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Efficient Hub-Based Platooning Management Considering the Uncertainty of Information

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Abstract: Platooning technology, which reduces fuel consumption by decreasing aerodynamic drag, is emerging as a key solution for enhancing road efficiency and environmental sustainability in logistics. Conventional vehicle-to-vehicle communication has limitations when forming platoons across multiple trucking companies. To overcome these limitations, a hub-based platooning system has been proposed, enabling coordinated vehicle platoons through hubs distributed along highways. This study develops a mathematical model to optimize platoon formation at hubs, considering the reality that uncertainty in vehicle arrival times can be resolved as vehicles approach the hub and use vehicle-to-hub communication. The model applies robust optimization techniques to consider worst-case vehicle arrival scenarios and examine how the range of data exchange points—where exact arrival times become known—affects platoon efficiency. Numerical experiments demonstrate that if the range of data exchange points is sufficiently wide, optimal efficiency can be achieved even under uncertainty. Sensitivity analysis also confirms that reducing uncertainty enhances energy savings efficiency. This study provides practical insights into forming vehicle platoons in uncertain environments, contributing to the economic and environmental benefits of the logistics industry. Future studies could extend the model to multiple hubs and consider stochastic disruptions, such as communication failures.

Keywords: hub; platooning; energy savings; mathematical model; robust optimization; uncertainty; data exchange points; vehicle-to-hub communication

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1. Introduction

Platooning technology, which involves the grouping of multiple vehicles to enhance fuel efficiency and optimize road usage through coordinated driving, has garnered considerable attention in the fields of transportation and logistics [1]. By minimizing aerodynamic drag through the synchronized movement of a lead vehicle and its trailing vehicles, platooning significantly reduces fuel consumption [2]. This reduction in air resistance not only contributes to energy savings but also promotes environmental sustainability. Moreover, the economic advantages, such as lower operational costs, make platooning an attractive option for logistics companies. Additionally, traffic management authorities view this technology as a promising solution for improving road traffic efficiency. Consequently, platooning is emerging as an innovative approach to address both economic and environmental challenges in modern transportation systems [3].

Previous research on platooning has predominantly focused on cooperative driving facilitated by vehicle-to-vehicle (V2V) communication. For instance, Lee et al. [4] demonstrated the fuel-saving potential of platooning among heterogeneous vehicles, while Chen et al. [5] observed similar benefits when combining automated and human-driven vehicles. These studies emphasize the role of direct communication between vehicles to maximize fuel efficiency through platooning. A drone-based decentralized platooning system using ultra-wideband technology has been proposed, addressing the latency and scalability issues of V2V communication [6]. In addition to V2V communication, there have been several studies on control systems, such as Li et al. [7], who proposed a solution for controlling platoons under denial-of-service attacks, and Villenas et al. [8], who implemented a control system for string stability of platoons. However, these systems are insufficient to enable coordinated planning across multiple trucking companies. Greater efficiency can be achieved through cooperation between companies, as this increases the opportunities to form larger and more efficient platoons.

To address these limitations, hub-based platooning systems have recently been proposed as a more structured approach to platoon management [9]. Unlike traditional V2V communication, hub-based systems facilitate information exchange between vehicles and a central hub. In this system, vehicles provide the hub with key information—such as estimated arrival times, required departure times to meet delivery deadlines, and vehicle types—before their arrival. The hub then processes these data to form optimal platooning configurations, thereby enhancing energy savings for all participating vehicles.

Hub-based platooning is particularly advantageous when fleets from multiple logistics companies utilize the same hub [10]. The hub can synchronize arrival schedules and operating times for vehicles from different companies, maximizing the collective benefits of platooning while improving overall logistical and traffic management efficiency [11]. This system not only increases the likelihood that individual vehicles will join a platoon but also enables hubs to predict and organize platooning groups based on vehicle arrival times and routes.

This study seeks to optimize the hub-based platooning system by investigating how hubs can effectively manage vehicle information to form optimal platoon groups, even under conditions of uncertainty. A mathematical model is developed to simulate the hub-based platooning system, and various scenarios are analyzed to assess the efficiency of platoon formation. Additionally, a decision-making framework is proposed to help hubs optimize platooning in the face of uncertain information, ensuring the system's robustness and operational efficiency.

This paper is organized as follows: In Section 2, previous studies on vehicle platooning are reviewed. In Section 3, the problem description, notation, mathematical model, and robust optimization are presented. In Section 4, the numerical experiments are presented to verify the optimal solution when the uncertainty of the arrival times of vehicles entering the hub varies or when the extent to which the arrival times of vehicles are known exactly (range of data exchange points) varies. Finally, in Section 5, the results and insights of this study are presented as conclusions.

2. Literature Review

Vehicle platooning has been widely studied due to its benefits such as reduced energy consumption and improved traffic throughput [12]. Many studies have demonstrated the effectiveness of vehicle platooning in reducing energy consumption. Hussein and Rakha [13] developed a model for homogeneous vehicles that captures the effect of vehicle position within a platoon and the distance gap between vehicles on the drag coefficient. This model was developed for light-duty vehicles (LDVs), buses, and heavy-duty trucks (HDTs). It was found that fuel savings for LDVs, buses, and HDTs were up to 5%, 17%, and 12%. Yang et al. [14] simulated the energy efficiency of passenger car platooning based on the DrivAer model. The vehicle driving equations were used to deduce a vehicle fuel efficiency model based on aerodynamic drag coefficients. The average fuel-saving rate for vehicles in the platoon was about 4-8%. Jo and Kim [15] aimed to analyze the aerodynamic interaction between vehicles forming a platoon by varying the platoon formation conditions. A total of four HDVs were driving in a platoon at 100 km/h while varying the distance gap between the vehicles. Compared to HDVs traveling alone, the stagnation pressure in front of the following vehicle and the drag forces generated by the leading and following vehicles were reduced by 51%, 56%, and 52%, respectively. Tsugawa et al. [16] analyzed the energy savings depending on the distance gap between vehicles in a platooning experiment of three or four heavy-duty trucks. Typically, when the trucks were fully loaded and traveling at 80km/h, the average fuel savings were 8% for a 10 m gap and 15% for a 4 m gap. Noruzoliaee et al. [17] found that truck platooning leads to annual cost savings of USD 868 million and a reduction in road infrastructure investment needs of USD 4.8 billion.

With the proven energy savings of vehicle platooning, many studies have been conducted to find ways to optimize the energy savings. Pi et al. [18] reviewed the literature on energy savings in vehicle platooning and analyzed two methods of energy savings. The principle of energy saving based on aerodynamics is to reduce the air resistance of vehicles by shortening the distance between vehicles. The principle of energy saving based on speed optimization is to make the engine/motor operate more efficiently by optimizing the acceleration and deceleration behavior of the vehicle. Liu et al. [19] developed a simulation–optimization framework to address the challenge of quantifying energy savings from vehicle platooning. The energy consumption model utilized a hybrid prediction formula for reducing aerodynamic drag in multi-vehicle formations. Numerical experiment results showed that focusing on forming as many platoons as possible and longer platoon lengths maximizes energy savings. Lee et al. [4] presented a platooning strategy that is optimal for energy saving for heterogeneous electric vehicles on a single route. A mathematical model-based optimization technique was used to determine the number of vehicles forming a platoon and the position of each vehicle type in the platoon. Since the type of neighboring vehicles affects the energy savings of each vehicle, it was found that a platoon configuration with a bell-shaped pattern is effective for energy savings. These studies examined how platoons should be formed and operated with V2V communication to maximize energy savings in vehicle platoons. However, since each vehicle has different origins, destinations, departure times, arrival times, vehicle owners, and so on, it is necessary to study who, where, and how to organize the vehicle platoon.

Hub-based platooning is a useful solution to the aforementioned issues. In hub-based platooning, vehicle platooning is performed at strategically placed platooning hubs along the highway network. In this case, the hubs distributed across the highway network act as platoon service providers (PSPs). A PSP is the entity that facilitates and manages the formation and operation of platoons. If vehicles with different origins and destinations overlap in their departure times from a hub, a PSP forms a platoon of these vehicles and moves them to a different hub. Larsen et al. [9] presented a model for optimizing truck platooning formed at hubs. The problem was solved using local search heuristics based on dynamic programming, and the result showed a 4-5% cost savings. However, they assumed that trucks' arrival times at hubs follow a uniform random distribution in a specific time interval. As trucks arrive near the hub, the PSP knows almost exactly when trucks will arrive at the hub from vehicle-to-hub (V2H) communication, but this is not considered. Johansson et al. [20] studied optimal hub-based platoon formation in hubs deployed along a highway. They divided into decentralized, distributed, and centralized policies based on the level of information exchange between hubs and conducted a simulation study on three hubs in northern Sweden to compare the results for each policy. The profits of the centralized policy were found to be 8% and 4.5% higher than the decentralized and distributed policies, respectively. However, they focused on hubs having prior knowledge of truck arrivals through hub-to-hub (H2H) communication and overlooked information exchange through V2H communication. Even if there is information exchange via H2H communication, the exact time of arrival is unlikely to be known until the vehicle is near the hub.

As mentioned earlier, previous research in vehicle platooning has examined how to maximize energy savings by adjusting the speed and the distance gap between vehicles forming a platoon through V2V communication [4,18,19]. This means that they focused on how to operate the formed platoon. However, the challenge is how to form a platoon when the vehicles have different origins, destinations, departure times, arrival times, and company affiliations. To address this problem, many studies have been conducted on hub-based platooning. For a PSP at a hub to plan vehicle platooning, the arrival times of vehicles entering the hub are important. Since it is difficult to perfectly predict traffic conditions, the arrival times of vehicles are subject to uncertainty. However, if a vehicle has reached the neighborhood of the hub, its arrival time can be known with certainty. Previous research on hub-based platooning overlooks this arrival time uncertainty and the extent to which the arrival time can be known precisely [9,20]. Larsen et al. [9] assumed that the arrival of a truck to a hub follows a uniform random distribution in time intervals. However, if the truck is close to the hub, the arrival time, which was uncertain, will become deterministic. Johansson et al. [20] dealt with inter-hub communication through decentralized, distributed, and centralized policies. However, even if the hub receives information about the truck that departed from the previous hub, the arrival information of the truck may vary due to the distance between the hubs. After all, communication between the vehicle and the hub must be considered.

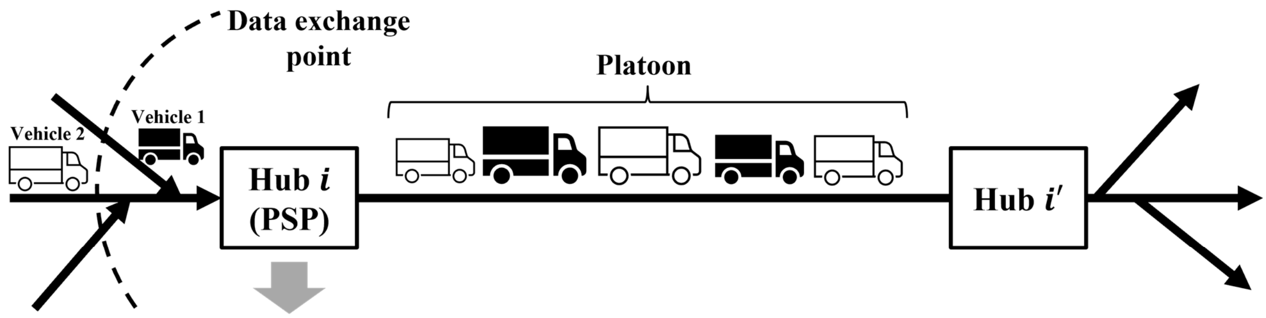
Robust optimization is a modeling methodology combined with computational tools to handle optimization problems where the data are uncertain and known to belong to a set of uncertainty sets [21]. Cao et al. [22] studied the scheduling of electric vehicle aggregators. Uncertainty in the upstream grid price was modeled using robust optimization techniques. The proposed technique enabled robust scheduling of electric vehicle aggregators. Rahbari et al. [23] aimed to develop a model of the canned food supply chain under uncertain conditions such as pandemics. They suggested the need to use a robust optimization approach to solve the uncertainty problem. Shen et al. [24] dealt with energy system optimization under uncertainty. They presented a robust optimization model by introducing a set of uncertainties into the deterministic optimization model. Despite higher energy consumption in robust optimization, the proposed method balances energy costs and robustness. As such, robust optimization is often used to reflect uncertainty.

This study aims to investigate the optimal hub-based platooning for energy savings by varying the range of data exchange points, i.e., the extent to which the arrival time of a vehicle is known precisely, in the presence of such uncertainty. To conduct the study under uncertainty, robust optimization is applied.

3. Model Development

3.1. Problem Description

A hub acting as a PSP forms vehicle platooning to maximize energy savings by assuming that each vehicle visiting the hub has different trucking companies, origins, destinations, vehicle sizes, estimated arrival time at the hub, and the latest possible time it should leave the hub. The energy savings from vehicle platooning come from reducing air resistance by having vehicles travel in platoons, keeping them closely spaced. When the arrival time of a vehicle at a hub is uncertain and the exact arrival time is only known when the vehicle enters within a certain range around the hub, which is a PSP, this enables us to analyze how to form vehicle platooning to maximize energy savings. The trucking company of the vehicles visiting the hub, the size of the vehicles, their estimated arrival time at the hub, and the latest possible time they should leave the hub are already known to the hub. Of the known information, the estimated arrival time at the hub is uncertain because it depends on traffic conditions. However, if the vehicle is within a certain range around the hub, i.e., within the data exchange range, the exact arrival time of the vehicle can be known. The origins and destinations of vehicles are ignored because traveling between hubs that are located in the middle of various origins and destinations is considered. In this work, the aim is to develop an operational strategy to form efficient vehicle platooning that maximizes energy savings, under situations where the arrival time of a vehicle to a hub is uncertain, but this uncertainty disappears when the vehicle enters within the range of data exchange points around the hub. The problem description is illustrated in Figure 1.



Vehicle No.	Company	Size	Latest departure time	Estimated arrival time	Arrival time
1	A	Small	6	[0, 4]	2
2	B	Medium	9	[3, 7]	Unknown
⋮	⋮	⋮	⋮	⋮	⋮

Platoon No.	departure time	Position in the platoon				
		1st	2nd	3rd	4th	···
1	4	Vehicle 1	Vehicle 3	Vehicle 2	X	···
2	6	Vehicle 8	Vehicle 4	Vehicle 6	Vehicle 5	···
⋮	⋮	⋮	⋮	⋮	⋮	⋮

Figure 1. Problem description.

One of the optimization techniques, ‘robust optimization’, is used to derive the results. Robust optimization is one of the optimization techniques that can be applied when making conservative decisions. It is mainly used to derive results conservatively by assuming the worst case when there is uncertainty in the model or parameters. Robust optimization is divided into the constraint robustness problem and the objective robustness problem depending on whether the uncertainty exists in the constraint or the objective function. In this study, the uncertainty of vehicle arrival time, which is a parameter included in the constraint, presents a constraint robustness problem.

3.2. Notations

In this study, a mathematical model-based optimization technique is applied to derive an optimal operating system for forming vehicle platooning. A notation to represent the decision variables, parameters, and the index set used in the developed mathematical model is defined as shown in Table 1.

Table 1. Decision variables, parameters, and index sets.

Decision Variables		
z_p	:	The time when platoon p leaves the hub
$k_{p,i}$	:	1 if vehicle i is allocated to platoon p, otherwise 0
$x_{p,o,i}$	:	1 if vehicle i is allocated to position o in platoon p, otherwise 0
$y_{p,o,i,i'}$	:	1 if vehicle i and i' is allocated to position o and $o+1$, respectively, in platoon p, otherwise 0
Parameters		
s_i^{enter}	:	Estimated arrival time of vehicle i
s_i^{out}	:	Latest possible time vehicle i should leave from the hub
$fs_{i,i'}$	:	Energy saving of vehicle i' during unit time T, when vehicle i is located in front of it in the platoon [W]
$rs_{i,i'}$	:	Energy saving of vehicle i during unit time T, when vehicle i' is located in back of it in the platoon [W]
vt_i	:	Type of the vehicle i
$mass_i$	:	Mass of the vehicle i [kg]
A_i	:	Frontal area of the vehicle i [m^2]
μ_{rr}	:	Constant of the rolling resistance
g	:	Gravity acceleration [m/s^2]
ρ	:	Air density [kg/m^3]
C_d	:	Aerodynamic drag coefficient
r	:	Time interval to know exactly when a vehicle will arrive through V2H (i.e., range of data exchange points)
tp	:	Time point that determines which platoon should leave the hub
M	:	Big number
Index sets		
I	:	Set of vehicles
T	:	Set of time
P	:	Set of platoons
O	:	Set of position in a platoon
U	:	Set of uncertainty in the arrival time of the vehicle at the hub

3.3. Mathematical Model

Equation (1) is an objective function that maximizes the energy savings during unit time caused by vehicle platooning. When two vehicles are consecutively positioned in the same platoon, the energy savings of the rear vehicle due to the front vehicle and the energy savings of the front vehicle due to the rear vehicle are summed.

$$Maximize \sum_{p=1}^{P} \sum_{o=1}^{O-1} \sum_{i=1}^{I} \sum_{i'=1}^{I} y_{p,o,i,i'} \cdot \left(fs_{i,i'} + rs_{i,i'} \right) \tag{1}$$

Equations (2)–(6) are used to calculate the energy savings of the rear vehicle due to the front vehicle and the energy savings of the front vehicle due to the rear vehicle for two consecutively positioned vehicles in the same platoon [4]. Equation (2) represents the energy consumption of a vehicle at time t in a situation without vehicle platooning. Equations (3) and (4) represent the energy consumption of the rear vehicle and the front vehicle at time t in a situation where the two vehicles are positioned consecutively in the same platoon. Equations (2)–(4) represent energy consumption at a specific point in time t. Therefore, integrating Equation (2) indicates the energy consumption during unit time T in the absence of vehicle platooning, and integrating Equations (3) and (4) indicates the energy consumption of the rear vehicle and the front vehicle during unit time T in the presence of vehicle platooning. Equations (5) and (6) represent the energy savings of the rear vehicle due to the front vehicle during unit time T and the energy savings of the front vehicle due to the rear vehicle during unit time T for two vehicles positioned consecutively in the same platoon.

$$\begin{aligned} P_i(t) \quad &= \Big[(\mu_{rr} \cdot mass_i \cdot g) + (0.5 \cdot \rho \cdot A_i \cdot C_d \cdot v(t)^2) + (mass_i \cdot g \cdot \sin(\varphi(t))) \\ &+ (1.05 \cdot mass_i \cdot a(t)) \Big] \cdot v(t) \qquad \forall i \in I \end{aligned} \tag{2}$$

$$\begin{aligned} fP_{i,i'}(t) \quad &= \Big[(\mu_{rr} \cdot mass_{i'} \cdot g) + fe_{i,i'} \cdot (0.5 \cdot \rho \cdot A_{i'} \cdot C_d \cdot v(t)^2) \\ &+ (mass_{i'} \cdot g \cdot \sin(\varphi(t))) + (1.05 \cdot mass_{i'} \cdot a(t)) \Big] \\ &\cdot v(t) \qquad \forall i, i' \in I \end{aligned} \tag{3}$$

$$\begin{aligned} rP_{i,i'}(t) \quad &= \Big[(\mu_{rr} \cdot mass_i \cdot g) + re_{i,i'} \cdot (0.5 \cdot \rho \cdot A_i \cdot C_d \cdot v(t)^2) \\ &+ (mass_i \cdot g \cdot \sin(\varphi(t))) + (1.05 \cdot mass_i \cdot a(t)) \Big] \\ &\cdot v(t) \qquad \forall i, i' \in I \end{aligned} \tag{4}$$

$$fs_{i,i'} = \int_0^T P_{i'}(t)dt - \int_0^T fP_{i,i'}(t)dt \qquad \forall i, i' \in I \tag{5}$$

$$rs_{i,i'} = \int_0^T P_i(t)dt - \int_0^T rP_{i,i'}(t)dt \qquad \forall i, i' \in I \tag{6}$$

Equations (7)–(9) constrain vehicles, platoons, and positions in the platoon from being duplicated. Equation (7) indicates that each vehicle can only be allocated to one platoon. Equation (8) indicates that each vehicle can only be allocated to one position in one platoon. Equation (9) represents that only one vehicle can be allocated to a specific position in a specific platoon.

$$\sum_{p=1}^{P} k_{p,i} \le 1 \qquad \forall i \in I \tag{7}$$

$$\sum_{p=1}^{P} \sum_{o=1}^{O} x_{p,o,i} \le 1 \qquad \forall i \in I \tag{8}$$

$$\sum_{i=1}^{I} x_{p,o,i} \le 1 \qquad \forall p \in P, \forall o \in O \tag{9}$$

Equations (10) and (11) constrain the departure order of the platoon and the order in which positions are allocated in the platoon. Equation (10) indicates that the platoon leaves the hub in order. For example, the second platoon must leave the hub earlier than the third platoon. Equation (11) represents that a vehicle must be allocated to the front position in the platoon before a vehicle can be allocated to the back position. For example, if a vehicle is not assigned to the fourth position in a certain platoon, it will not be assigned to the next positions in that platoon, which are the fifth, sixth, and seventh positions.

$$z_p \geq z_{p-1} \qquad \forall p \in \{2, \ldots, P\} \tag{10}$$

$$\sum_{i=1}^{I} x_{p,o+1,i} \leq \sum_{i=1}^{I} x_{p,o,i} \qquad \forall p \in P, \forall o \in \{1, \ldots, O-1\} \tag{11}$$

Equations (12) and (13) represent the relationship between the decision variables.

$$y_{p,o,i,i'} \leq \frac{x_{p,o,i} + x_{p,o+1,i'}}{2} \qquad \forall p \in P, \forall o \in \{1, \ldots, O-1\}, \forall i, i' \in I \tag{12}$$

$$\sum_{o=1}^{O} x_{p,o,i} = k_{p,i} \qquad \forall p \in P, \forall i \in I \tag{13}$$

Equations (14) and (15) show the time relationship between a platoon and the vehicles allocated to it. Equation (14) represents that a platoon can depart after the estimated arrival time of the vehicles allocated to it. Equation (15) represents that a platoon must depart earlier than the latest possible time that the vehicles allocated to it should leave the hub.

$$z_p \geq k_{p,i} \cdot s_i^{enter} \qquad \forall p \in P, \forall i \in I \tag{14}$$

$$z_p \leq M \cdot \left(1 - k_{p,i}\right) + s_i^{out} \qquad \forall p \in P, \forall i \in I \tag{15}$$

Equations (1)–(15) are formulas that form the vehicle platooning when there is no uncertainty in the arrival time of the vehicle at the hub. Equation (16) represents the relationship between the departure time of a platoon and the arrival time of a vehicle, when there is uncertainty in the arrival time of the vehicle allocated to the platoon. If the expected arrival time of a vehicle is greater than the sum of the time point that determines which platoon should leave the hub and the range of data exchange points (i.e., $s_i^{enter} > tp + r$), then Equation (16) applies because the vehicle is still outside the range of data exchange points. In the opposite case (i.e., $s_i^{enter} \leq tp + r$), the vehicle is inside the range of data exchange points and the arrival time of the vehicle is known exactly, in which case Equation (14) is applied.

$$z_p \geq k_{p,i} \cdot \left(s_i^{enter} + u\right) \qquad \forall p \in P, \forall i \in I, \forall u \in U \tag{16}$$

4. Numerical Experiment

4.1. Parameter Settings

A total of 10 vehicles are scheduled to visit a hub during a specific time period of the day. Vehicles 1–5 belong to trucking company A, and vehicles 6–10 belong to trucking company B. Without the hub acting as a PSP, these 10 vehicles would only form platoons with vehicles belonging to the same trucking company. But here, the hub, which is the PSP, coordinates their relationship. Regardless of the trucking company the vehicles belong to, they are all grouped together to form platoons. The values of the parameters μ_{rr}, g, ρ, and C_d used to find energy savings are taken from existing studies [4]. The rolling resistance coefficient, which represents the typical value of a car tire on asphalt, and the air density, approximated to the sea-level value in the international standard atmosphere, were both referenced from the study by Ko and Jang [25]. The type of vehicle, expected arrival time, and the latest possible time it should leave were set arbitrarily. Uncertainty is represented by the index set U. Specifically, in Cases 1 and 2 of the numerical experiments, the uncertainty is set to ±4. In the sensitivity analysis, the results are compared as the uncertainty varies from ±0 to ±6. Uncertainty represents the maximum deviation of vehicle arrival time, and the uncertainty of arrival time is considered using a fixed value. The values of the system parameters and index sets can be found in Tables 2 and 3.

Table 2. System parameters.

Symbol	Value
s_i^{enter}	{0, 6, 8, 12, 16, 4, 10, 12, 12, 18}
s_i^{out}	{6, 12, 14, 18, 22, 10, 16, 18, 18, 24}
vt_i	{s, l, m, m, l, m, m, m, l, s} (s: small size; m: mid-size; l: large size)
μ_{rr}	0.02
g	9.81
ρ	1
C_d	1.2
M	1,000,000

Table 3. Index sets.

Symbol	Value
I	{1, 2, 3, 4, 5, 6, 7, 8, 9, 10}
T	{0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24}
P	{1, 2, 3, 4, 5}
O	{1, 2, 3, 4, 5, 6, 7, 8}
U	{−4, −3, −2, −1, 0, 1, 2, 3, 4}

Depending on the type of vehicle, i.e., its size, $mass_i$, A_i, $fs_{i,i'}$, and $rs_{i,i'}$ are set [4], and the values of these parameters can be seen in Tables 4 and 5.

Table 4. Parameters based on the type of vehicle.

Symbol	Value		
	$vt_i = s$	$vt_i = m$	$vt_i = l$
$mass_i$	1000	2500	5000
A_i	3.03	4.33	6.23

Table 5. Parameters based on the type of vehicles in front and rear that form the platoon.

Symbol		Value		
		$vt_{i'} = s$	$vt_{i'} = m$	$vt_{i'} = l$
$fs_{i,i'}$	$vt_i = s$	7,541,333	9,229,653	11,208,889
	$vt_i = m$	8,618,667	10,767,929	13,450,667
	$vt_i = l$	9,696,000	12,306,204	15,692,444
$rs_{i,i'}$	$vt_i = s$	3,232,000	3,770,667	4,309,333
	$vt_i = m$	3,845,689	4,614,827	5,383,964
	$vt_i = l$	4,483,556	5,604,444	6,725,333

4.2. Results: Case 1

In this study, robust optimization is utilized to derive the results. By applying robust optimization, the uncertainty in the estimated arrival time of vehicles at the hub is considered, and vehicle platooning is formed by assuming the worst-case scenario. The python (v3.9.7) software used is Anaconda3 with version 4.10.3.

Vehicle platooning for 10 vehicles scheduled to visit the hub is not determined at once. This is because the uncertainty varies depending on when the decision is made. In this study, the order in which vehicle platooning is determined is as follows: First, the vehicle that should leave the hub the earliest among all vehicles is the basis for when the vehicle platooning decision is made. Vehicle 1 has the earliest departure time, with $s_i^{out} = 6$. Second, the hub decides which vehicle to allocate to the platoon that should leave the hub at time $t = 6\ (= tp)$. If the range of data exchange points r is 1, the arrival time of the vehicle with $s_i^{enter} \leq tp + r = 7$ can be known exactly, while the arrival times of the remaining vehicles are still uncertain. At this time, vehicles 1, 2, and 6 form a platoon and leave the hub. Third, among the remaining vehicles, except vehicles 1, 2, and 6 that left the hub, the vehicle that should leave the hub the earliest is the basis for when the vehicle platooning decision is made. Among the remaining vehicles, vehicle 3 has the earliest departure time, with $s_i^{out} = 14$. Fourth, the hub decides which vehicle to allocate to the platoon that should leave the hub at time $t = 14$. This method is repeated until all vehicles have left the hub.

The results of changing the range of data exchange points in a situation where the uncertainty of the vehicle's arrival time at the hub is ± 4 are shown in Table 6. An uncertainty of ± 4 means that, for example, although the expected arrival time of vehicle 4 is $s_i^{enter} = 12$, it has a possibility of arriving at any time in the time range $[12 - 4,\ 12 + 4]$. If there is no uncertainty in the arrival times of the vehicles, then vehicles 1 and 6 form a platoon to leave the hub at time $t = 6$, vehicles 2, 3, 7, and 9 form a platoon to leave the hub at time $t = 12$, and vehicles 4, 5, 8, and 10 form a platoon to leave the hub at time $t = 18$, resulting in the maximum energy savings. When there is uncertainty in the arrival time of the vehicles, the optimal result is obtained in the case of the range of data exchange points $r \geq 6$. It was expected that the narrower the range of data exchange points, the greater the uncertainty and the more inefficient the result, but the results of the numerical experiment are different. As the range of data exchange points narrowed from 5 to 0, the total energy savings increased. This is likely because vehicle platooning is not a single decision, but rather a series of decisions. It seems that this is because earlier decisions made under uncertainty affect later decisions.

Table 6. The result of vehicle platooning with an uncertainty of ± 4 in the vehicle's arrival time at the hub.

Data Exchange Point	Platooning	Company A's Energy Savings	Company B's Energy Savings	Total Energy Savings
$r = 0$	1, 2, 6/3, 4, 7, 8, 9/5, 10	64,635,342	51,822,541	116,457,883
$r = 1$	1, 2, 6/3, 4, 7, 8, 9/5, 10	64,635,342	51,822,541	116,457,883
$r = 2$	1/2, 3, 6/4, 5, 7, 8, 9/10	56,921,279	54,369,812	111,291,091
$r = 3$	1/2, 3, 6/4, 5, 7, 8, 9/10	56,921,279	54,369,812	111,291,091
$r = 4$	1/6/2, 3, 4, 7, 8, 9/5, 10	46,767,645	58,679,145	105,446,790
$r = 5$	1/6/2, 3, 4, 7, 8, 9/5, 10	46,767,645	58,679,145	105,446,790
$r \geq 6$	1, 6/2, 3, 7, 9/4, 5, 8, 10	60,691,046	61,217,029	121,908,075

4.3. Results: Case 2

In Case 1, it was found that energy savings are maximized when the range of data exchange points is above a certain value. However, the results of Case 1 showed that when the range of data exchange points was narrower than a certain value, the total energy savings increased as the range of data exchange points narrowed. This result may not be typical, so an additional numerical experiment is conducted. In Case 2, vehicle 6's expected arrival time at the hub and the latest possible departure time from the hub are increased by two units each. The other parameters are the same as in Case 1.

The results of Case 2 are shown in Table 7. It can be reconfirmed that the energy savings are maximized when the range of data exchange points is wider than a certain value. In addition, unlike the results of Case 1, the total energy savings when the range of data exchange points is wider ($6 \leq r \leq 11$) is larger than when the range is narrower ($0 \leq r \leq 5$). In other words, energy savings are maximized when the range of data exchange points is wider than a certain value, but the relationship between the range of data exchange points and total energy savings is not constant when the range is smaller than a certain value. In Case 1, the optimal result is obtained when $r \geq 6$, while in Case 2, the optimal result is obtained when $r \geq 12$. The range of data exchange points that lead to the optimal result is different for each case. However, it can be seen that even if the result is not optimal, it is possible to achieve a near-optimal result if the range of data exchange points is wide enough.

Table 7. The result of vehicle platooning when only the expected arrival and latest possible departure time information for vehicle 6 is changed.

Data Exchange Point	Platooning	Company A's Energy Savings	Company B's Energy Savings	Total Energy Savings
$r = 0$	1, 2, 6/3, 4, 7, 8, 9/5, 10	64,635,342	51,822,541	116,457,883
$r = 1$	1, 2, 6/3, 4, 7, 8, 9/5, 10	64,635,342	51,822,541	116,457,883
$r = 2$	1/3, 6/2, 4, 7, 8, 9/5, 10	54,041,635	51,405,155	105,446,790
$r = 3$	1/3, 6/2, 4, 7, 8, 9/5, 10	54,041,635	51,405,155	105,446,790
$r = 4$	1/3, 6/2, 4, 7, 8, 9/5, 10	54,041,635	51,405,155	105,446,790
$r = 5$	1/3, 6/2, 4, 7, 8, 9/5, 10	54,041,635	51,405,155	105,446,790
$r = 6$	1, 6/2, 3, 7, 9/4,5, 8, 10	60,691,046	61,217,029	121,908,075
$r = 7$	1, 6/2, 3, 7, 9/4,5, 8, 10	60,691,046	61,217,029	121,908,075
$r = 8$	1, 6/2, 3, 7, 9/4,5, 8, 10	60,691,046	61,217,029	121,908,075
$r = 9$	1, 6/2, 3, 7, 9/4,5, 8, 10	60,691,046	61,217,029	121,908,075
$r = 10$	1, 6/2, 3, 7, 9/4, 5, 8, 10	60,691,046	61,217,029	121,908,075
$r = 11$	1, 6/2, 3, 7, 9/4, 5, 8, 10	60,691,046	61,217,029	121,908,075
$r \geq 12$	1/2, 3, 6, 7/4, 5, 8, 9, 10	56,921,279	67,370,132	124,291,411

4.4. Results: Sensitivity Analysis

In Cases 1 and 2, the numerical experiments focused on the impact of changing the range of data exchange points. In this section, the focus is on the uncertainty of the estimated arrival time of the vehicle at the hub, rather than the range of data exchange points. The total energy savings are examined by changing the uncertainty of the arrival time while keeping the range of data exchange points fixed. This is to investigate the relationship between information uncertainty and total energy savings. The results of the sensitivity analysis are shown in Table 8. With the range of data exchange points fixed at two in Case 1, the result of vehicle platooning is compared while increasing the uncertainty of the estimated arrival time of the vehicle at the hub from zero. The total energy savings decrease as the uncertainty increases. For example, it is possible to see the difference by comparing the case with the uncertainty of 0 and ± 1. Vehicle 1 should be the first to leave the hub, and its time is $t = 6$. Therefore, the first platoon is determined at $t = 6$. In the case with the uncertainty of 0, the hub knows the exact arrival times of all the vehicles, so it forms a platoon with vehicles 1 and 6 and sends them out as a result of maximizing energy savings. However, when uncertainty is ± 1, the hub only knows the exact arrival times of vehicles 1, 2, 3, and 5, those with estimated arrival times $s_i^{enter} \leq 8$, because the platoon decision time is $t = 6$ and the range of data exchange points is $r = 2$. The remaining vehicles have a possibility of arriving 1 unit time later than their estimated arrival time. As a result of this uncertainty and to maximize energy savings, unlike the case with no uncertainty, the hub forms a platoon with vehicles 1, 2, and 6 and sends them out. This decision also affects the next platooning decision after the first one. In other words, it is found that increasing the uncertainty of the vehicle's expected arrival time at the hub is a major factor in the inefficiency of vehicle platooning for energy savings.

Table 8. Sensitivity analysis for uncertainty in Case 1 with the range of data exchange points $r = 2$.

Uncertainty	Platooning	Company A's Energy Savings	Company B's Energy Savings	Total Energy Savings
±0	1, 6/2, 3, 7, 9/4, 5, 8, 10	60,691,046	61,217,029	121,908,075
±1	1, 2, 6/3, 4, 7, 8, 9/5, 10	64,635,342	51,822,541	116,457,883
±2	1, 2, 6/3, 4, 7, 8, 9/5, 10	64,635,342	51,822,541	116,457,883
±3	1/2, 3, 6/4, 5, 7, 8, 9/10	56,921,279	54,369,812	111,291,091
±4	1/2, 3, 6/4, 5, 7, 8, 9/10	56,921,279	54,369,812	111,291,091
±5	1/2, 3, 6/4, 5, 7, 8, 9/10	56,921,279	54,369,812	111,291,091
±6	1/6/2, 3, 4, 7, 8, 9/5, 10	46,767,645	58,679,145	105,446,790

5. Conclusions

In this study, hub-based platooning is examined to efficiently form and operate a platoon considering the uncertainty of vehicles' expected arrival times at a hub. Hub-based platooning is one of the appropriate methods for vehicle platooning with vehicles that have different trucking companies, origins, destinations, departure times, and arrival times. Two cases of numerical experiments and sensitivity analysis were performed. The results of vehicle platooning were derived by changing the extent to which vehicles' arrival times are known precisely, i.e., the range of data exchange points, and by changing the uncertainty of vehicles' estimated arrival times at hubs. The results showed that when the range of data exchange points is wide enough, it is possible to achieve optimal results for energy savings even with uncertainty. It was also found that reducing the uncertainty of a vehicle's arrival time is efficient for energy savings. It was found that when the range of data exchange points is not sufficiently wide, this can lead to ineffective energy-saving vehicle platooning. The results suggest that the first decision made with only partial information can influence subsequent decisions, making them less energy-efficient than if the range of data exchange points were narrower.

The implications of this study are as follows: First, it considers the uncertainty of vehicles' arrival times at hubs, while considering the reality that this uncertainty disappears over time, i.e., as vehicles get closer to hubs. Although there has been research on hub-based platooning before, previous research examined either a dichotomous situation where arrival time information is known or unknown through communication, or a situation where the arrival times are uniformly distributed over a range of times. Second, the impact of changes in the range of data exchange points and the uncertainty of the vehicle's arrival time at the hub on hub-based vehicle platooning was investigated. It is most important to accurately predict a vehicle's estimated arrival time at the hub. The smaller the range of estimated arrival times, i.e., the less uncertainty there is, the more energy-efficient vehicle platooning can be organized. When it is difficult to improve prediction accuracy, the focus should be on expanding the range of data exchange points, i.e., the range over which the vehicle's arrival time is known exactly via V2H. If the range of data exchange points is sufficiently wide, optimal results can be achieved, and even if it is not, near-optimal results can be achieved. The results of this study can provide a basis for what factors need to be considered in the future when autonomous driving technology is developed to realize vehicle platooning in practice. Third, the main findings can be used in the following ways in real-life logistics scenarios: By collecting vehicle arrival time data in real-time from logistics hubs and optimizing the vehicle platooning, energy consumption can be reduced, and operating costs can be lowered. Strategies to expand the range of data exchange or improve the accuracy of arrival time prediction can reduce uncertainty and enable more efficient vehicle platooning. Applying the proposed model to the entire hub network will maximize energy savings in large-scale logistics systems.

The limitations of this study are, first, that the model was simplified by considering only one hub and a few vehicles. This was to analyze the principles of the proposed technique more clearly by reducing the complexity of the model. In future research, we plan to examine operational efficiency by considering multiple hubs and many vehicles. Second, stochastic situations were not considered. Stochastic situations such as V2H communication failure are likely to occur. These situations are expected to have a significant impact on vehicle platooning, so it is important to understand their impact. Third, applying robust optimization led to results that were overly conservative. Since robust optimization makes decisions based on the worst-case scenario, the efficiency of vehicle platooning may appear lower than it actually is. The methods to resolve this include distributed optimization, stochastic optimization, and hybrid robust–stochastic approaches. Distributed optimization has the advantage of performing optimization independently at each hub or vehicle unit and making dynamic decisions using real-time data. Stochastic optimization is an approach based on modeling uncertainty as a probability distribution to optimize average performance. The hybrid robust–stochastic approach is a mixed model that reflects both extreme and common cases. In our future work, we aim to make robust optimization less restrictive by applying methods to reduce its conservatism. Fourth, robust optimization typically addresses uncertainty by focusing on a predefined range rather than relying on probabilistic assumptions. In this study, the range of uncertainty was considered to effectively model worst-case scenarios, aligning with the core concept of robust optimization. Future research will explore advanced methodologies that integrate robust optimization with probabilistic techniques, such as distributionally robust optimization, to enhance the realism of uncertainty modeling. This would allow us to reflect uncertainty more realistically by incorporating probabilistic models, while still maintaining the robustness inherent in robust optimization.

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