal size of a platoon on the highway.

We calculate the number of ATs traveling ahead of and behind AT v in the same platoon along the highway, represented by A_v and B_v:

$$A_v = \sum_{w \in \boldsymbol{V}, w \neq v} p_{vw}, \quad \forall v \in \boldsymbol{V}, \tag{11}$$

$$B_v = \sum_{w \in \boldsymbol{V}, w \neq v} p_{wv}, \quad \forall v \in \boldsymbol{V}. \tag{12}$$

Let M_3 be a sufficiently large parameter satisfying $M_3 \geq s-1$. For the follower AT, we have constraints to determine its position in the platoon as follows:

$$\beta_v \leq x_v, \quad \forall v \in \boldsymbol{V}, \tag{13}$$

$$\frac{A_v}{M_3} \leq \beta_v \leq A_v, \quad \forall v \in \boldsymbol{V}, \tag{14}$$

where constraint (13) ensures that an AT can only be designated as a follower AT in a platoon if it traverses the highway; constraint (14) indicates that if AT v has at least one vehicle traveling ahead of it in the same platoon, it must be a follower AT. Otherwise, AT v cannot be a follower AT.

For the lead AT, we have constraints to determine its position in the platoon as follows:

$$\alpha_v \leq x_v, \quad \forall v \in \boldsymbol{V}, \tag{15}$$

$$\alpha_v \leq B_v, \quad \forall v \in \boldsymbol{V}, \tag{16}$$

$$\alpha_v \leq 1 - \frac{A_v}{M_3}, \quad \forall v \in \boldsymbol{V}, \tag{17}$$

$$\alpha_v \geq \frac{B_v}{M_3} - A_v, \quad \forall v \in \boldsymbol{V}, \tag{18}$$

where constraint (15) ensures that an AT can only be designated as a lead AT in a platoon if it traverses the highway, constraint (16) represents that if there are vehicles traveling behind AT v in the same platoon, AT v has the potential to be a lead AT, and constraints (17) and (18) ensure that AT v can be a lead AT only if it has no vehicle traveling ahead of it and has vehicles traveling behind it in the same platoon.

The notations in this study are summarized in Table 1.

Table 1. Problem notations.

Parameters	
$\boldsymbol{V}$	Set of ATs
$\boldsymbol{R}$	Set of cargos
τ_v, τ'_v	Earliest departure and latest departure time for AT $v \in \boldsymbol{V}$
m_v	Self-weight of AT $v \in \boldsymbol{V}$
u_v	Load capacity of AT $v \in \boldsymbol{V}$
q_r	Quantity of cargo $r \in \boldsymbol{R}$
$[a_r, b_r]$	Pickup time window for cargo $r \in \boldsymbol{R}$
D	Length of highway
f_1, f_2, f_3	Composite coefficients related to travel speed, engine structure, and road condition
σ_l, σ_f	Reduction parameters of air resistance for lead and follower AT
π	USD price for fuel per liter
s	Maximal size of a platoon on the highway
Variables	
x_v	Binary variable indicating whether AT $v \in \boldsymbol{V}$ traverses the highway
y_{vr}	Binary variable indicating whether AT $v \in \boldsymbol{V}$ traverses the highway with cargo $r \in \boldsymbol{R}$
p_{vw}	Binary variable indicating whether AT $v \in \boldsymbol{V}$ will follow AT $w \in \boldsymbol{V}$ over the highway
λ_v	Binary variable indicating whether AT $v \in \boldsymbol{V}$ will lead a platoon over the highway
β_v	Binary variable indicating whether AT $v \in \boldsymbol{V}$ follows some truck(s) over the highway
t_v	Continuous variable indicating the time AT $v \in \boldsymbol{V}$ starts traversing the highway

3. Model Formulation

With the above-mentioned decision variables and parameters, we formulate a MILP model for the TSPP-C as follows:

[TSPP-C]

$$\min \quad \sum_{v\in \boldsymbol{V}} [\pi f_1 x_v - \pi f_2(\sigma_l \alpha_v + \sigma_f \beta_v) + \pi f_3(\sum_{r\in \boldsymbol{R}} q_r y_{vr} + m_v x_v)] \tag{19}$$

subject to constraints (1) and (2), (6)–(18), and

$$x_v \le 1, \quad \forall v \in \boldsymbol{V}, \tag{20}$$

$$\sum_{v\in \boldsymbol{V}} y_{vr} \ge 1, \quad \forall r \in \boldsymbol{R}, \tag{21}$$

$$\tau_v x_v \le t_v \le \tau'_v x_v + M_4(1 - x_v), \quad \forall v \in \boldsymbol{V}, \tag{22}$$

$$a_r y_{vr} \le t_v \le b_r y_{vr} + M_4(1 - y_{vr}), \quad \forall v \in \boldsymbol{V}, r \in \boldsymbol{R}, \tag{23}$$

$$x_v, \alpha_v, \beta_v, p_{vw}, y_{vr} \in \{0, 1\}, \quad \forall v, w \in \boldsymbol{V}, r \in \boldsymbol{R}, \tag{24}$$

$$t_v \ge 0, \quad \forall v \in \boldsymbol{V}. \tag{25}$$

Constraint (20) indicates that ATs are not compulsory to depart from terminal A. Constraint (21) indicates that each cargo must be transported from terminal A to terminal B. Constraint (22) indicates that ATs must depart from terminal A within the departure time window if required to transport cargo, where M_4 is a sufficiently large parameter satisfying $M_4 \ge \max_{v\in \boldsymbol{V}}\{\tau'_v\} - \min_{v\in \boldsymbol{V}}\{\tau_v\}$. Constraint (23) implies that there must be an AT to pick up the cargo at terminal A in the pickup time windows. Constraints (24) and (25) define the domains of the decision variables.

4. Numerical Experiments

This section presents the results of extensive numerical experiments on randomly generated instances. The mathematical model proposed in this study is implemented in Gurobi 11.0 via C++. We first give the experiment settings, including the values of parameters and details of instance generation. Then, we evaluate the proposed model [TSPP-C] on instances with different sizes. Finally, we provide an impact analysis to investigate the impact of two influential factors: maximal platoon size (platoon capacity) and the load capacity of AT. Numerical experiments are implemented in C++ and executed on a personal computer equipped with an Intel(R) Xeon(R) W-2102, 2.90 GHz CPU, and 16 GB of RAM.

4.1. Instance Generation

We generate a highway with a length of 240 km from terminal A to terminal B. We set the free-flow speed of ATs as 80 km/h. The self-weight and the load capacity of each AT are assumed to be 1.5×10^4 kg and 3×10^4 kg, respectively. The values of other parameters in Equation (3) are chosen from a previous study by [15]. The load of each cargo is randomly distributed in the range of $[1 \times 10^3, 5 \times 10^3]$ (unit: kg), safely within the typical load range for less-than-truckload transportation to terminals [25]. The fuel price per liter is assumed to be USD 1.3. The maximal size of a platoon on each road link is set to be 3. The reduction factors of air resistance for the lead and follower AT are assumed to be 0.1 and 0.5, respectively.

To reflect the general performance of the proposed model, we randomly generate five instances for each group with the same number of ATs and cargos. We set the length of scheduling time for instances as 12 (unit: hour). The time windows for ATs are set with a relatively large gap. To test the general performance of the proposed model, for each AT $v \in \boldsymbol{V}$, τ_v is randomly distributed in the first three hours, while τ'_v is randomly distributed in the last three hours, which aligns with the morning departures and evening arrivals of trucks in cargo transportation [26,27]. For the time window of cargo, we randomly set the earliest departure time and the latest departure time in the interval of $[0, 12 - ST]$ (unit: hour), where ST denotes the travel time across the highway. The instance groups are labeled by the number of ATs $|\boldsymbol{V}|$, the number of cargos $|\boldsymbol{R}|$, and the identification number ID, named by "$|\boldsymbol{V}|$-$|\boldsymbol{R}|$-ID", e.g., "5-10-3" means No.3 instance group with 5 ATs and 10 cargos.

4.2. Computational Performance

Tables 2 and 3 display the computational results of small-size and large-size instances computed by Gurobi. The maximum computation time for Gurobi is 3600 s. The column "Obj (USD)" indicates the objective value of the best solution computed by Gurobi. The column "Time (s)" indicates the computation time of Gurobi for obtaining the best solution. The column "Gap" gives the solution gap computed by Gurobi. Note that Gap = 0 means the optimal solution is found by Gurobi.

Table 2. Computational results for small-size instances.

Instance Group	Obj (USD)	Time (s)	Gap	Instance Group	Obj (USD)	Time (s)	Gap
5-10-1	505	1	0.00%	10-40-1	804	42	0.00%
5-10-2	586	1	0.00%	10-40-2	872	79	0.00%
5-10-3	678	1	0.00%	10-40-3	684	22	0.00%
5-10-4	554	1	0.00%	10-40-4	676	19	0.00%
5-10-5	554	1	0.00%	10-40-5	772	6	0.00%
5-20-1	623	1	0.00%	10-60-1	989	2810	0.00%
5-20-2	530	2	0.00%	10-60-2	893	2110	0.00%
5-20-3	439	1	0.00%	10-60-3	868	618	0.00%
5-20-4	535	2	0.00%	10-60-4	947	1411	0.00%
5-20-5	535	1	0.00%	10-60-5	868	853	0.00%

Table 3. Computational results for large-size instances.

Instance Group	Obj (USD)	Time (s)	Gap	Instance Group	Obj (USD)	Time (s)	Gap
15-80-1	1276	3600	1.83%	30-200-1	2860	3600	4.04%
15-80-2	1140	3600	1.90%	30-200-2	2750	3600	2.98%
15-80-3	1140	3600	1.96%	30-200-3	2769	3600	3.89%
15-80-4	1156	3600	1.73%	30-200-4	3012	3600	3.43%
15-80-5	1173	3600	1.90%	30-200-5	2746	3600	3.43%
15-100-1	1563	3600	1.57%	30-240-1	3325	3600	4.60%
15-100-2	1408	3600	1.53%	30-240-2	3415	3600	3.05%
15-100-3	1402	3600	1.51%	30-240-3	3452	3600	4.58%
15-100-4	1461	3600	2.26%	30-240-4	3406	3600	4.14%
15-100-5	1456	3600	2.40%	30-240-5	3402	3600	3.34%

According to computational results in Table 2, we can see that Gurobi can solve the instances to optimality within 3600 s due to the manageable problem size and fewer decision variables. This demonstrates that Gurobi reliably finds optimal solutions for small-scale problems. As the number of ATs and cargo increases, the required computation time grows correspondingly. The instances with 5 ATs and 10 cargos consume the least computation time, with an average time of 1 s. The rapid computation times make this approach highly practical for real-time decision-making in small-scale applications. For instance, such efficiency could be beneficial in logistics systems requiring dynamic and frequent re-optimization. However, when the number of ATs increases to 10 and the number of cargos increases to 60, although Gurobi can solve them to optimality within 3600 s, the average computation time becomes around 1560 s. Moreover, according to computational results in Table 3, none of the instances were solved to optimality within the 3600 s time limit using Gurobi, highlighting scalability challenges as the problem size increases. The rise in the instance size significantly impacts Gurobi's performance. For example, the "30-240" group consistently shows larger gaps, indicating that solution quality deteriorates as problem complexity increases. However, the relatively small Gap values for large-scale instances, ranging from 1.53% to 4.14%, suggest that near-optimal solutions are achieved even for complex problems and the proposed methodology can be effectively applied to practical problems. It is worth noting that the fixed time limit of 3600 s may only allow Gurobi to reach near-optimal solutions for larger problem instances.

As Gurobi may encounter difficulties with larger problem instances due to their complexity, heuristic and metaheuristic approaches, such as Genetic Algorithms (GA) and Simulated Annealing (SA), can be used. For example, in the case of a Genetic Algorithm (GA), each individual in the population, referred to as a "chromosome", represents a potential solution to the problem. This solution may encode key elements, such as the sequence of trucks, cargo assignments, and platooning groups. Specifically, a chromosome could define the order in which trucks pick up and deliver goods, as well as the specific platooning schedule to minimize fuel costs. The selection process in a GA involves evaluating each chromosome's fitness, which is determined by how well the solution meets the problem's objectives (e.g., minimizing fuel consumption). Solutions that perform well are given a higher probability of being selected to produce offspring. The crossover operator is then used to combine features from two parent chromosomes, generating offspring that may exhibit improved performance compared to their parents. This process allows the algorithm to explore a wider solution space and potentially find better solutions. To further enhance exploration and avoid converging prematurely on local optima, the GA introduces random mutations, such as reordering the truck schedule or reassigning cargo. These small random changes help to diversify the search process, ensuring that the algorithm does not become stuck in suboptimal solutions.

4.3. Impact Analysis

We conduct an impact analysis on two influential factors in the TSPP-C: the maximal size of the platoon (i.e., platoon capacity) and the load capacity of AT. The number of platoons, the number of ATs in operation, and the transportation cost are presented. We apply the Gurobi to test the instances with 30 ATs and 240 cargos.

To examine the effects of platoon capacity on the system performance, we analyze the solutions for the TSPP-C with varying platoon capacities by setting $s \in \{1, 2, 3, 4\}$ in constraint (10). The results are shown in Figure 3. Note that platooning is not permitted in the TSPP-C if the platoon capacity is 1. It is evident that increasing platoon capacity reduces operational costs, underscoring the fuel-saving benefits of platooning. We observe that there exists a threshold ($s = 2$) beyond which further increases in platoon capacity will not result in additional cost savings and the platoon number increasing. Therefore, for instances involving up to 30 ATs and 240 cargos, a platoon capacity of two should be sufficient to minimize total fuel cost.

For the load capacity of AT, we will examine the solutions for the TSPP-C with different load capacities of AT by setting $u_v \in \{2.5, 3, 3.5, 4\}$ (unit: 10^4 kg). The results are displayed in Figure 4. It can be seen that increasing the load capacity leads to a reduction in transportation costs, suggesting that a larger load capacity improves transportation efficiency. This is consistent with our expectation that a larger load capacity results in a higher degree of cargo consolidation. In addition, there is a declining trend in the number of ATs in operation as the load capacity increases. It starts from about 27 ATs at a load capacity of 2.5×10^4 kg and decreases to approximately 20 ATs at a load capacity of 4.0×10^4 kg, implying that cargo consolidation leads to transportation resource savings. Moreover, the platoon number remains constant across different load capacities, indicating that changes in load capacity do not affect the number of platoons.

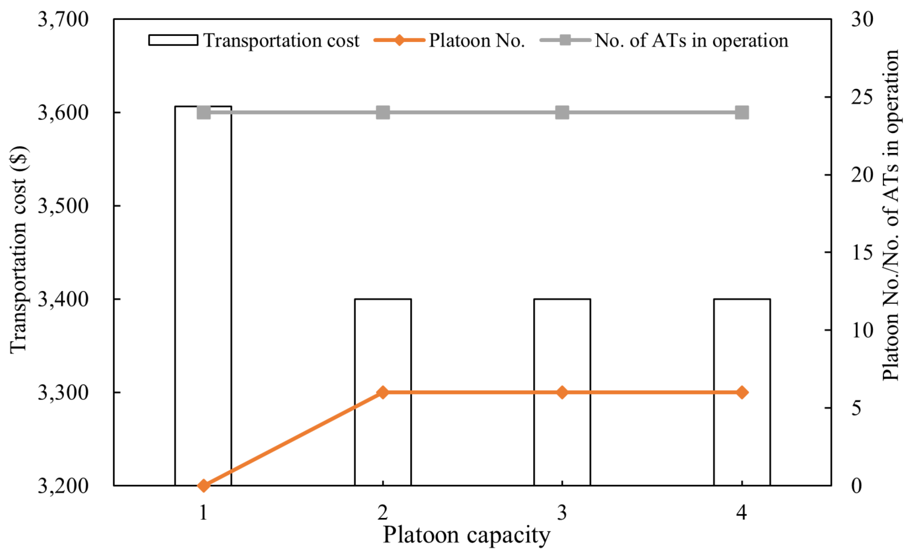

Figure 3. Impact analysis on platoon capacity.

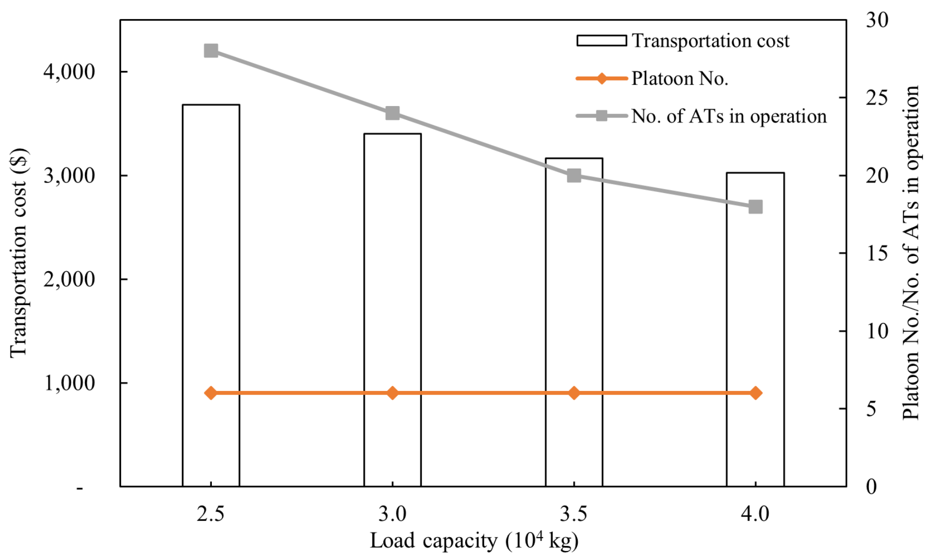

Figure 4. Impact analysis on load capacity.

5. Conclusions

This study investigates the AT scheduling and platooning problem while considering cargo consolidation. ATs transport less-than-truckload cargo from supplier terminals to customer terminals on a highway, forming platoons and performing cargo consolidation to minimize the total operation cost. An effective MILP model is proposed for the problem, which is implemented by Gurobi. Extensive numerical experiments are performed to validate the effectiveness of the model. The results show that small-scale instances (less than 10 cargos and 60 ATs) are solved to optimality within 3600 s while large-scale instances (more than 10 cargos and 60 ATs) are solved to near-optimality, with an average gap of less than 5%. An impact analysis is conducted to assess the effects of several key factors on system performance and to provide managerial insights.

We provide a detailed analysis of the associated costs and benefits. Costs associated with this method include capital investments. Autonomous vehicles require advanced sensors, computing systems, and specialized maintenance, leading to elevated capital expenditures. The establishment of platooning systems necessitates communication infrastructure to ensure precise vehicle synchronization. Additionally, integrating cargo consolidation systems requires further financial investment. On the operational side, ongoing costs include regular maintenance, software updates, and personnel training, as human oversight remains indispensable for monitoring and managing the system. Despite the upfront costs, the benefits of this method are substantial. The elimination of driver requirements in autonomous trucking significantly reduces labor costs. Platooning decreases fuel consumption by minimizing aerodynamic drag, while cargo consolidation improves transportation efficiency and further reduces operational expenses. Environmentally, the method lowers fuel consumption, thereby reducing greenhouse gas emissions. Furthermore, the system enhances safety by reducing human error and creating predictable traffic patterns, lowering the risk of accidents. In conclusion, while the upfront costs are high, the long-term benefits—such as labor savings, fuel efficiency, and environmental sustainability—make autonomous truck scheduling and platooning systems a potentially transformative solution for the logistics industry. Proper implementation and pilot programs will be crucial for realizing these benefits effectively.

Future research directions include the following. First, efficient algorithms need to be developed to address instances involving large numbers of cargo and ATs. Second, given that cargo transportation often spans large areas with multiple intersections and road links, the TSPP-C can be extended to a network-based AT routing and platooning framework. Third, to address fluctuations in cargo transportation demand, future research can explore dynamic planning for truck platooning combined with cargo consolidation using real-time optimization methods.

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