Facilitating Cooperative Truck Platooning for Energy Savings: Path Planning, Platoon Formation and Benefit Redistribution

by

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To mom and dad, who taught me the power of humour, calmness and perseverance.

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LIST OF ABBREVIATIONS

ACC Adaptive Cruise Control

BB Budget Balance

BNE Bayesian Nash Equilibrium

CACC Cooperative Adaptive Cruise Control

CAV Connected Automated Vehicles

DMP Deterministic Matching Procedure

EE Economic Efficiency

EPBB Ex-post Budget Balance

EPIC Ex-post Incentive Compatible/Compatibility

EPIR Ex-post Individual Rational/Rationality

HV Human-driven Vehicles

HDV Heavy-duty Vehicles

LHS Left Hand Side

OD Origin-Destination

OEM Original Equipment Manufacturer

RHS Right Hand Side

SMP Stochastic Matching Procedure

V2I Vehicle to Infrastructure

V2V Vehicle to Vehicle

WTP Willingness-to-pay

ABSTRACT

Enabled by the connected and automated vehicle (CAV) technology, cooperative truck platooning that offers promising energy savings is likely to be implemented soon. However, as the trucking industry operates in a highly granular manner so that the trucks usually vary in their operation schedules, vehicle types and configurations, it is inevitable that 1) the spontaneous platooning over a spatial network is rare, 2) the total fuel savings vary from platoon to platoon, and 3) the benefit achieved within a platoon differs from position to position, e.g., the lead vehicle always achieves the least fuel-saving. Consequently, trucks from different owners may not have the opportunities to platoon with others if no path coordination is performed. Even if they happen to do so, they may tend to change positions in the formed platoons to achieve greater benefits, yielding behaviorally unstable platoons with less energy savings and more disruptions to traffic flows.

This thesis proposes a hierarchical modeling framework to explicate the necessitated strategies that facilitate cooperative truck platooning. An empirical study is first conducted to scrutinize the energy-saving potentials of the U.S. national freight network. By comparing the performance under scheduled platooning and ad-hoc platooning, the author shows that the platooning opportunities can be greatly improved by careful path planning, thereby yielding substantial energy savings. For trucks assembled on the same path and can to platoon together, the second part of the thesis investigates the optimal platoon formation that maximizes total platooning utility and benefits redistribution mechanisms that address the behavioral instability issue. Both centralized and decentralized approaches are proposed. In particular, the decentralized approach employs a dynamic process where individual trucks or formed platoons are assumed to act as rational agents. The agents decide whether to form a larger, better platoon considering their own utilities under the pre-defined benefit reallocation mechanisms. Depending on whether the trucks are single-brand or multi-brand, whether there is a complete information setting or incomplete information setting, three mechanisms, auction, bilateral trade model, and one-sided matching are proposed. The centralized approach yields a near-optimal solution for the whole system and is more computationally efficient than conventional algorithms. The decentralized approach is stable, more flexible, and computational efficient while maintaining acceptable degrees of optimality. The mechanisms proposed can apply to not only under the truck platooning scenario but also other forms of shared mobility.

CHAPTER 1

Introduction

1.1 Background and Motivation

Cooperative vehicle platooning refers to a fleet of virtually-linked vehicles traveling with low headway, enabled by connected and automated vehicle (CAV) technologies such as cooperative adaptive cruise control and reliable vehicle to vehicle (V2V) communication. With the coordination in the driving operations, vehicle platooning is capable of improving safety, fuel economy as well as traffic efficiency. Since it can be performed by using a human-driven connected vehicle as the leading vehicle and partially automated vehicles the following or trailing ones, cooperative vehicle platooning is often viewed as the interim stage of the transition from regular human-driven vehicles to fully autonomous vehicles.

A mass number of studies and implementation efforts of vehicle platooning focus specifically on commercial trucking or freight transportation. Comparing to passenger vehicles, commercial trucks are operated more frequently and regulated, making the implementation and management easier. Above all else, platooning yields promising economic benefits: 1) The energy-saving benefits due to aerodynamic drifting. When trucks are traveling close enough, a leading vehicle reduces aerodynamic drag over the front surface of the following vehicles (Hammache et al., 2002; Levedahl et al., 2010); at the same time, higher pressure is generated between vehicles, providing the leading vehicle a push (McAuliffe et al., 2017). Besides, smoother longitudinal acceleration owing to synchronized vehicle operations also yields less fuel consumption (Alam, 2011). Experiments show that when the inter-vehicle distance is around 10 meters, the average reduction of fuel consumption per vehicle in a platoon can reach up to 10% (McAuliffe et al., 2017). 2) Labor-costs savings owing to vehicle automation and assistance. Platooning is envisioned to release the drivers' driving burden on following trucks in different degrees depending on the levels of automation, whether using a single driver or teamwork (Robbert Janssen, 2015; Bakermans, 2016; Albiński et al., 2020). In general, platooning will help reduce the idle time of trucks and eventually lead to labor-cost savings. Fuel consumption and labor costs are two dominant components of the truck operating cost, occupying 30% and 38% of the total truck operational cost on average, respectively (Figure 1.1, data source: Murray & Glidewell (2019)). Therefore, the expected economic benefits are anticipated to be the driving force for freight companies to investigate and implement the concept of truck platooning.

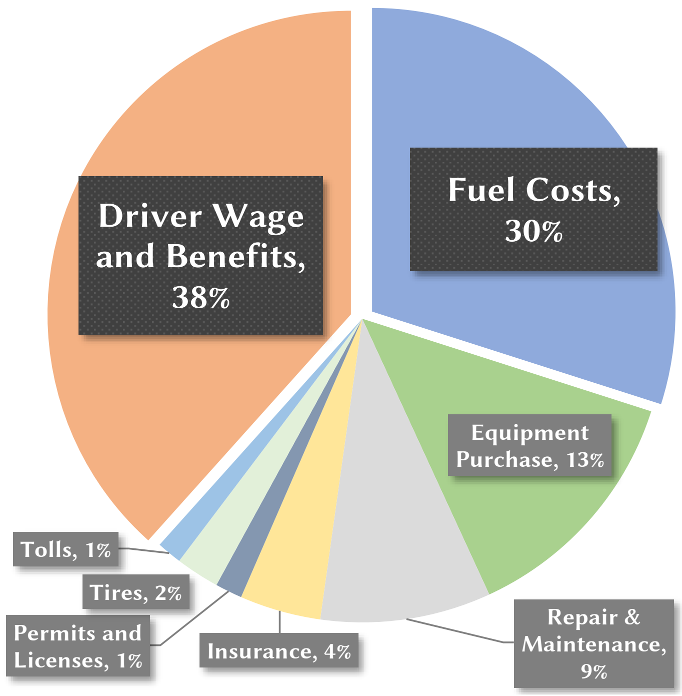


Figure 1.1: Truck operating cost break down

Though technically well-grounded, the adoption of cooperative truck platooning is still in a slow process. It involves different stakeholders, from either public or private sector, to fulfill various tasks in facilitating truck platooning (Figure 1.1). Specifically, the auto manufacturers or the original equipment manufacturers (OEMs) are technology developers who initiate the new technology. Freight companies, namely shippers and carriers, are buyers and customers of truck platooning that wish to perform planning and management strategies, either intra-organizational or inter-organizational, to maximize their own profits. Government and regulators are responsible for providing infrastructure support and traffic regulations to facilitate truck platooning operations on roads and to mitigate the adverse effects on normal traffic flows and infrastructure.

Currently, the overall economic benefits that are achievable by truck platooning is still ambiguous as no real implementation is performed. The other way around, the unclear

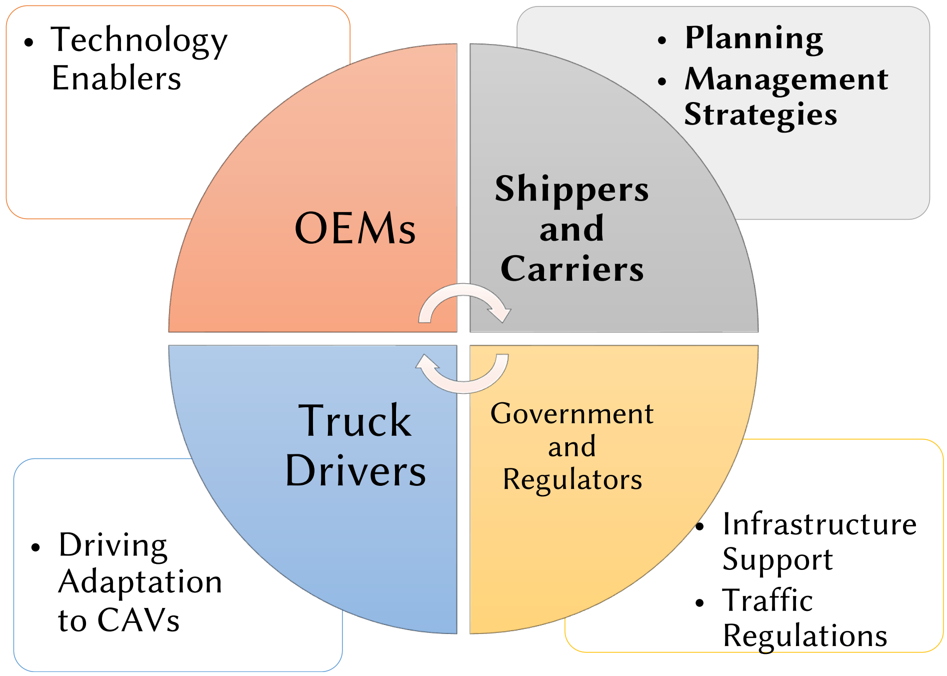


Figure 1.2: Identified stakeholders and their roles in truck platooning

prospect also impedes freight companies to adopt such technology. Therefore, this thesis considers the necessary planning and management strategies to facilitate truck platooning from a societal perspective. As Bakermans (2016) positioned the stakeholders and their roles in the 'technology push and market pull' principle, this thesis can be viewed as a part of 'market pull'.

In practice, three barriers matter to the success of truck platoons' operations. First and foremost, location matters.rucking industry operates in a highly fragmented manner. More than 90% of enterprises are owner-operators. Even the most significant operators have only a small portion of the market share (Cook, 2019). As a result, trucks operate at different locations and times according to their own schedules. When the market penetration rate is low, it is likely that trucks are scattered both spatially and temporally, hence making the ad-hoc platooning rare. Second, formation matters. Trucks that are capable of platooning can have different vehicle types and configurations, depending on their OEMs and use purposes. Even if 'platoonable' vehicles have been gathered on the same road, the diversity of types and configurations contributes to platoons' various formations, in terms of the platoon speed, length, and vehicle sequences. Wind-tunnel experiments suggested that aerodynamic drag is influenced by vehicle shape and size (Hammache et al., 2002; Browand & Hammache, 2004). Vehicle sequence, headways, platoon speed, and platoon length all play an important role in determining the fuel efficiency of a platoon (Tsuei & Savaş, 2001; Schito & Braghin, 2012; McAuliffe et al., 2018).

Therefore, given a set of vehicles, there exist "greenest" platoon formations that achieve the highest energy savings. Third, position matters. Each vehicle in a platoon may benefit differently from platooning. More specifically, their energy savings differ from each other. A recent field test of a three-heavy-truck platoon showed that the trailing vehicle saved the most at gaps longer than 12 meters, the middle vehicle saved the most at shorter gaps, while the leading vehicle saved the least at all gaps (McAuliffe et al., 2018).

From the above observations, one can easily sense the necessity of truck schedules' planning to increase the platooning opportunities over a wide traffic network, which has been investigated by many recent studies (Larsson et al., 2015a; Larson et al., 2016; Bhoopalam et al., 2018). Nevertheless, most of them focus on constructing mathematical models. Few of them applied these models to evaluate the platooning opportunities and the resulted energy-saving potentials in a real freight market. 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 energy-saving potentials over a large traffic network from the planning perspective.

Furthermore, another question that is usually neglected by previous research is the underlying conflict between a system operator and owners of vehicles. On the one hand, the system operator aims to facilitate the formation of an energy-saving platoon, ideally, the greenest one. This is not difficult to achieve if all vehicles belong to one owner, such as a freight transportation company, because doing so would save the owner's substantial amount of energy expenditure. On the other hand, as introduced earlier, the chances are that those vehicles would belong to different owners, even in the era of automated driving. Consequently, some of them may not be willing to form a platoon, as they, e.g., the leading vehicles, may benefit little. Even if a platoon is formed, since each vehicle may benefit differently, some will have the incentive to leave the platoon to drive alone or join another, should such an opportunity arises. This conflict of interest will compromise the opportunity of forming a platoon and, more importantly, the stability of the platoon. Furthermore, the instability will have an adverse impact on traffic flow efficiency. This behavioral instability of platooning has been alluded to in the literature, e.g., (Shladover et al., 2015; Puplaka, 2016; Bhoopalam et al., 2018), but has not yet been explored or resolved.

In this sense, the second research task is resolving the behavioral instability issue, through platoon formation and benefit redistribution. The underlying assumption of this modeling approach is that all individual trucks are rational agents trying to maximize their own utilities. Conceptually, the method on platoon formation assembles 'platoonable' vehicles in close proximity to maximize the total energy-saving. Meanwhile, benefit redistribution mechanisms allocate the achieved benefit for all participants such that no individuals have incentives to switch positions in the formed platoon format or leave the current system for greater benefits. As no uniform solution can settle all controversies, the solution measures diversify based on different scenarios. Section 1.2 elaborates on the settings and methodologies taken of each scenario.

1.2 Problem Statement and Research Goals

The rest of the thesis is built around two ultimate research goals:

- quantifying energy-saving potentials,
- addressing the behavior instability.

Four distinct but relevant studies are presented through chapter 3 to chapter 6, where chapter 3 fulfills the first research goals and chapter 4 to chapter 6 fulfill the second under single-brand and multi-brand truck platooning scenarios. To embark upon the detailed analysis, the definition of behavioral stability is formally presented as following:

Definition 1.2.1. A benefit redistribution mechanism is said to achieve *behavioral stability* if it ensures that no vehicle would like to switch positions or leave the platoon to achieve greater utility.

1.2.1 Understanding the Energy-Saving Potentials of Truck Platooning

Several prior studies have estimated the energy-saving potentials over Europe (Liang et al., 2014; Bakermans, 2016) and U.S. freight networks (Muratori et al., 2017; Lammert et al., 2018). However, as the data source and the estimation methods vary, there is no universal understanding. In addition, none of the studies evaluated the impact of truck's itinerary planning on energy-saving improvement. Due to this reason, this thesis continues to substantiate the platooning's benefits in fuel economy via real-world data and a mathematical planning model. The data describes U.S. freight origin-destination (OD) demands by trucks in 2012 from Freight Analysis Framework Version 4 (FAF^4), which is produced by the Bureau of Transportation Statistics and the Federal Highway Administration (BTS & FHWA, 2016). Trucks' routing decisions and time schedules are determined by a scheduled planning model proposed by Abdolmaleki et al. (2019). The challenge of this study comes from big data, which requires the simplification of real freight network and the development of efficient heuristic or approximation algorithms.

The large-scale optimization problem is solved by an efficient heuristic algorithm with solution quality guaranteed. In this study, the author contributes to

- quantifying the energy-saving amount with and without scheduled planning over the U.S. national freight network,
- recognizing the impacts on energy savings by different platoon sizes,
- identifying the correlations between trip distance and the associated energy savings,
- providing a cost-benefit analysis on platooning technology investment for the individual truck owners.

1.2.2 Addressing Behavioral Instability for Single-Brand Truck Platooning

This study concentrates on the scenario when 'platoonable' trucks have an identical vehicle type and configuration, but their drivers possess different values on driving maneuvers. Consequently, the total amount of energy savings is fixed when the truck number is set, and a regulated operational speed is given, i.e., platoon formation becomes trivia. All that matters is who leads the platoon so that the total labor-saving is maximized while every participant satisfies with the schedule. Viewer the leading vehicles as the seller of the platooning service while the followers the buyers, an auction mechanism is then designed to allow all trucks to bid for the following positions in the platoon.

Several key properties are worth mentioning in the field of mechanism design. *Economic efficiency* measures the attainable social welfare under the outcome. *Incentive compatibility* ensures that the action each agent plays in equilibrium must be a best response. Under the revelation principle (Myerson, 1981), any incentive compatible mechanism is equivalent to the one where each agent truthfully reports their private information, or in other words, their types. *Individual rationality* says that any rational individual must obtain a larger benefit by participating in the game otherwise, they will leave. The fourth property is *budget balance* or sometimes be referred to as *revenue neutral*. Under the strict budget balance, the sum of all payments equals zero, implying that the payments are transferred among all the agents. A relaxed condition is weakly budget balance, meaning that the payment summation is negative thus, a mechanism designer can earn profit from it. The pivotal challenge in designing the auction comes from the fundamental truth that all good economic properties can hardly be achieved simultaneously. Moreover, since the 'role' each agent plays is ambiguous, some classic mechanisms cannot be easily implemented. Unlike classical auction settings that define the seller and the buyers explicitly, the seller in our auction setting is undetermined until the auction has been processed, which leads to the controversy of incentive compatibility and budget balance. Taking all these properties into account, the author contributes to

- proving the impossibility of achieving any equilibria under the desired properties,
- providing an auction format with an explicit payment rule that satisfies the behavioral stability, budge balance constraints while achieving economic efficiency.

1.2.3 Addressing Behavioral Instability for Multi-Brand Truck Platooning: The Centralized Approach

The centralized approach focuses on the static state. A set of 'platoonable' vehicles with the same origin and destination need to be formed into platoons considering that the maximum platoon size is limited. To fulfill such a goal, a central controller is responsible for information gathering, platoon formation, and benefit redistribution. As no existed functions quantifying the platooning benefit is available, a utility function is developed at first. A mathematical model is established to find the platoon formation with maximum system benefit by specifying which vehicles should be platooned together and their platoon speeds and positions. Based on that, a mechanism that originated from cooperative game concepts is developed and applied to redistribute the total system benefit. In this study, the author contributes to

- developing a utility function to properly approximate a vehicle's platooning benefit,
- formulating a mathematical program for the platoon formation problem,
- proposing a computationally efficient solution algorithm for the platoon formation problem based on column-generation
- evaluating well-known benefit allocation mechanisms, such as *Shapely Value* ((Shapley, 1953) and *the Core* of cooperative games (Gillies, 1959) for their compatibility in this study,
- identifying a workable redistribution mechanism that satisfies the budget balance constraint and fairness property.

1.2.4 Addressing Behavioral Instability for Multi-Brand Truck Platooning: The Decentralized Approach

Though the centralized approach finds the optimal platoon formations, the high computational expensive may restrain its scalability and stability in real-world implementations. Due to this concern, this study explores a decentralized dynamic process for simultaneous platoon formation and benefit redistribution. Such a decentralized process is practical, considering the technology enablers such as V2V communication and the computational power residing in automated vehicles. The vehicles are assumed to be owned by rational agents, either individuals or companies, who aim at minimizing their own operational costs by platooning. Consequently, if no central controller exists, their strategies and behaviors in forming platoons can be analyzed by assuming that they are playing a noncooperative game. However, as each agent also possesses hidden information, the concepts and theories from the domain of mechanism design are applied to allure agents to participate in platooning and report truthfully. Essentially, the author contributes to

- formulating the dynamic process on platoon formation and benefit redistribution,
- specifying rules for agents to follow and develop proper payment functions so that they are willing to deviate from the desired formation of platoons by methods of bilateral trading and one-sided matching,
- comparing the decentralized and centralized approach in terms of computational time, solution quality and behavioral stability.

1.3 Dissertation Outline

The remainder of the thesis is organized as follows. Chapter 2 provides an overview of the current research on truck platooning, providing readers with a general idea of how this thesis fits into the big picture. Pertinent theoretical concepts utilized are introduced to assist a better understanding of models and analysis. Chapter 3 presents the estimation of energy-saving potentials by truck platooning, using realistic truck OD demand data of the U.S. national freight network. Chapter 4 discusses the auction mechanism that ensures behaviorally stable platoons for single-brand trucks. Chapter 5 provides the centralized platoon formation and benefit redistribution for behaviorally stable platooning. Chapter 6 presents the decentralized game-theoretical approaches for platoon formation and benefit redistribution.

CHAPTER 2

Literature Review

The investigations on cooperative vehicle platooning, especially on truck platooning, are an active research area that draws keen attention from academia, industry, and government agencies. This chapter hence provides an overview of the relevant research, which is conducted from the following perspectives: vehicle technologies, potential benefits and impacts, planning and management strategies. The third perspective on planning and management, which is closely related to the topics of this thesis, is reviewed in details. Technical preliminaries on mechanism design, the methodology used heavily in this thesis, are presented in the last section of this chapter to assist readers in understanding the modeling and analysis in relevant chapters.

2.1 Technical Enablers

Over the years, the research interests on connected and automated vehicles, specifically on vehicle platooning, generate a tremendous amount of papers. Some survey papers thus provide reviews and prospects of these studies from different angles. Kavathekar & Chen (2011) is one of the first survey papers that provided a general introduction to the evolution of vehicle platooning, applications, and the categorizations of research questions by reviewing the literature from 1994 to 2010. The authors stated that at that time, it was 'very difficult to find a variety of applications related exclusively to platooning', which is not the case nowadays. In terms of the research questions, the paper has broadly classified them into the following categories: *inter-vehicle communication methodologies*, *collision avoidance and obstacle detection methodologies*, *design of lateral and longitudinal control systems*, and *string stability*. From then on, many subsequent studies also fall into these categories.

Among all the topics, vehicle communication is the very most fundamental one that involves discussions from different domains, including communication engineering, mechanical engineering, and transportation engineering. On the one hand, the performance of a platoon is primarily affected by the cyber vehicular network's efficiency. On the other hand, physical movements will also influence the performance of vehicular networking. Jia et al. (2015) provided a detailed introduction on vehicular networking architecture and standards used for platooning and discussed the interaction of platoon traffic and vehicular networking.

Many researchers in control theory and transportation engineering are of great interest in investigating control dynamics with string stability (Milanés & Shladover, 2014; Tuchner & Haddad, 2017; Y. Li et al., 2018; M. Wang, 2018). Loosely speaking, string stability refers to the property that the disturbances of system states would not be amplified when it propagates along a tightly operated vehicle string. Obviously, string instability would trigger safety issues within the platoons as well as disturbance to the surrounding traffic flows. However, studies in this field use various definitions and, hence, adopt different analytical methods, making direct comparisons and evaluations difficult. Feng et al. (2019) recently concluded and compared the available definitions on string stability in a comprehensive way, providing valuable discussions and insights for future investigations.

Another stream of research focuses on the controls of platoons' physical processes when a platoon's state changes from one to another. To name a few, joining (two platoons join together), merging (one CAV merges into a platoon), splitting (one or multiple vehicles leave one platoon). The control variables are usually vehicles' speed and acceleration. Saeednia et al. (2016); M. Saeednia & Menendez (2017) utilized the consensus control theory to model the platoon forming process of two vehicles. In their schemes, the two vehicles reach a uniform speed under close headway either by the leading vehicle decelerates, or by the following vehicle accelerates, or both. In the series of papers, Xiong et al. (2019, 2020) developed a stochastic dynamic programming approach to coordinate the randomly arrived vehicles at a merging junction into platoons, under which the total cost composed by fuel cost and travel delay is minimized. These studies particularly considered the forming process of 'platoonable' vehicles themselves, assuming that there is no interruption from the surrounding traffic flows, or vice versa. In contrast, Duret et al. (2019) studied the platoon's splitting process near on-ramps and off-ramps on highways and freeways, which is obligatory to create gaps for mandatory lane changes of surrounding traffic. Their approach is conducted in two layers. The tactical layer decides when and where to yield a safe and comfortable gap that maximizes throughput. The operational layer controls the deceleration and acceleration to create gaps that are efficient, safe, and comfortable to the merging vehicles. Due to its importance to successful real-time implementation, the control of platoons' forming and splitting processes under the consideration of surrounding normal traffic is anticipated to be studied more extensively soon.

2.2 Quantifying the Benefits and Impacts

The benefits of truck platooning are known to be fuel savings, labor-cost savings as well as improved safety. The adverse impact of truck platooning, as many doubt, would be traffic deficiency for mixed traffic flows. Therefore, quantifying these benefits and impacts is crucial to assist the decision-makers. This section thus reviews papers that contribute to this decision.

2.2.1 Fuel Savings

Experiments focus on energy-saving performance before 2016 are reviewed by Tsugawa et al. (2016). Lammert et al. (2014) estimated that for two-vehicle platoon, there is 2.7% $\sim$ 5.3% savings on fuel consumption for the leading truck; and 2.8% $\sim$ 9.7% for the following truck. In recent years, (McAuliffe et al., 2017) suggests that for three-vehicle platoon, the leading truck has -0.7% $\sim$ 0.3% savings on fuel consumption, the middle truck has a 6.1% $\sim$ 9.4%, and the trailing truck has a 9.9% $\sim$ 11.7%. The exact value depends on the traveling speed and headway. Theses studies provide ground truth for the research problem concerned in this thesis: the unfair distribution of benefits among positions and the hidden hazard on behavioral instability.

Paper	Data Source	Data Size	Data Feature
Liang et al. (2014)	Scania HDVs	1,773 vehicles	trajectory data
Bakermans (2016)	road freight transport data Statistical Netherlands	1,026,467 trips	origins and destinations
Muratori et al. (2017)	NREL's Fleet DNA	3,170,079 vehicle-miles	speed profile
Lammert et al. (2018)	Volve Trucks	57,000 vehicles 210 million miles	trajectory data

Table 2.1: Description of data sources in previous empirical studies

As discussed before, the possibility of platooning in real traffic network is restrained by the variations of truck operations. The dissimilarity of trucks' departure time choices and routing decisions confines a platooning partner's availability for a single truck. Liang et al. (2014) examined the position data of 1800 heavy-duty vehicles (HDVs) in a region of Europe. They found by assuming that two HDVs are capable of platooning if their distance is no greater than 100 meters, the distance with spontaneous platooning is only 1.21% of all the distance traveled. Moreover, even if a nearby partner is available, whether the two trucks can platoon depends on their operating speeds and the road's geometric conditions. For instance, roads with low free-flow speed and small capacity are not suitable for platooning. Using a time threshold of 15 minutes and a speed threshold of 50 mph, Muratori et al. (2017) analyzed the speed profiles of 200 Class 8 vehicles contained in NREL's Fleet DNA database, concluding that 65.6% of the total available 3,170,079 vehicle-miles are 'platoonable'.

Nevertheless, the platooning performance can be improved by proper planning and coordination. Liang et al. (2014) proposed three coordination schemes, namely *catch-up coordination*, *departure coordination* and *transport coordination*. The first two coordination schemes allow a HDV to platoon with its most promising partner in the coordination horizon by simply acceleration or changing departure time. Instead of focusing on the vehicles, the third scheme inspects the platooning possibility of the examined roadways, determined by the condition if more than one vehicle enters the road within a certain time interval. When the coordination horizon is set to be 20 km, at most 10.76% vehicle-miles is 'platoonable' under the proposed departure coordination. A similar study conducted by Lammert et al. (2018) examined data from over 57,000 Class 8 vehicles that traveled more than 210 million miles in the United States. Using both speed threshold and spatial threshold, the authors concluded that 55.7% vehicle-miles are 'platoonable'. Noticing that the threshold is assumed to be that "the vehicle observed at least one potential partner within a 15-mile radius and 15-minute travel time window", the authors inherently permitted a vehicle to change their speed or departure time for platooning with others. However, the exact coordination schemes haven't been articulated explicitly. Nevertheless, it is worth noting that the result concluded from the U.S. is much more promising than Europe's.

The caveats of previous studies are apparent as well. First of all, oversimplified thresholds for platooning presumably overvalue the potentials. Besides, data-driven approaches are primarily affected by the scale of the data set and the deployed methodology. Using only trajectory data inevitably leads to underestimated results, as the data set usually does not contain all vehicles' information existed in the study period. In this way, some latent platooning opportunities are neglected. Furthermore, when the analysis is based on OD demand data while ignoring the platooning opportunities among trucks with different ODs (Bakermans, 2016), the resulted potentials would be underestimated as well.

The study elaborated in chapter 3 utilizes the OD demand data with scheduled platoon planning to provide an upper bound of the energy-saving potential that can be achieved in the U.S. national freight network. It implies that if the result of this analysis is not promising, energy savings cannot be considered the driving-force for investigating truck platooning.

2.2.2 Labor-Cost Savings

Due to the increased utilization of the trucks and less idle time resulted, potential users also expect truck platooning reduce labor costs significantly. Robbert Janssen (2015) is among the first few to quantify such benefits by envisioning two scenarios. The first scenario has two drivers for a two-truck platoon, under which the driver of the following vehicle can rest while his/her truck is still driving under the navigation of the leading vehicle. The authors anticipated that 45 minutes of resting time could be saved per driver per workday, leading to a daily 8% savings. The second scenario supposes one instead of two drivers working for a two-truck platoon. Thus, it can lead to 15% to 25% daily working-hour reduction. Nevertheless, both scenarios can only be achieved under high vehicle automation levels that promise at least conditional automation, thereby are not suitable for the current implementation.

Another method to achieve labor-cost savings is allowing drivers to exceed the regulated working hour if they followed others in platoons. To assess the exact labor savings under this setting, researchers and potential users need to consider both drivers' working schedules and the platooning opportunities along the traveling path in the studied region. section 2.3.1 will introduce two recent studies focusing on the platoon planning model frameworks (Stehbeck, 2019; Albiński et al., 2020), which provide the assessment as a byproduct.

2.2.3 Traffic Efficiency

Preferably, vehicle platooning increases road capacity by reducing headway. However, when considering its impact on the surrounding traffic composed by human-driven vehicles, it is still uncertain whether truck platooning is a blessing or a curse to the overall traffic efficiency. Possible drawbacks of truck platoon root in its relatively large size and the constrained capabilities in acceleration when crawling upgrades (Chen et al., 2017). With a relatively long length, truck platoons can easily block others' mandatory lane-changing behaviors at highways' on-/off-ramps. With limited acceleration capability, truck platoons are also likely to be moving bottlenecks for the surrounding passenger vehicles on sags. Therefore, evaluating the overall efficiency of mixed traffic flows is of great importance.

Though well recognized, this line of research, like many other directions of truck platooning studies, is still in a nascent stage that far from reaching consensus yet. One reason is that field experiments and observations are impractical so that researchers resort to analytical or simulation-based models that vary from one to another. Table 2.2 summarizes and compares some notable studies in terms of the following aspects: the microscopic car-following and lane-changing models used for platooning vehicles, the assumption of background traffic's movements or arrival patterns to the studied road segments, the infrastructure geometries of the studied road segments, the allocation strategy of lane capacities, and the performance measures adopted.

Jin et al. (2018) utilized an analytical fluid model to capture the random arrivals of CAVs at a highway bottleneck. Their finding suggests that smaller platoon length and higher arrival frequencies generate smaller traffic queues. Segmented priority rule (one lane dedicated to truck platoon when it arrives) may not necessarily outperform sharing lane (proportional priority rule), unless the intra-platoon headway is very short.

Utilizing a micro-simulation model, Calvert et al. (2019) concluded that truck platooning may have a small negative effect on the total non-saturated traffic flows, but a much larger negative effect on saturated traffic flows. In the meantime, the positive impact on capacity improvement coming from shorter intra-platoon headway is only marginal.

Using a basic freeway segment with no ramps or bottlenecks as studied area, Jo et al. (2019) shown the benefits of truck platooning on capacity improvement and travel time reduction through a simulation study using both micro-simulator and macro-simulator.

From the papers briefly introduced above, one can sense that as the study objects and methodologies vary, no conclusive result has been affirmed for this debatable problem on traffic efficiency. It implies that future studies focusing on this topic are still of need. The results obtained may vary case by case so that the policymakers should consider their own situation and needs when generating regulations and management schemes for truck platooning.

2.2.4 Safety and Driver's Adoption

The safety improvement is always referred to as one of the significant benefits of truck platooning. However, the systematic literature review conducted by Axelsson (2016) revealed that there is an evident lack of comprehensive safety analysis using well-established methods, partially because the previous methods are insufficient to handle a cooperative system, such as platooning. Furthermore, due to the lack of implementation, many studies have to rely on simulations and testings. Another issue that requires investigation

Paper	Infrastructure geometry	Traffic flow models: CAV	Traffic flow models: HV	Lane	Performance measures
Jin et al. (2018)	highway bottleneck	fluid model	CTM		traffic queue
Calvert et al. (2019)	highway corridor on-ramps, off-ramps waving sections	LMRS (Schakel et al., 2012) IDM+ (Schakel et al., 2010) CACC car-following			speed delay string stability
Jo et al. (2019)	freeway segment no ramps or bottlenecks	modified VISSIM model	VISSIM model		capacity travel time

Table 2.2: Key components of traffic efficiency studies

to gain understanding is on drivers' adoptions of automated vehicles, which has been introduced by Axelsson (2016) excellently as well. In recent two years, there is also a stream of research interests in understanding human responses when resuming control back from vehicles (B. Zhang et al., 2019).

2.2.5 Infrastructure Impact

Last but not least, truck platooning can drastically increase the dynamic loading to transportation infrastructure structures, e.g., pavement and bridge. However, these studies are beyond the range of this thesis and the author's expertise. Therefore, only a few recent studies are briefly reviewed to serve the readers that might have an interest. Gungor & Al-Qadi (2020) drawn the attention of truck platooning on pavement longevity, as it would cause a channelized load application and hinder the healing properties of asphalt concrete. The authors proposed a mathematical program to optimize platoons' lateral positions to decelerate pavement damage accumulation and, consequently, increase pavement service life. Yarnold & Weidner (2019) and Sayed et al. (2020) conducted the studies to indicate the impact of truck platooning on bridges separately, showing that this new technology will 'necessitate new policies, regulations, and standards for both new and existing bridges'.

2.3 Planning, Management and Operational Support

2.3.1 Planning

The quantification of energy savings using trajectory data implies that the truck platooning benefits are small, considering that the market penetration rate at the early stage of technology adoption is low, and trucks operate under customized schedules. Thus, carefully path planning for trucks is the key to increasing platooning opportunities over a network and efficiently reaping the benefits. Mathematically, this type of problem belongs to the genre of vehicle routing problem, a classical problem that has been extensively investigated in operation research. However, the planning for truck platooning uniquely considers trucks' cooperative operations, that is vehicles travel on the same road segment at the same time, to maximize the system welfare.

Bhoopalam et al. (2018) provided a literature review on the planning problem, concluding most of the relevant studies conducted before 2018. Generally, the planning problem assumes that a central controller exists to coordinate the trucks' routing, departure time, resting, and even speed decisions after the truck owners provided the trip information.

Depending on when the trips are announced, the authors categorized the studies into the following three scenarios:

- Scheduled platoon planning. All trips are announced before the start of the operations. It is also referred to as off-line or static planning.
- Real-time platooning. Some of the trips are announced during their executions. It is also referred to as online or dynamic platoon planning.
- Opportunistic platooning. Trucks that are in close proximity of each other form platoons dynamically on road without any announcement or prior planning. It is also referred to as spontaneous, ad-hoc or on-the-fly platooning.

Nearly all studies summarized in this survey paper concentrate on modeling scheduled platoon planning problems. Oftentimes, the model objectives are minimizing the total fuel consumption over the studied network (Larson et al., 2013; Larsson et al., 2015b). Several also include travel delays into consideration (W. Zhang et al., 2017; Meisen et al., 2008). In terms of control variables, the majority models assume that fuel consumption of a platoon is a function of its vehicle number, which allows them to consider only the path choices and time schedules in high-level planning problems. Van de Hoef (2016), on the other hand, is one of the only few that applied a speed-dependent fuel consumption model and formulated an optimization problem to control the vehicle trajectories in the study scope.

In recent two years, there is a continuation of enthusiasm in the planning problem. Abdolmaleki et al. (2019) is the first to utilize a time-expanded network to model the itinerary planning of truck platoons. This approach significantly simplifies model complexity and assures the existence of efficient solution algorithms. Both exact algorithm based on outer approximation and approximation algorithm that guarantees a good solution lower bound were proposed. Albiński et al. (2020) applied a similar model structure when studied the scheduled platoon planning, which they referred to as 'the day-before' truck platooning planning problem. Their model distinguishes the time-expanded network into a truck layer and a platoon layer. The former contains the single truck's movements, and the latter includes the movement of platoons. This model also considers truck drivers' working hour regulation. Using a parameter varying from zero to one to indicate the proportion of task-relief effect for drivers on the following trucks, this model quantifies the labor-cost savings, or personnel cost savings named by the authors, resulting from longer working hours. Similarly, Stehbeck (2019) proposed a mixed-integer program on a spatial network to identify the labor-cost savings introduced by platooning. However, as itinerary planning for trucks under driving time regulations is a NP-hard problem (Goel & Vidal, 2014), and these two studies have not exploited the model structure to generate efficient algorithms, the problem sizes solved in these two papers are relatively small.

The review indicates that research on real-time platooning is still absent, though it is essential in practical terms. Real-time platooning would provide quick responses to uncertainties confronted in reality, such as the supply uncertainty from manufacturers and retailers, the demand uncertainty from customers, and the travel time uncertainty due to driver scheduling, congestion, work zones, and hazard, etc. However, to implement such schemes, innovative and fast online solution algorithms need to be developed, and this would also be one of the author's future studies.

2.3.2 Platoon formation

Previous theoretical and experimental analyses have revealed two key facts pertinent to platoon formations. Firstly, aerodynamic drag reduction, the preeminent cause of energy savings in platoons, is affected by multiple factors, including the individual vehicle's shape and size (Hammache et al., 2002; Browand & Hammache, 2004), and vehicle sequence, headway, speed and length in platoons (Tsuei & Savaş, 2001; Schito & Braghin, 2012; McAuliffe et al., 2018). Therefore, given a set of vehicles, there exists the 'greenest' platoon formations that achieve the largest amount of energy savings. Secondly, experimental studies on truck platooning found that vehicles in a platoon benefit differently, e.g., the lead vehicles save little (Alam, 2011; Tsugawa et al., 2011, 2016; McAuliffe et al., 2017). Consequently, some drivers or owners of vehicles may not be willing to join or stay in the platoon even if they are advised to do so, yielding behaviorally unstable platoons. The instability further leads to chaos in traffic flows, which is likely to bring unnecessary traffic congestion. As previous studies mainly focus on the design of optimal control strategies to guarantee string stability and maintain the desired spaces of platoon (S. E. Li et al., 2017; M. Wang, 2018), few have considered the behavioral side of the problem, i.e., ensuring drivers or owners' willingness to form and maintain the platoon. It is, however, particularly critical for human-driven connected vehicles or privately-owned automated vehicles. Benefit redistribution mechanisms are therefore proposed to address such an instability concern. Accordingly, the second part of the thesis contributes to the integrated analysis of truck platoon formation and benefit redistribution, which are closely interacted with each other. To the best of the author's knowledge, this thesis is one of the pioneering work under this topic.

2.3.3 Benefit Sharing

The concept of benefit sharing in platooning is widely recognized in the studies of truck platooning. However, there is only a handful of papers and reports that provides detailed discussions on this topic, mostly done by European researchers. Moreover, these papers only apply mature concepts in allocation, which cannot settle the instability concern stated earlier.

Stehbeck (2019) applied several benefit allocation mechanisms that are studied well in the field of cooperative game, including *Shapley Value* (Shapley, 1953), *the Nucleolus* (Schmeidler, 1969), *Equal Profit Method*, and *Weighted Cost*, to a three-truck platooning scenario to show their performance. These mechanisms are also elaborated and assessed in chapter 5. The results show that they are incompatible with a system with a relatively large number of trucks that should be formed into more than one platoon.

Johansson & Mårtensson (2019) proposed game-theoretic models for benefit-sharing. In their problem setting, all vehicles have the same origin and destination but different default schedules. The way they platoon with each other is by changing departure time. This problem setting also considers a long-term platoon relationship among different transportation companies, so that the benefit-sharing can be conducted during one trip or multiple trips. Three decentralized sharing mechanisms base on noncooperative approaches and another based on the cooperative approach are stated and evaluated. The first model, *Even Out*, randomly assigns a platoon leader who receives monetary compensation from its follower. The second model, *Score System*, increases vehicles' scores when they are platoon leaders and decreases their scores when they are platoon followers. These two models utilize Nash equilibria as the solution concepts. The third model, *Market*, assigns a subset of vehicles as sellers/leaders and the rest followers/buyers at first, then allows the buyers and sellers to decide who to follow and who can follow to maximize their utilities. The fourth model considers an optimization problem to maximize the total energy-saving benefits and minimize the total time delay.

Comparing to the studies introduced above, the content presented in chapter 4 to chapter 6 provides a more profound analysis by especially focusing on the behavioral stability issue. For instance, Johansson & Mårtensson (2019) claims that no actual individual profit needs to be revealed by the individual vehicles, thus leaves some space for misreporting and makes the benefit-sharing mechanisms vulnerable. Instead of using the Nash equilibrium concept, this thesis mainly focused on equilibria that are incentive compatible, excluding the concern on deception.

Though not the focus of this thesis, it should be noticed that a few papers also provide insights on the implementation issues of benefit-sharing mechanisms that might occur in reality. As such mechanisms will be applied in an inter-organizational system, Stehbeck (2019) pointed out that trust and information transparency are crucial for success; Axelsson et al. (2020) restated the mechanisms proposed in Johansson & Mårtensson (2019)'s paper and evaluated them in terms of efficiency and customer acceptance. By further analyzing the commercial relations among different stakeholders such as OEMs, transportation companies (stated as the haulers in their paper), service providers, and infrastructure providers, they also indicated that there is no need to bring a third-party service provider in the money-based benefit-sharing system.

2.4 Theoretical Preliminaries

Mechanism design is a field in economics that designs economic mechanisms, or incentives, towards desired objectives. It inherits the strategic settings in game theory that assumes players behave rationally and focuses on the class of games with private information. However, instead of finding the equilibrium solutions under a given game structure as traditional game theory, it starts with the outcome that satisfies desired properties and traces back to the causing mechanisms, which are usually functions of players' private information. For this reason, mechanism design is sometimes referred to as 'reverse game theory.' Precisely, in this thesis, the acknowledged preferred outcome is forming behaviorally stable platoons, meaning that no individual vehicles in them can gain greater benefits by manipulation, such as providing incorrect information or changing positions. The analysis hence discusses the existence and formats of the proper mechanisms that can successfully implement such an outcome.

Mathematically, consider a game defined by a tuple $(\mathcal{N}, \Theta, \mathcal{A}, \chi, \mathcal{U})$ where

- $\mathcal{N} = \{1, 2, ..., n\}$ is the finite set of players or agents.
- $\Theta = \Theta_1 \times \cdots \times \Theta_n$, where Θ_i is the space of private information for agent i. Each individual's private information is also called her *type*. The agent and mechanism designer normally share a common prior distribution ϕ on Θ.
- $\mathcal{A} = \mathcal{A}_1 \times \cdots \times \mathcal{A}_n$ is the set of actions, where $\mathcal{A}_i = \{..., a_i, ...\}$ is the set of actions available to agent $i \in \mathcal{N}$.
- χ is the space of outcomes. An outcome function $\chi : \mathcal{A} \to \chi$ connects each joint strategy a to an outcome in χ.

- Each agent has an *ex post* utility function $U_i : \chi \times \Theta \times \mathbb{R}^n \to \mathbb{R}$, which is given by

$$U_i(\chi, \theta, p) = V_i(\chi, \theta) - t_i$$

  where

  - V_i is the payoff function of agent i, indicating the valuation she obtains under the outcome χ and the given joint type θ,
  - $t = t_1 \times \cdots \times t_n \in \mathbb{R}^n$ is the vector of transfers. An transfer function $t : \mathcal{A} \to \mathbb{R}^n$ determines a transfer for each agent given joint action a.

The utility function stated above is defined under the *quasilinear environment*, since the transfers p enter every player's utilities quasilinearly. The mechanism is constructed by the tuple $< \mathcal{A}, \chi, t >$, where *chi* and t are selected subject to certain constraints. In mechanism design problems, oftentimes the actions equal to sending messages, which are subject to players' true types. Mathematically, it can be formulated as $a_i = a(\theta_i), a : \Theta_i \to \mathcal{A}_i$, $\forall i \in \mathcal{N}$. However, if the action is revealing the type itself, that is to say, $\mathcal{A}_i = \Theta_i$, $\forall i \in \mathcal{N}$, then the mechanism is called a *direct mechanism*.

Mechanism design problems normally can be formulated as optimization problems that maximize certain objectives by determining χ and t under required constraints. Objective functions that are commonly seen include maximizing social welfare, $\sum_i v_i(\chi(a(\theta)), \theta)$, and maximizing revenue, $\sum_i t_i(a))$. If the attainable social welfare under an outcome is maximized, the mechanism is called *economic efficient*.

Core constraints include *incentive compatibility*, *individual rationality*, and *budget balance*. They ensure the outcome under the designed mechanism is an equilibrium solution for all players. Under the *Revelation Principle* (Myerson, 1981), any mechanisms that are incentive compatible is equivalent to the one that each agent truthfully reports her type. In this way, all mechanisms can convert into direct mechanisms.

2.4.1 Incentive Compatibility

Depending on the extent that private information is disclosed, there are three classes of incentive compatibility: interim, ex post and dominant strategy incentive compatibility.

Definition 2.4.1. (IIC) A mechanism (a^*, χ, t) is said to be *interim incentive compatible* if the following conditions are satisfied:

$$\begin{aligned}&\mathbb{E}[V_i(\chi(a^*(\theta))),\theta) - t_i(a^*(\theta))|\theta_i] \geq \\ &\mathbb{E}[V_i(\chi(a_i, a^*_{-i}(\theta_{-i})),\theta) - t_i(a_i, a^*_{-i}(\theta_{-i}))|\theta_i], \forall a_i \in \mathcal{A}_i,\ \forall i \in \mathcal{N}\end{aligned} \tag{2.4.1}$$

Here, the resulting strategy a^* describes the situation when every agent maximizes her expected conditional utility when she knows her own type. Thus, the outcome, $\chi(a^*\theta))$, is a *Bayesian Nash equilibrium*. Suppose function $\hat{\chi} : \Theta \to \chi$ satisfies $\hat{\chi}(\theta_i) = \chi(a^*(\theta_i))$, $\forall i \in \mathcal{N}$, it is also said that the mechanism (a^*, χ, t) implements $\hat{\chi}$ in Bayesian Nash equilibrium. Here, $\hat{\chi}$ is the direct mechanism that complies with the Revelation Principle. Though widely used in applications of mechanism design problems, the IIC mechanism can be easily sabotaged once there is information leakage.

Definition 2.4.2. (EPIC) A mechanism (a^*, χ, t) is said to be *ex post incentive compatible* if the following conditions are satisfied:

$$V_i(\chi(a^*(\theta))),\theta) - t_i(a^*(\theta)) \geq V_i(\chi(a_i, a^*_{-i}(\theta_{-i})),\theta) - t_i(a_i, a^*_{-i}(\theta_{-i})),\ \forall a_i \in \mathcal{A}_i,\ \forall i \in \mathcal{N} \tag{2.4.2}$$

Clearly, the outcome $\chi(a^*(\theta))$ is an ex post Nash equilibrium where every agent maximizes her ex post utility for all possible realizations of other agents' private information when all other agents play their equilibrium strategies as well. One can also conclude that if EPIC is satisfied, then IIC must be satisfied as well. In other words, satisfying EPIC is a sufficient condition for satisfying IIC.

Definition 2.4.3. (DSIC) A mechanism (a^*, χ, t) is said to be *dominant strategy incentive compatible* if the following conditions are satisfied:

$$V_i(\chi(a^*_i(\theta_i), a_{-i})),\theta) - t_i(a^*_i(\theta_i), a_{-i}) \geq V_i(\chi(a_i)),\theta) - t_i(a),\ \forall a_i \in A^t_i,\ \forall i \in N^t \tag{2.4.3}$$

DSIC mechanism aligns with dominant strategies in noncooperative game with perfect information and is the strongest condition of all three. This time, any arbitrary agent i under a^* maximizes her ex post utility for all possible realizations of other agents' privation information and all possible strategies others take.

2.4.2 Individual Rationality

Individual rationality describes the condition when agents are willing to join the game, rather than opt out. Suppose that agents who opt out the game will receive zero utility, then it is rational for them to stay if they can obtain non-negative utility (either ex ante, interim, or ex post) by staying in the game. Similarly, individual rationality can be categorized into three classes.

Definition 2.4.4. (EAIR) A mechanism (a^*, χ, t) is said to be *ex ante individual rational* if the following conditions are satisfied:

$$\mathbb{E}[V_i(\chi(a^*(\theta))), \theta) - t_i(a^*(\theta))] \geq 0. \tag{2.4.4}$$

Definition 2.4.5. (IIR) A mechanism (a^*, χ, t) is said to be *interim individual rational* if the following conditions are satisfied:

$$\mathbb{E}[v_i(\chi(a^*(\theta))), \theta) - t_i(a^*(\theta))|\theta_i] \geq 0. \tag{2.4.5}$$

Definition 2.4.6. (EPIR) A mechanism (a^*, χ, t) is said to be *ex post individual rational* if the following conditions are satisfied:

$$V_i(\chi(a^*(\theta))), \theta) - t_i(a^*(\theta)) \geq 0. \tag{2.4.6}$$

2.4.3 Budget Balancing

The last constraint introduced is *budget balancing*, or *revenue neutral*. Under strict budget balancing, the sum of all transfers equals zero, meaning that the mechanism designer neither substitutes the mechanism, nor gains revenue from the mechanism. A relaxed condition is weakly budget balancing, where the sum of all transfers is non-negative. In this case, the mechanism designer gains profits from the mechanism, which is preferable in many applications. Indeed, many auctions are designed in the way that the expected sum of transfers is maximized. The following context provides the related notations of budget balancing.

Definition 2.4.7. (EABB) A mechanism (a^*, χ, t) is said to be ex ante budget balance, if

$$\sum_i \mathbb{E}[t_i(a^*(\theta))] = 0 \tag{2.4.7}$$

Definition 2.4.8. (EPWBB) A mechanism (a^*, χ, t) is said to be ex post weakly budget balance, if

$$\sum_i t_i(a^*(\theta)) \geq 0 \tag{2.4.8}$$

Definition 2.4.9. (EPBB) A mechanism (a^*, χ, t) is said to be ex post budget balance, if

$$\sum_i t_i(a^*(\theta)) = 0 \tag{2.4.9}$$

It should be mentioned that some literature also uses ex post budget balance loosely to refer ex post weakly budget balance. However, this thesis strictly distinguishes the two definitions.

CHAPTER 3

Estimating Energy-Saving Potentials: the Planning Perspective

3.1 Introduction

Previous studies investigate truck platooning potentials on energy savings in large-scale traffic networks from two perspectives. The first provides platoon path planning that maximizes the total fuel-savings by tools of optimization (Larson et al., 2013, 2015). The second delves into the current truck data to anticipate the platooning rates if little or no coordination provided (Liang et al., 2014; Muratori et al., 2017; Lammert et al., 2018). This empirical study is among the first to integrate realistic data and mathematical programming to build an empirical understanding in energy-saving potentials. For more details, the author looks into U.S. truck origin-destination demand from Freight Analysis Framework (BTS & FHWA, 2016) and generates the truck schedules under reasonable assumptions of time-dependent flow distributions. Unlike vehicle trajectory data that can only be obtained from a small set of vehicles, the truck OD demand data is comparatively easier to access and manipulate with. An integer programming model established by Abdolmaleki et al. (2019) is applied to optimize trucks' itineraries, namely to assign trucks with proper travel routes, travel speeds, and departure times, in order to provide more platooning opportunities and thus maximizes the total energy savings. The result obtained from this model is called scheduled platooning.

In this study, the challenge lies in using an integer program to handle large-scale networks with heavy traffic demands. It is because that the computational time increases exponentially to the number of vehicles in the network. Data pre-processing is conducted at first to ease the computational burden, resulting in clustered truck demands and simplified mathematical presentation of the studied real highway system. An approximation algorithm is then implemented to accelerate the computation. The result obtained can be used as a starting point to perform sensitivity analysis and evaluate the influence from the elasticity of truck demand, tightness of time schedules, the rigidity of selected travel routes on total benefit. Overall, this empirical study is expected to provide the rationale for the investment in truck platooning.

3.2 Data Processing

There are two tasks in the data processing. The first task utilizes the geospatial data from Freight Analysis Framework version 4 (FAF^4) database to generate an abstract graph presenting U.S. national highway system. In the abstract graph, each edge or link represents a road, and each node represents an intersection of two roads or the origin or destination of the trucks. The weight of edge represents the free-flow travel time, determined by the road capacity and their average daily traffic volume.

The second task produces hourly truck origin-destination (OD) demands. FAF^4 coarsely divides the whole country into 132 FAF zones, so that the original data only contains annual truck tonnage by commodities between each pair of the zones. Noruzoliaee & Zou (2018) transferred the annual truck tonnage to an annual truck volume between FAF zones, and an annual truck volume between counties in the year 2012, 2020 (forecast value) and 2045 (forecast value). Considering that there are 3143 counties nation-wide, counties are further clustered into a median level of regions, allowing the author to produce hourly truck demands from an origin region to a destination region. It is also worth noting that since truck demands are generated from commodity flows, this study only optimizes trips from full-load trucks while dismissing empty truck trips, which can also be consolidated into platoons. The business model of using truck platooning to transport empty trucks, thus resolve the realistic truck imbalance issue, is considered in (Hirata & Fukaya, 2020).

3.2.1 Network Representation

FAF^4 network covers over 446,142 miles of roads consisting of 67,0427 roadway links, most of which are not platoonable. Hence only the links that lie in one of the following systems are selected:

- Interstate Highway System (IHS)
- National Freight Network (NFN) excluding IHS
- Other Principal Arterial (OPA) defined by HPMS

Besides, roadways in Hawaii and Alaska are disregarded. Roadways in the lower functional class are not considered due to its low mobility. After the first round of selection, 3,108 counties and 11,576 roadways as shown in figure 3.1(a) are included in the study range. It can be seen that the east part is much denser than the west part, and the metropolitan areas are much denser than the rural areas. Though realistic, such a graph is not suitable to use as the input for the mathematical program. Therefore, a more evenly spaced abstract network representing the roadway network structure of the contiguous states, as well as fit for modeling purpose, needs to be constructed.

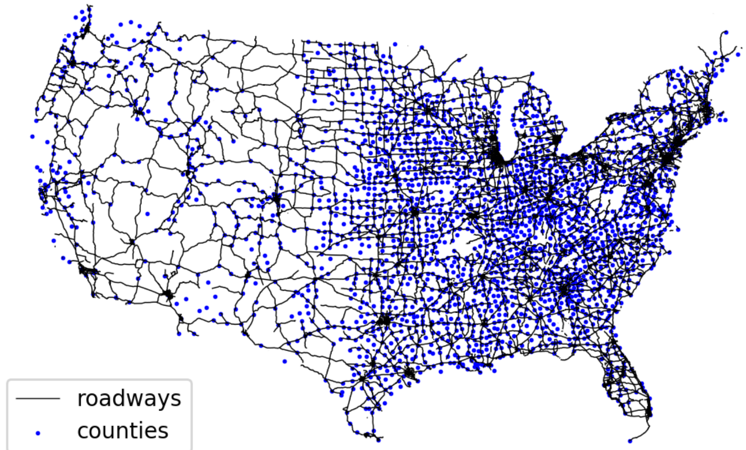
As the road networks in metropolitan areas are usually denser than other areas, the original network can cause trouble when applying an approximation algorithm to optimize truck schedules. The simplification contributes to a more evenly spaced network, which eases the complexity of using the algorithm and makes sense considering that highways in the metropolitan areas are usually busy with normal traffic flows and are not suitable for platooning. graph, there is only one edge connects them.

The construction of the desired abstract graph mainly repeats the following three steps: county clustering, roadway combinations, and network cleaning. A clustering algorithm named DENCLUE (Hinneburg & Gabriel, 2007) is implemented here to cluster nearby counties into larger regions. In each region, roadways that are close to each other are further combined into artificial roadways with higher capacities to simplify the network (figure 3.2). The last step cleans the network by removing geometric data errors from the original data set and isolated, short, and unused roadways, leaving for a simple connected graph. For example, in the areas around Los Angeles and San Deigo (figure 3.3), roadways that are not used to transfer demands are disregarded; for each pair of nodes in the graph, there is one edge connects them.

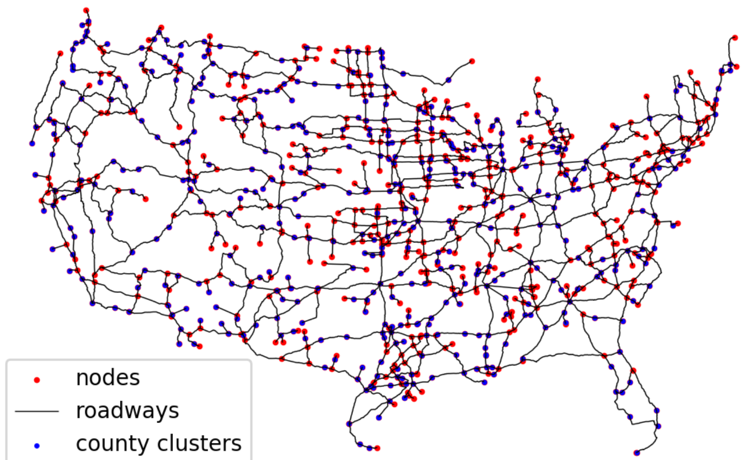
	County	Nodes	Edges
Before	3108	N/A	670472
After	445	934	1237

Table 3.1: Comparison between the original physical network and the reconstructed network

As a result, the final abstract graph contains 1237 links and 934 nodes, among which 445 of them are region centers (Figure 3.1(b)).



(a) The simplified network after road selection



(b) The abstract graph of roadway network Network

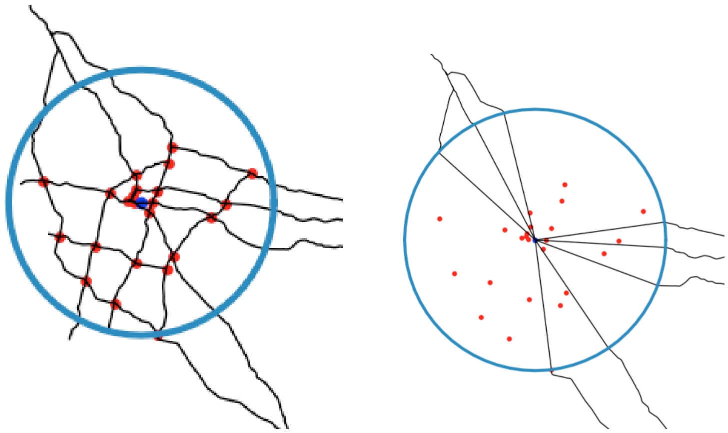
Figure 3.1: Physical network reconstruction

3.2.2 Truck Demand Generation

As suggested in Noruzoliaee & Zou (2018), five platoonable truck types ("tractor plus semitrailer combination" configuration with types of "dry van", "platform", "reefer", "livestock", and "automobile") out of 45 different truck configurations contained in FAF[4] are selected. Their traffic volume is aggregated into platoonable truck OD volume between FAF zones, which occupy 38.1% of total truck volume in the United States.

Noruzoliaee & Zou (2018) used a matrix disaggregation equation (equation 3.2.1) to convert the truck demands between FAF zones to those between counties:

$$Flow_{i,j} = Flow_{I,J} \times p_i \times a_j \tag{3.2.1}$$



(a) Before (b) After

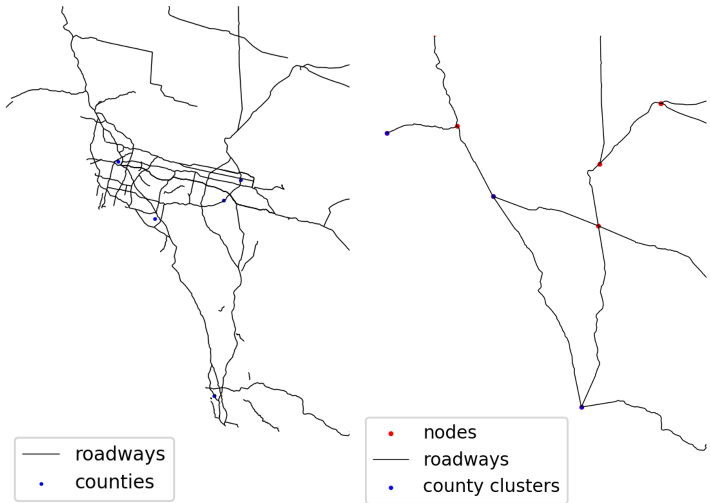
Figure 3.2: Roadway combinations

where truck flow from FAF zone I to FAF zone J is represented by $Flow_{I,J}$, and that from county i to county j is represented by $Flow_{i,j}$. The production factor p_i is represented by the ratio of county employment to region employment, and the ratio of county population to region population serves as the attraction factor a_i.

In this study, the county-level truck OD demands are aggregated into region-level truck OD demand, consistent with the abstract graph derived early. The annual truck demand is uniformly distributed to obtain the daily truck OD demand. Furthermore, the hourly truck OD demands are generated by using 0.09 as the off-peak-hour K-factor and 0.11 as the peak-hour K-factor. The OD pairs with daily truck flow less than one are neglected. After the filtering, 81.3% of all platoonable truck volume will be used as input of the following mathematical program.

3.3 The Itinerary Planning Model

The integer program established by Abdolmaleki et al. (2019) is utilized to assigns trucks with proper travel routes, speeds, and departure times to increase platooning opportunities for trucks on the same roads, thus to maximize the total energy savings. Specifically, the model is constructed on a time-expanded network $G(N, L)$. Each link $l \in L$ connects two virtual nodes, (t_i, s_i), $(t_j, s_j) \in N$, indicating the path from a physical location s_i at one time t_i to the same or another physical location s_j at a later time t_j. In this way, the only set of constraints except for the definition of fuel consumption function are flow conservation constraints, which converts the original problem to a minimum concave cost network



(a) Before (b) After

Figure 3.3: Physical network cleaning

flow problem that is relatively easier to solve. The model is formulated as the following:

$$\min_{x,Y} \quad \sum_{l \in L} f_l(Y_l) \tag{3.3.1a}$$

$$s.t. \quad \sum_{\substack{t_i, s_i: \\ l=(t_i,s_i;t,s) \in L}} x_l^k - \sum_{\substack{t_j, s_j: \\ l=(t,s;t_j,s_j) \in L}} x_l^k = d_s^k, \ {}^{\forall k: G_k \bigcap l \neq \emptyset,}_{\forall s \in N(G)} \tag{3.3.1b}$$

$$y_l^c = \sum_{\{k | k \in K_c\}} x_l^k ; \forall 1 \leq i \leq C \tag{3.3.1c}$$

with

$$x_l^k = \begin{cases} 1 \text{ If } k \text{ travels on } l \\ 0 \quad \text{Otherwise} \end{cases} \tag{3.3.1d}$$

$$d_s^k = \begin{cases} -1 & \text{If } s{=}O(k) \\ 1 & \text{If } s{=}D(k) \\ 0 & \text{Otherwise} \end{cases} \tag{3.3.1e}$$

The flow conservation constraints are given in equation 3.3.1b. At each physical location s, parameter d_s^k equals -1 if s is vehicle k's origin, 1 if s is vehicle k's destination, and 0 otherwise (equation 3.3.1e). The model permits the existence of multiple vehicle classes, which is denoted by a set C. Each class of vehicles have the same type and configuration. The dependent variable y_l^c hence indicates the number of vehicles in class c on the spatial-temporal link l. The vector Y_l concludes the number of vehicles in all class es. The function

$f_l(Y_l)$ plots the relationship between vehicle numbers and the overall fuel consumption on link l. The only assumption here is that for each variable y_l^c, the function $f_l(Y_l)$ is a concave and monotonically increasing function.

It can be seen that this model is rather abstract with a certain degree of flexibility. To apply it in this empirical study, the author simply assumes that all trucks are in the same class in terms of their energy-saving property. Also, a unit of truck OD demand is transferred by one truck, from its origin to destination. In this way, the uploading and unloading work in the freight business and empty truck trips have been neglected in the study.

3.4 The Solution Algorithm

For a large-scale network with enormous demand, the approximation algorithm is applied. The author assumes that on each spatial-temporal link, the fuel consumption under platooning, denoted as f_l, increases with the number of vehicles. The energy savings under platooning, denoted as δ_l, increase with the number of vehicles available to platoon.

If the schedule does not increase each individual's energy consumption compared to their original schedules, one can conclude that

$$\min \sum_l f_l(\mathbf{Y_l^k}) \Longleftrightarrow \max \sum_l \delta_l(\mathbf{Y_l^k})$$

.

In this way, the algorithm first conducts a pre-processing step to identify each vehicle's spatial-temporal paths that contribute to the same amount of energy consumption under the scenario without platooning. Based on the joint set of the generated paths, a path in the time-expanded network that has the most potential on energy savings is found, all vehicles are then guided to travel on the overlapping part of this path and its own paths. This process is conducted iteratively until no vehicles can reroute to gain greater platooning opportunities. More detailed explanations on the algorithm is elaborated in Abdolmaleki et al. (2019).

3.4.1 Rolling Horizon

The recurrent daily freight demand varies in the trip distance and time windows (Figure 3.4). 92.0% of the trips end on the first day, 6.6% of the trips end on the second day, and 1.4% of the trips end on the third day. Applying the mathematical model only to the daily

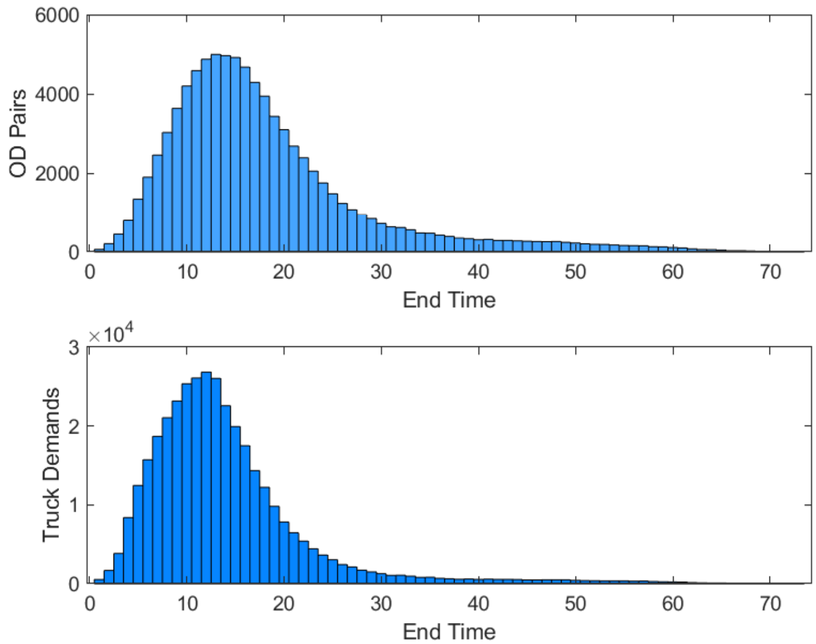


Figure 3.4: Distribution of freight demands by the trip end time

demand will obviously lead to an underestimated result. For simplicity, a rolling horizon approach is adopted to address this concern. As suggested in figure 3.5, the planning horizon is three days, and the rolling horizon is one day. The analysis is conducted on the third day's result.

3.4.2 Monte-Carlo Simulation

Due to the enormous size of the studied network, a one-hour resolution is applied when constructing the time-expanded network. The coarse resolution can contribute to an over-estimated result, as it suggests that trucks departing at 0:00 can platoon with those leaving at 0:59. A Monte-Carlo simulation approach is applied to resolve this concern by randomly generating the departure time of each truck and only allowing those who depart during the same time interval to platoon together. Such a time interval is thus used as a surrogate resolution. Three time intervals, 10 minutes, 15 minutes and 30 minutes are selected as the surrogate resolutions.

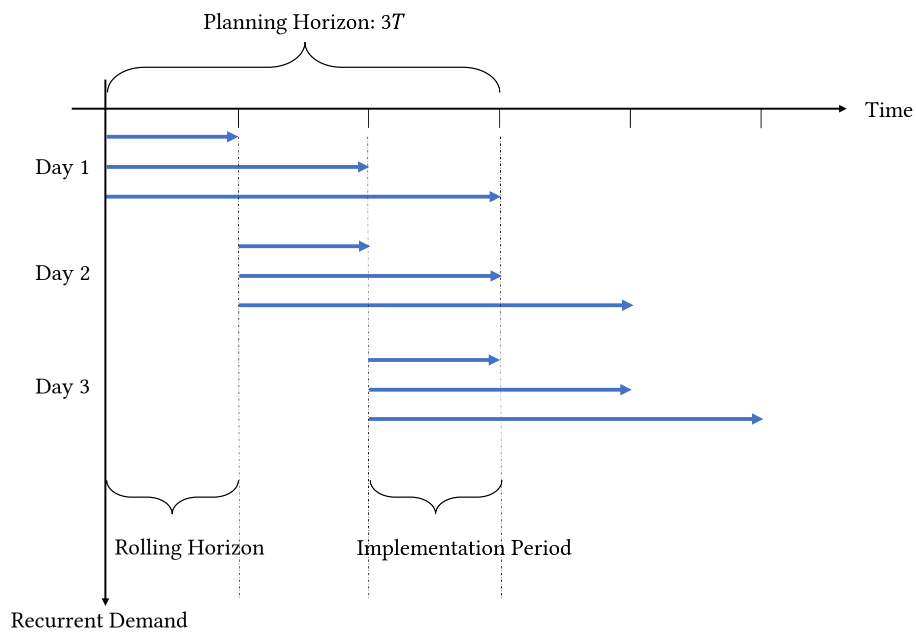


Figure 3.5: The rolling horizon scheme

Parameter	Value
Fuel Consumption Rate	6.4 mpg
α	0.1
Maximum platoon size	2 ~ 7
Fuel price range	\$ 2.152/gal ~ \$3.365/gal
Average fuel price	\$ 2.850/gal
Average annual truck tractor miles until replacement	70,000 miles
Average number of years until replacement	7
Price of technology	\$ 4,000 ~ \$ 11,000

Table 3.2: Key parameters in the empirical study

3.4.3 Other Parameters

The fuel consumption function is given by

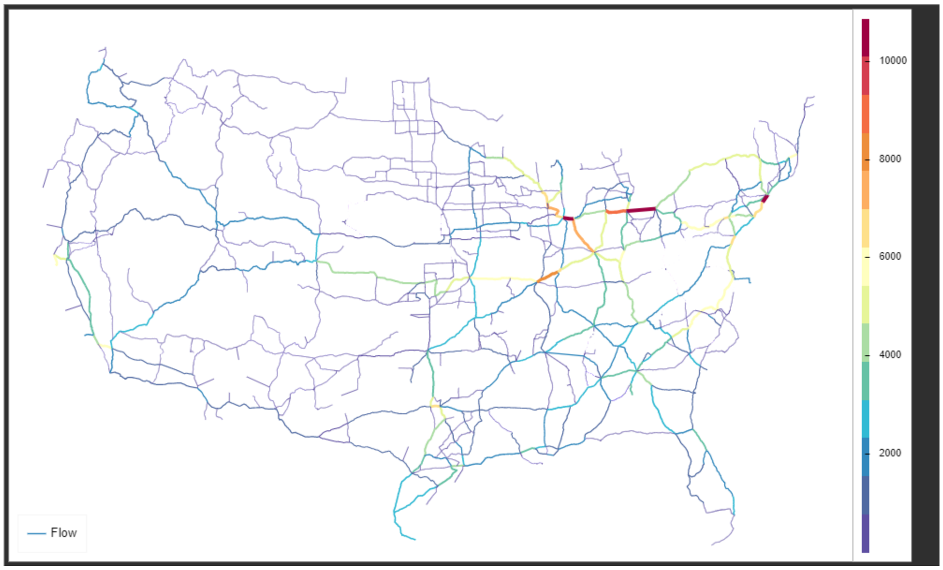
$$f_l(m) = (m - \alpha(m-1))f_0, \ \forall l \in L, m = \min\{\bar{N}, n\}$$

where n is the number of vehicles available on the spatial-temporal link l, and $\bar{N}$ is the maximum allowable platoon size, α indicates the energy-saving percentage.

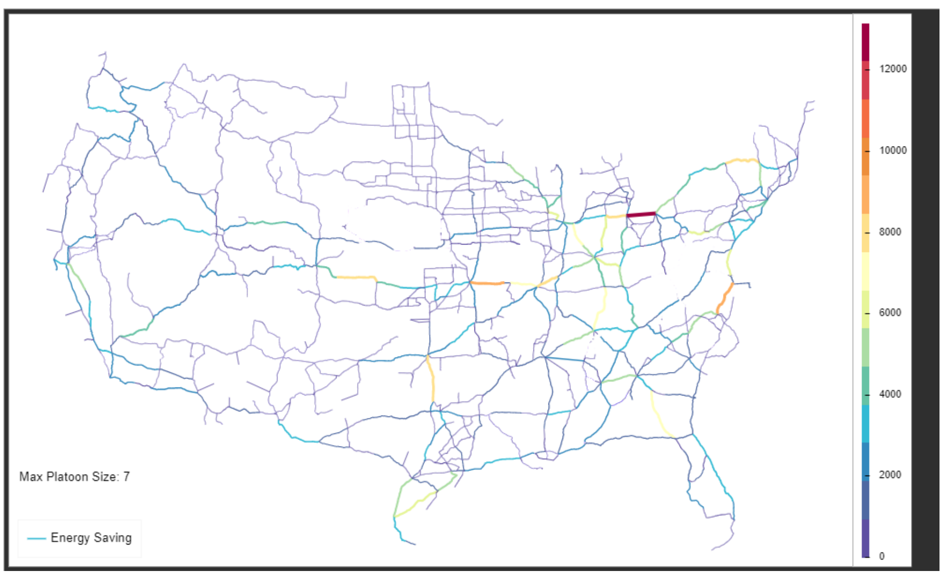
Several vital parameters are listed in table 3.2. Specifically, the fuel consumption rate, average annual truck tractor miles, and the average number of years until replacement come from Murray & Glidewell (2019). The energy-saving percentage of following trucks from platooning, denoted as α, is selected from previous similar studies (Larson et al., 2016). Fuel price range and average fuel price can be found from the website of U.S. Energy Information Administration (EIA, 2020). The price of technology is estimated by the National Traffic Safety Administration (NHTSA).

3.5 Results and Discussions

3.5.1 Network-level Potential



(a) Total daily flow



(b) Energy savings with $\bar{N} = 7$

Figure 3.6: Scheduled truck platooning over U.S. freight network

With the generated routing and schedule of individual trucks, the total daily flow of the U.S. national freight network is presented in figure 3.6(a). One can tell that the truck movements in the great lakes area, east coast from Boston to Washington D.C., are relatively busier than other parts of the country. Figure 3.6(b) presents the energy savings when the maximum platoon size is seven, shown a similar trend of total daily flow.

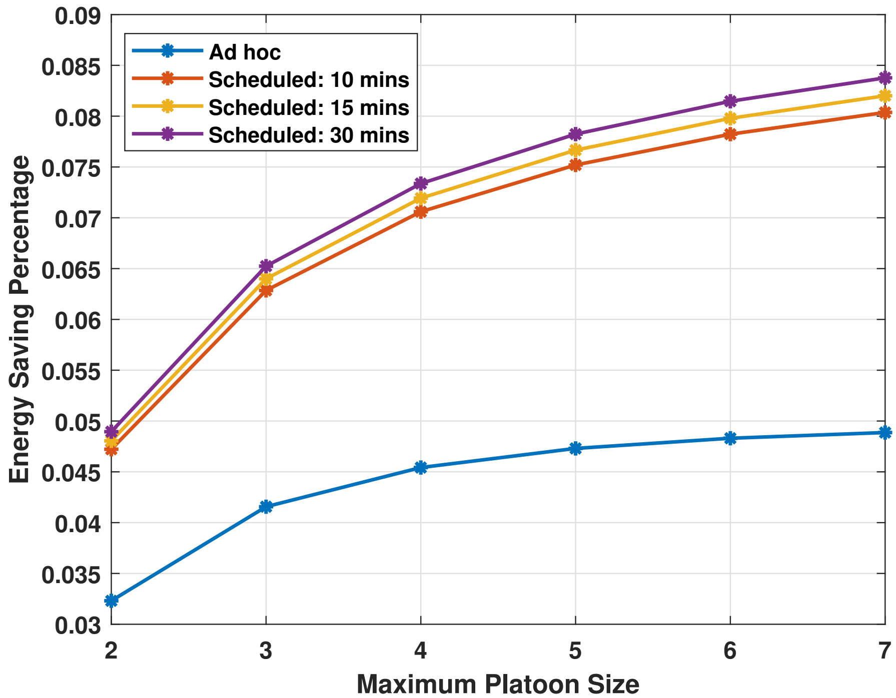
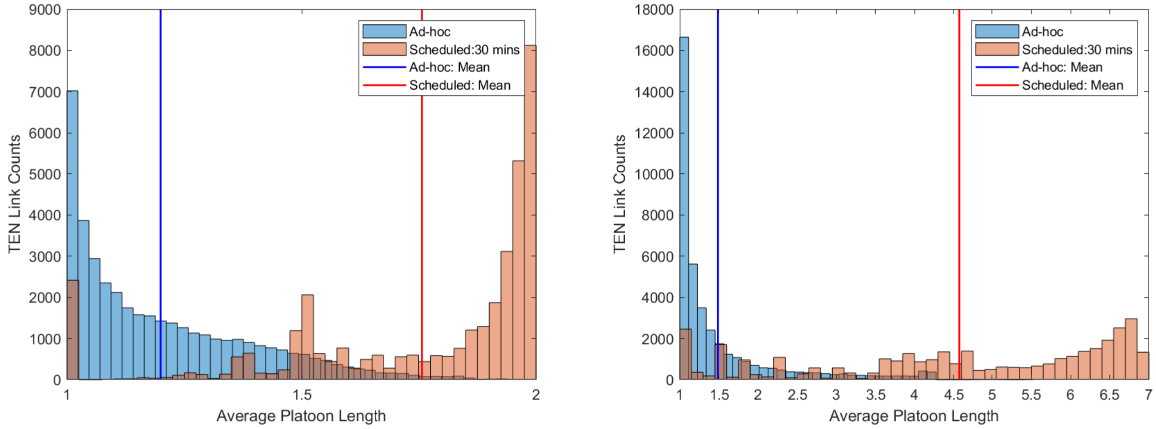


Figure 3.7: Total energy-saving percentage w.r.t. platoon length limit

The average energy-saving percentages under different maximum platoon sizes are presented in figure 3.7. Clearly, the percentage increases with the maximum platoon size under both scheduled and ad-hoc platooning scenarios. However, the marginal increase of the former scenario is much larger than that under the latter one. On average, scheduled platooning can lead to more than 1.5 times of energy-saving percentage. In addition, using a coarser resolution also contributes to a higher saving percentage, though marginally. The exact data of energy-saving percentages can be found in A.

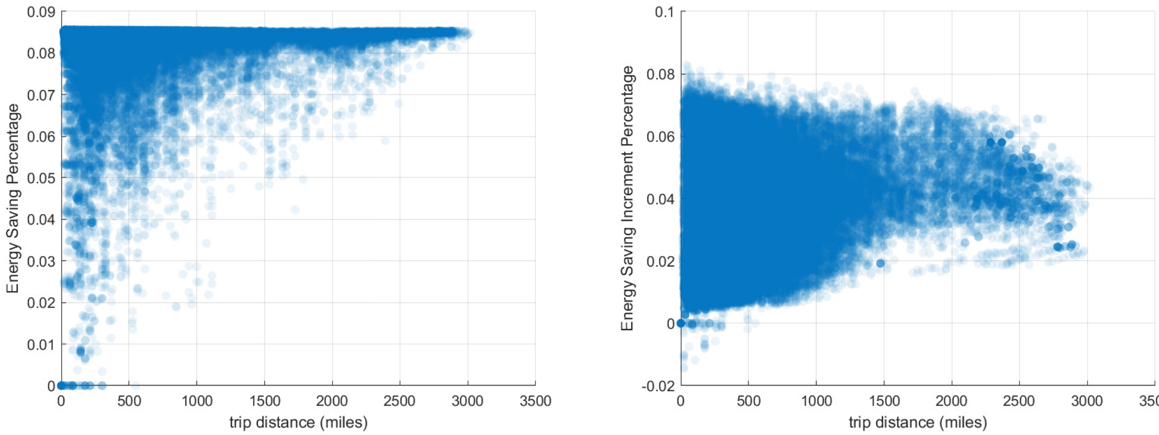


(a) $\bar{N} = 2$ (b) $\bar{N} = 7$

Figure 3.8: Average platoon length per hour per link

Figure 3.8 compares the platoon size distribution over truck links under scheduled and ad-hoc platooning when maximum allowable platoon size is two and seven, respectively. It can be seen that compared to ad-hoc platooning, scheduled platooning has a bigger platoon size on average. Furthermore, the average platoon size under ad-hoc platooning increases subtlety with the maximum allowable platoon size, and the average size number reaches two. It indicates that if no scheduled planning is performed on platooning, there is no need to impose a platoon size limit, as ad-hoc platooning does not generate long platoons.

3.5.2 OD-based Performance



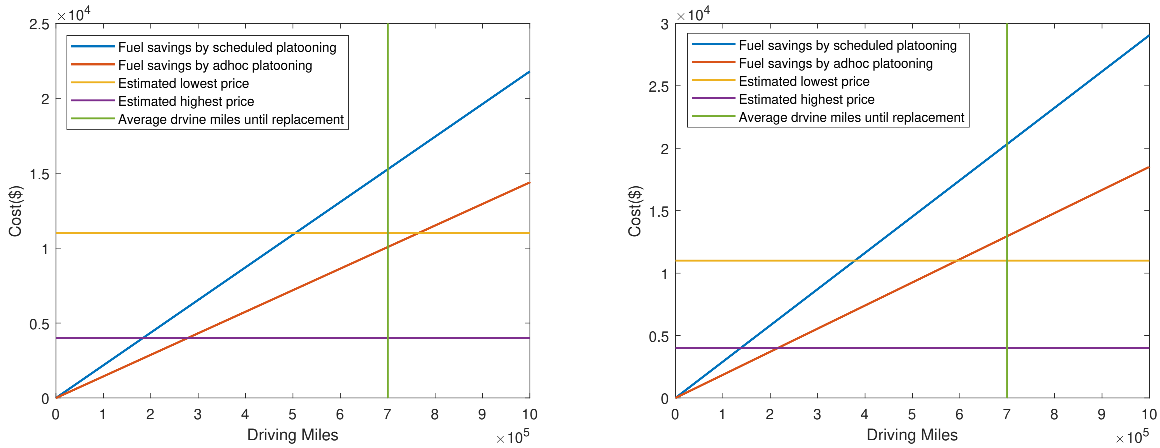
(a) Absolute value under scheduled platooning (b) Increment from ad-hoc platooning to scheduled platooning

Figure 3.9: Energy-saving percentage w.r.t. trip distance, $\bar{N} = 7$

Three key results are revealed when inspecting the performance of energy savings based on specific origin and destination pairs. First of all, truck platooning benefits to both short-distance trips and long-distance trips. Second, the longer distance the trip travels, the higher the average energy-saving percentage the trip can receive. Third, the variance of energy-saving percentage increment from ad-hoc to scheduled platooning decreases with the increase in travel distances. These findings generally are quite the opposite of those from another empirical study using Netherlands' national freight data, which says that the feasible platoonable flows mainly appear in relative short routes with high truck volume (Bakermans, 2016). Two reasons can be asserted for this contradiction. Firstly, U.S. is much larger than the Netherlands in terms of area. Therefore the former also embeds a higher demand on long-distance truck trips. The Netherlands' result could be more promising if the cross-border truck trips are included in the analysis. Secondly, unlike this empirical study that conducts path planning and permits platooning of trucks with different O.D.s, Bakermans (2016)'s study only allows trucks to decelerate or accelerate to platoon with others with the same O.D. The comparative results, once again demonstrate the necessity of scheduled platooning.

3.5.3 Individual Owner's Perspective

Individual truck owners care about the profits by investigating the technology. Therefore, a cost-benefit analysis is conducted with results presented in figure 3.10. Here, the purple horizontal line indicates the estimated lowest price of purchasing, while the yellow



(a) $\bar{N} = 2$ (b) $\bar{N} = 3$

Figure 3.10: Cost-benefit analysis for platoon investigation

horizontal line indicates the estimated highest price of purchasing. The green vertical line indicates the average driving miles per truck before replacement. The oblique blue line indicates the monetary savings of energy from scheduled platooning, and the oblique red line indicates that from ad-hoc platooning. The intersecting points of any oblique lines and horizontal lines are break-even points. The exact data are presented in table A.2. Conservatively, when only ad-hoc platooning is implemented, and the max platoon size is set to be two, truck owners can not gain profits before replace the truck tractor on average. However, when increasing the maximum platoon size only by one, truck owners can also gain profits from merely ad-hoc platooning. One reason that contributes to the promising result is that the U.S. freight demand is huge enough, so platooning opportunities are many. Nevertheless, scheduled platooning is more profitable. However, the results may be overestimated since the operational cost of the central operator who performs the scheduled planning has not been considered.

3.6 Conclusion

This chapter estimates the truck platooning opportunities and the associated energy-saving potentials of the overall U.S. freight network, by applying the itinerary planning model to generate routing and schedules for the daily truck demands. The numerical results reveal that the energy-saving potential is promising: using a piece-wise linear fuel consumption where there is 10% energy-saving for each following vehicle and 0 for the leading vehicle, the average energy-saving of the whole network can achieve to

8.37% at most. Further analysis shows that the result of energy-saving is more robust for long-distance trips, while it varies for short-distance trips. However, they all obtain considerable savings on average. The cost-benefit analysis indicates that truck platooning is financially reliable for truck owners, even if considering the energy-saving benefits only. It can be expected that with the introduction of labor-cost savings, truck platooning market is more promising in the future.

It should be emphasized that such a study is conducted on the overall truck demand of the whole U.S. network, so that the result can be considered as an upper bound of that realized in practice, achieved only if market penetration rate of truck platooning is 100% and all trucking companies are willing to cooperate together. Therefore, the benefit redistribution mechanisms investigated in the following chapter are necessary strategies to promote inter-organizational cooperation.

CHAPTER 4

Behavioral Stability in the Single-Brand Scenario: An Auction Scheme

4.1 Introduction

This chapter focuses on the benefit redistribution mechanism for single-brand truck platooning. The term single-brand describes the situation where all vehicles are identical in terms of their type and configuration. Under this circumstance, all the platoon members contribute equally to energy savings when they operate at deliberate speed. Therefore, one can intuitively believe that equally share the energy-saving benefits, and a simple egalitarian mechanism would serve the purpose. However, it is only a part of the story. Considering the current level of vehicle automation, it is inevitable that the leading vehicle's driver takes more effort on maneuvering the truck than her peers on the following vehicles. Hence, leading a platoon can be viewed as providing a labor-saving service, where the driver of the leading vehicle is the seller while rest are buyers. Buyers value the service differently depending not only on their wage levels but also on the degree of tiredness, working hours, the deviation from the original schedules after platooning. Therefore, they own different willingness-to-pays (WTPs).

To maximize the amount of labor savings, or in other words, to achieve economic efficiency (EE) under behavioral stability, the author utilizes an auction as the mechanism which determines the position and the transfer function. All drivers, or agents, raise a bid to indicate their WTPs for the platooning service. The one with the least WTP is therefore selected as the leader and collect a certain amount of payments. Compared to the standard auction formats where buyers and sellers are determined before the auction, this auction is unique. Determining the seller, which is also the leader, is an outcome of the auction. Therefore, the author names this auction as *auction for leader determination* in the following context. In the remainder of this chapter, section 4.2 provides the basic setting and the assumption; section 4.3 provides an impossible result and its proof; section 4.4 gives the transfer function and how it is implemented along the route; finally section 4.5 concludes this chapter.

4.2 The Basic Model

The auction is defined by a tuple $(\mathcal{M}, \Theta, \mathcal{A}, \chi, U)$ where

- $\mathcal{M} = \{1, 2, ..., m\}$ is the finite set of agents. Each agent $i \in \mathcal{M}$ represents a driver that is willing to participating in truck platooning through auctions.

- $\Theta = \Theta_1 \times \cdots \times \Theta_m$, where Θ_i is the space of private information (or "types") for agent i. Here, the private information of agent i, $\theta_i \in \Theta_i$, is her WTP for the platooning service. Agents are also assumed to be symmetric. Accordingly, each type space, $\Theta_i, i \in \mathcal{M}$, is a continuous space bounded by $\underline{\theta}$ below and $\overline{\theta}$ above and $0 < \underline{\theta} \leq \bar{\theta} < \infty$. Any randomly selected $\theta_i \in \Theta_i$ follows a common prior distribution ϕ.

- $\mathcal{A} = \mathcal{A}_1 \times \cdots \times \mathcal{A}_m$ is the set of actions, where $\mathcal{A}_i$ is the set of actions available to agent $i \in \mathcal{M}$. Assuming this auction is a direct mechanism, the action agent i takes is bidding a value, $\hat{\theta}_i$, to represents her WTP. Therefore, $\mathcal{A}_i = \Theta_i, \forall i \in \mathcal{M}$.

- χ is the space of outcomes. Each outcome $\chi \in \chi$ represents a possible leader determination in the formed platoon. The outcome is generated from the joint action of all agents.

- Each agent has an utility function

$$U_i(\chi(\hat{\theta}), \theta, p) = V_i(\chi(\hat{\theta}), \theta) - p_i(\hat{\theta}) \tag{4.2.1}$$

  where

  - V_i is the valuation agent i obtained under outcome χ given joint type θ,
  - $p = p_1 \times \cdots \times p_m \in \mathbb{R}^m$ is the vector of payment, specifically determined by the joint action a.

A few assumptions are made based on the setting above. First of all, the utility, valuation, and payment are defined per unit distance. This assumption allows the auction scheme to be utilized in real-time. Second, the energy-saving benefit is assumed to be equally shared by all platoon members. As all trucks have the same vehicle configuration and the formed platoon is operated at deliberate speed, the energy-saving benefit is only a function of the number of vehicles in the platoon, which can be denoted as $\delta(m)$.

As the outcome, the agent with the least bid becomes the leading truck. A random agent in the tie is chosen as the leading truck if there is a tie on bids. Under the consideration that no external authority will subsidize the formation of platoons, nor gain profits from it, the auction is *ex post budget balance* (EPBB):

$$\sum_{i \in \mathcal{M}} p_i(\hat{\theta}) = 0 \tag{4.2.2}$$

Accordingly, the utility functions can be written as

$$U_i(\hat{\theta}_i, \hat{\theta}_{-i}) = \begin{cases} \frac{1}{m}\delta(m) + \sum_{j:j\neq i} p_j(\hat{\theta}), & \text{if } \hat{\theta}_i < \hat{\theta}_j,\ \forall j \neq i \\ \frac{1}{m}\delta(m) + \frac{1}{|T|}\theta_i + \frac{1}{|T|}\sum_{j:j\neq i} p_j(\hat{\theta}) - \frac{|T|-1}{|T|}p_i(\hat{\theta}), & \text{if } \exists j \neq i s.t.\ \hat{\theta}_i = \hat{\theta}_j < \hat{\theta}_k,\ \forall k \neq i, j \\ \frac{1}{m}\delta(m) + \theta_i - p_i(\hat{\theta}), & \text{if } \exists j \neq i, s.t.\ \hat{\theta}_j < \hat{\theta}_i \end{cases} \tag{4.2.3}$$

Here, $|T|$ denotes the number of agents that bid the least value. The vector $(\hat{\theta}_i, \hat{\theta}_{-i})$ is another form of vector $\hat{\theta}$ where $\hat{\theta}_{-i}$ is the vector in $\mathbb{R}^{m-1}$ that represents the other agents' bids.

Another constraint, behavioral stability, guarantees that under the given outcome from $\hat{\theta}$, no agent would like to switch positions or leave the platoon to obtain greater benefits. Particularly, no followers would like be the leader, and vice versa. Easy to see, *ex post incentive compatibility* (EPIC) and *ex post individual rationality* (EPIR) are sufficient condition for behavioral stability. And by the Revelation Principle (Gibbard, 1973; Dasgupta et al., 1979), such an auction is *truth-telling*. Mathematically,

$$\theta_i = \arg\max U_i(\hat{\theta}_i, \theta_{-i}), \forall i \in \mathcal{M},\ \forall \hat{\theta}_i \in [\underline{\theta}, \overline{\theta}]. \tag{4.2.4}$$

Furthermore, if the mechanism is incentive compatible, economic efficiency is automatically achieved since the agent with the real least WTP is allocated as the leader.

4.3 The Impossibility Result

Ideally, one expects to find a transfer function, $p(\theta)$, such that the auction is EE, EPBB and EPIC simultaneously. However, the analysis in this section shows that it is impossible to achieve such a goal.

Theorem 4.3.1. For the auction for leader determination, there is no mechanism that can be implemented in ex post equilibrium to achieve economic efficiency under the constraint of ex post budget balance.

To prove this, the author starts with Groves Theorem (Groves, 1973) that characterizes the class of mechanisms with economic efficiency and ex post incentive compatible. The result shows that Gloves mechanism cannot achieve ex post budget balance for the auction studied in this chapter. Based on this result, the author further proves that ex post incentive compatible and budget balance cannot exist simultaneously.

4.3.1 Grove Mechanisms

Lemma 4.3.1. *Grove mechanisms do not satisfy ex post budget balance under the auction for leader determination.*

Proof. Without loss of generality, assume that all agents' realized WTPs follow the sequence below:

$$\theta_1 < \theta_2 < \cdots < \theta_m.$$

making agent 1 the leading vehicle.

Consider the well-known VCG auction (mechanism) (Vickrey, 1961; Clarke, 1971; Groves, 1973), which is a special case under the Groves mechanism family. the transfer function can be written as

$$\begin{aligned} p_1(\theta) &= -\theta_2 + \frac{m-1}{m}\delta(m) - \delta(m-1) \\ p_j(\theta) &= \frac{m-1}{m}\delta(m) - \delta(m-1), \forall 2 \leq j \leq m \end{aligned}$$

Though resulted EPIC and EE, the total budget is $-\theta_2 + (m-1)\delta(m) - m\delta(m-1) \neq 0$, violating the EPBB constraint. Even worse, when the energy-saving benefit is relatively small comparing to the labor-saving benefit, the total budget is negative meaning that an external authority needs to subsidize the platoon.

Next, consider the more general forms of Grove mechanisms:

$$p_1(\theta) = -[\sum_{2 \leq k \leq m} \theta_k + \frac{m-1}{m}\delta(m)] + h_1(\theta_{-1}) \tag{4.3.1a}$$

$$p_j(\theta) = -[\sum_{2 \leq k \leq j-1,\ j+1 \leq k \leq m} \theta_k + \frac{m-1}{m}\delta(m)] + h_j(\theta_{-j}),\ \forall j \neq 1 \tag{4.3.1b}$$

where $h_i : \theta_{-i} \rightarrow \mathbb{R}, \forall i \in \mathcal{M}$.

By assumption, the leader always collects a positive amount of payment and the followers always pay positive amounts, no matter whether the position allocation is efficient. These conditions can be mathematically presented as

$$\sum_{k\in m,k\neq 1} \theta_k + \frac{m-1}{m}\delta(m) - h_1(\theta_{-1}) > 0 \tag{4.3.2a}$$

$$\sum_{k\in M,k\neq j} \theta_k + \frac{m-1}{m}\delta(m) - \theta_1 - h_j(\theta_{-j}) < 0, \ \forall j \neq 1 \tag{4.3.2b}$$

$$\sum_{k\in M,k\neq 1} \theta_k - \theta_2 + \frac{m-1}{m}\delta(m) - h_1(\theta_{-1}) < 0 \tag{4.3.2c}$$

$$\sum_{k\in \mathcal{M},k\neq j} \theta_k + \frac{m-1}{m}\delta(m) - h_j(\theta_{-j}) > 0, \ \forall j \neq 1 \tag{4.3.2d}$$

Specifically, equation 4.3.2a and equation 4.3.2b describe the payment when all agents reveal their true WTPs; equation 4.3.2c states that if agent 1 misreports and becomes a following vehicle, it will pay; while equation 4.3.2d states that if any other agent misreports and becomes the leader, it will collect.

Rearranging the above constraints leads to the following results:

$$\sum_{k\in \mathcal{M},k\neq 1} \theta_k - \theta_2 + \frac{m-1}{m}\delta(m) < h_1(\theta_{-1}) < \sum_{k\in \mathcal{M},k\neq 1} \theta_k + \frac{m-1}{m}\delta(m) \tag{4.3.3a}$$

$$\sum_{k\in \mathcal{M},k\neq i} \theta_k - \theta_1 + \frac{m-1}{m}\delta(m) > h_i(\theta_{-i}) > \sum_{k\in \mathcal{M},k\neq i} \theta_k + \frac{m-1}{m}\delta(m), \ \forall i \neq 1 \tag{4.3.3b}$$

Combining equation set 4.3.1 and equation set 4.3.3, the payments are bounded as follows:

$$\begin{aligned} -\theta_2 &< p_1(\theta_{-1}) < 0, \\ 0 &< p_j(\theta_{-j}) < \theta_1, \ j > 1, \\ -\theta_2 &< \sum_{i\in\mathcal{M}} p_i(\theta_{-i}) < (m-1)\theta_1. \end{aligned}$$

However, EPBB leads to

$$p_1(\theta_{-1}) = -\sum_{j\neq 1} p_j(\theta_{-j}) \in [-(m-1)\theta_1, 0],$$

indicating that agent 1's payment depends on her WTP, which is contradict to the assumption that p_1 is a only function of θ_{-1}. □

4.3.2 Two-sided EPIC

This subsection shows that under the EPBB constraint, if EPIR is imposed as well, there is no way to achieve EPIC. As a preparation, the definition of EPIC in the auction is described as the following.

Definition 4.3.1. EPIC for all vehicles is denoted as *two-sided EPIC* to emphasize that it is the incentive-compatible equilibrium for both seller and buyer side. Similarly, EPIC only for the buyer side or the seller side is referred to as *buyer-side EPIC* or *one-sided EPIC*.

Lemma 4.3.2. In the setting of auction for leader determination with EPBB and EPIR, the followers (buyers) are EPIC only if they pay a uniform price, p, independent of any followers' WTPs.

Proof. This can be proved by contraposotive. Denote the set of followers as $\mathcal{F}$. Suppose a transfer function is discriminate. There are two cases for p_i, the payment by follower i:

1. p_i is a function of θ_i. Once the function is known, all followers would like to misreport to pay $p^* = \min\{p_i, i \in \mathcal{F}\}$ under the *ex post* environment, hence not EPIC. As a simple example, suppose $\frac{\partial p_i}{\partial \theta_i} > 0$. Consequently, all followers can bid $\theta_1 + \epsilon$ with $\epsilon > 0$ being a very small number to pay less than he/she supposed to.

2. p_i is a function of θ_{-i}, denoted as $p_i(\theta_{-i})$. Under the constraint of EPIR, all m agents should be platoon members so that they are either the leader or the followers. Under the EPBB constraint,
$$p_i(\theta_{-i}) = -\sum_{j \neq i, j \in \mathcal{M}} p_j(\theta_{-j}),\ \forall i \in \mathcal{M} \tag{4.3.4}$$
If there exists an agent j with function $p_j(\theta_{-j})$ where (θ_{-j}) includes θ_i, then p_i is a function of θ_i as well. It leads the analysis back to the first case, which does not ensure EPIC. In this sense, for all follower i, $p_i(\theta_{-i})$ should only be a function of $\theta_k, \forall k \in \mathcal{M}/\mathcal{F}$. In other words, the followers' payment is a uniform price and is independent of any followers' WTPs.

□

Theorem 4.3.2. *Under EPIR, EPBB and EE, there is no mechanism that can provide two-sided EPIC for the auction for leader determination.*

Proof. The proof starts with the conditions that characterize the buyer-side EPIC. Denote $\mathcal{F}$ as the set of following vehicles. Under lemma 4.3.2, $\forall i \in \mathcal{F}$ has no incentive to misreport if misreporting cannot change the leader-follower allocation. Therefore, the only case that needs to be considered is when leader-follower allocation changed by misreporting. Suppose that each follower pays p, the leader will collect $(m-1)p$ under EPBB and EE. EPIC requires that

$$\theta_i - p \geq (m-1)p \Rightarrow p \leq \frac{1}{m}\theta_i, \forall i \in \mathcal{F}$$

Together with equation 4.3.2, it leads to

$$p \leq \frac{1}{m}\min\{\theta_i,\ i \geq 2\} = \frac{\theta_2}{m} \tag{4.3.5}$$

Similarly, the seller-side EPIC can be characterized. The following inequality shows the condition that the seller has no incentive to misreport for being a seller.

$$(m-1)p \geq \theta_1 - p \Rightarrow p \geq \frac{\theta_1}{m} \tag{4.3.6}$$

In sum, the upper and lower bounder of p are given as

$$\frac{\theta_1}{m} \leq p \leq \frac{\theta_2}{m} \tag{4.3.7}$$

Lemma 4.3.2 demonstrates that p cannot be a function of θ_2 under buyer-side EPIC, so that p is a function of θ_1, satisfying equation 4.3.7. There are multiple ways to create such a function, for instance,

$$p = \frac{\theta_1}{m}.$$

As θ_1 is unknown before the auction, p is further set to be $\frac{\hat{\theta}_1}{m}$ where $\hat{\theta}_1$ is agent 1's reported WTP.

In this case, one can easily see that agent 1 has the incentive to report $\hat{\theta}_1$ greater than θ_1 to increase its utility. It suggests that under the buyer-side EPIC, the seller-side EPIC cannot be achieved.

Similarly, if p is set to be a function of $\hat{\theta}_2$, agent 1 has no incentive to misreport, meaning that the seller-side EPIC is achieved. But as lemma 4.3.2 suggests, agent 2 has the incentive to misreport therefore the buyer-side EPIC fails this time.

□

4.4 The Transfer Function and its Implementation

4.4.1 A Linear Transfer Function

It should be noted that a mechanism with EPIC and EPIR is the sufficient condition for behavioral stability, but not the necessary condition. Based on theorem 4.3.2, the following transfer function ensures behaviorally stability.

Corollary 4.4.1. Suppose that agents in $\mathcal{M}$ bid $\hat{\theta}_1, \hat{\theta}_2, , \cdots, \hat{\theta}_m$. Denote the payment by any follower as p_F and that by the leader as p_L, a linear transfer function:

$$p_F \;\; = \tfrac{1}{m}\theta^*, \; p_L \;\; = -\frac{m-1}{m}\theta^*, \tag{4.4.1}$$

with $\theta^* = \min\{\hat{\theta}_1, \hat{\theta}_2, , \cdots, \hat{\theta}_m\}$ ensures behavioral stability for all agents in the auction for leader determination.

Proof. The proof of EPIR is trivial, as the transfer function guarantees that all agents gain positive utilities.

The proof of the conclusion that no agents will switch positions is undertaken from both follower's and leader's side.

(**Follower's side**) Recall lemma 4.3.2, all followers have no incentive to switch positions within themselves by misreporting under transfer function equation 4.4.1. The following proof indicates that they have no incentive to be the leader as well.

Suppose that agent 1 reports $\hat{\theta}_1$ and becomes a leader. For any follower j with $\theta_j > \hat{\theta}_1$, her utility by truth-telling is

$$u_j(\theta_i) = \frac{1}{m}\delta(m) + \theta_j - \frac{1}{m}\hat{\theta}_1$$

However, if agent j misreports $\hat{\theta}_j = \min\{\hat{\theta}_1, \hat{\theta}_2, , \cdots, \} < \hat{\theta}_1 < \theta_j$ and be the leader, her "forged" utility would be

$$u_j(\hat{\theta}_j) = \frac{1}{m}\delta(m) + \frac{m-1}{m}\hat{\theta}_j$$

Comparing the two utilities, it is easy to see that

$$u_j(\hat{\theta}_j) = \frac{1}{m}\delta(m) + (m-1)\hat{\theta} < \frac{1}{m}\delta(m) + \hat{\theta}_1 - \frac{1}{m}\hat{\theta}_1 < u_j(\theta_i),$$

which proves followers are EPIC.

(**Leader's side**) Suppose that agent 1 has the smallest true WTP, θ_1 and agent 2 has the second smallest one, θ_2, it is easy to prove that agent 1 has no incentive to be the follower.

Suppose agent 1 misreports $\hat{\theta}_1$ and becomes the follower, it forged utility would be

$$u_1(\hat{\theta}_1) = \frac{1}{m}\delta(m) + \theta_1 - \frac{1}{m}\theta_2$$

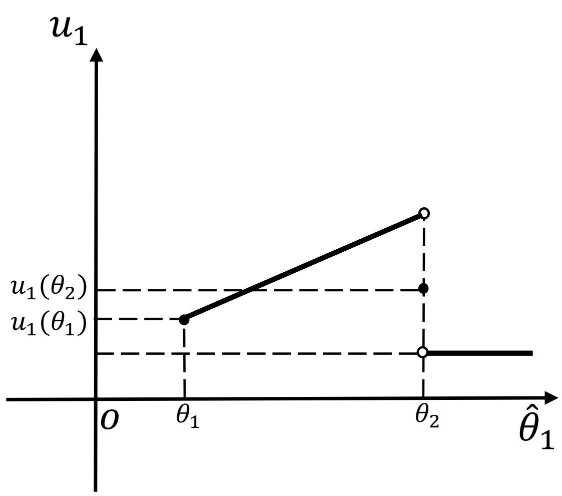
Since $\theta_2 > \theta_1$, the forget utility is no greater than the truth-telling utility:

$$u_1(\hat{\theta}_1) < \frac{1}{m}\delta(m) + \theta_1 - \frac{1}{m}\theta_1 = u_1(\theta_1)$$

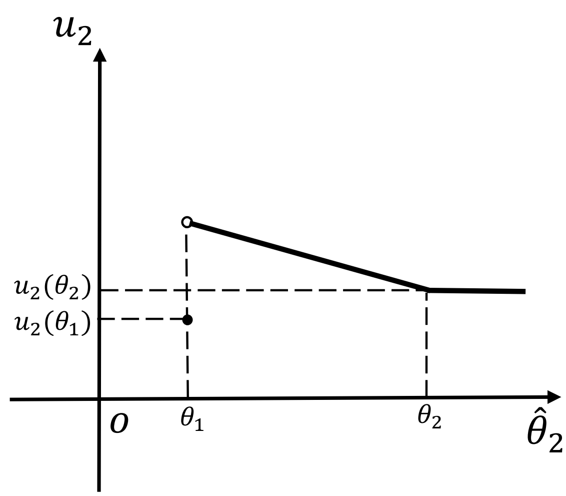
In sum, no agents would like to switch positions or leave the platoon, and behavioral stability is achieved by this transfer function. □

It should be noticed that agent 1 is not EPIC, the question then comes to agent 1's best response when all others are EPIC. Notice that when $\hat{\theta}_1 < \theta_2$, $u_1(\hat{\theta}_1)$ is a monotonically increasing function of $\hat{\theta}_1$, so that agent 1 would like to increase her bid to obtain a greater utility. However, if $\hat{\theta}_1 = \theta_2$, the tie-breaking rule is applied, meaning that agent 1 has half probability to be the leader and half to be the follower. Her forged utility thereby is

$$u_1 = u_2 = \frac{1}{2}(m-1)p(\hat{\theta}_1, \hat{\theta}_2) + \frac{1}{2}(\theta_1 - p(\hat{\theta}_1, \hat{\theta}_2)) = \frac{1}{2}(\hat{\theta}_1 + (m-2)p(\hat{\theta}_1, \hat{\theta}_2))$$



(a) Utility functions of agent 1 when $t = \frac{\theta_1}{m}$



(b) Utility functions of agent 2 when $t = \frac{\theta_2}{m}$

Figure 4.1: Misreporting strategies and utility functions

Let $p(\hat{\theta}_1) = \frac{\hat{\theta}_1}{m}$ where agent 1 has the incentive to misreport $\hat{\theta}_1 > \theta_1$ until $\hat{\theta}_1 = \theta_2$. Its utility function on $[\theta_1, \theta_2]$ is illustrated in figure 4.1(a). When $\hat{\theta}_1 = \theta_2$, agent 1 can be either the leader or a follower with equal probability, thus its utility is

$$u_1(\theta_2) = \frac{1}{m}\delta(m) + \frac{1}{2}(\theta_1 - \frac{\theta_2}{m}) + \frac{1}{2}(m-1)\frac{\theta_2}{m} = \frac{1}{m}\delta(m) + \frac{1}{2}\theta_1 + \frac{m-2}{2m}\theta_2$$

Clearly,

$$u_1(\theta_2) < \frac{1}{m}\delta(m) + \frac{(m-1)(\theta_2 - \varepsilon)}{m} = \frac{1}{m}\delta(m) + \frac{m-1}{m}p(\theta_2 - \varepsilon)$$

with ε be a really small positive value. On the other hand, if agent 1 misreports $\theta_2 + \varepsilon$,

$$u_1(\theta_2 + \varepsilon) = \theta_1 - \frac{\theta_2}{m}$$

$$u_1(\theta_2 + \varepsilon) - u_1(\theta_2) = \frac{1}{2}(\theta_1 - \theta_2) < 0$$

Therefore, the utility function of agent 1 is discontinuous, as illustrated by figure 4.1(a). Consequently there is no best response for agent 1 nor equilibrium for this auction.

Remarks: One who familiar with multi-unit auctions can easily notice that this transfer function is a variation of Vickery Auctions (Krishna, 2009). To see this, consider forming a platoon with m trucks is selling the platooning service for $m-1$ units, meaning that the demand is m where the supply is $m-1$. Those who win the auction pay an amount that is determined by the one who loses. Then the auctioneer (mechanism designer) collects the payment. For this reason, the Vickery Auction is different from the auction for leader determination because the latter requires EPBB.

4.4.2 The Implementation

For implementation, assume that agent 1 misreports a random value between θ_1 and θ_2 with uniform distribution, its average extra gain would be $\frac{m-1}{m}(\theta_2 - \theta_1)$, which appears to be no harm to the platoon. Since the auction is simple enough, it can be applied flexibly whenever single-brand trucks are willing to platoon together:

1 Initially, if individual trucks meet at a hub or a parking lot and move towards the same direction, they can conduct such an auction to determine the leadership.

2 The auction can also be performed dynamically, in correspondence to different vehicle routes. If new trucks come to the already-formed platoon, or some platoon members have to leave for destination, the auction will performed again to allocate the new leadership as well as the payment. If two formed platoons meet on-the-fly and are willing to form a larger platoon, they only need to bid the leading trucks' WTPs.

4.4.3 Other Transfer Functions

As previously stated, no dominant mechanisms exist in this auction setting. Mechanisms other than the linear transfer function described can be implemented. Several important classes as well as their pros and cons are introduced here.

4.4.3.1 Variations of Linear Transfer Function

The simplest variation would be letting

$$p_F = \frac{\hat{\theta}_2}{m}, p_L = -\frac{m-1}{m}\hat{\theta}_2$$

Obviously, all agents other than agent 2 have no incentive to misreport. Agent 2 would like to decrease its reported value until that equals θ_1. As presented in figure 4.1(b), its utility function is also discontinuous. No equilibrium exists under this payment function as well.

Another mechanism would be letting

$$p_F = \frac{\hat{\theta}_2}{m-1}, \ p_L = -(m-2)p_F$$

as well as enforcing agent 2, the agent with the second-lowest bid, out of the platoon. In this way, EPIC and EPBB are guaranteed. But clearly, an amount of $\delta(m) - \delta(m-1) + \theta_2$ of surplus losses. This mechanism is inspired by McAfee (1992)'s trade reduction rule for double auction. However, it is not quite suitable for the platooning problem since the number of agents is relatively small thus the surplus loss is non-negligible.

4.4.3.2 The Reserve Price

Reserve price is often used in auctions, providing the minimum price that a seller is willing to accept for selling an item. Normally, if the seller is determined before the auction, reserve price ensures ex post incentive compatible. Because a buyer only buys the item if its valuation is greater than the reserve price, she always obtains non-negative utility; a seller only sells the item if at the reserve price, making her utility non-negative well. However, reserve price does not lead to promising results for the platooning problem, as indicated by the analysis below.

Assume there is a reserve price p with $\underline{\theta} < p < \overline{\theta}$ for being the followers in a platoon. Intuitively, the agents with valuation no less than p can be followers. Consequently, there are three scenarios:

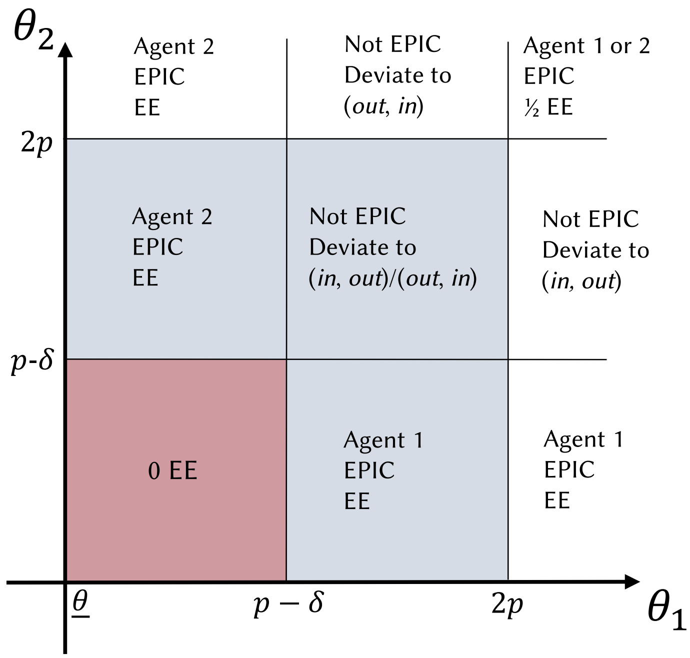


Figure 4.2: Outcome under the reserve price mechanism for two-agents scenario

- $\theta_i \geq p$, $\forall i \in \mathcal{M}$. The mechanism designer can randomly select an agent to be the leader, and the rest be the followers.
- $\exists i \in \mathcal{M}, s.t. \theta_i \geq p$ and $\exists j \neq i \in \mathcal{M}, s.t. \theta_j < p$. The mechanism designer can randomly select an agent with a valuation less than p to be the leader, the agents with valuation greater than p will be the followers. A platoon is formed
- $\theta_i < p$, $\forall i \in \mathcal{M}$. The reserve price is higher than all agents' valuations, no platoon can be formed.

Considering the scenario with two agents, which are numbered 1 and 2. Assume agents have types θ_1 and θ_2, respectively. Each will also obtain additional energy-saving benefit δ by platooning. When a reserve price is given, each agent can take one of the two actions, responding either *in* or *out*. The taken action is determined by a threshold policy. It means that for the arbitrary agent $i, i \in \{1, 2\}$, if $\theta_i < p - \delta$, agent i signals *out*; otherwise, agent i signals *in*, In sum, there are four outcomes: (*in*, *in*), (*in*, *out*), (*out*, *in*), (*out*, *out*). Following analysis checks whether they are EPIC equilibria and economic efficiency.

(A) When θ_1, $\theta_2 < p - \delta$. Both agents signal *out* and obtain zero utility, which is EPIR since signalling *in* will lead to negative utility.

(B) Assume $p - \delta < \theta_1 < 2p$. Agent 1 signals *in*. There are three cases depending on the value of θ_2:

1. $\theta_2 < p - \delta$. Accordingly, agent 1 becomes the follower and pays p to agent 2, both agents obtain positive utilities. Agent 1 would not deviate to signal *out* since doing so will lead to zero utility. Agent 2 would not deviate to signal *in*, because she will obtain $u_2' = \frac{1}{2}(\theta_2 + \delta - p) + \frac{1}{2}(\delta + p)$, which is less than her current utility, $\delta + p$. Therefore, (*in*, *out*) is EPIC.

2. $p - \delta \leq \theta_2 < 2p$. Both agents signal *in* and each of them is selected as the leader with equal probability, making $u_1 = \frac{\theta_1}{2} + \delta$, $u_2 = \frac{\theta_2}{2} + \delta$. Because $p > \theta_1, \theta_2$, both agents have incentives to deviate and signal *out*, thereby to increase their utility to $p + \delta$. Once one of them deviates to signal *out*, the other would not signal *out* because doing so will lead to zero utility instead of positive one. Hence (*in*, *in*) is not EPIC. Agents will deviate to two different equlibria: (*in*, *out*) and (*out*, *in*). Both equilibria can achieve half economic efficiency on average

3. $\theta_2 \geq 2p$. To make it happen, suppose $p < \frac{\overline{\theta}}{2}$. Similar to case 2, both agents signal *in* and each of them becomes the leader with half probability. Agent 1 then has the incentive to deviate to *out*, because doing so she can obtain $p + \delta$, which is greater than $\frac{\theta_1}{2} + \delta$. If agent 1 deviates, agent 2 will still signal *in* because doing so she obtains $\theta_2 - p + \delta \geq \frac{\theta_2}{2} + \delta$. Therefore, (*in*,*in*) is not EPIC and (*out*, *in*) is an efficient equilibrium.

(C) Assume $\theta_1 \geq 2p$. Agent 1 signals *in*. There are also three cases depending on the value of θ_2:

1. $\theta_2 < p - \delta$. Agent 2 signals *out*. Accordingly, agent 1 becomes the follower and pays p to agent 2, both agents obtain positive utilities. Similar to the case in part (B), case one, (*in*, *out*) under this case is EPIC as well.

2. $p - \delta \leq \theta_2 < 2p$. As a result, (*in*, *in*) is not EPIC. Agent 2 will deviate to signal *out*. The resulted outcome (*in*, *out*) is an efficient equilibrium.

3. $\theta_2 \geq 2p$. Both agents signal *in* and each of them becomes the leader with half probability. No agents will deviate to signal *in* as doing so will deteriorate her utility. As a consequence, (*in*, *in*) is EPIC but it only achieves half efficiency on average.

One can see from the above analysis that even for the simple scenario with two agents, reserve price cannot guarantee ex post incentive compatible and will always have loss on surplus. In addition, if this mechanism is used, the mechanism designer needs to consider optimize p so that the expected economic efficiency can be maximized. Due to these complexities, the author does not recommend implementing the reserve price scheme.

4.5 Conclusion

As a conclusion of this chapter, an auction mechanism is established for benefit redistribution in the single-brand truck platooning scenario. The result of impossibility is stated and proved. It indicates that under the auction for leader determination, no dominant strategy can be implemented in ex post equilibrium under budget balance constraint to achieve economic efficiency. This result is not only workable for platooning, but also insightful for other formats of shared mobility when the roles of agents within the shared mobility are uncleared. Nevertheless, a simple linear transfer function is proposed. Theoretically, it is proved to achieve behavioral stability for all platoon members in the ex post environment. It is practically simple enough to be implemented either in a hub center before trucks depart for next stops when trucks meet on the highway in the motion.

As for the future work, the auction could be applied to a path planning model for platooning with the consideration of working hour regulations. In this way, it can help measure the overall labor-savings over a general network.

It should also be mentioned that this chapter omits the consideration of limited platoon length, thus makes the analysis tractable. If the assumption on platoon length limit is imposed and support it is $\overline{L}$, at least $\lceil m/\overline{L} \rceil$ number of leaders should be determined for m trucks. If auctions are still used as the mechanism format for benefit redistribution, the competition among auctions needs to be considered, which topic is reviewed by Haruvy et al. (2008). Specifically, there are two interesting research questions to work on:

1. When platoons are formed by individual trucks, an entry price could be set to endogenously determine the number of buyers in each auction.

2. When platoons are formed by individual trucks, an entry price could be set to determine the number of buyers in each auction endogenously. Such a problem is referred to as *bidder migration* (Lin & Jank, 2008) and has not been intensively studied in literature. Part of the reason dues to an empirical finding, which suggests that bidders usually prefer not to migrate if they have already joined one (Haruvy et al., 2008). The rule can also prevent that once a platoon is formed, the members are supposed not to leave unless they reach the destination. However, this topic is still intriguing in terms of its theoretical value.

CHAPTER 5

Behavioral Stability in the Multi-Brand Scenario: A Centralized Approach

5.1 Introduction

This chapter concentrates on a more general and complex scenario: multi-brand truck platooning. The trucks can be 'platoonable' together possess different vehicle configurations and types, thus contribute differently to the total energy savings of the platoons they formed. To conduct the study, the researcher envisions a freeway system where vehicles are capable of platooning and their information is communicated to a central controller in the cloud. The central controller searches for an optimal platoon formation that maximizes the platoon benefit, and then applies the benefit allocation mechanism to redistribute the benefit among platoon members to incentivize drivers or owners to form, and more importantly, maintain the optimal platoon formation. Note that in designing the allocation mechanism, this chapter is not interested in microscopic driving behaviors such as car following and gap acceptance involved in the process of forming and maintaining a platoon as introduced in chapter 2 and assume that they will be done properly and efficiently. Instead, the focus is on drivers or owners of vehicles' economic consideration or calculation for platooning.

The remainder of the chapter is organized as follows. Section 5.2 states the problem settings and basic considerations and then introduces the cost and utility functions. Section 5.3 presents a mathematical programming model as well as its solution algorithm for determining the optimal platoon formation. Section 5.4 defines a cooperative platooning game, based on which the allocation mechanism is designed. Section 5.5 extends the analyses by considering the emissions reduction. Lastly, Section 5.6 concludes this chapter.

5.2 Problem Settings

5.2.1 Basic Considerations

Consider a freeway segment shared by various types of "platoonable" vehicles. Without the loss of generality, it is assumed that the freeway segment is one unit distance. A *platoon* is defined as a set of vehicles traveling with the same speed and low headway. Vehicles of different types can platoon together, e.g. heavy-duty trucks can platoon with passenger vehicles. However, the platoon size is assumed to be limited. Therefore, if there are a large number of vehicles, several platoons may be formed. The term *platoon formation* is referred to all these platoons in the system hereinafter. It specifies the platoon that each vehicle belongs to and its position in the platoon. Among various platoon formations a system may generate, the optimal one yields the most benefits. It is assumed that when entering the freeway segment, all vehicles reveal their private information truthfully to the central controller, which subsequently determines the optimal platoon formation and assigns vehicles to proper platoons and specifies their positions.

The following table (Table 5.1) provides the notations used throughout this Chapter.

Table 5.1: Notations

Indexes	
i	Vehicle.
q	Vehicle type.
j	Platoon.
k	Platoon pattern.
Sets	
$\mathcal{M}$	Set of all vehicles, $i \in \mathcal{M}$. The size of $\mathcal{M}$ is m.
$\mathcal{Q}$	Set of vehicle types, $q \in \mathcal{Q}$.
$\mathcal{N}$	Set of all platoons, $j \in \mathcal{N}$. The size of $\mathcal{N}$ is n.
$\mathcal{K}$	Set of all platoon patterns, $k \in \mathcal{K}$.
$\mathcal{M}(q)$	Set of all vehicles of type q, a subset of $\mathcal{M}$.
$\mathcal{N}(k)$	Set of all platoons of pattern k, $k \in \mathcal{K}$.
$PF^*(\mathcal{M})$	Set of all platoons in the optimal platoon formation of vehicle set $\mathcal{M}$.
Parameters	
v_i	The desired speed of vehicle i when traveling alone.
v_j	Optimal speed of platoon j.
α_i	Disutility weight of vehicle i, which measures the disutility associated with the deviation of the current platoon speed from its desired speed.
γ	Fuel price.
c_i^0	Vehicle i's cost when traveling as singleton.
F_i^0	Vehicle i's fuel consumption as a singleton, a function of speed.
$\mathbf{P}$	A square matrix indicating vehicle positions in a given platoon.
$F_i(v, n, \mathbf{P})$	Vehicle i's fuel consumption in platoon with speed v, platoon size n and vehicle sequence $\mathbf{P}$.
U_i^j	The utility of vehicle i being in platoon j.
U_j	Total utility of platoon j.
$\mathbf{u}$	A $n \times 1$ vector containing valuations of all platoons.
l	The maximum number of vehicles.
$\mathbf{A}$	A $m \times n$ matrix that maps platoon and vehicle, where the entry a_{ij} equals 1 if vehicle i belongs to platoon j, and 0 otherwise.
m^q	The number of vehicles of vehicle type q, $\forall q \in \mathcal{Q}$.
m_k^q	The number of vehicles of vehicle type q in platoon pattern k.
$\mathbf{e}$	$m \times 1$ identity vector.
$\mathbf{e}^q$	$m \times 1$ vector with entry equal to 1 if it corresponds to vehicle type q, otherwise equal to 0.
Variables	
$\mathbf{x}$	$n \times 1$ binary variable vector indicating whether a platoon is presented in the optimal platoon formation.
$\mathbf{y}$	Dual variable, $\mathbf{y} \in \mathbb{R}^m$.
v	Continuous variable, indicating the speed of a platoon.
$\mathbf{z}$	$m \times 1$ binary variable vector indicating whether vehicles are in the candidate platoon.

5.2.2 Cost and Utility

the fuel that a vehicle consumes in the freeway system is modelled as a function of its speed:

$$F_i^0(v) = \beta_{i3}^0 v^2 + \beta_{i2} v + \beta_{i1} + \frac{\beta_{i0}}{v}$$

Here, F_i^0 represents the fuel consumption of vehicle i when it travels alone and β_{i3}^0, β_{i2}, β_{i1} and β_{i0} are vehicle-specific parameters. This fuel consumption function is general enough to replicate power-based models such as comprehensive modal emission model (CMEM) (Scora & Barth, 2006), and approximate regression-based statistical models such as MOVES (EPA, 2014) and VT-Micro model (Ahn et al., 2002). Using c_i^0 to define vehicle i's travel cost when it travels alone,

$$c_i^0 = \gamma F_i^0(v_i)$$

in which γ is the unit fuel price.

When vehicle i joins a platoon, the air drag reduction yields energy savings. Without the loss of generality, the effect of aerodynamic drifting is assumed to be captured by reducing the coefficient of β_{i3}^0. According to CMEM (Scora & Barth, 2006), the parameter can be specified as follows:

$$\beta_{i3}^0 = \frac{1}{2}\rho C_d A_i$$

where C_d is the air drag coefficient and A_i is vehicle i's frontal area and ρ is a constant parameter (in CMEM, the term $\beta_{i2}v$ captures the engine-related fuel consumption; the term β_{i1} provides the fuel consumption due to acceleration, upgrade and friction and the term $\frac{\beta_{i0}}{v}$ describes fuel consumption used for accessory purpose such as air conditioning.) The reduction of air drag would yield a smaller value of β_{i3}^0, denoted as β_{i3}. The reduction depends on platoon size and vehicle sequence. The vehicle sequence is identified by a $n \times n$ matrix, $\mathbf{P}$, where n is the platoon size, and the entity P_{ij} equals 1 when vehicle i locates in the platoon's jth position and 0 otherwise. The fuel consumption of vehicle i traveling in a platoon is then given by

$$F_i(v, n, \mathbf{P}) = \beta_{i3}(n, \mathbf{P})v^2 + \beta_{i2}v + \beta_{i1} + \frac{\beta_{i0}}{v}$$

Furthermore, when a vehicle joins a platoon, it is assumed that the vehicle will not only consider its fuel consumption, but also the disutility it suffers by joining. When the platoon's travel speed deviates from the vehicle's desired speed, disutility arises due to the concern over safety if the platoon travels too fast or additional travel delay if the platoon speed is too slow. The term $\alpha_i(v_j - v_i)^2$ is then used to represent the disutility, where the disutility weight α_i describes vehicle i's sensitivity to the deviation. Therefore, using c_i^j to define the cost of vehicle i's cost when it joins platoon j, the following equation is obtained:

$$c_i^j = \gamma F_i(v_j, n_j, \mathbf{P}_j) + \alpha_i(v_j - v_i)^2$$

Vehicle-specific parameters v_i and α_i are the private information assumed to be known by the control center. Notice that both the fuel consumption and disutility are convex functions of the platoon speed v_j, so is the cost of vehicle i in platoon j.

The utility or benefit for vehicle i to join a platoon j is thus the difference of the costs defined above:

$$U_i^j(v_j, \mathbf{P}_j) = c_i^0 - c_i^j = \gamma(F_i^0(v_i) - F_i(v_j, n_j, \mathbf{P}_j)) - \alpha_i(v_j - v_i)^2$$

The total utility of platoon is

$$U_j(v_j, \mathbf{P}_j) = \sum_{i=1}^{n_j} U_i^j(v_j, \mathbf{P}_j) = \sum_{i=1}^{n_j} c_i^0 - \gamma \sum_{i=1}^{n_j} F_i(v_j, n_j, \mathbf{P}_j) - \sum_{i=1}^{n_j} \alpha_i(v_j - v_i)^2 \tag{5.2.1}$$

which is a concave function of the platoon speed v_j. Note that the above does not consider additional cost that may incur in forming a particular platoon. However, the proposed optimal platoon formation problem and its solution algorithm can be easily extended to consider such a cost.

A set of numerical examples are provided to illustrate the cost and utility function characteristics (Figure 5.1). The platoons are composed by heavy-duty trucks with the same desired speed and disutility weight. The platoon size limit is assumed to be 7. The numerical examples have identified the benefit of platooning, as the maximum utility of a platoon is increasing.

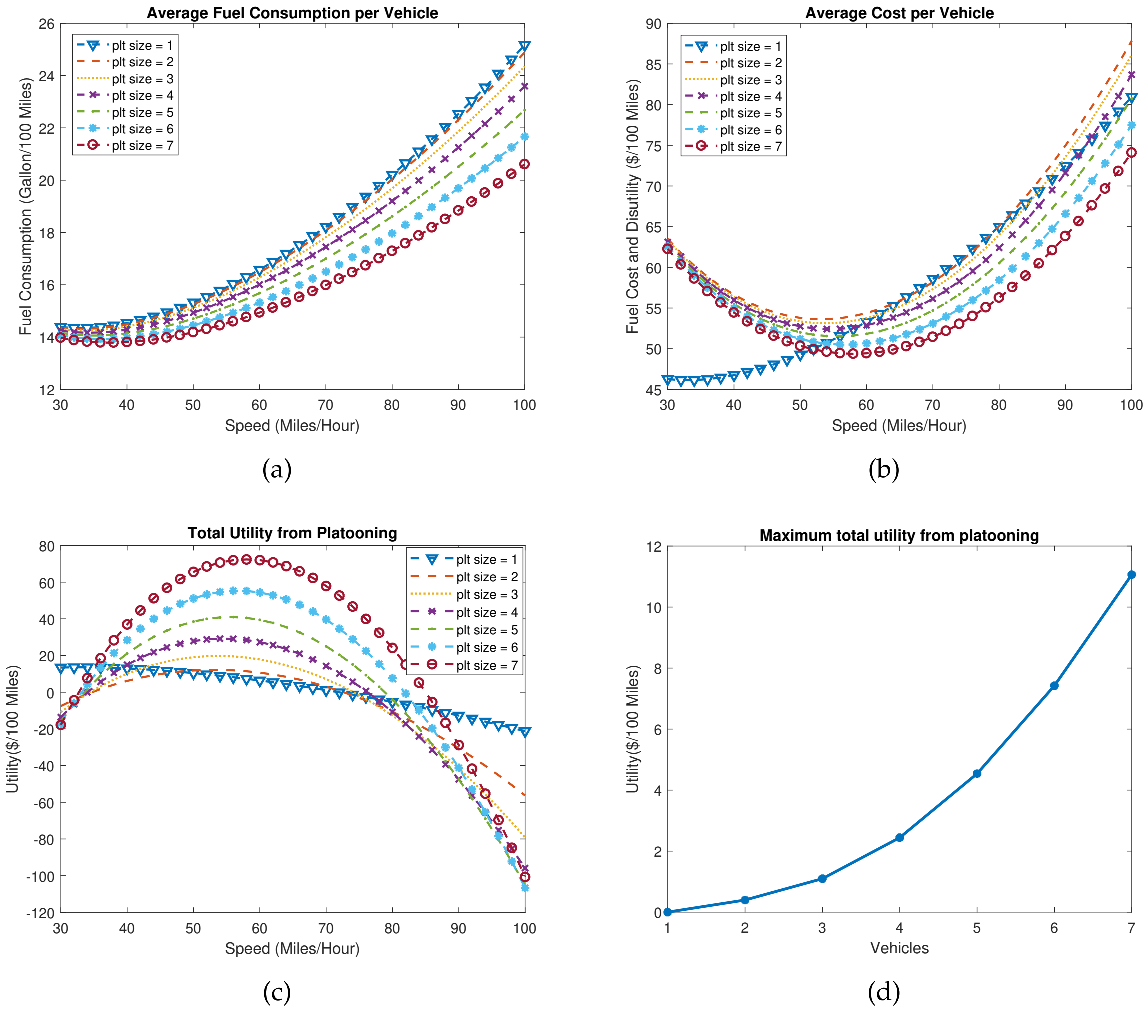


Figure 5.1: Vehicle performance in platoons

5.2.3 Platoon Patterns

When the vehicles forming a platoon are known, the platoon utility U_j is a function of speed v_j and vehicle sequence $\mathbf{P}_j$. To find the maximum utility of the platoon u_j, a mixed-integer nonlinear program (5.2.2) needs to be solved to determine the optimal platoon speed and vehicle sequence:

$$u_j = \max_{v_j, \mathbf{P}_j} U_j(v_j, \mathbf{P}_j) \tag{5.2.2a}$$

$$s.t. \quad v^l \le v_j \le v^u \tag{5.2.2b}$$

$$\mathbf{P}_j \in \mathcal{P}_j \tag{5.2.2c}$$

where $U_j(v_j, \mathbf{P}_j)$ is the platoon utility obtained from equation (5.2.1); v^l, v^u are lower and upper speed limits; $\mathcal{P}_j$ is the set containing all possible platoon sequences $\mathbf{P}_j$. Since the platoon size is finite, $\mathcal{P}_j$ is a finite set. The maximum utility u_j, which is also referred as the *valuation* of platoon j later in the paper, is thereby guaranteed.

Solving the mixed-integer nonlinear program (5.2.2) is not trivial. For one thing, the size of problem is large: with a platoon size n_j, the size of $\mathcal{P}_j$ is $n_j!$. More importantly, the parameter $\beta_{i3}(n_j, \mathbf{P}_j)$ is hard to estimate empirically. As a remedy, optimizing the vehicle sequence is not the focus in this paper. Instead, platoon *pattern*, which specifies the number of vehicles in a platoon by their types, is considered. A pattern k is defined as a tuple $(m_k^1, \cdots, m_k^q, \cdots)$, where m_k^q is the number of vehicles of type q. it is assumed that the vehicle sequence for each pattern can be determined in advance, e.g., a sequence of larger and heavier vehicles being in front of smaller and lighter ones. The parameters $\beta_{i3}(n_j, \mathbf{P}_j)$ can be estimated accordingly for each pattern. Consequently, the platoon fuel consumption is determined only by its pattern and speed:

$$F^k(v) = \beta_3^k v^2 + \beta_2^k v + \beta_1^k + \frac{\beta_0^k}{v}, \quad \forall k \in \mathcal{K}$$

Denote the pattern of platoon j as $k(j)$, the objective $U_j(v_j, \mathbf{P}_j)$ in (5.2.2) is hence replaced by

$$U_j^{k(j)}(v_j) = \sum_{i=1}^{n_j} c_i^0 - \gamma F^{k(j)}(v_j) - \sum_{i=1}^{n_j} \alpha_i (v_j - v_i)^2$$

In addition, the constraint (5.2.2c) is removed, yielding the following simplified problem:

$$\begin{aligned} \max_{v_j} \quad & U_j^{k(j)}(v_j) \\ s.t. \quad & v^l \leq v_j \leq v^u \end{aligned}$$

This problem is convex and can be solved efficiently. The individual vehicles' utilities are then determined sequentially.

5.3 Finding Optimal Platoon Formation

This section focuses on the optimal platoon formation of a general system when multiple platooning opportunities exist simultaneously. Using the utility function constructed in the previous section, a mathematical program is proposed to define the *platoon formation* (*PF*) problem. The solution algorithm and numerical examples are then presented.

5.3.1 The Formulation

Assume that the system has a vehicle set $\mathcal{M}$ with m vehicles, which can form a total number of n possible platoons. Note that a platoon is determined by its vehicle composition, as vehicle sequence in this paper is not optimized. Hereinafter, the term *platoon* and *platoon composition* are used interchangeably. All platoons belong to a platoon set $\mathcal{N}$. The author defines $\mathbf{A}$ as a $m \times n$ platoon incidence matrix, in which one column corresponds to one platoon and entity a_{ij} equals 1 if vehicle i belongs to platoon j, and 0 otherwise. Take a system of three vehicles indexed 1, 2 and 3 as an example. All possible platoons formed by these vehicles can be listed as $\{1\}$, $\{2\}$, $\{3\}$, $\{1,2\}$, $\{1,3\}$, $\{2,3\}$, $\{1,2,3\}$. The matrix $\mathbf{A}$ is thus written as

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & 0 & 1 & 1 & 0 & 1 \\ 0 & 1 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 1 & 1 & 1 \end{bmatrix}$$

An integer program is formulated to find the optimal platoon formation:
PF:

$$\max_{\mathbf{x}} \quad \mathbf{u}^T\mathbf{x} \tag{5.3.1a}$$

$$s.t. \quad \mathbf{A}\mathbf{x} = \mathbf{e} \tag{5.3.1b}$$

$$\mathbf{x} \in \{0,1\}^n \tag{5.3.1c}$$

where $\mathbf{x}$ are the binary variables indicating whether or not platoons are selected; $\mathbf{u}$ is a $n \times 1$ vector that stores valuations of all possible platoons, which are derived by solving (5.2.2); $\mathbf{e}$ is a $m \times 1$ identity vector. The objective in (5.3.1a) maximizes the total valuation of the system, and the constraints in (5.3.1b) assigns a vehicle to one and only one platoon.

5.3.2 The Solution Algorithm

The *PF* formulation is conceptually straightforward, but practically difficult to prepare. For one thing, the number of possible platoon compositions, n, can be enormous: when the platoon size limit is l, it is $n = \sum_{i=1}^{\min\{l,m\}} \binom{m}{i}$. Moreover, for each platoon composition, (5.2.2) needs to be solved to determine its valuation u_j.

Alternatively, a column generation approach (CG) is employed to solve this problem. It starts from solving a restricted problem under a subset of $\mathcal{N}$, and then check whether the complement set has a better platoon that can be added to the current set to further enhance the original objective value. In developing the algorithm, the author first relaxes the original integer program *PF* into a linear program denoted as *L-PF*. The integer variable

$\mathbf{x}$ is relaxed into a non-negative continuous variable. Denoting the dual variable as $\mathbf{y}$, $\mathbf{y} \in \mathbb{R}^m$, the Lagrangian of *L-PF* is given by

$$
\begin{aligned}
\mathcal{L} &= \mathbf{u}^T\mathbf{x} - \mathbf{y}^T(\mathbf{A}\mathbf{x} - \mathbf{e}) \\
&= \mathbf{y}^T\mathbf{e} + (\mathbf{u}^T - \mathbf{y}^T\mathbf{A})\mathbf{x}
\end{aligned}
$$

Since the number of rows is fixed to m and $\mathbf{A}$ is a full-rank matrix, the size of the basis of this linear program, $\mathcal{B}$, equals m. For a non-basic variable x_j, $\forall j \in \mathcal{N}/\mathcal{B}$, its reduced cost satisfies

$$
u_j - \mathbf{y}^T\mathbf{A}_j \leq 0 \tag{5.3.2}
$$

at optimality. Here, $\mathbf{A}_j$ is the jth column of $\mathbf{A}$.

CG is processed as follows:

1. Initialize the problem with a subset of platoons $\mathcal{S}$, $\mathcal{S} \subseteq \mathcal{N}$, the corresponding valuation vector and incidence matrix are $\mathbf{u}_\mathcal{S}$ and $\mathbf{A}_\mathcal{S}$ respectively. By solving the restricted linearized problem (*RL-PF*), the current optimal solution $\mathbf{x}^*_\mathcal{S}$ and the dual variable $\mathbf{y}^T_\mathcal{S}$ are determined.
RL-PF:

$$
\begin{aligned}
\max_{\mathbf{x}} \quad & \mathbf{u}^T_\mathcal{S}\mathbf{x} \\
s.t. \quad & \mathbf{A}_\mathcal{S}\mathbf{x} = \mathbf{e} \\
& \mathbf{x} \geq 0
\end{aligned}
$$

2. To examine whether the optimal solution $\mathbf{x}^*_\mathcal{S}$ is also optimal for *L-PF*, whether the inequality (5.3.2) is violated is checked by solving the following subproblem:
SP:

$$
\min_{\mathbf{z}} \quad \mathbf{y}^T_\mathcal{S}\mathbf{z} - u(\mathbf{z}) \tag{5.3.3a}
$$

$$
s.t. \quad \mathbf{e}^T\mathbf{z} \leq l \tag{5.3.3b}
$$

$$
\mathbf{z} \in \{0, 1\}^n \tag{5.3.3c}
$$

Here, the variable $\mathbf{z}$ identifies the vehicles in the candidate platoon. The constraint (5.3.3b) forces the number of vehicles in the candidate platoon to be within size limit l. The objective (5.3.3a) minimizes the reduced cost, in which $u(\mathbf{z})$ defines the maximum utility of platoon composition $\mathbf{z}$. Recall that in section 5.2.3 platoon pattern is considered in determining the maximum utility. For each pattern, there is a subproblem:

SP-K:

$$\min_{\mathbf{z},v} \quad \sum_{i\in\mathcal{M}}(y_{s_i} - c_i^0)z_i + \gamma(\beta_3^k v^2 + \beta_2^k v + \beta_1^k + \frac{\beta_0^k}{v}) + \quad \textstyle\sum_{i\in\mathcal{M}} \alpha_i z_i (v - v_i)^2 \tag{5.3.4a}$$

$$s.t. \quad \sum_{i\in\mathcal{M}(q)} z_i = m_k^q, \qquad \forall q \in \mathcal{Q} \tag{5.3.4b}$$

$$v^l \leq v \leq v^u \tag{5.3.4c}$$

$$z_i \in \{0, 1\}, \qquad \forall i \in \mathcal{M} \tag{5.3.4d}$$

where the objective (5.3.4a) expresses the reduced cost of the platoon under pattern k; (5.3.4b) sets the number of vehicles per type in composition $\mathbf{z}$ according to pattern k; (5.3.4c) confines the speed limit. The bilinear term $z_i v$ appeared in the objective (5.3.4a) is further linearized by applying McCormick Inequalities (McCormick, 1976):

$$\begin{aligned}
\min_{z,v,w} \sum_{i\in\mathcal{M}}(y_{s_i} - c_i^0)z_i + \gamma(\beta_3^k v^2 + \beta_2^k v + \beta_1^k + \frac{\beta_0^k}{v}) + \quad & \textstyle\sum_{i\in\mathcal{M}}(\alpha_i w_i^2 - 2\alpha_i v_i w_i + \alpha_i v_i^2 z_i) \\
s.t. \quad (5.3.4b) - (5.3.4c), & \\
w_i \leq v^u z_i, & \qquad \forall i \in \mathcal{M} \\
w_i \leq v_i, & \qquad \forall i \in \mathcal{M} \\
w_i \geq v - (1 - z_i)v^u, & \qquad \forall i \in \mathcal{M} \\
w_i \geq 0, & \qquad \forall i \in \mathcal{M} \\
z_i \in \{0, 1\}, & \qquad \forall i \in \mathcal{M}
\end{aligned}$$

SP is then solved by enumerating all possible patterns; for each pattern, *SP-K* is solved to find the optimal platoon composition. The number of patterns is subject to the number of vehicle types and the platoon size limit. For example, when there are 3 types of vehicles and the platoon size limit is l, the number of patterns is $\frac{l(l^2+6l+11)}{6}$, which is much smaller than the number of all possible platoons. Moreover, *SP-K*s can be solved in parallel to provide a set of better platoons, thereby improving the computational efficiency.

3. Check the solutions of *SP*. If all have negative reduced costs, the optimal solution of *L-PF* is found and the algorithm stops. Otherwise, go back to step 1 and substitute $\mathbf{A}_\mathcal{S}$ and $\mathbf{u}_\mathcal{S}$ with $\mathbf{A}_{\mathcal{S}'}$ and $\mathbf{u}_{\mathcal{S}'}$, in which $\mathcal{S}' \setminus \mathcal{S}$ contains all newly found platoons that have positive reduced costs.

4. When CG stops, columns and valuations generated from *L-PF* are used as the input data to the original *PF* problem and solve it directly. A flowchart of this algorithm is provided in Figure 5.2.

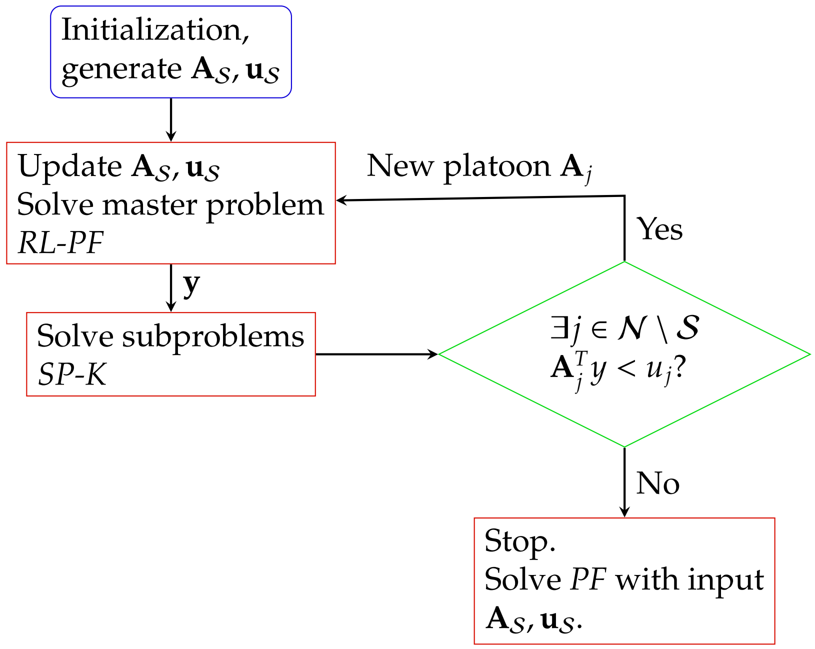
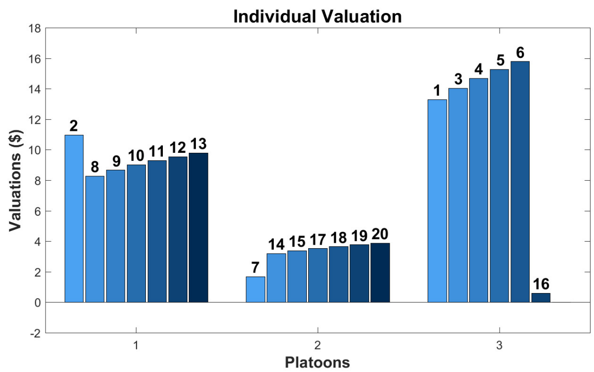


Figure 5.2: Flowchart of column generation algorithm

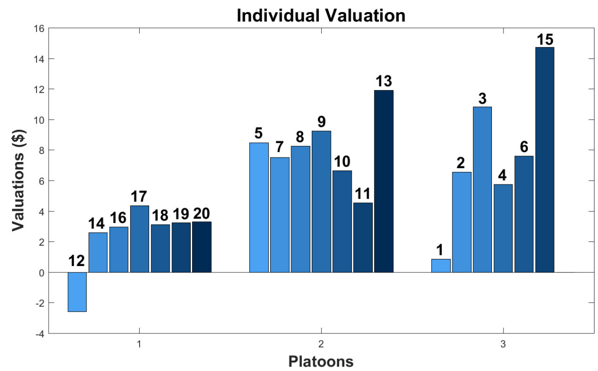
5.3.3 Numerical Examples

In this section, the optimal platoon formations are searched for a system with 20 vehicles, which consists of 6 heavy-duty vehicles, 7 medium-duty vehicles and 7 light-duty vehicles. Vehicle types are indicated by H, M and L respectively. This section examines four scenarios, depending on whether vehicles in the system have homogeneous desired speed or not, and zero disutility weights or not.

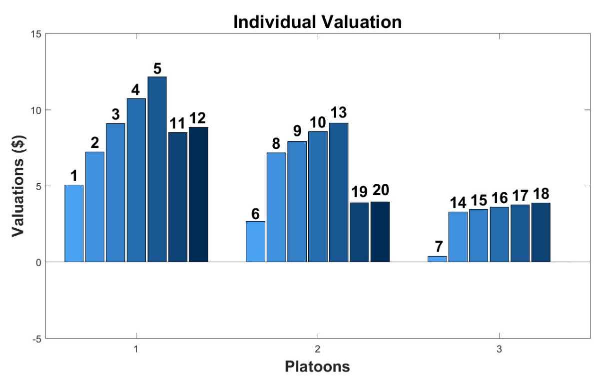
Table 5.2 provides the optimal solutions of *PF*s. Input data, including the total number of vehicles, number of vehicles per type, disutility weights and desired speeds, are provided. As the output, the total valuation is the optimal solution from *PF* with parameters from *L-PF*, while the supremum of total valuation is the optimal objective value of *L-PF*, which serves as an upper bound of total valuation. In the numerical examples, the optimality gaps are quite small, suggesting that the CG procedure yields good quality solution, if not the optimal one. The optimal platoon compositions are represented as sets, and the subscript of each vehicle represents its vehicle type. In addition, Figure 5.3 specifies the individual valuations of all vehicles under different scenarios.



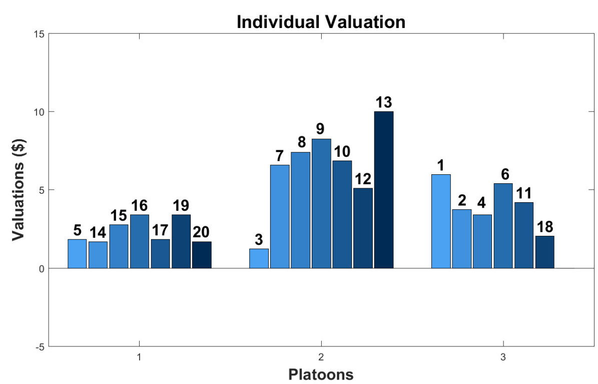
(a) Case 1: Vehicles with homogeneous speed, no disutility



(b) Case 2: Vehicles with heterogeneous speeds, no disutility



(c) Case 3: Vehicles with homogeneous speed and disutility



(d) Case 4: Vehicles with heterogeneous speeds and disutility

Figure 5.3: Individual valuation obtained in platoons

Table 5.2: PF optimal solutions

Common Input Data	
Number of vehicles	$m = 20$
Number of vehicles per type	$m_H = 6$, $m_M = 7$, m_L=7
Case 1	
Disutility weight	$\alpha_i = 0,\ \forall i \in \mathcal{M}$
Desired speeds	$v_i = 72$ mph, $\forall i \in \mathcal{M}$
Total valuation	162.45 (relative gap ≤ 2.6%)
Supremum of total valuation	166.73
Platoon formation	$p_1 = \{2_H, 8_M, 9_M, 10_M, 11_M, 12_M, 13_M\}$ $p_2 = \{7_M, 14_L, 15_L, 17_L, 18_L, 19_L, 20_L\}$ $p_3 = \{1_H, 3_H, 4_H, 5_H, 6_H, 16_L\}$
Optimal speeds	$v_1 = 48$ mph, $v_2 = 66$ mph, $v_3 = 38$ mph.
Case 2	
Disutility weight	$\alpha_i = 0,\ \forall i \in \mathcal{M}$
Desired speeds	$\mathbf{v} = [74, 58, 65, 53, 68, 56, 69, 71, 73, 62, 50, 55, 78, 52, 75, 65, 81, 50, 62, 51]$
Total valuation	120.03 (relative gap ≤ 3.4%)
Supremum of total valuation	124.30
Platoon formation	$p_1 = \{12_M, 14_L, 16_L, 17_L, 18_L, 19_L, 20_L\}$ $p_2 = \{5_H, 7_M, 8_M, 9_M, 10_M, 11_M, 13_M\}$ $p_3 = \{1_H, 2_H, 3_H, 4_H, 6_H, 15_L\}$
Optimal speeds	$v_1 = 66$ mph, $v_2 = 48$ mph, $v_3 = 38$ mph.
Case 3	
Disutility weight	$\alpha_i = 5 \times 10^{-4},\ \forall i \in \mathcal{M}$
Desired speeds	$v_i = 72$ mph, $\forall i \in \mathcal{M}$
Total valuation	123.28 (relative gap ≤ 5.3%)
Supremum of total valuation	130.37
Platoon formation	$p_1 = \{1_H, 2_H, 3_H, 4_H, 5_H, 11_M, 12_M\}$ $p_2 = \{6_H, 8_M, 9_M, 10_M, 13_M, 19_L, 20_L\}$ $p_3 = \{7_M, 14_L, 15_L, 16_L, 17_L, 18_L\}$
Optimal speeds	$v_1 = 60$ mph, $v_2 = 67$ mph, $v_3 = 71$ mph.
Case 4	
Disutility weight	$\alpha_i = 5 \times 10^{-4},\ \forall i \in \mathcal{M}$
Desired speeds	$\mathbf{v} = [74, 58, 65, 53, 68, 56, 69, 71, 73, 62, 50, 55, 78, 52, 75, 65, 81, 50, 62, 51]$
Total valuation	86.86 (relative gap ≤ 2.7%)
Supremum of total valuation	89.25
Platoon formation	$p_1 = \{5_H, 14_L, 15_L, 16_L, 17_L, 19_L, 20_L\}$ $p_2 = \{3_H, 7_M, 8_M, 9_M, 10_M, 12_M, 13_M\}$ $p_3 = \{1_H, 2_H, 4_H, 6_H, 11_M, 19_L\}$
Optimal speeds	$v_1 = 64$ mph, $v_2 = 63$ mph, $v_1 = 50$ mph.

The numerical results show that when disutility weights are relatively small, longer platoons are more preferable by the system. When considering the individual valuations, the numerical results present uneven distributions as speculated in the previous sections. For example, Figure 5.3-(a) indicates that heavier vehicles enjoy more benefits than lighter vehicles when vehicles have homogeneous speed and zero disutility weight. In addition, although the leading vehicle contributes the most to a platoon, it usually is not the one who benefits the most; In some cases, they even suffer from platooning, like vehicle 12 in Figure 5.3-(b).

5.3.3.1 Computational Efficiency

The CG is coded in GAMS (R. E. Rosenthal, 2010) where CPLEX is used to solve *L-PF* and *PF* and DICOPT is used to solve *SP-K*. As CG may not guarantee globally optimality, a comparison is conducted to demonstrate the algorithm's computational efficiency.

A typical algorithm that ensures global optimality of an integer program is Branch-and-Price (BnP) Algorithm (Barnhart et al., 1998), which serves as a benchmark of the comparison study. However, as the method requires column generation at every iteration before convergence, it is computationally inefficient. Numerical experiments indicated that even when the problem size is fixed, the running time of BnP varies drastically with respect to the variations on the input data, branching rules and node selection rules. An improved dynamic programming (IDP) algorithm (Rahwan & Jennings, 2008) is selected as another benchmark. IDP is commonly used in the field of multi-agent systems to solve coalition structure generation problems, a genre which the platooning problem belongs to. Instead of solving a mathematical program, IDP directly searches the optimal platoon formation from all possible formations in a relatively ordered fashion. More importantly, IDP's running time is relatively stable when the problem size is fixed.

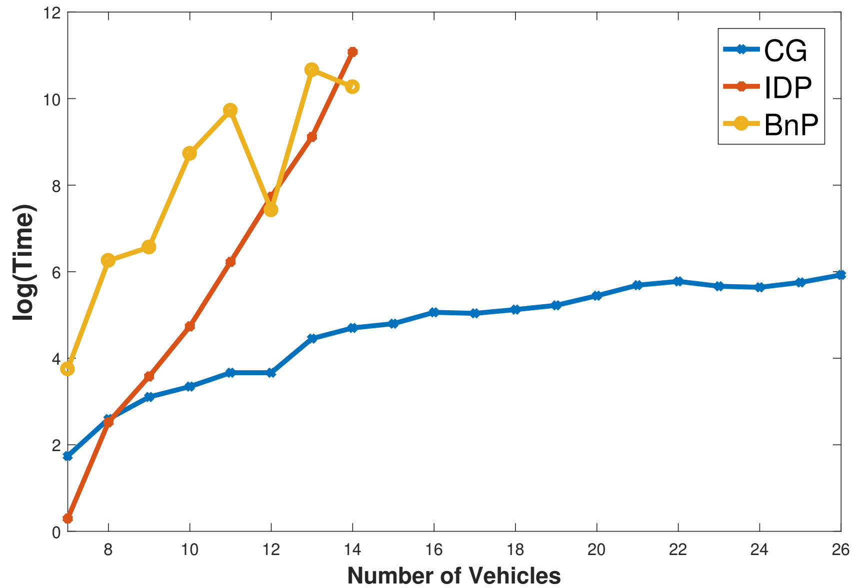


Figure 5.4: Comparison of running time

The three algorithms are compared by their running time and solution qualities. All the experiments are conducted on a Intel Core i7-6700 HQ 2.6 GHZ processor with 16.0 GB RAM. IDP is conducted in MatLab 2016b, using the embedded parallel computing mode with all 4 cores; CG and BnP are mainly conducted in GAMS 23.6, and the data processing is in MatLab 2016b. The “grid” solve facility in GAMS is employed to solve the subproblems *SP-K*s in parallel. Figure 5.4 compares the logarithmic value of running time of the three algorithms with respect to problem size. The computational time of BnP and IDP grows exponentially, making the problem intractable when vehicle number reaches 15. Comparatively, CG solves the problem very fast. It usually provides the solution within 6 minutes when the system has no more than 26 vehicles. Meanwhile, CG achieves global optimality in all comparisons, when the problem size is no more than 14 vehicles. In summary, CG is a suitable algorithm to generate the optimal platoon formation estimation.

5.4 The Construction of A Cooperative Game

In this section, the author proposes an allocation mechanism to redistribute the achieved benefit from the optimal platoon formation. Concepts in cooperative game theory are used to establish our allocation mechanism This theory has been applied in the cost/benefit allocation problems for several collaborative transportation schemes, see, e.g., Özener &

Ergun (2008); E. C. Rosenthal (2017); J. Wang et al. (2018). Well-known allocation concepts, such as *Core-center* (González-Díaz & Sánchez-Rodríguez, 2007), *Nucleolus* (Schmeidler, 1969), and *Shapley Value* (Shapley, 1953), are often applied. Below the cooperative platooning game is defined first, followed by the allocation mechanism with its properties and numerical examples.

5.4.1 Definition and Property

The cooperative game herein is about participating in the platooning system. If a vehicle decides to join the system, it is bounded by an agreement that specifies platoon compositions, vehicle sequence, speed and the payoff generated by the allocation mechanism. If a vehicle refuses to follow the binding agreement, it will be excluded from the game.

Definition 5.4.1. The *platooning game* is confined by a pair $(\mathcal{M}, V)$, where $\mathcal{M} = \{1, 2, 3, ..., m\}$ is the set of vehicles, or equivalently, agents or players, and V is the characteristic function of the game. The characteristic function is given by

$$V(\mathcal{I}) : 2^{|\mathcal{I}|} \to \mathbb{R}, \quad \forall\, \mathcal{I} \subseteq \mathcal{M}.$$

which maps every subset of $\mathcal{M}$ to a real number. The subset where vehicles joining together is also called a *coalition*. This characteristic function is nothing but the summation of valuations of platoons formed by all the vehicles in the given coalition under its optimal platoon formation. □

The characteristic function contributes several fundamental properties to this game, which are elaborated as follows.

Proposition 5.4.1. The platooning game defined above is a *zero-normalized* game with *transferable utility* and its characteristic function is *supperadditive*.

In the above, the zero-normalized game means that the characteristic function maps any unit set to zero. When a game is with transferable utility, the benefit achieved by the game can be expressed as a real number, so that it can be distributed among the agents in a conceivable way. Superadditivity refers to the condition that the valuation of a union of disjoint coalitions is always no less than the summations of the coalitions' separate valuations. Mathematically,

$$V(\mathcal{I}) \geq V(\mathcal{S}) + V(\mathcal{T}), \quad \forall \mathcal{S} \cup \mathcal{T} = \mathcal{I},\ \mathcal{S} \cap \mathcal{T} = \emptyset. \tag{5.4.1}$$

□

Proof. The three properties are easy to check. First of all, since the utility has been monetized and a characteristic function is given, the utility can be distributed among all vehicles without loss. Therefore, the game is a transferable utility game.

Secondly, by the definitions of cost function and valuation function, the valuation for vehicle travelling alone is zero, in other words, $V(\{i\}) = U_i^{\{i\}} = 0$.

To prove supperadditivity, consider the optimal platoon formations in set $\mathcal{I}$, $\mathcal{S}$ and $\mathcal{T}$ satisfying conditions in equation (5.4.1). By definition,

$$V(\mathcal{S}) = \sum_{p \in PF^*(\mathcal{S})} u_p,\ V(\mathcal{T}) = \sum_{p \in PF^*(\mathcal{T})} u_p.$$

Noticing that the platoon formation $\{PF^*(\mathcal{S}),\ PF^*(\mathcal{T})\}$ is a platoon formation of the set $\mathcal{I}$ but may not be the optimal one, one can show that

$$V(\mathcal{I}) = \sum_{p \in PF^*(\mathcal{I})} u_p \geq \sum_{p \in \{PF^*(\mathcal{S}),\ PF^*(\mathcal{T})\}} u_p = V(\mathcal{S}) + V(\mathcal{T}).$$

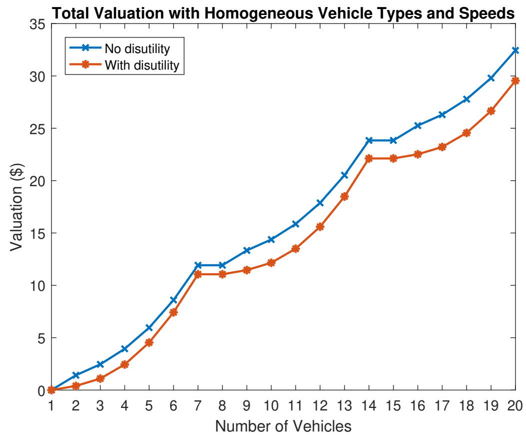
□

Further exploration of the characteristic function and the game property is challenging. As the valuation of each subset is achieved by solving the corresponding PF problem, there is no closed-form expression available for the characteristic function V in general. In addition, the platooning game is not a *convex game*, which means that V is not *supermodular*, i.e., the following inequality,

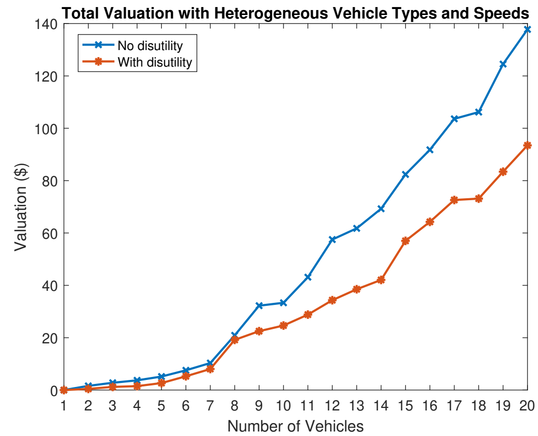
$$V(\mathcal{S} \cap \mathcal{T}) + V(\mathcal{S} \cup \mathcal{T}) \geq V(\mathcal{S}) + V(\mathcal{T}),$$

is not satisfied by V. Two numerical examples are provided in Figure (5.5) to show the non-convexity, where the relationship between set size and valuation under two different scenarios are presented. Subfigure 5.5-(a) shows the homogeneous scenario: all vehicles have the same vehicle type, desired speed and disutility weight. In this case vehicle sets are identical to their sizes. In a more general scenario where the vehicle types and desired speeds vary, the valuation of a set cannot be identified by the set size. Figure 5.5-(b) shows one of the many cases. The data are from Case 2 and 4 in Section 5.3.3. Notice that because different vehicles contribute different marginal valuations to the existing sets, a particular *arriving order* of vehicles is determined at first: lighter vehicles always arrive before heavier ones. Both scenarios show that the valuation function is monotonically increasing due to superadditivity, but not convex.

Due to the complexity of the characteristic function, well-known allocation concepts



(a) Homogeneous vehicle type and desired speed



(b) Heterogeneous vehicle types and desired speeds

Figure 5.5: Total valuation with respect to number of vehicles

do not work well for the platooning game. For example, the core may be empty as the game is non-convex, and Shapley Value is computationally inefficient. To see this, let's first introduce the concept of *desirability* together with *player-desirability fair allocation*.

Definition 5.4.2. Rosenbusch (2011). *Desirability.* Of two players i and j in a given coalition $\mathcal{I}$, player i is called more desirable than player j, if for all subset $\mathcal{S} \subseteq \mathcal{I}$, there is

$$V(\mathcal{S} \cup \{i\}) \geq V(\mathcal{S} \cup \{j\})$$

which is denoted as $i \succeq j$. An payoff $\mathbf{w}$ is called a *player-desirability fair allocation* if

$$i \succeq j \Rightarrow w_i \geq w_j, \quad \forall i, j \in \mathcal{I}$$

□

5.4.1.1 Discussions on Established Allocation Concepts

This section introduces several well-established allocation concepts existed in the field of cooperative game theory. By discussion, the readers should have a general idea of the computational difficulty of applying them in the platooning game.

The well-known *Shapley Value* is a player-desirability fair allocation mechanism. It can be mathematically expressed as

$$\phi_i(V) = \sum_{\mathcal{I} \subseteq \mathcal{M} \setminus \{i\}} \frac{|\mathcal{I}|!(|\mathcal{M}| - |\mathcal{I}| - 1)!}{|\mathcal{M}|!}(V(\mathcal{I} \cup i) - V(\mathcal{I}))$$

Although the equation is concise, $m2^{m-1}$ *PF* problems need to be solved to determine the payoff vector, which is computationally expensive.

The core of a game is the set of payoff vectors that satisfies

$$\sum_{i \in \mathcal{M}} w_i = V(\mathcal{M}), \sum_{i \in \mathcal{I}} w_i \geq V(\mathcal{I}), \forall \mathcal{I} \subseteq \mathcal{M}$$

By applying any payoff vector in a core, it is guaranteed that no subset of agents would like to deviate from the grand coalition to reallocate the benefit within themselves. However, core may be empty and whether it is true or not can be checked by the following linear program:

$$\begin{aligned} \min \quad & \textstyle\sum_{i \in \mathcal{M}} w_i \\ s.t. \quad & \textstyle\sum_{i \in \mathcal{I}} w_i \geq V(\mathcal{I}), \forall \mathcal{I} \subseteq \mathcal{M} \end{aligned}$$

Though the linear program is simple, solving it requires to predetermine the value of 2^{m-1} nonempty subcoaliation of $\mathcal{M}$, which again, is difficult. Moreover, since there is a large percentage that the valuation function of platooning game is not convex, core may be empty.

Finally, the allocation under *nucleous* concept is given as following:

$$w = \arg\min\{\max\{V(\mathcal{I}) - \sum_{i \in \mathcal{I}} w_i, \forall \mathcal{I} \subseteq \mathcal{M}\}\}, w \in \mathbf{R}^{|\mathcal{M}|}$$

It should be noted that nucleous is always unique for a given game and is always in the core if core is non-empty.

5.4.2 The Allocation Mechanism

A benefit allocation mechanism based on fairness consideration is stated below. The mechanism is simple and easy to compute. Its properties is discussed and a numerical example is presented to demonstrate its performance.

5.4.2.1 Fair Allocation Mechanism

Definition 5.4.3. The *fair allocation mechanism* (FAM) allocates benefit to any agents by their *marginal contributions* to the system. The benefit received by each agent is named as its *payoff*. Mathematically, the payoff vector $\mathbf{w}$ from FAM is given by

$$w_i = \frac{\delta_i}{\sum_{j \in \mathcal{M}} \delta_j} V(\mathcal{M}), \quad \forall i \in \mathcal{M}. \tag{5.4.2}$$

in which $\delta_i = V(\mathcal{M}) - V(\mathcal{M}_{-i})$ is the marginal contribution and $\mathcal{M}_{-i}$ denotes the largest subset of $\mathcal{M}$ that excludes i. □

To redistribute the benefit, the system requires each vehicle i pays an amount of μ_i, which is

$$\mu_i = u_i^j - w_i, \quad \forall i \in \mathcal{M}, \ j \in PF^*(\mathcal{M})$$

The sign of μ_i can be positive or negative.

FAM coincides with *weak desirability* and can be categorized as a *player-weak-desirability fair allocation* defined below:

Definition 5.4.4. (Rosenbusch, 2011). *Weak Desirability.* Of two players i and j in a given coalition $\mathcal{I}$, player i is called more weakly desirable than player j, if

$$V(\{i\}) \geq V(\{j\}) \text{ and } V(\mathcal{I}_{-i}) \leq V(\mathcal{I}_{-j})$$

Here, $\mathcal{I}_{-i}$ denotes the largest subset of $\mathcal{I}$ that excludes i. Weakly-desirability is denoted as $i \trianglerighteq j$. A vector $\mathbf{w}$ is called a *Player-Weak-Desirability Fair Allocation* if

$$i \trianglerighteq j \Rightarrow w_i \trianglerighteq w_j, \quad \forall i, j \in \mathcal{I}$$

Furthermore, in a zero-normalized game such as the platooning game,

$$i \trianglerighteq j \Leftrightarrow V(\mathcal{I}_{-i}) \leq V(\mathcal{I}_{-j})$$

□

It is easy to check that under FAM, $\forall i, \ j \in \mathcal{M}$, when $i \trianglerighteq j$, $\delta_i \geq \delta_j$, therefore $w_i \geq w_j$. Consequently, if these two agents possess the same marginal contribution, they receive the same payoff; if a player make zero marginal contribution, then it will receive zero payoff. These two properties are known as *substitution property* and *dummy player property*. Besides, FAM in the platooning game satisfies several other properties listed below:

Proposition 5.4.2. In the platooning game, FAM provides a non-negative payoff vector, $\mathbf{w}$, which is *group rational*, *individual rational* and *Pareto optimal*. When several platoons exist in the system, FAM is indifferent to the exact platoon formation implemented, as long as it is optimal for a given system. □

Specifically, group rationality is also known as *budget balancing*, which means that $\sum_{i \in \mathcal{M}} w_i = V(M)$. Individual rationality suggests that $w_j \geq V(\{j\}), \forall j \in \mathcal{M}$, i.e., a vehicle would be better off by participating in the platooning system or it will not leave the system unilaterally. Pareto optimality indicates that no vehicle can unilaterally increase its payoff, without making at least one individual in the system worse off. The proposition indicates that if several optimal platoon formations exist in a system, the payoff for each vehicle is independent of which platoon formation is applied, as the vehicle's payoff is not directly determined by the platoon it belongs to. This property will prevent vehicles to change the platoon formation unilaterally.

Proof. By definition, the summation of w_i satisfies:

$$\sum_{i \in \mathcal{M}} w_i = \sum_{i \in \mathcal{M}} \frac{\delta_i}{\sum_{j \in \mathcal{M}} \delta_j} V(\mathcal{M}) = V(\mathcal{M})$$

Therefore group rationality is proved. The reason behind group rationality is that platooning game is a game with transferable utility.

To prove the individual rationality, simply notice that all vehicles make non-negative marginal contribution to the system, so that their payoffs are non-negative; meanwhile, the game is a zero-normalized game. Since all vehicles can receive the payoff no less than the amount when they drive alone, it is irrational for vehicles to leave as a singleton.

Pareto optimal is a consequence of optimal platoon formation and group rationality. Since optimal platoon formation generates the maximum amount of benefit, and group rationality distributes all the benefit to vehicles, Pareto optimality must be attained. Moreover, all payoffs under optimal platoon formation and group rationality are Pareto optimal. □

Although agents are assumed to report real private information, in practice they may misreport to try to game the system. However, since misreporting will easily lead to a change in the optimal platoon formation, it is in general difficult, if not impossible, for agents to find a dominant misreporting strategy to ensure being better-off. Therefore preventing misreporting is not of particular interest in this paper.

5.4.2.2 Exception of FAM Implementation

The implementation of FAM requires the summation of marginal contributions to be strictly positive:

$$\sum_{j \in \mathcal{M}} \delta_j > 0 \tag{5.4.3}$$

which indicates that at least one of the marginal contributions is strictly positive. Since function V is supperadditive, the marginal contribution satisfies

$$\delta_i \geq 0, \quad \forall i \in \mathcal{M}$$

FAM is therefore workable for the platooning game in most scenarios. However, there exists one type of scenarios where the FAM (5.4.3) fails.

Consider the homogeneous scenario depicted in Figure 5.5-(a). As sets are identical to their sizes, a substitute function $v(s)$ is used to replace $V(\mathcal{S})$ in which the small letter s indicate the size of set $\mathcal{S}$. Under the assumption that platoon size limit is 7, v is a piecewise convex function. By the nature of utility function, the optimal platoon formation of one set always contains the longest platoons it can form. The valuation function is thus

$$v(s) = \lfloor \frac{s}{7} \rfloor v(7) + v(s - 7\lfloor \frac{s}{7} \rfloor). \tag{5.4.4}$$

As a consequence, $v(7m+1) = v(7m)$, $\forall m \in \mathbb{Z}^+$, because of the zero-normalized property.

Consider a platooning game with a system of $7m+1$ homogeneous vehicles where $m \in \mathbb{Z}^+$. The marginal contribution of each individual vehicle satisfies:

$$\delta_i = v(7m+1) - v(7m) = 0, \ \forall 1 \leq i \leq 7m+1.$$

In other words, if a vehicle is the last to join the system, it makes no marginal contribution to the system. Consequently, FAM cannot be used to generate payoffs for the vehicles.

The failure of FAM is rooted in the weak desirability, in which the marginal contributions of vehicles to subsystems have been neglected. To correct this deficiency, the author resorts to Shapley Value. Though it is computationally expensive in general, it can be generated efficiently in this special game. Notice that the characteristic function defined in equation (5.4.4) satisfies

$$v(7m+i) = mv(7) + v(i), \ \forall 1 \leq i \leq 7, m \in \mathbb{Z}^+.$$

The marginal contribution for the vehicle arriving the $7m + r$th is

$$v(7m' + r) - v(7m' + r - 1) = v(r) - v(r - 1),\ \forall 1 \le r \le 7, m' \le m \in \mathbb{Z}^{+}.$$

Then the Shapley Value for the game with $7m + 1$ vehicles provides

$$w_i = \sum_{m'=1}^{m-1} \sum_{r=2}^{7} \frac{(7m' + r)!(7m - 7m' - r)!}{(7m + 1)!}(v(r) - v(r - 1)).$$

Notice that the payoff is an equal share and Shapley Value satisfies budget balancing, the payoff can be further simplified as

$$w_i = \frac{v(7m + 1)}{7m + 1}$$

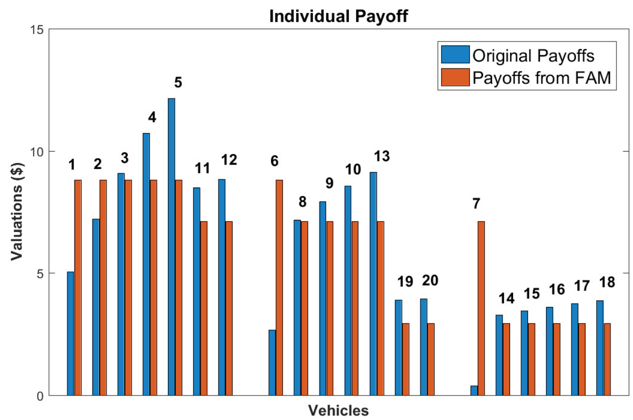
5.4.3 Numerical Examples

In this section, the author revisits the system with 20 vehicles stated in Section 5.3.3. The data used here are the same as those in Case 2 in Table 5.2, in which all vehicles have the same desired speed. Figure 5.6-(a) compares the valuation before the allocation and the final payoff. As a result, all leading vehicles are compensated more than their original valuations. Furthermore, vehicles of the same type receive the same amount of payoff regardless of the their platoons and positions. As such individual vehicles will not have incentive to unilaterally leave the system or change positions with others.

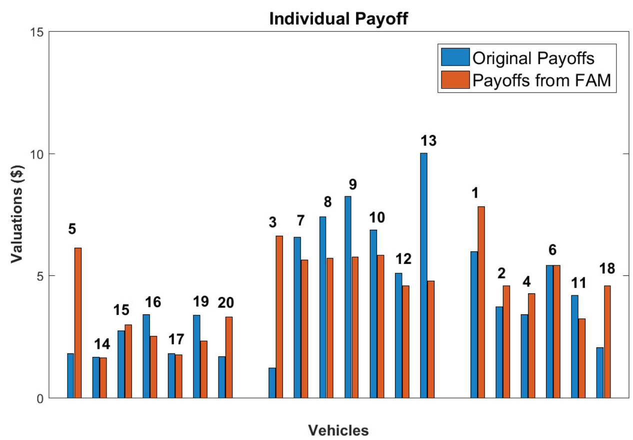
The heterogeneous counterpart applies the data from Case 4 in Table 5.2. The results are represented in Figure 5.6-(b). Because of speed heterogeneity, no two individual vehicles receive the same payoff in this example. The valuation are transferred within the system, not only within the same platoons. Comparing the total platoon payment: $u_p - \sum_{i \in p} w_i$, one can find that platoon 1 and 3 are compensated by platoon 2 and receive valuations of 4.15 and 2.32 respectively. Therefore, it is possible for platoon 2 to leave the system as a whole and form their own system to achieve greater individual payoffs. This indicates that subcoalition stability may not be satisfied under FAM, because

$$\exists\, \mathcal{S} \subset \mathcal{M}, \quad s.t. \sum_{i \in \mathcal{S}} w_i < V(\mathcal{S})$$

In other words, FAM is not in the core of the platooning game, which can be empty.



(a) Vehicles with homogeneous vehicles speed



(b) Vehicles with heterogeneous vehicle types and speeds

Figure 5.6: Comparison of individual utility and payoff

5.5 System with The Emission Concern

Another benefit from platooning is traffic emission reduction. However, vehicles usually lack of incentives to form a platoon that minimizes traffic emissions, because, the formation may not necessarily be the most fuel efficient; and the benefit from emissions reduction are indirect or even negligible to these vehicles. To address such an externality, one additional agent, the government, is introduced to the platooning game. The new agent cares for the broader societal impact and aims to reduce traffic emissions.

To quantify the social cost of traffic emissions, traffic emissions are estimated as follows:

$$E_{hq} = a_{hq}F + r_{hq}$$

where F is the fuel consumption rate, and h represents a pollutant such as CO, CO_2 , HC or NO_x; q represents vehicle types; a_{hq}, and r_{hq} are coefficients and E_{hq} is the emission amount of pollutant h. The utility of the government is

$$u_g = \sum_h \gamma_h \sum_q (E^0_{hq} - E^{\mathcal{M}}_{hq})$$

where γ_h is the unit cost of pollutant h; E^0_{hq} is the total emission amount of pollutant h when vehicles travel alone, while E^M_{hq} is the total emission amount of pollutant h after platoons are formed.

When the government agent is involved, the system objective is to maximize both the vehicles' utility: $\mathbf{u}^T\mathbf{x}$, and the government's utility: u_g, which may lead to a new optimal platoon formation. FAM can still be applied to generate payoffs for agents. Using V' to denote the new valuation, the government's marginal contribution is

$$\delta_g = V'(\mathcal{M}) - V(\mathcal{M})$$

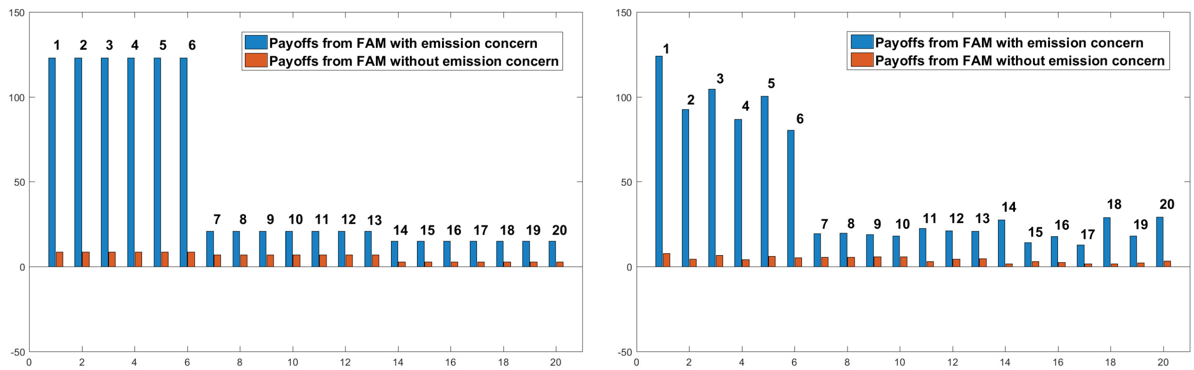
Use the same the system of 20 vehicles as an example. Four types of pollutants, CO_2, CO, HC, NO_x are considered. The coefficients of linear regression models are retrieved from Scora & Barth (2006), where the social costs of emission are retrieved from Shindell (2015), which are measured originally in 2007 US dollar using a discount rate of 5%, and converted into the 2018 value using the inflation rate of 2% (IMF, 2018). The data are shown in Table 5.3.

Table 5.3: Emission coefficients and cost

	a_{xq}			r_{xq}			cost
	H	M	L	H	M	L	(damages per ton in 2018 US $)
CO_2	3.20	3.20	3.20	0.00	0.00	0.00	33.57
CO	7.56e-3	0.70e-3	8.10e-3	0.00	0.00	0.00	509.78
HC	7.03e-4	0.30e-3	0.90e-3	0.00	0.20e-2	0.30e-2	3.36e3
NO_x	1.95e-2	0.32e-2	0.26e-2	1.65e-2	0.00	0.00	8.33e4

Figure 5.7 presents the comparisons of vehicles' payoffs under the systems with and without the emission concern. Clearly, vehicles receive higher payoffs under the system with the emission concern. Meanwhile, the government receives positive payoffs as well. In the homogeneous scenario, it receives a payoff of 603.06, which occupies 37.82% of the total system valuation; while in the heterogeneous scenario, it receives a payoff of 513.23, which occupies 36.85% of the total system valuation. As discussed, the payoffs are indirect and may occur in a long term, which requires the government agent to compensate the

vehicles from its operations budget. However, the compensation only occupies around 60% of the cost that the government agent would pay to manage the damages from the same amount of emissions. FAM thus offers a win-win cooperation between vehicles and the government.



(a) Vehicles with homogeneous desired speed (b) Vehicles with heterogeneous desired speeds

Figure 5.7: Fair allocation mechanism for systems with emission concern

5.6 Conclusion

In this chapter, the author identifies the optimal platoon formation and proposed a fair benefit allocation mechanism to ensure behavioral stability for the optimal platoon system. When a considerable number of "platoonable" vehicles present in the system, our platoon formation problem specifies which vehicles should be platooned together and their platoon speeds to achieve the maximum system benefit. The FAM addresses fairness concern, and satisfies group rationality, individual rationality and Pareto optimality. The model framework is further extended to the setting with an environmental concern, under which both the vehicles and the society (represented by the government) can benefit from the FAM.

Although the model framework is developed on a freeway segment, it can be applied to problems at the network level. However, the implementation of such a system requires a central controller, which may be costly in practice. One of the future research directions is to determine the platoon formation and benefit allocation in a distributed fashion by leveraging vehicle-to-vehicle communication and the computational power residing at the vehicle level. Lastly, the author notes that fuel-saving control strategies can be integrated into vehicle platooning to achieve higher energy savings, such as the pulse-and-glide control (S. E. Li et al., 2015). Other innovations leveraging vehicle connectivity and automation may further increase energy efficiency of vehicle platoons (Vahidi & Sciarretta, 2018). Our future research will also look into exploring these emerging opportunities.

CHAPTER 6

Integrated Platoon Formation and Benefit Redistribution: Bargaining and Matching

6.1 Introduction

In this chapter, the author envisions a decentralized platooning system to perform platoon formation and benefit redistribution for multi-brand trucks, motivated by two practical considerations. Firstly, the centralized approach introduced in the previous chapter requires a central controller, which is likely to be costly in terms of communication expenses in decision-making at such a detailed level. Secondly, the medium that realizes platoon formation and benefit redistribution is mainly V2V communication and Vehicular Adhoc Networks (VANET) associated, which is a distributed system by nature. Therefore, the decentralized system is less costly in terms of computational expense and more robust in terms of communication, thus, flexible, scalable, and real-time implementable. It then contributes to a hierarchical framework for platoon operations. A central controller determines the upper-level decision on path planning, and detailed-level decisions on forming platoons and redistributing benefits are made by individual vehicles following given guidance.

In this decentralized platooning system, game-theoretical approaches are applied to model the interactions among different individuals and their decision-making. The drivers or owners of vehicles are assumed to be rational agents, who aim to minimize their operational cost in the platoon formation game. In particular, the game is modeled as a two-player game, whose equilibrium outcome is expected to be behaviorally stable. The preliminary analysis in section 6.2 implies that if the benefit obtained directly from platooning is non-transferable, there are likely that no behaviorally stable equilibrium exists. Therefore, this chapter's main focus is designing proper transfer functions that redistribute benefit that induces the expected equilibrium, which is conveyed in section 6.3 and section 6.4. Two constraints are imposed on the problem due to the absence of central controllers in the decentralized system. Firstly, the mechanism is budget balanced, meaning that the sum of all transfers equals zero since no authority is taking responsibility for subsidizing the system or benefiting from the system. Secondly, compared to the centralized system, agents under this case are more likely to have private information, which is often referred to as their *types*. The designed transfers hence are functions of the outcome as well as agents' type. In this sense, the mechanism should be incentive compatible. Briefly speaking, there is no way for the agents to misreport their type for being better-off.

When transfer functions and action space in the game are specified, the platoon-formation game can be conducted between any pair of agents once they have direct communication. Therefore, the decentralized system admits multiple platoon formations simultaneously and disjointly. A vehicle can also merge into a formed platoon via the game, until the platoon size limit is reached. Consequently, the platoon formation in a decentralized system is a dynamic process, and the sequence of forming platoons depends on the communication network topology. Such a process will be formally defined in section 6.2.

The rest of this chapter first is organized as follows. Section 6.2 introduces the general dynamic process that applies to all game-theoretical approaches. To be brief, the integrated platoon formation and benefit redistribution are iteratively performed between a pair of agents, where each agent presents the whole platoon formed from the preceding stage. Section 6.3 illustrates the games when trading with a random player is allowed, which can be categorized into the class of bargaining game, roommate matching, respectively, are established to describe the whole procedure.

6.2 Preliminary Analysis

6.2.1 The Equilibria Without Trading

Imagine two vehicles, denoted as agent i and agent j, meet on the fly and platoon spontaneously. This process can be described by a classic two-player non-cooperative game. In this game, each player has two actions, either *lead* or *follow* the other agent, resulting in utility u_x^L or u_x^F, $\forall x \in \{i, j\}$ if a platoon is formed. If both choose the same action, no platoon will be formed, resulting in zero utilities, table 6.1 shows the game's strategic form.

In this simple game, the existence and uniqueness of pure equilibrium solutions depend on utilities' values. Thinking of the energy-saving mechanisms in vehicle platooning,

		j	
		L	F
i	L	(0, 0)	$(u_i^F,\ u_j^L)$
	F	$(u_i^L,\ u_j^F)$	(0, 0)

Table 6.1: Two-player platoon formation game

it is reasonable to assume that

$$u_i^F > u_i^L > 0,\ u_j^F > u_j^L > 0.$$

As a result, there always exists two pure Nash equilibria: (L, F) and (F, L). Since being the follower achieves a higher utility, the leader under one equilibrium has the incentive to deviate, making the current equilibrium unstable. With the existence of two equilibria, there is also a certain chance that the two players end up with a less efficient equilibrium outcome. For instance, if $u_i^F + u_j^L > u_i^L + u_j^F$, being in (L, F) achieves a smaller total utility than being in (F, L), which is unfavorable from the system's perspective. One may argue that the concept of Nash equilibrium is too weak to induce the desired outcome. Nevertheless, even if the refinements of Nash equilibrium, such as *"trembling hand" perfect equilibrium* (Bielefeld, 1988) and *proper equilibrium* (Myerson, 1978), are applied, there will invariably be two pure equilibria since the game is symmetric.

The problem then leads to how to generate a unique Nash equilibrium that is also efficient. Thinking of $\mathbf{u}'$, an alternative set of utilities satisfies the following conditions:

$$\begin{aligned} {u'}_i^L &> 0 > {u'}_i^F, \\ {u'}_j^F &> {u'}_j^L > 0, \\ {u'}_i^F + {u'}_j^L &> {u'}_i^L + {u'}_j^F. \end{aligned}$$

If this set of utilities is the case in the platoon formation game, the game admits a unique and efficient pure Nash equilibrium (F, L).

One way to achieve the result is introducing a pair of side-payments, $(p_1,\ p_2)$, to the original utilities by letting

$$\begin{aligned} {u'}_i^F = u_i^F - p_1,\ {u'}_j^L = u_j^L + p_1 \\ {u'}_j^F = u_i^F - p_2,\ {u'}_i^L = u_i^L + p_2 \end{aligned}$$

Contrary to the centralized system envisioned in chapter 5, these payments cannot be assigned by a controller directly but need to be induced by proper transfer functions. The transfer functions work as regulations that agents must obey when joining the decentralized system and consider when making their moves. Section 6.3 deliberates the existence and exact forms of such transfer functions under both complete and incomplete information settings.

All the analysis above focuses on the interplay between two randomly connected vehicles. Nevertheless, chances that multiple vehicles that are capable of platooning at the same time exist, leading to two latent hurdles. Firstly, an individual vehicle may tend to platoon with many instead of one vehicle simultaneously. Such a case has been investigated in chapter 5 when a central controller exists, while the. The author thereby restricts the interplay among vehicles limited to two, resulting in a dynamic platoon formation process described in section 6.2.2. Secondly, even if each vehicle only interacts with one at a time, she is willing to choose the 'best' one to platoon with. If no mechanism is given, choices that conflict with each other might exists. For instance, two or more vehicles choose one particular vehicle to platoon with. Thus, a one-sided matching mechanism is introduced in section 6.4 to settle the controversy.

6.2.2 The Dynamic Platoon Formation Process

As introduced earlier, the platoons are assumed to form through a dynamic process. Specifically, in each step of the process, t, a game is defined by a tuple $(\mathcal{M}_t, \Theta_t, \mathcal{A}_t, \chi_t, \mathbf{u}_t)$ where

- $\mathcal{M}_t$ is the finite set of current agents. Each agent $i \in \mathcal{M}_t$ represents a formed platoon of m_i vehicles, with $m_i \leq l$ where l is the platoon length limit.

- $\Theta_t = \Theta_1 \times \cdots \times \Theta_{|\mathcal{M}_t|}$ is the type space for all agents, where Θ_i is the type space of agent i, the true value is its own private information. By assumption, all agents know a common prior distribution ϕ on Θ_i, $\forall i \in \mathcal{M}_t$ that their private information follows.

- $\mathcal{A}_t = \mathcal{A}_1 \times \cdots \times \mathcal{A}_{|\mathcal{M}_t|}$ is the set of actions, where $\mathcal{A}_i = \{..., a_i, ...\}$ is the set of actions available to agent $i \in \mathcal{M}_t$, and a_i is determined by its realized type θ_i.

- χ_t is the space of outcomes. An outcome function $\chi^t : \mathcal{A}_t \to \chi_t$ maps a joint action a to an outcome in χ_t.

- Assuming that agents are risk neutral, the utility function is defined as

$$u_i(\chi(a), \theta, p) = V_i(\chi(a), \theta) - p_i(a),\ \forall i \in \mathcal{M}_t \tag{6.2.1}$$

  Here, $\mathbf{u}_t = \{u_1, ..., u_i, ..., u_{|\mathcal{M}_t|}\}$. V_i is the valuation that agent i obtains under outcome $\chi(a)$, given the joint type θ. Transfer functions $p_i : \mathcal{A} \rightarrow \mathbb{R}$, $\forall i \in \mathcal{M}_t$ provide the payment for each agent. The utility is defined per unit distance.

As briefly mentioned in the introduction section, the underlying communication network affects the sequence of platoon formation. The communication network is mathematically expressed as an undirected graph $G(\mathcal{M}_t, E_t)$. Each agent is a vertex in the set $\mathcal{M}_t$. If agent j can directly communicate with agent i and vice versa, there is an edge $e(i, j) \in E_t$. Agent j is then referred to as *a neighbor* of agent i and all agents that are neighbors of agent i construct its neighborhood, $\mathcal{N}(i)$. Clearly, only neighbors can directly interact with each other in the game. In other words, for each agent, its obtained utility only depends on the actions of agents in her neighborhood.

More specifically, the game in each step is composed of multiple basic games with an identical setting. Each basic game is conducted between two neighbors, for instance, i and j. The outcome $\chi(a_i, a_j)$ represents whether a new platoon is formed or not, and the characteristics of the formed platoon such vehicle sequence and platoon speed, as well as the associated valuations and payment. The newly formed platoon, denoted as k becomes an agent of time step $t + 1$. In this way, the communication network in time step $t + 1$, $G(\mathcal{M}_{t+1}, E_{t+1})$, bridges that in time step t, $G(\mathcal{M}_t,\ E_t)$ by the following relationships:

$$\begin{aligned} i,\ j \in \mathcal{M}_t;\ i,\ j \notin \mathcal{M}_{t+1} \\ k \in \mathcal{M}_{t+1};\ k \notin \mathcal{M}_t \\ \forall h\ s.t.\ e(h, j) \in E_t \text{ or } e(h, i) \in E_t,\ e(h, k) \in E_{t+1} \end{aligned}$$

Moreover, once a platoon is formed, it will not be dissembled in the following steps, though individual vehicles can leave the formed platoon when they reach their destinations. Beside, new agents outside of the system are allowed to join the process in each step. As a result, when the number of agents in the system is finite, the dynamic process will always terminates when no new agents can be generated by forming platoons. Under this umbrella, the

6.3 The Bilateral Trade Model for Bargaining

6.3.1 The General Model

To induce behaviorally stable platoons and improve efficiency, side-payment is introduced to the two-player platoon formation game. Since the following vehicles usually achieve greater benefits than the leading vehicles, it is further assumed that the following agent pays the leading agent. In other words, the leader is the seller of the platooning service, and the follower can be viewed as a buyer of this service. Side-payment needs to be designed, such that the roles of seller and buyer are properly assigned to the agents, and both parties satisfy their utilities, resulting in an efficient and stable equilibrium.

The general model setting is given as follows:

- In each step t, a random pair of neighbors $(i, j) \in \mathcal{M}^t$ plays the game.
- Before playing, both agents have zero utilities.
- For any arbitrary agent i, its action set is a continuous interval B_i , where $\forall b_i \in B_i$, $b_i \geq 0$.
- The outcome is determined by the relative magnitude of b_i and b_j. The agent with a lower bid automatically becomes the leader and collects the payment, the other follows and pays. If there is a tie in the bid, no side-payment occurs. Each agent has half probability of being the leader. Notice that if an agent is composed of multiple vehicles, its internal vehicle sequence won't be changed by the outcome.
- Two side-payment formats are considered. The first format is denoted as *independent payment*, meaning that each agent collects or pays what she bids. Consequently, the utilities are

$$u_i = V_i^L + p^* = V_i(\chi(b_i, b_j), \theta_i) + b_i, \text{ if } b_i < b_j, \tag{6.3.1}$$

$$u_i = V_i^F - p^* = V_i(\chi(a_{i2}, a_{j1}), \theta_i) - b_i, \text{ if } b_i > b_j. \tag{6.3.2}$$

  The second format is names as *interdependent payment*, meaning that the payment occurred, p^*, is a function of both b_i and b_j. Considering that the game is symmetric, the payment function is assumed to be $p^* = \frac{1}{2}(b_i + b_j)$. The associated utilities are

$$u_j = V_j^L + p^* = V_j(\chi(a_{i1}, a_{j2}), \theta_i) + \frac{1}{2}(b_i + b_j), \text{ if } b_i < b_j, \tag{6.3.3}$$

$$u_i = V_i^F - p^* = V_i(\chi(a_{i2}, a_{j1}), \theta_i) - \frac{1}{2}(b_i + b_j), \text{ if } b_i > b_j. \tag{6.3.4}$$

Clearly, independent payment rule does not satisfy budget balancing, but its analysis is fundamental thus it is included in this chapter.

- The average utility under a tie of bids is

$$u_i = \frac{1}{2}(V_i^L + V_i^F) \tag{6.3.5}$$

Clearly, the utility function in the ex post sense is a piece-wise linear function. An agent's utility is monotonically increasing to her own bid if she's a leader, and monotonically decreasing if she's a follower. Whether the utility function is a continuous one or not will further depend on the realized bid.

- The side-payment transferred is further allocated to each vehicle within the agent evenly. In this way, each vehicle always increases its utility since the agents are individual rational , meaning that *cross-monotonicity* is satisfied.

This model imitates the classic *bilateral trade model* (Myerson & Satterthwaite, 1983), which describes the bargaining problems between a buyer and a seller for a single object, and a trade only occurs when the buyer's bid is higher than seller's valuation. Differently, a trade always occurs in this model since the one with a higher bid becomes the buyer (follower), and the other becomes the seller (leader) accordingly. Besides, each trader in the bilateral trade model has a type that is equivalent to her valuation. However, type can be further specified in this model when considering the quantifiable benefits from platooning. It is known that a lead vehicle receives energy-saving benefits while following vehicles receive both energy-saving and labor-saving benefits. In general, the energy-saving amount depends on the vehicle types and configurations, headway, and speed in operation. Though varying from agent to agent, these parameters can be easily discovered by all thus are regarded as *public information*. Quite the contrary, the value of labor savings is possessed by agents differently. Considering factors include but not limited to each one's wage level, the degree of drivers' tiredness, the intensity of driving maneuvers under platooning, and the deviation from the original schedules after platooning. For this reason, the value of labor savings is regarded as each agent's *type*

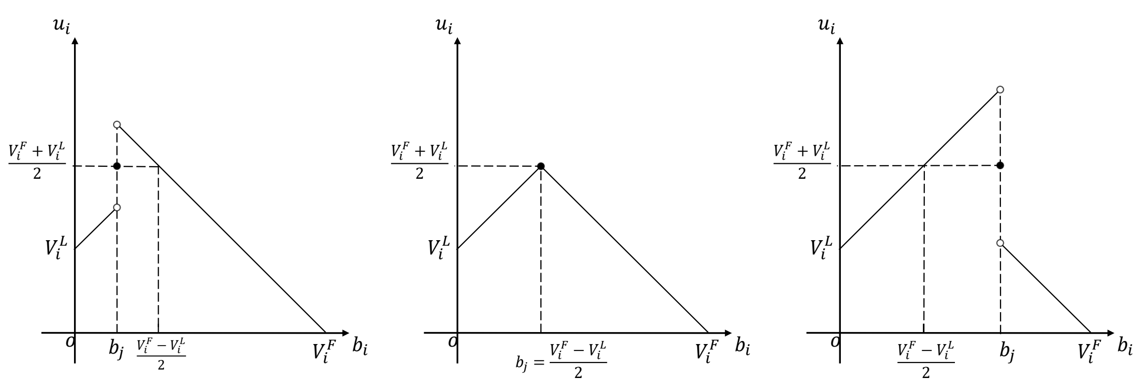
Depending on whether agents are willing to reveal their type truthfully or not before the game is conducted, the general model stated above further tailors for two different settings, namely the complete information setting and the incomplete information setting.

6.3.2 The Complete Information Setting

With the complete information setting, both agents' valuations are public. For each agent, her action space is an one-dimensional interval bounded by the non-negativity requirement of the bid, and the individual rationality constraint. To find the equilibrium of a game, we first study what is an agent's best response to the other's proposed bid, which are different under the two proposed payment functions, independent payment and interdependent payment.

6.3.2.1 Independent Payment

With the independent payment rule, an agent's cardinal utility only depends on her bid once her position is determined. In other words, the other's bid only affects her position. Therefore, each agent's action space is entirely dependent on her own valuations. Take agent i as an example, her action space is $[0,\ V_i^F]$, which is produced by non-negativity constraint $b_i \geq 0$ and individual rationality $V_i^L + b_i \geq 0,\ V_i^F - b_i \geq 0$.



(a) $b_j < \frac{1}{2}(V_i^F - V_i^L)$ (b) $b_j = \frac{1}{2}(V_i^F - V_i^L)$ (c) $b_j > \frac{1}{2}(V_i^F - V_i^L)$

Figure 6.1: Utility function of agent i with independent payment

When $b_i = \frac{1}{2}(V_i^F - V_i^L)$, the utilities from being the leader and being the follower is the same: $V_i^L + b_i = V_i^F - b_i = \frac{1}{2}(V_i^F + V_i^L)$. Agent i hence is indifferent to the position. When $b_i < \frac{1}{2}(V_i^F - V_i^L)$, being a follower dominates being a leader. When $b_i > \frac{1}{2}(V_i^F - V_i^L)$, being a leader dominates being a follower. By comparing the relative size of b_j and $\frac{1}{2}(V_i^F - V_i^L)$, agent i takes different response:

1. If $b_j < \frac{1}{2}(V_i^F - V_i^L)$, agent i's utility function is illustrated in figure 6.1(a). Clearly, agent i will bid $b_i \in (b_j, \frac{1}{2}(V_i^F - V_i^L)]$ to ensure her following position and a utility at least no less than $\frac{1}{2}(V_i^L + V_i^F)$. Since the utility is decreasing to b_i, she will try to bid b_i as small as possible. However, she will not bid $b_i = b_j$ since doing so results in a utility of $\frac{1}{2}(V_i^L + V_i^F)$, which is less than $V_i^F - b_j$. Therefore, agent i has no best response when agent j bids $b_j < \frac{1}{2}(V_i^F - V_i^L)$.

2. If $b_j = \frac{1}{2}(V_i^F - V_i^L)$, agent i has a best response: $b_i = b_j$ (figure 6.1(b)).

3. If $b_j > \frac{1}{2}(V_i^F - V_i^L)$, agent i's utility function is illustrated in figure 6.1(c). Agent i will bid $b_i \in [\frac{1}{2}(V_i^F - V_i^L), b_j)$ to ensure her leading position and a utility at least no less than $\frac{1}{2}(V_i^L + V_i^F)$. Since now the utility function is increasing to b_i, she will try to bid b_i as large as possible . However, she will not bid $b_i = b_j$ since doing so results in a utility of $\frac{1}{2}(V_i^L + V_i^F)$, which is less than $V_i^L + b_j$. Accordingly, agent i has no best response under this case as well.

Because of symmetry, the only condition admits an equilibrium is when $V_i^F - V_i^L = V_j^F - V_j^L = p$, where p some constant value that both agents bid. However, the prerequisite for this condition is that the total utility achieved by the two agents is indifferent to their positioning, which only happens for single-brand trucks and homogeneous drivers. In other words, for the multi-brand scenario studied in this chapter, there is no equilibrium solution exists under the independent payment function.

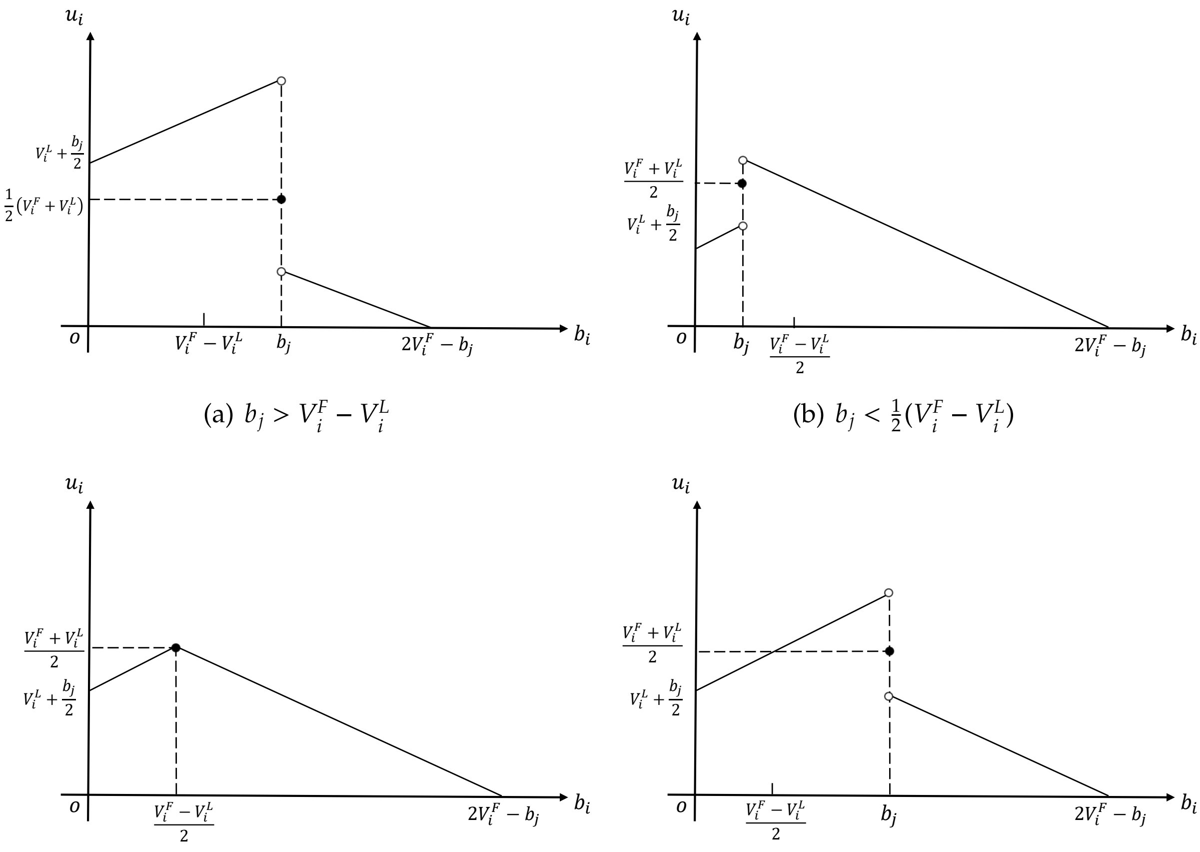
6.3.2.2 Interdependent Payment

When move to the interdependent payment rule, an agent is not only affected by her opponent's bid in the position determination, but also in her cardinal utility. Therefore, an agent's action space depends on her own valuation, as well as her opponent's bid. Assume agent j bids b_j, the action space of agent i is then $B_i = [0, 2V_i^F - b_j]$.

Agent i's utility function depends on the value of b_j as well.

1. If $b_j > V_i^F - V_i^L$, being the leader is always better than being the follower, $\forall b_i \in B_i$, as figure 6.2(a) suggested. Agent i then needs to bid $b_i < b_j$. However, when $b_i < b_j$, her utility function is increasing and $V_i^L + \frac{1}{2}(b_j + b_j) > V_i^F > \frac{1}{2}(V_i^L + V_i^F)$, she has no best response under this case.

2. If $b_j \leq V_i^F - V_i^L$, the analysis is akin to that under the independent payment rule: different utility functions can be drawn under the cases when b_j is less than, or equals, or greater than $\frac{1}{2}(V_i^F - V_i^L)$ (figure 6.2(b), figure 6.2(c) and figure 6.2(d)). Clearly, the only case that admits a best response for agent i is when $b_j = \frac{1}{2}(V_i^F - V_i^L)$.



(a) $b_j > V_i^F - V_i^L$

(b) $b_j < \frac{1}{2}(V_i^F - V_i^L)$

(c) $b_j = \frac{1}{2}(V_i^F - V_i^L)$

(d) $V_i^F - V_i^L > b_j > \frac{1}{2}(V_i^F - V_i^L)$

Figure 6.2: Utility function of agent i with interdependent payment

Therefore, even with interdependent payment function, there is no equilibrium exists for the multi-brand scenario under the two-agent platoon formation game.

6.3.2.3 A Cooperative Alternative

The analysis above indicates that if agents are perfectly rational in the non-cooperative game with linear payments setting, there is no way to achieve an equilibrium nor a behavioral stable platoon. The cooperative alternative works as follows. A pair of non-negative payment, p_i and p_j, is giving to the agents i and j respectively. Based on that, the agents report what position they would like to take. To ensure at least weakly budget balance, agent i becomes the leader if $p_i \leq p_j$ and vice versa. Based on individual rationality, $p_i \leq V_i^F$ and $p_j \leq V_j^F$.

Suppose that $V_i^L + V_j^F > V_j^L + V_i^F$, meaning that when agent i be the leader and j the follower, the total utility of the two is maximized. Easy to see, when

$$V_i^L + p_i \geq V_i^F - p_i \Rightarrow p_i \geq \frac{1}{2}(V_i^F - V_i^L),$$

agent i's best response is being the leader. Accordingly, the best responses of two agents

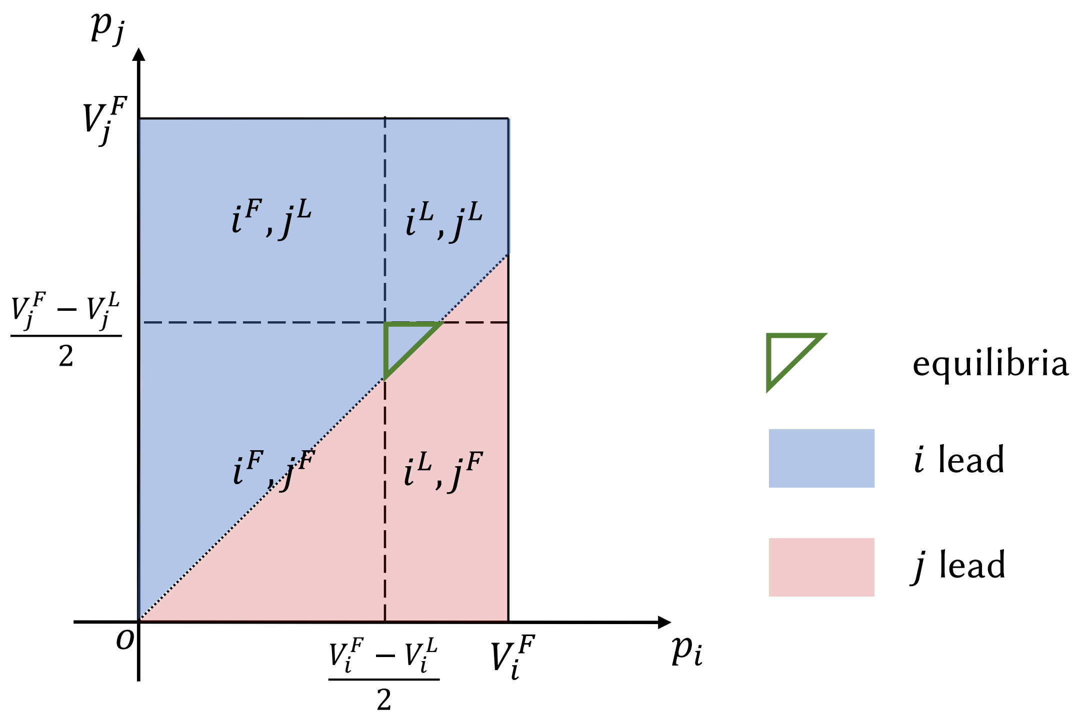


Figure 6.3: Agents' best responses under given payments

under given p_i and p_j are shown in the two-dimensional diagram in figure 6.3. For explanation, a notation i^L indicates that the best response for i is being the leader in the marked region of the diagram. By comparing the relative size of p_i and p_j, agent j takes the leading position in the lower triangle region that is colored in pink, while agent i takes the leading position in the upper right angle trapezoid region that is colored in blue. Combining these with the best responses, it can be seen that when

$$p_i \geq \frac{1}{2}(V_i^F - V_i^L),\ p_j \leq \frac{1}{2}(V_j^F - V_j^L),\ p_j \geq p_i, \tag{6.3.6}$$

there exist equilibria. The region of equilibria is outlined by the green triangle. As the equilibrium outcome, agent i is the leader who collects p_i and agent j is the follower who pays p_j, aligning with the most efficient outcome since $V_i^L + V_j^F > V_j^L + V_i^F$. Furthermore, when enforcing $p_i = p_j = p$ that satisfies

$$\frac{1}{2}(V_i^F - V_i^L) \leq p \leq \frac{1}{2}(V_j^F - V_j^L), \tag{6.3.7}$$

budget balancing is ensured. Therefore, all the efficiency is received by the agents and the equilibria with p satisfying equation 6.3.7 are Pareto optimal. In addition, it is behavioral stable since given such a payment, no agent would like to switch her position.

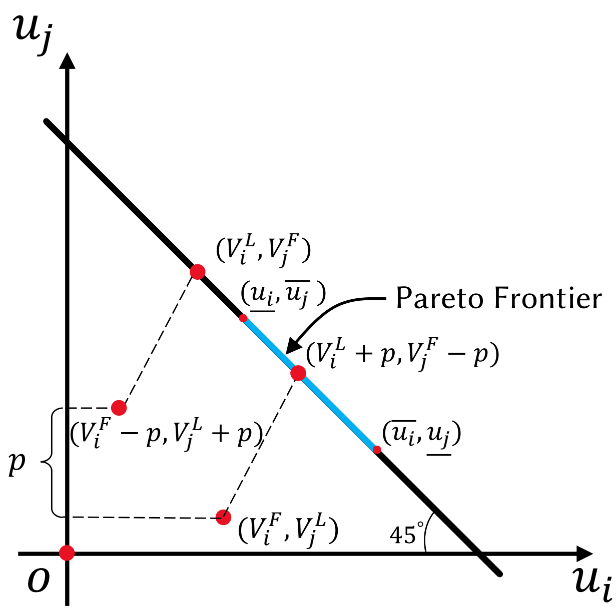


Figure 6.4: Pareto optimal solutions

Figure 6.4 shows the Pareto Frontier in the two-dimension plane of u_i and u_j. It is a segment on the 45 degree oblique line, since the utilities agent received are bounded by equation 6.3.6. In this figure, $(\underline{u_i}, \overline{u_j})$ and $(\overline{u_i}, \underline{u_j})$ confine the boundary of the Pareto Frontier, where

$$\underline{u_i} = \frac{1}{2}(V_i^F + V_i^L),\ \overline{u_i} = V_i^L + \frac{1}{2}(V_j^F - V_j^L),\ \underline{u_j} = V_j^F - \frac{1}{2}(V_i^F - V_i^L),\ \overline{u_j} = \frac{1}{2}(V_i^F + V_i^L),$$

Among all the Pareto optimal solutions, the author chooses a unique *Nash bargaining solutio*n derived from

$$p^* = \arg\max_p \{(V_i^L + p - (V_i^F - p))(V_j^F - p - (V_j^L + p)) \mid p \geq 0\}, \tag{6.3.8}$$

which gives

$$p^* = \frac{1}{4}[(V_i^F - V_i^L) + (V_j^F - V_j^L)].$$

In this way, $(V_i^F - p, V_j^L + p)$ is considered as the disagreement point, or the threat of the Nash bargaining game.

6.3.3 The Incomplete Information Setting

Though Nash bargaining solution provides an equilibrium with Pareto optimality, it is not ex post incentive compatible. As a simple example, if agent i reports $\hat{V}_i^F$ greater than V_i^F, her true valuation of being the follower, she can collect more from agent j. In fact, since all Pareto optimal payments depend on agents' valuations, there is no way to guarantee ex post incentive compatible under the complete information setting.

For this reason, the assumption of complete information is relaxed to achieve hopefully, a Bayesian equilibrium that is interim incentive compatible. Under the incomplete information setting, the valuations of any random agent i are further refined as functions of her type, θ. Using δ_i to represent her energy-saving benefits, agent i thereby has valuation

$$V_i^L = \delta_i^L$$

if she is the leader, and valuation

$$V_i^F = \delta_i^F + k\theta_i$$

if she is a follower.

Here, the constant k is introduced to be consistent with the utility function defined in chapter 5, which is composed of energy-saving benefits and a disutility term. The disutility term represents the deficiency when the vehicle deviates from its original speed after joining the platoon, scaled by her sensitivity to the deviation. Here, the author assumes that if an agent becomes a follower, she has to change her speed to the leader's while the leader does not need to. Therefore, the disutility of agent i can be modelled as $\alpha\theta_i(v_i - v_j)^2$, where v_i and v_j are agents' speeds before platooning and $\alpha\theta_i$ is agent i' sensitivity. Therefore, the valuation for agent i being the following is $V_i^F = \delta_i^F - \alpha(v_i - v_j)^2\theta_i + \theta_i = \delta_i^F + (1 - \alpha(v_i - v_j)^2)\theta_i$. For simplification, $(1 - \alpha(v_i - v_j)^2)$ is further denoted by k and $0 < k < 1$ for both agents.

When θ_i is the private information enclosed to agent i herself, agent j and other agents only know that $\theta_i \in [\underline{\theta}, \overline{\theta}]$, and it follows a cumulative distribution function $F : \Theta \to [0, 1]$, with probability density function $f : \Theta \to \mathbb{R}$. Moreover, functions F and f are assumed to be continuous and differentiable. Consequently, each agent propose a bid to maximize her expected utility.

6.3.3.1 Independent Payment

With independent payment rule, the utility function of agent i is formulated as

$$u_i = \begin{cases} \delta_i^L + b_i, & \text{if } b_i < b_j \\ \frac{1}{2}(\delta_i^L + \delta_i^F + k\theta_i), & \text{if } b_i = b_j \\ \delta_i^F + k\theta_i - b_i, & \text{if } b_i > b_j \end{cases}$$

Her expected utility is

$$\mathbf{E}u_i(\theta_i, b_i, b_j) = Pr(b_i > b_j)(\delta_i^F + k\theta_i - b_i) + Pr(b_i = b_j)(\delta_i^F + k\theta_i + \delta_i^L) + Pr(b_i < b_j)(\delta_i^L + b_i)$$

Without loss of generality, the strategy b_j from agent j can be assumed as a function of her type, denoted as $\sigma_j(\theta_j)$. Here, the author assumes in advance that σ_j is differentiable and strictly increasing non-cooperative to θ_j. These assumptions will be verified after the exact form of σ_j is derived. Agent i's expected utlty function can be further simplified as

$$\begin{aligned} \mathbf{E}u_i(\theta_i, b_i; \sigma_j) &= Pr(\theta_j < \sigma_j^{-1}(b_i))(\delta_i^F + k\theta_i - b_i) + Pr(\theta_j > \sigma_j^{-1}(b_i)(\delta_i^L + b_i) \\ &= F(\sigma_j^{-1}(b_i))(\delta_i^F + k\theta_i - b_i) + (1 - F(\sigma_j^{-1}(b_i)))(\delta_i^L + b_i) \end{aligned} \tag{6.3.9}$$

Assume that $\mathbf{E}u_i$ is maximized when b_i is in the interior of its feasible region, the first order condition gives

$$\frac{\partial \mathbf{E}u_i(\theta_i, b_i; \sigma_j)}{\partial b_i}|_{b_i = b_i^*} = 0$$

$$\Longleftrightarrow$$

$$f(\sigma_j^{-1}(b_i))(\sigma_j^{-1}(b_i))'(\delta_i^F + k\theta_i - b_i) - F(\sigma_j^{-1}(b_i)) + (1 - F(\sigma_j^{-1}(b_i))) - f(\sigma_j^{-1}(b_i))(\sigma_j^{-1}(b_i))'(\delta_i^L + b_i) = 0$$

which implies that

$$2F(\sigma_j^{-1}(b_i)) - 1 = \frac{1}{\sigma_j'(\sigma_j^{-1}(b_i))} f(\sigma_j^{-1}(b_i))(\delta_i^F + k\theta_i - \delta_i^L - 2b_i) \tag{6.3.10}$$

However, since agents i and j benefit differently from energy savings, no symmetric assumption can be made to produce the Bayesian Nash equilibrium for general distribution functions. As a remedy, the author assumes that F is a uniform distribution function. All the analysis followed tailor to this specific distribution assumption.

Suppose that σ_j is a linear function of θ_j:

$$\sigma_j(\theta_j) = a_j\theta_j + c_j,$$

where $a_j > 0$, coinciding with the strictly increasing assumption. Besides, non-negativity of b_j and individual rationality require that $a_j\underline{\theta} + c_j \geq 0,\ a_j\overline{\theta} + c_j \leq \delta_j^F + k\overline{\theta}$. Therefore, the probability for agent i to be the leader is

$$F(\sigma_j^{-1}(b_i)) = \begin{cases} 0, & \text{if } b_i < a_j\underline{\theta} + c_j, \\ \frac{b_i - c_j - \underline{\theta}a_j}{(\overline{\theta}-\underline{\theta})a_j}, & \text{if } a_j\underline{\theta} + c_j \leq b_i \leq a_j\overline{\theta} + c_j, \\ 1, & \text{if } b_i > b_i \leq a_j\overline{\theta} + c_j\ . \end{cases} \tag{6.3.11}$$

Taking equation 6.3.11 into equation 6.3.9, the first order condition leads to

$$b_i = \frac{k}{4}\theta_i = \frac{1}{4}[2c_j + (\underline{\theta} + \overline{\theta})a_j + \delta_i^F + \delta_j^F] \tag{6.3.12}$$

Similarly, let $\frac{\partial \mathbf{E}u_j(\theta_j,b_j;\sigma_i)}{\partial b_j}|_{b_j=b_j^*} = 0$:

$$b_j = \frac{k}{4}\theta_j = \frac{1}{4}[2c_i + (\underline{\theta} + \overline{\theta})a_i + \delta_j^F + \delta_i^F] \tag{6.3.13}$$

Combining equation 6.3.12 and equation 6.3.13, one can conclude that

$$a_i = a_j = \frac{k}{4}, \tag{6.3.14}$$

$$c_i = \frac{1}{3}(\delta_i^F - \delta_i^L) + \frac{1}{6}(\delta_j^F - \delta_j^L) + \frac{k}{8}(\underline{\theta} + \overline{\theta}), \tag{6.3.15}$$

$$c_j = \frac{1}{3}(\delta_j^F - \delta_j^L) + \frac{1}{6}(\delta_i^F - \delta_i^L) + \frac{k}{8}(\underline{\theta} + \overline{\theta}). \tag{6.3.16}$$

Under these conditions, it is easy to see that any agent's expected utility is a concave function of her bid, and the maximum is achieved in the interior. Therefore, the outcome

$$b_i = \sigma_i(\theta_i),\ b_j = \sigma_j(\theta_j) \tag{6.3.17}$$

is a Bayesian Nash equilibrium (BNE). In other words, the mechanism under the independent payment rule with agents using $\sigma_i(\theta_i)$ and $\sigma_j(\theta_j)$ as strategies is interim incentive compatible.

The lower bound of $\sigma_i(\theta)$ is $\frac{k}{4}\underline{\theta} + \frac{1}{3}(\delta_i^F - \delta_i^L) + \frac{1}{6}(\delta_j^F - \delta_j^L) + \frac{k}{8}(\underline{\theta} + \overline{\theta})$, which is clearly non-negative. The upper bound of $\sigma_i(\theta)$ is $\frac{k}{4}\overline{\theta} + \frac{1}{3}(\delta_i^F - \delta_i^L) + \frac{1}{6}(\delta_j^F - \delta_j^L) + \frac{k}{8}(\underline{\theta} + \overline{\theta})$. Comparing it with $k\overline{\theta} + \delta_i^F$, since $\frac{k}{4}\overline{\theta} + \frac{k}{8}(\underline{\theta} + \overline{\theta}) < k\overline{\theta}$, as long as $\frac{1}{3}(\delta_i^F - \delta_i^L) + \frac{1}{6}(\delta_j^F - \delta_j^L) < \delta_i^F$, individual rationality is guaranteed for all $\theta \in [\underline{\theta}, \overline{\theta}]$. In practice, if such condition cannot be satisfied making the expected utility under the BEN negative, agent can exit the trade to maintain interim individual rationality.

The last part discusses the ex post economic efficiency. When using the BNE solution, i will be the leader and j will be the follower if $\sigma(\theta_i) > \sigma(\theta_j)$:

$$\sigma(\theta_i) > \sigma(\theta_j) \quad \Rightarrow \quad \delta_j^L + \delta_i^F + \frac{3k}{2}\theta_i > \delta_i^L + \delta_j^F + \frac{3k}{2}\theta_j \tag{6.3.18}$$

Let $\Delta\delta = \delta_i^L + \delta_j^F - \delta_j^L - \delta_i^F$. Comparing equation 6.3.18 with ex post efficiency formulated by

$$\delta_j^L + \delta_i^F + k\theta_i > \delta_i^L + \delta_j^F + k\theta_j,$$

it is easy to see that when $\theta_i - \theta_j \in (\frac{2}{3k}e, \frac{1}{k}e)$, the trade is ex post inefficient.

6.3.3.2 Interdependent Payment

When using interdependent payment rule, the utility function of agent i can be written as

$$u_i = \begin{cases} \delta_i^L + \frac{1}{2}(b_i + b_j), & \text{if } b_i < b_j \\ \frac{1}{2}(\delta_i^L + \delta_i^F + k\theta_i), & \text{if } b_i = b_j \\ \delta_i^F + k\theta_i - \frac{1}{2}(b_i + b_j), & \text{if } b_i > b_j \end{cases}$$

Similarly, the author assumes that that agent j's bid is a function of θ_j, denoted as $\sigma_j(\theta_j)$. Assume σ is a continuous, differentiable, and strictly increasing function, thus $Pr(\sigma_j(\theta_j) = b_i) = 0$. The expected utility of agent i is

$$\begin{aligned} \mathbf{E}U_i(\sigma_j, b_i|\theta_i) &= (\delta_i^F + k\theta_i - \frac{1}{2}b_i)F(\sigma_j^{-1}(b_i)) - \frac{1}{2}\int_0^{\sigma_j^{-1}(b_i)} \sigma_j(\theta_j)f(\theta_j)d\theta_j \\ &\quad +(\delta_i^L + \frac{1}{2}b_i)(1 - F(\sigma_j^{-1}(b_i))) + \frac{1}{2}\int_{b_i}^{\bar{b}_j} \sigma_j(\theta_j)f(\theta_j)d\theta_j \end{aligned} \tag{6.3.19}$$

Notice that the strategies under this expected utility function are not symmetric. Again, suppose F is a uniform distribution on $[\underline{\theta}, \overline{\theta}]$; agent j applies a linear strategy, meaning that

$$\sigma_j(\theta_j) = a_j\theta_j + c_j,$$

where $a_j > 0$, $a_j\underline{\theta} + c_j \geq 0$, $a_j\overline{\theta} + c_j \leq 2(\delta_j^F + k\overline{\theta}) - a_j\overline{\theta} - c_j$.

Similarly, by assuming that the maximum of $\mathbf{E}U_i$ is achieved in the interior, the first order conditions lead to

$$\begin{aligned} a_j &= \frac{k}{3} \\ c_j &= \frac{3}{8}(\delta_j^F - \delta_j^L) + \frac{1}{8}(\delta_i^F - \delta_i^L) + \frac{k(\underline{\theta} + \overline{\theta})}{2} \\ a_i &= \frac{k}{3} \\ c_i &= \frac{3}{8}(\delta_i^F - \delta_i^L) + \frac{1}{8}(\delta_j^F - \delta_j^L) + \frac{k(\underline{\theta} + \overline{\theta})}{2} \end{aligned}$$

Therefore, the mechanism with Baynesian Nash equilibrium strategy

$$\sigma_i(\theta_i) = \frac{k}{3}\theta_i + \frac{3}{8}(\delta_i^F - \delta_i^L) + \frac{1}{8}(\delta_j^F - \delta_j^L) + \frac{k(\underline{\theta} + \overline{\theta})}{2} \tag{6.3.20}$$

under the interdependent payment rule is interim incentive compatible.

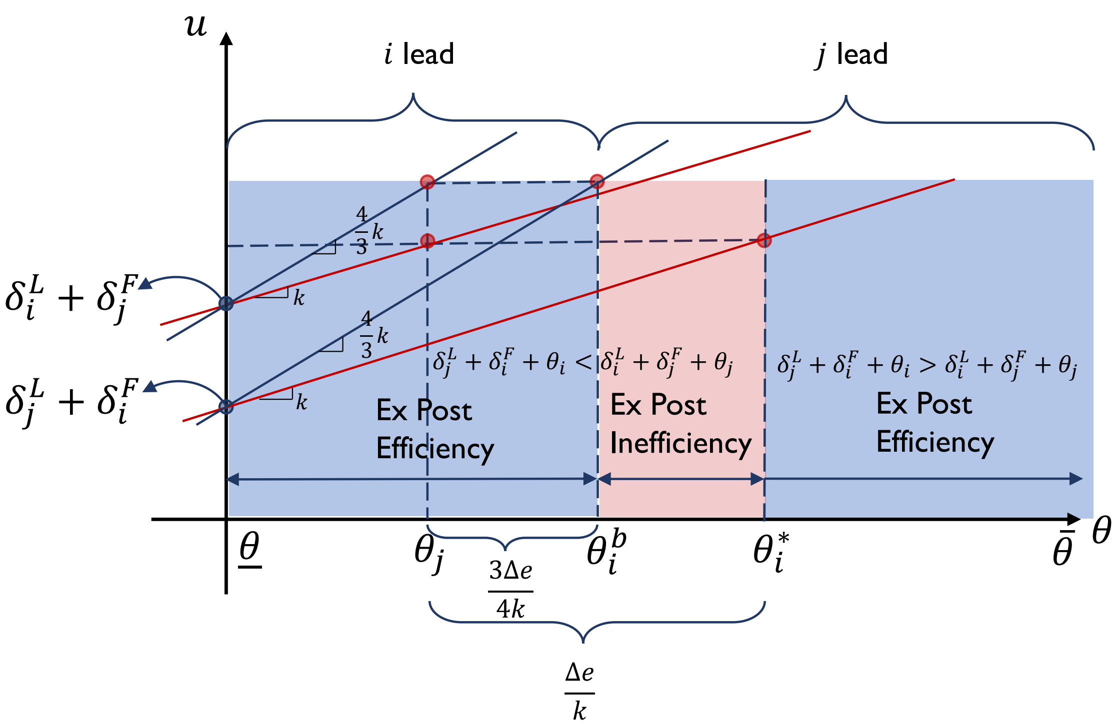


Figure 6.5: Ex post trade efficiency under interdependent payment

This time, the bargaining result when agent i wins and be the follower implies that

$$\delta_i^F + \delta_j^L + \frac{4}{3}k\theta_i > \delta_j^F + \delta_i^L + \frac{4}{3}k\theta_j$$

Comparing to ex post efficiency condition, one can conclude that when

$$\theta_i - \theta_j \in (\frac{3\Delta e}{4k}, \frac{\Delta e}{k}),$$

the trade is ex post inefficient.

In figure 6.5, the x axis indicates agents' type, and the y axis indicates their utility. When agent j has the type θ_j, θ_i^b is the lowest type of agent i that ensures her the following position, and θ_i^* is the lowest type of agent i that ensures the efficient outcome is achieved when she is the follower. If $\theta_i < \theta_i^b$, the bargaining results in that agent i being the leader and ex post efficient.

Comparing to the result under independent payment rule, interdependent payment rule maintains ex post budget balance and decreases the region of ex post inefficiency. As stated in Myerson-Satterthwaite Theorem (Myerson & Satterthwaite, 1983), "the efficient outcome function is not Bayesian implementable with ex post individual rationality and ex ante budget balance." The BNE solution under interdependent payment rule is thus the best outcome one can achieve and will utilized in the numerical examples.

6.4 A One-Sided Matching Market

6.4.1 The General Model

When multiple platooning opportunities exist, an agent will naturally tend to platoon with a better partner, instead of a randomly chosen one in her neighborhood. This intuition contributes to the idea of matching. Essentially, it follows the principle of *roommate matching* problems (Gale & Shapley, 1962), a class of economic models that describes how graduate students choose each other as their roommate. The matching process in platoon formation is described as follows:

- In each time step t, agents broadcast their basic information within their neighborhoods.
- Each agent thus calculates and ranks their neighbors based on the utility the neighbors can bring to it. The preference list is generated accordingly, dnoting as

$P(i), \forall i \in \mathcal{M}^t$. The most preferrable neighbor of agent i is denoted as $P(i, 1)$, the second most is denoted as $P(i, 2)$, and so on.

- Each agent then proposes the matching requirement in the order of her preference list. In the meantime, she also receives proposals from her neighbors. If both agree to pair with each other, they become a pair in the matching and are referred to as partners of each other. An agent is also allowed to form no platoons with others, either because there are an odd number of agents, or because matching with others deteriorates her own utility.

Readers from the transportation research community might be more familiar with bipartite matching, or two-sided matching problems. A typical example is the matching of passenger and driver in the ride-sourcing market. Unlike bipartite matching where the agents are divided into two sides and no agent can pair with another from the same side, the agents here are not distinguishable thus making the matching of interest a one-sided matching.

The core solution concept in all kinds of matching problems is *stability*. Generally speaking, stability ensures each agent has no incentive to change its current partner, either because the current partner is the most preferable one, or because her preferred ones prefer others than her. Unfortunately, as (Irving, 1985) proved, stability in the one-sided matching problems may not always exist, contrary to the fact that it always exists in bipartite matching problems.

Section 6.4.2 first provides a formal definition of stability, then introduces a benefit reallocation mechanism that secures the stability in the matching for platoons. Based on that, two algorithms that can conduct the matching entirely in the decentralized fashion are described in section 6.4.3, with pros and cons of each algorithms are briefly introduced. In section 6.4.4, the economic efficiency of the decentralized algorithm is further confirmed by its equivalent optimization problem.

6.4.2 Stability

Definition 6.4.1. ***Blocking Pair***
Under a matching M, a pair (i, j) that does not belong to M, and both prefer each other to their current partner in M is called a *blocking pair*.

Definition 6.4.2. ***Stability***
A matching M is called *stable* if there doesn't exist any blocking pairs.

An simple example is provided to concretize the two concepts. Four agents with their preferences are listed below. The symbol $\geq_i$ indicates that agent i prefers the left hand side (LHS) than the right hand side (RHS). The four agents can construct a matching with two pairs. For instance, a matching m is composed by pairs (1, 2) and (3, 4). Then, (2, 3) is a blocking pair since 2 prefers 3 to 1 and 2 prefers 2 to 4, making m unstable.

$$\begin{array}{r|l} 1: & 2 \geq_1 3 \geq_1 4 \\ 2: & 3 \geq_2 1 \geq_2 4 \\ 3: & 1 \geq_3 2 \geq_3 4 \\ 4: & 3 \geq_4 2 \geq_4 1 \end{array}$$

In fact, one can enumerate all possible matchings and find that there is no stable matching. The reason is that agent 1 prefers agent 2 than agent 3, and agent 2 prefers agent 3 than agent 1, and agent 3 prefers agent 1 than agent 2, resulting in a cycle of ordinal preference:

$$2 \geq_1 3 \geq_2 1 \geq_3 2$$

Chung (2000) named this kind of cycles as 'odd ring'. He has also proved that its' absence is a sufficient condition of stable matching. Utilizing his conclusion, a benefit redistribution mechanism that secure stability is introduced below.

To simplify stability analysis, the author first set the incentive compatibility issue aside temporarily. As introduced earlier, agents build their preferences based on the utility that they can achieve when platoon with others. However, there may be multiple forms of platoons, differing in vehicle sequence and travelling speed, that a pair of agents can achieve when their internal vehicle sequences are allowed to change. Suppose at any arbitrary step t, the platoons that can be formed by a random pair of neighbors i and $j \in \mathcal{M}^t$ constitutes an outcome space $\chi_{i,j}$, among which the optimal one is $\chi^*_{i,j}$, and the associated total utility is $r_{i,j}$:

$$r_{i,j} \geq V_i(\chi, \theta_i, \theta_j) + V_i(\chi, \theta_i, \theta_j), \ \forall \chi \in \chi_{i,j} \tag{6.4.1}$$

In practice, such an optimal form for a single platoon can be easily calculated without using the computational power of the centralized controller, thus it can be done distributed by the agents. For notation simplification, let $w_i(r_{i,j}) = V_i(\chi^*_{i,j}, \theta_i, \theta_j) - p_i(\theta_i, \theta_j) = u_i(\chi^* i, j, \theta_i, \theta_j)$, namely the utility of agent i under the optimal outcome $\chi^*_{i,j}$ and latent payment function $p_i(\theta_i, \theta_j)$. Proposition 6.4.1 describes the property of w that ensures stability.

Proposition 6.4.1. *Suppose $w_i(\cdot)$, $\forall i \in \mathcal{M}^t$ is a monotonically increasing function to its input variable. If agent i receives a utility of $w_i(r_{i,j})$ when matching with agent j, no odd rings exist in their preferences.*

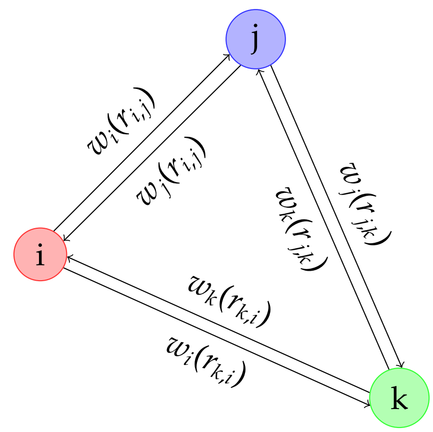


Figure 6.6: Stable matching

Proof. By contradiction, assume there exists odd rings, meaning that there are agents 0, 1..., n such that for each agent i,

$$i - 1 \geq_i i + 1 (\text{mod } n).$$

Since preferences are generated from utilities, and w_i is a monotonically increasing function, one can further conclude that

$$w_i(r_{i,i-1}) \geq w_i(r_{i,i+1})$$
$$\Longleftrightarrow$$
$$r_{i,i-1} \geq r_{i,i+1}$$

It follows that

$$r_{n0} \geq r_{01} \geq ... \geq r_{n-1,n} \geq r_{n0} \Rightarrow r_{n0} \geq r_{n0}.$$

In the inequalities stated above, if there exists at least one strict preference, one can conclude $r_{n0} > r_{n0}$, which is clearly incorrect. The equilibrium happens if and only if $r_{i,i-1} = r_{i,i+1}$, $\forall i$. If that happens, all pairs of agents in the ring will achieve the same amount of utility, making them indifferent to the matching outcome. No instability issue needs to be addressed. □

Two corollaries can be easily obtained.

Corollary 6.4.1. Under the weakly budget balance constraint, the utility function should satisfies

$$w_i(r_{i,j}) + w_j(r_{i,j}) \leq r_{i,j}, \forall i \in \mathcal{N}(j), j \in \mathcal{N}(i).$$

The simple format of w:

$$w_i(r_{i,j}) = w_j(r_{i,j}) = \frac{1}{2} r_{i,j}$$

satisfies both the strict budget balance constraint and the monotonicity property. This format will be used in following context. *Consequently, the transfer functions are*

$$p_i = \frac{1}{2} r_{i,j} - V_i(\chi^*_{i,j}, \theta_i, \theta_j), p_j = \frac{1}{2} r_{i,j} - V_j(\chi^*_{i,j}, \theta_i, \theta_j)$$

Corollary 6.4.2. Due to individual rationality, agents i and j will never pair with each other if $r_{i,j} < 0$.

6.4.3 The System Evolution

Under the one-sided matching environment, each agent can propose to and receive proposals from her neighbors simultaneously. Based on whether a rejection is received, the agent updates her preference list. Two agents only pair with each other if they are their first preference in their most updated preference lists. When applying one-side matching in the dynamic process, each matched pair will become a new agent in the next step. Depending on the moment that the new agent influences the rest agent's pairing procedure, two algorithms are proposed accordingly.

Algorithm 1 describes a stochastic matching procedure (SMP). Under this procedure, once two agents are paired, all their neighbors will be notified and reproduce their preference lists by considering the newly generated agent, regardless of whether they have paired with others or not. In this way, an agent is influenced by the emerging agents during her pairing procedure, so that she is likely to reproduce her preference list several times before pairing with a partner. The stochasticity stems from the fact that the pairings are conducted asynchronously and distributively. As a result, the final system outcome is unpredictable. Due to this concern, the second algorithm that guarantees a deterministic outcome is proposed.

Data: Vehicle Information
Result: Platoon Formation and Individual Payoffs
while *exists agent that has nonempty preference list* **do**
  $t \leftarrow t + 1$;
  for $\forall i \in \mathcal{M}$ **do**
    Update its preference list $P(i)$.
  end
  for $\forall i \in \mathcal{M}$ **do**
    Propose to agent $P(i, 1)$; **for** agent $P(i, 1)$ **do**
      Check its preference list $P(P(i, 1))$;
      If $P(P(i, 1), 1) = i$, **Match** i **and** $P(i, 1)$ to generate the new agent i';
      Agent i' **broadcast** its information to its neighborhood, which is also the former agent i and former agent $P(i, 1)$'s neighborhoods;
      Break;
      Else, $P(i, 1)$ deletes all neighbors inferior to i.
    end
  end
end

Algorithm 1: ***The Stochastic Matching Procedure***

Compared to SMP, the deterministic matching procedure (DMP) enforces neighbors only consider the newly generated agent once they complete the current pairing. Therefore, only if a matching for current agents is completed can the dynamic process forward to the next step. DMP applies the first phase of Irving's algorithm (Irving, 1985) in each step. The determinism of the outcome is proved in proposition 6.4.3. Before that, two related properties are stated and proved.

Data: Vehicle Information
Result: Platoon Formation and Individual Payoffs
while *exists agent that has nonempty preference list* **do**
  $t \leftarrow t + 1$;
  for $\forall i \in \mathcal{M}$ **do**
    Update its preference list $P(i)$.
  end
  for $\forall i \in \mathcal{M}$ **do**
    Propose to agent $P(i, 1)$; **for** agent $P(i, 1)$ **do**
      Check its preference list $P(P(i, 1))$; **If** $P(P(i, 1), 1) = i$, **Match** i **and** $P(i, 1)$ into the new agent i' with empty preference list;
      Broadcast to its neighborhood, who delete either i or $P(i, 1)$ or both;
      Else, $P(i, 1)$ deletes all neighbors inferior to i.
    end
  end
end

Algorithm 2: ***The Deterministic Matching Procedure***

Proposition 6.4.2. *A matching is finished when all agents have empty preference lists, indicating whether the agent is matched with another agent, or stays single.*

Proof. This can be simply proved by contradiction: If agent i with a nonempty preference list $P(i)$ is unmatched, then all agents on $P(i)$ are unmatched. Otherwise, if an arbitrary agent j on $P(i)$ has been matched with someone else, see k, j would broadcast the matching to i and i would delete j. Therefore i must have an empty preference list. □

Since the number of agents is finite in the dynamic platoon formation process, preposition 6.4.2 ensures that both algorithms will terminate in finite steps.

Lemma 6.4.1. *In each step of DMP, the agent pair that achieves the maximum total utility must be matched.*

Proof. If the maximum total utility is achieved by pair i, j, meaning that $r_{i,j} \geq r_{k,l}, \forall k, l$, the following inequalities must stay true as well:

$$w_i(r_{i,j}) \geq w_i(r_{i,k}), \forall k \in \mathcal{N}(i)$$
$$w_j(r_{i,j}) \geq w_j(r_{i,k}), \forall k \in \mathcal{N}(j)$$

Equivalently, i is the first preference on j's list and vise versa. By the proposing sequence, both of them will first send propose to each other and they will be matched accordingly. □

Proposition 6.4.3. *Algorithm 2 always results in a deterministic outcome.*

Proof. In each step t, lemma 6.4.1 ensures that the pair of agents with the maximum total utility will be matched and then removed. Among the rest agents, the pair with the maximum total utility will be matched. As the number of agents is finite and the total utility can be ordered, the matching will always terminate at a finite number of steps, say m steps. The total utility is then the summation of the m largest total utilities generated by m disjoint pairs of agents. For this reason, the outcome at the end of each step is deterministic. When no agents outside join the matching system during the dynamic process, the final outcome will always be fixed. □

6.4.4 The Optimization Perspective

As introduced previously, the purpose of matching is allowing agents to find better partners to improve the total system utility. Therefore, the matching procedures can be regarded as decentralized heuristic algorithms that solve the following optimization problem:

$$\max_{z} \quad \sum_{e(i,j)\in E} w_{i,j} z_{i,j} \tag{6.4.2a}$$

$$\sum_{j\in\mathcal{N}(i)} z_{i,j} \leq 1 \tag{6.4.2b}$$

$$z_{i,j} = z_{j,i}, \ \forall e(i,j) \in E \tag{6.4.2c}$$

$$\max\{\sum_{k:e(i,k)\in E} w_{i,k} z_{i,k} - w_{i,j}(1 - z_{i,j}), \sum_{k:e(j,k)\in E} w_{j,k} z_{j,k} - w_{j,i}(1 - z_{j,i})\} \geq 0, \ \forall e(i,j) \in E \tag{6.4.2d}$$

$$z_{i,j} \in \{0, 1\}, \forall e(i,j) \in E \tag{6.4.2e}$$

Here, agents' communication network is represented by a general graph $G(\mathcal{M}, E)$. If $i, j \in \mathcal{M}$ are neighbors, there is an edge $e(i,j) \in E$. The objective 6.4.2a maximizes the system total utility by pairing two agents with each other. A binary variable $z_{i,j}$ indicates whether i matches with j. Hence constraint 6.4.2b states that each agent can match at most one other agent in its neighborhood and constraint 6.4.2c regulates the matching is reciprocal: if i matches with j, j matches with i as well. Equation 6.4.2d mathematically describes matching stability.

Theorem 6.4.1. By using the transfer function $p_i(\theta_i, \theta_j) = w_i(r_{i,j}) - V_i(\chi^*_{i,j}, \theta_i, \theta_j)$, DMP in each step generates the matching with the maximum system utility that guarantees stability, equivalently, DMP provides the optimal solution of Problem 6.4.2.

Proof. Denote the stable matching from DMP is m. By contradiction, suppose that there exists another matching m', which is also stable and has greater system utility than m, denoted as

$$u(m') > u(m).$$

Comparing m and m', there must exists some pair $(i,\ j)$ matched in m', but unmatched in m:

$$(i,\ j) \in m',\ (i,\ j) \notin m \tag{6.4.3}$$

Besides, those pairs that are both matched and unmatched under m and m' are not of interest in this proof. Assume that agents i and j are matched with $p(i)$ and $p(j)$, respectively, the possible relationships among $r_{i,j},\ r_{i,p(i)}$ and $r_{j,p(j)}$ can be discussed:

1. For all $(i, j) \in m'$ and $(i, j) \notin m$, $r_{i,p(i)} \geq r_{i,j}$ and $r_{j,p(j)} \geq r_{i,j}$.

   Such a relationship is impossible since it will lead to

   $$u(m) \geq u(m')$$

   thus contradict to the assumption in equation 6.4.3. Therefore there must exists a pair (i, j) such that

   $$r_{i,j} > \min\{r_{i,p(i)},\ r_{j,p(j)}\}.$$

2. Suppose that there exists a pair $(i, j) \in m$ such that $r_{i,p(i)} > r_{i,j}$ and $r_{j,p(j)} > r_{i,j}$, satisfying $r_{i,j} > \min\{r_{i,p(i)},\ r_{j,p(j)}\}$. However, it is also impossible because under the stability definition, such a pair (i, j) is a blocking pair for matching m, contradicting to the fact that m is a stable matching generated from DMP.

3. Therefore, every $(i,\ j)$ must satisfy

   $$r_{i,j} > \min\{r_{i,p(i)},\ r_{j,p(j)}\}, \quad r_{i,j} < \max\{r_{i,p(i)},\ r_{j,p(j)}\}. \tag{6.4.4}$$

   Suppose that $r_{i,p(i)} > r_{i,j} > r_{j,p(j)}$ w.l.o.g. Under stability constraint, if $p(i)$ does not match with i under m', it must match with another agent, denoted as $g^{(1)}p(i)$. Otherwise, if all $p(i)$ stays single under m', $r_{i,p(i)} + r_{j,p(j)} > r_{i,j} + 0$ making $u(m') < u(m)$, a contradiction to the assumption as well. In this way, the pair $(p(i), g^{(1)}p(i))$ is another pair that matches under m' and unmatches under m. The previous analysis can be applied to it as well. Following this logic, one can get a list of agents $g^{(2)}p(i)$, $g^{(3)}p(i)$, ..., such that

$$(g^{(2n)}p(i),\ g^{(2n+1)}p(i)) \in m',\ (g^{(2n+1)}p(i),\ g^{(2n+2)}p(i)) \in m,\ n \geq 0,\ n \in \mathbb{Z},$$
$$r_{g^{(2n+3)}p(i),\ g^{(2n+2)}p(i)} > r_{g^{(2n+2)}p(i),\ g^{(2n+1)}p(i)} > r_{g^{(2n+1)}p(i),\ g^{(2n)}p(i)}, n \geq 0,\ n \in \mathbb{Z}.$$

As figure 6.7 shows, the matching under m' is colored in red, and that under m is

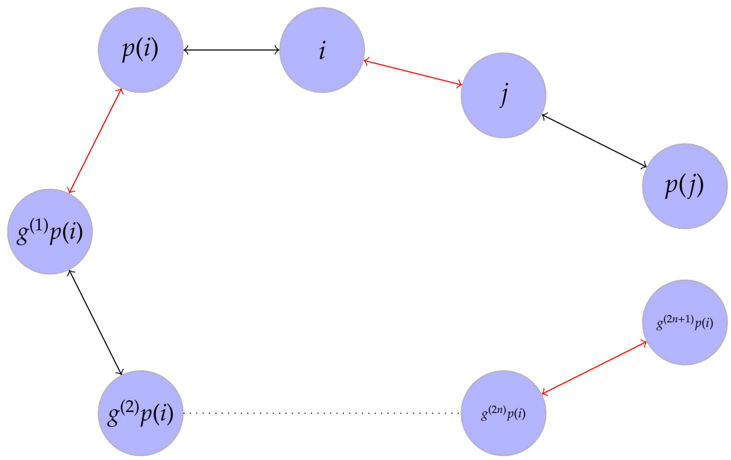


Figure 6.7: List of agents under matched pairs in m and m'

colored in black.

Since the number of agents in each step is finite, the list is finite long as well. Assume that the last element in the list $g^{(2n+1)}p(i)$, $n \in \mathbb{Z}_+$. Moreover, stability indicates that

$$P(g^{(2n)}p(i), 1) = g^{(2n+1)}p(i), \quad P(g^{(2n+1)}p(i), 1) = g^{(2n)}p(i).$$

In other words, $g^{(2n)}p(i)$ and $g^{(2n+1)}p(i)$ are the first preferences of each other. If it is not the case, one can always lengthen the list based on previous analysis. However, as m is generated by DMP and according to Lemma 6.4.1, we also have

$$P(g^{(2n-1)}p(i), 1) = g^{(2n)}p(i), \quad P(g^{(2n)}p(i), 1) = g^{(2n-1)}p(i).$$

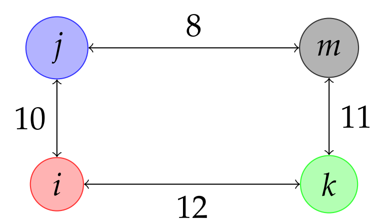
Together with the previous conditions, agent $g^{(2n)}p(i)$ has two first preferences, which is obviously a contradiction when the preference is strictly ordered. On the other hands, if the last element in the list is $g^{(2n)}p(i)$, $n \in \mathbb{Z}_+$,

$$\sum_{k=1}^{n} r_{g^{2n}p(i),g^{2n-1}p(i)} + r_{p(i),i} + r_{j,p(j)} > \sum_{k=2}^{n} r_{g^{2n-1}p(i),g^{2n-2}p(i)} + r_{g^{1}p(i),p(i)} + r_{i,j},$$

meaning that the difference parts between m and m' generated by (i, j) has a greater value in m than in m'. If all the difference parts between m and m' are represented in this list, $u(m) > u(m')$ accordingly. If not, combining all the results from disjoint lists, one can still achieve a result of $u(m) > u(m')$.

In sum, a stable and more efficient matching m' does not exist. m achieves the maximum system utility among all stable matchings.

A toy example showing that is as follows: In the system four agents can be matched



into two pairs. According to Algorithm 2 we have $(i, k), (j, m) \in m$ and $(i, j), (m, k) \in m'$. Clearly

$$u(m') = 21 > 20 = u(m)$$

But under m', (i, k) is a blocking pair which must be matched through DMP. $\square$

6.5 Numerical Examples

In this section, numerical examples are conducted to compare the proposed models as well as the centralized platoon formation approach stated in chapter 5 in terms of solution quality and computational efficiency. Cases with vehicle numbers varying from 7 to 25 are generated. Two scenarios, depending on whether the labor-saving benefit is included in the utility function, are provided. The first scenario utilizes the utility function developed in chapter 5 to create a complete information environment. Therefore, the Nash bargaining solution is used when applying the bilateral trade model. The second scenario considers utility with both energy-saving and labor-saving. On the one hand, when applying the bilateral trade model, the valuation of labor-saving as a random parameter so that the Bayesian equilibrium solution is utilized. One the other hand, when applying one-sided matching to this scenario, it is assumed that labor-saving is completely known by all to generate the preference lists, which is necessary for stable matching.

6.5.1 Utility without Labor-Saving

When applying the bilateral trade model, the author formulates the utility functions for agent i being the leader and the follower when platoon with agent j, respectively, by referencing the fuel consumption function developed in chapter 5:

$$u_i(L) \quad = \quad \gamma \sum_{m \in M(i)} [F_m^0(v_m) - F_m(v_{(i1)}, n_i + n_j, \begin{bmatrix} \mathbf{P(i)} & 0 \\ 0 & \mathbf{P(j)} \end{bmatrix})] + p^* \tag{6.5.1}$$

$$\begin{aligned} u_i(F) \quad &= \quad \gamma \sum_{m \in M(i)} [F_m^0(v_p) - F_p(v_{(j1)}, n_i + n_j, \begin{bmatrix} \mathbf{P(j)} & 0 \\ 0 & \mathbf{P(i)} \end{bmatrix})] \\ &+ \sum_{m \in M(i)} [\alpha_m (v_{i1} - v_m)^2] - \sum_{p \in P(i)} [\alpha_m (v_{j1} - v_m)^2] - p^* \end{aligned} \tag{6.5.2}$$

Here, the set of vehicles contained in agent i is denoted as$M(i)$; the desired speed of vehicle m is v_m while $v_{(i1)}$ is the operation speed of agent i; the term $\mathbf{P(i)}$ is the matrix representing the vehicle sequence in agent i; the term $\sum_{m \in M(i)} [\alpha_m (v_{i1} - v_m)^2] - \sum_{p \in P(i)} [\alpha_m (v_{j1} - v_m)^2]$ describes the disutility in speed deviation and the sensitivity term α_m is assumed to be known; finally, p^* represents the side-payment determined by Nash bargaining solution.

Figure 6.8: Efficiency comparisons of the centralized approach, Nash bargaining solution, and one-sided matching for utilities without labor-saving

For each case, 200 times of the dynamic process has been conducted when applying the bilateral trade model with the Nash bargaining solution, which results in a range of random outcomes. On average, the generated total benefits achieve 52% of the global optimality generated by solving the optimal platoon formation in the centralized approach (purple box plots in figure 6.8). It is acceptable since this model does not optimize vehicle sequence and operating speed.

When applying the one-sided matching, every pair of agents needs to solve the simplified version of problem 5.2.2 to find the optimal form of their platoon and the associated maximum utility. Overall, DMP performs better than SMP. A simple example where each agent at most four neighbors suggests that the average efficiency achieved by SMP is 61% while that by DMP is 64%. For this reason, other numerical examples all use the result from DMP to compare the efficiency of one-sided matching with that of other methods.

When all agents are assumed to be connected, DMP achieves 67% of the global optimalities on average (blue dots in figure 6.8), which is 15% improvement comparing to the Nash bargaining solution. This improvement suggests that performing matching instead of randomly choosing another agent to platoon with, does not only improve an individual's utility but also improve the system's economic efficiency. However, compared to the centralized approach, there is still a 23% optimal gap on average. The optimization problem 6.4.2 stated in the previous section, reveals the crux why the decentralized approach is inferior to the centralized approach in terms of the result. Substantially speaking, the dynamic platoon formation process offers a heuristic algorithm framework for solving the original platoon formation problem. At each step of the process, one-sided matching generates the optimal solution with the constraint that one agent can only match with another one agent. Comparatively, the centralized approach can perform many-to-many matching all at once. The loss of economic efficiency is compensated in two aspects. Firstly, the behavioral stability is theoretically ensured by matching stability, which is, in general impossible in the centralized approach under the fair allocation mechanism. Secondly, one-sided matching can be completed very fast. The result can be verified by the computational time presented in table A.3.

6.5.2 Utility with Labor-Saving

Under this scenario, the author assumes that the valuations on labor-saving are known when conducting the optimal platoon formation in the centralized approach and the one-sided matching. Contrarily, to intimate the incomplete information setting in the bilateral trade model, each agent's exact valuation on labor-saving is assumed to be known only by herself. Her neighbors only know the distribution of this valuation. Accordingly, the Bayesian Nash equilibrium bargaining solution is used under the bilateral trade model.

When implementing the centralized approach to find the optimal platoon formation as a benchmark, a new subproblem reflecting labor-saving is generated and utilized: *SP-K′*:

$$\min_{\mathbf{z},\mathbf{h},v} \quad \sum_{i\in\mathcal{M}}(y_{s_i} - c_i^0)z_i + \gamma(\beta_3^k v^2 + \beta_2^k v + \beta_1^k + \frac{\beta_0^k}{v}) + \quad \textstyle\sum_{i\in\mathcal{M}} \alpha_i z_i (v - v_i)^2 + \theta_i h_i \tag{6.5.3a}$$

$$s.t. \quad \sum_{i\in\mathcal{M}(q)} z_i = m_k^q, \qquad \forall q \in \mathcal{Q} \tag{6.5.3b}$$

$$\sum_{i\in\mathcal{M}(q)} h_i = s_k^q, \qquad \forall q \in \mathcal{Q} \tag{6.5.3c}$$

$$h_i \leq z_i, \qquad \forall i \in \mathcal{M} \tag{6.5.3d}$$

$$v^l \leq v \leq v^u \tag{6.5.3e}$$

$$z_i \in \{0,1\}, \qquad \forall i \in \mathcal{M} \tag{6.5.3f}$$

$$h_i \in \{0,1\}, \qquad \forall i \in \mathcal{M} \tag{6.5.3g}$$

Here, the platoon pattern is determined tuple $(\mathbf{m}_k, \mathbf{s}_k)$. $\mathbf{m}_k = \{m_k^q, \ \forall q \in \mathcal{Q}\}$ is defined as that in chapter 5. $\mathbf{s}_k = \{s_k^q, \ \forall q \in \mathcal{Q}\}$ defines the leading vehicle's type.

Figure 6.9: Efficiency comparisons of the centralized approach, BNE bargaining solution, and one-sided matching for utilities with labor-saving

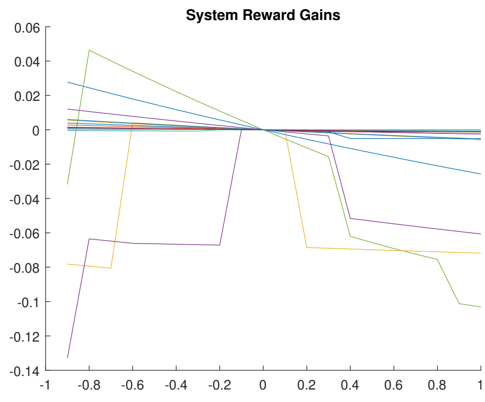
As for the result, the BNE bargaining solution under the bilateral trade model achieves 68% of the economic efficiency on average (purple box plots in figure 6.9), much better than the performance when labor-saving is not considered in the utility function. When all vehicles are neighbors to each other, one-sided matching achieves 72% of the economic efficiency on average (blue dots in figure 6.9), which is only 4% improvement comparing to the bargaining solution.

Clearly, when labor-saving utility is considered, the difference between matching and bargaining diminishes. Such a result can be well-explained. In this study, the labor-saving is of the same magnitude as energy-saving. While finding the formation with the maximum energy-saving benefit is a complicated combinatorial optimization problem, finding the formation with the most labor-saving benefit is much easier. Consequently, the advantage of optimization over simple methods is not significant when the benefit from both savings are relatively the same. Though the uncertainty on labor savings exists during the decision-making process, the ex post economic inefficiency of the BNE solution has been theoretically proved to be relatively small. It implies that if uncertainty appears linearly in the utility function (for instance, $u_i = \delta_i + \theta_i$), using a bilateral trade model with the BEN solution can achieve a satisfying level of optimality.

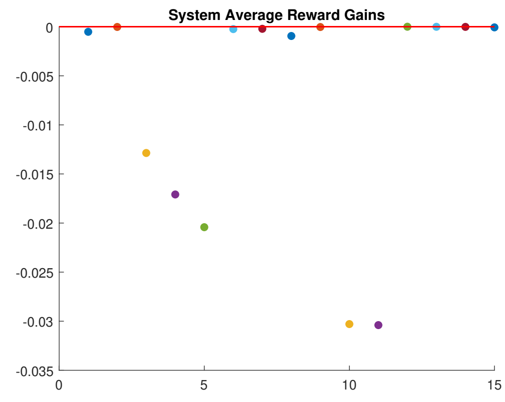
6.5.3 Sensitivity Analysis on One-Sided Matching

As previously mentioned, incentive compatibility has not been discussed in the one-sided matching market. One main reason it that theoretically, no mechanism implements stable matching in dominated either dominant strategies nor ex post equilibrium (Shoham & Leyton-Brown, 2008). Consequently, the one-sided matching studied here cannot guarantee the incentive compatibility by nature. One way to address this issue is relaxing the conditions on complete information to incomplete information, under which the stability in the Bayesian environment can be evaluated. However, doing so inevitably complicates the analysis while the efficiency improvement is marginal. Furthermore, the previous numerical examples have indicated that if uncertainty is a dominant component in utility function, the performance from bilateral trade model with BEN solution can already good enough. Therefore, the only concern for misreporting arises when some private information exists but its overall impact to the result is relatively small.

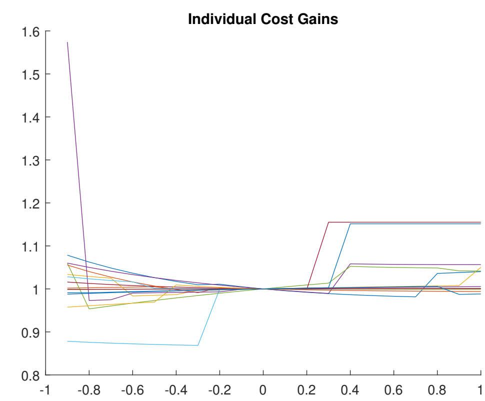
Here, a set of sensitivity analyses is conducted when agents have the incentive to misreport their disutility weight, which is assumed to be positively correlated to their labor-saving valuation. Each Agent can deteriorate her disutility weight from -100% to 100%. Two systems, one with 15 vehicles (figure 6.10) and another with 25 vehicles (figure 6.11), are evaluated by the four performance measures: the total system reward gains (utility increase) when one Agent misreports; the average system reward gains to each Agent regardless to her strategy; the individual cost gains when the Agent misreports; under the individual's average cost gain when she misreports. A few implications can be concluded from the results. First, there is no universal way for agents to misreport since some are better-off with lower reported weights, while others are being better-off with higher reported weights. Similarly, there is also no universal way for the whole system to be better-off by one Agent's misreporting. Furthermore, although misreport may lead to relatively large gains (10% increase in individual utility) for individuals, the whole system is usually robust to one agent's misreporting. Lastly, the more vehicles in the system, the more complex the result could be.



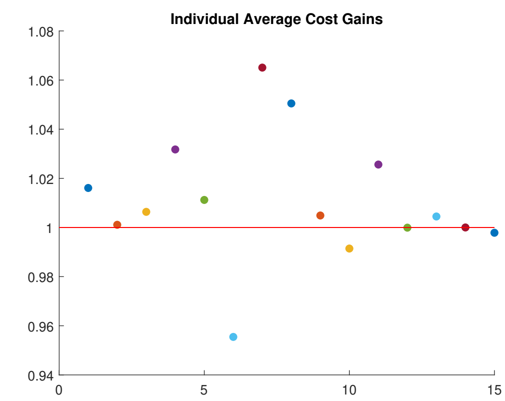
(a)



(b)



(c)



(d)

Figure 6.10: The individual gains and system influence by misreporting (number of vehicles: 15)

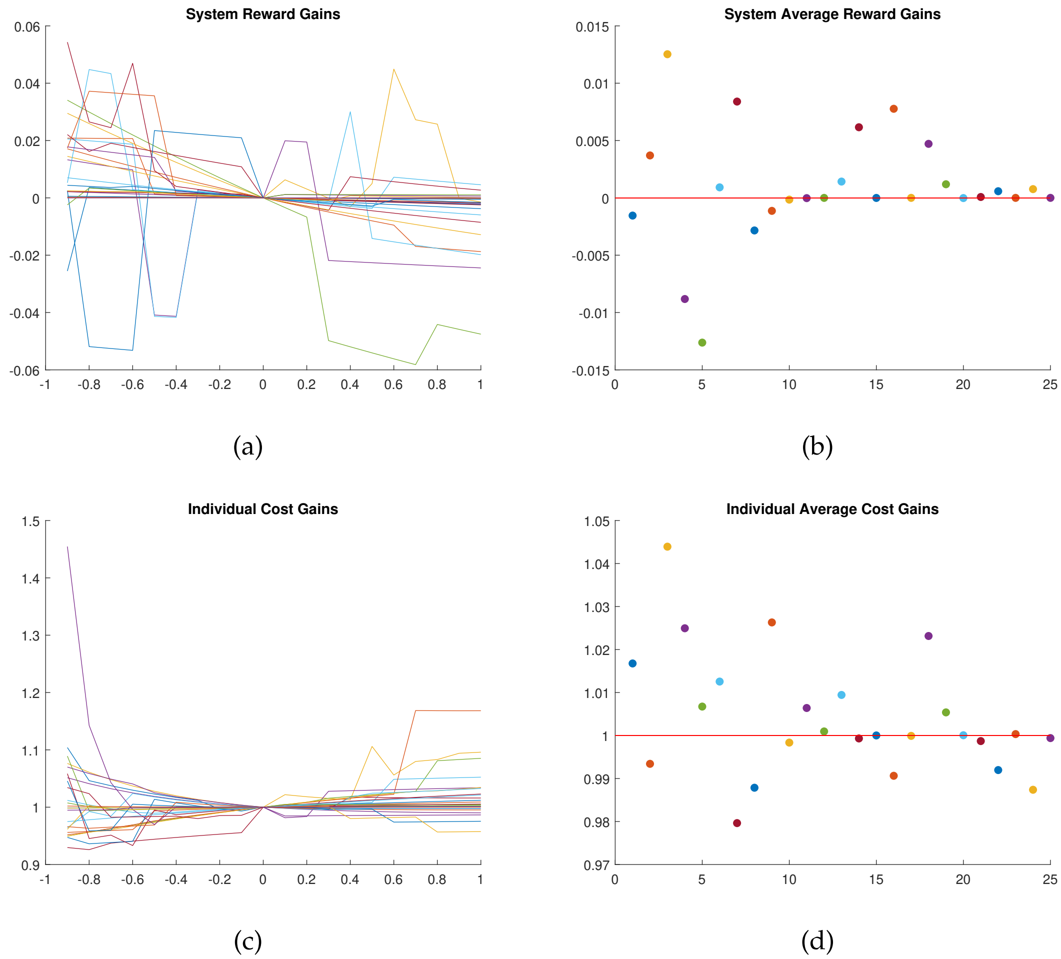


Figure 6.11: The individual gains and system influence by misreporting (number of vehicles: 25)

6.6 Conclusion

This chapter establishes a dynamic platoon formation process for multi-brand trucks in a decentralized platooning system, which is evolved by two agents coordinate with each other at each step. Depending on how agents choose partners to platoon with, a bilateral trade model and a one-sided matching market with the associated benefit redistribution mechanisms, are developed.

The theoretical analysis and comparative numerical examples indicate that these two models work differently thus can be more fitted in one scenario than the others. The bilateral trade model with the Bayesian Nash equilibrium solution performs well when a labor-saving utility or other types of utilities that are less likely to be accurately assessed by others is considerable. The matching mechanism works better when accurate information is easy to access, and complete information sharing is possible. There is no need to conduct a more complicated analysis of Bayesian stable matching since the efficiency gain is marginal.

Unlike the centralized approach that requires high computational power to conduct an integrated planning and management strategy for platoon operations, the decentralized platoon formation process with benefit redistribution also permits the possibility to incorporate path planning due to its computational efficiency. One possible way to do so is to revise the current utility function to include the expected utility that might encounter in the future by considering route choices and the associated platooning opportunities. This extension could deliver a workable strategy for the real-time operation of truck platooning system.

CHAPTER 7

Conclusion

7.1 Findings

Cooperative truck platooning is a striking innovation that utilizes CAV technology to reduce energy consumption, one of the dominant operating costs in the freight industry. As this implementation has not been widely adopted, it is obscure whether it holds a promising prospect in terms of financial reliability. This thesis hence emerges to identify the practical limitations and propose possible solutions to facilitate the inter-organizational truck platoon operations for a more significant system surplus. In particular, this thesis pinpoints two foreseeable barriers: the rare ad-hoc platooning opportunities over the network and the behavioral instabilities from truck owners. A hierarchical model framework is established to tackle these barriers from planning and management perspectives.

Chapter 3 looks into the macroscopic planning problem and investigates the energy-saving potentials of U.S. national daily long-distance truck demands. The empirical study shows that optimizing truck platoons' itineraries leads to an average of 7.2% savings on fuel consumption for the whole network, which is a considerable improvement comparing to the 4.4% savings from ad-hoc platooning. Cost and benefit analysis also indicates that scheduled truck platooning and a larger platoon size limit would help individual truck owners recover the investment cost before vehicle replacement.

To address the behavioral instability issue that arises in platoon operations, chapter 4 to chapter 6 discusses the integrated management strategy combining platoon formation and benefit redistribution, thereby resolve the controversy between system surplus and individual utilities. As no universal solution exists, these chapters provide multiple mechanisms to accommodate different settings.

Chapter 4 concentrates on single-brand trucks with a universal vehicle type and individualized willingness-to-pays. An auctioning mechanism is developed to determine the platoon leader that generates the maximum surplus, help trucks trade over the leadership, and evenly distribute the energy-saving benefit. The author proves that this mechanism is budged balanced and allows little deception in trading.

Chapter 5 and chapter 6 study the more complicated scenario of multi-brand truck platooning, where vehicles in platoon have multiple vehicle types and configurations, as well as different willingness-to-pays. Chapter 5 views the problem from a central planner's perspective and maximizes the system surplus. Using a novel utility function to approximate the individual utility that varies among the positions in platoons, a mixed non-linear integer program finds the optimal platoon formation associated with system optimum. A fair benefit reallocation mechanism is then performed to ensure trucks to stay in the optimal formation.

Utilizing the distributed communication structure embedded in CAV technology, chapter 6 envisions a decentralized platooning system where truck owners/drivers form behaviorally stable platoons through trading positions and transferring utility in a dynamic process under given mechanisms. Compared to the previously studied approach, these decentralized approaches are supreme in terms of computational efficiency as a trade-off of surplus deficiency. Theoretical proofs and numerical examples reveal two crucial conclusions. If platooning utilities can be evaluated accurately and shared in real-time, the one-sided matching mechanism helps achieve satisfying levels of system surplus. When the uncertainties in utilities are inevitable, a non-cooperative bargaining mechanism attains an exceptional system surplus.

7.2 Implications

7.2.1 Methodologies and Contributions

This thesis first adopts a data-driven optimization method to estimate the energy-saving potentials by truck platooning in U.S. national freight network. The convincible positive result obtained rationalizes the investigation of truck platooning technology and builds a solid ground for further detailed analysis. The optimization method is also general and flexible enough to accommodate different assumptions on the decisive parameters, including but not limited to daily truck demands, time window flexibility, fuel consumption functions, platoonable roadway network, etc. Therefore, it can perform as a supportive tool to evaluate different policies and strategies for truck platooning management. Although this empirical study itself does not intend to offer the exact operational schedules, the model can be extended with the consideration of practical concerns, which can be solved in real-time by updating the current algorithm.

Addressing the behavioral instability issue is essentially solving a resource allocation problem. Only when it has been settled will the inter-organizational collaborations be possible that the expected benefits can be achieved. To build the game-theoretical models, truck owners or drivers are assumed to be rational agents who maximize their individual utility with platooning opportunities. The mechanisms proposed in this thesis differ in three main perspectives: whether the platoonable trucks are single-brand or multi-brand, whether a central controller to coordinate the formation and transfers exist, and whether the exact utility is publicly accessible. Their similarities, differences, and advantages can be viewed comparatively.

The one-sided matching mechanism follows the same logic of the optimal platoon formation in the centralized approach. The former performs one-to-one matching to reduce computational complexity and maintain stability at each step. The latter performs many-to-many matching to achieve global optimality all at once and redistribute the benefit based on the optimal surplus.

The auction mechanism and the bilateral trade model are essentially the same: a bid is used to decide the 'ownership' of the leading position. However, since single-brand trucks contribute equality to the system's energy-saving benefit, an auction with multiple agents can be conducted simultaneously. For multi-brand trucks, their positioning matters to both labor-saving and energy-saving. The auction is limited to two agents for computation consideration, thus degenerates into a bilateral trade model. By comparing the results, one can also see that an ex post economic efficient outcome can be achieved from the auction mechanism, while that never happens in the bilateral trade model.

Moreover, by comparing the results under complete and incomplete information settings within the bilateral trade model, one can see that the complete information sharing actually sabotages the collaboration between two parties. This is due to the reason that each rational agent aims to maximize its ex post individual utility under the complete information setting, thus never finding a best response to the other's strategy. Ambiguity leads to better system performance. This thesis thereby is of great importance for two reasons. Firstly, as to the best of the author's knowledge, it is the first study that systematically investigates behavioral stability in platooning. Secondly, it establishes new game-theoretical models and mechanisms that can be used in cooperative truck platooning and other applications in transportation systems that own similar economic properties.

7.2.2 Limitations

Several limitations should also be pointed out here. The energy-saving benefit quantified in this thesis might be overestimated since the interactions between truck platoons and other traffic have been neglected, and the platoon merging and diverging process have been excluded from the discussion. These physical processes are very likely to consume more energies, which might diminish the utility gain from platooning. Nevertheless, with the development of truck platooning implementations and the deepening of understandings on energy-saving mechanisms, the utility function can be further improved.

As this thesis focuses on the competition and controversy among different vehicles, it presumes that the driver and the owner of the same vehicle have an agreed utility from truck platooning. However, there is very likely to be a divergence in utilities from truck owners and truck drivers. A simple example is that labor-saving is evaluated differently by the two parties. Typically, if there is a human on board, there are always labor costs even if platooning is performed. However, truck drivers can utilize platooning to perform other work or relax, decreasing their working intensity, and gaining utility. Further discussion on this topic might involve professional knowledge exceeds the domain of transportation engineering and operational research, but that in the human factor, law, etc., which is beyond the scope of this thesis.

7.3 Future Research

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 external effect of truck platoons on the overall transportation system through interactions with normal traffic flows. Moreover, this section discusses the possibility of implementing benefit redistribution mechanisms proposed in this thesis and other game-theoretical approaches to settle the resource allocation conflict and promote collaborations in other forms of shared mobility.

7.3.1 Real-Time Planning and Operations

Today's trucking industry is operated in a highly fragmented manner. More than 90 percent of enterprises in this industry are owner-operators, and even the largest operators have only a small portion of the market share. Serving as an important part of the supply chain, its operations also depend on uncertain customer demand. Consequently, truck operations are highly disaggregated and stochastic over time and space. When truck platooning services are provided to multiple truck companies through one single platform, it can be seen that trucks arrive to and leave from the highway system dynamically according to their own schedules, but the information may come to the platform only at the last minute. This research endeavors to propose a real-time platoon planning model that addresses the stochastic dynamic information on truck demands. Specifically, this model will incorporate truck driver hours of service rules when determining their rest hours and the shift schedules of leading vehicles in platoons. An efficient online algorithm can be developed to satisfy practical needs.

7.3.2 Policy and Regulations

Introducing cooperative truck platooning to freeways is likely to influence the freeway traffic efficiency by its mutual interactions with regular traffic flows. Truck platoons may cause both positive and negative impacts: on the one hand, truck platoons operating at closer headways bring a greater freeway capacity; on the other hand, truck platoons usually occupy relatively long distances so that traffic from on-ramps and to off-ramps may be blocked if they happen to operate nearby; additionally, trucks travel generally slower than passenger vehicles that make themselves moving bottlenecks, especially when they go on upgrade hills. The other way around, regular traffic flows may also interrupt the assembling and dissembling processes of truck platoons. These interactions result in a complicated dynamic system, which makes the traffic efficiency analysis obscure. State-of-the-art approaches either follow the simulation studies or analytical models. However, the analytical models beyond freeway capacity analysis are somewhat lacking. This research aims to develop a generic analytical model that describes the relationship between traffic efficiency indicated by travel time and speed and the influencing factors, including traffic conditions, geometric conditions, and platoons' characteristics. Such a model is not subject to specific conditions. It can be employed to analyze different scenarios to provide insights on future policies and regulations for managing freeway mixed traffic.

7.3.3 Beyond Truck Platooning

As a public good, the transportation system is always facing the spatial and temporal imbalance of supply and demand. With the popularization of smart mobile devices in recent years, the emerging concept of shared mobility brings new promises of consolidating transportation supplies and integrating similar transportation demands, thereby creating the social surplus, minimizing the social cost, and mitigating the supply-demand imbalance in urban areas. Well-known shared mobility patterns include ride-sourcing, peer-to-peer carpooling, shared bike and scooters that focus on a single mode. A growing research interest is also drawn on Mobility-as-a-Service (MaaS), which intends to provide seamless multimodal transportation services, thus increasing the utilization of public transit and easing traffic congestion.

Either the consolidation of supplies or the integration of demands inevitably leads to collaborations among different stakeholders. As they may hold interest conflict, mechanism design could serve as a tool to settle the disputes and promote the partnership. Some problems principally share the same structure with the truck platooning benefit redistribution problem, where the mechanisms developed in this thesis could be used as a reference. For instance, the peer-to-peer carpooling allows travelers with overlapped travel time and routes to share a ride together. If all peers own car and can drive, the question then leads to who should drive and who should take the ride, and how the travel cost is distributed among them, so that the total cost can be minimized. This is similar to the situation in truck platooning when all trucks can either be the leader or the follower but the roles need to be allocated in a way that the system utility is maximized. Therefore, the methods developed in this thesis could also be able to solve the driver/rider allocation and cost allocation problems in peer-to-peer carpooling.

APPENDICES

APPENDIX A

Numerical Results

A few tables of data that might be wordy to be listed in the chapter of the main contents are presented here. Table A.1 and table A.2 come from the empirical study in chapter 3. Table A.3 and table A.4 store the solution quality ad computational efficiency of two decentralized approaches on the platoon formation, namely bargaining and matching, comparing to that from the centralized approach. The numerical examples are conducted on an Intel Core i7-6700HQ 2.6GHZ processor with 16.0 GB RAM.

Max platoon size	2	3	4	5	6	7
Scheduled: 30 mins	4.90%	6.52%	7.34%	7.82%	8.15%	8.38%
Scheduled: 15 mins	4.80%	6.40%	7.19%	7.67%	7.98%	8.20%
Scheduled: 10 mins	4.72%	6.29%	7.06%	7.52%	7.82%	8.04%
Ad-hoc	3.23%	4.16%	4.54%	4.73%	4.83%	4.89%

Table A.1: Total energy-saving percentage w.r.t. platoon length limit

Max platoon size	2	3	4	5	6	7
Scheduled:30 mins	504,616	378,621	366,800	315,745	303,210	294,874
Ad-hoc	764,525	594,249	543,814	522,180	511,368	505,497

Table A.2: Break-even miles of truck platooning technology

Solution Quality			Computational Time (s)		
Bargaining		Matching	Centralized	Bargaining	Matching
Mean	STD	Mean			
56.4%	13.0%	73.9%	5.70	0.17	0.47
45.6%	8.8%	83.1%	13.40	0.12	0.30
55.0%	8.0%	64.5%	22.30	0.12	0.29
48.8%	10.9%	80.6%	28.37	0.10	0.24
53.0%	7.0%	55.6%	39.08	0.11	0.28
52.5%	7.3%	82.4%	39.09	0.12	0.27
46.2%	5.4%	69.6%	85.94	0.13	0.23
43.6%	7.2%	63.6%	110.00	0.12	0.26
51.7%	7.0%	62.8%	121.35	0.12	0.51
50.1%	5.8%	60.8%	157.79	0.12	0.24
51.4%	6.8%	61.0%	154.00	0.13	0.24
57.9%	8.7%	79.0%	168.02	0.17	0.29
55.5%	6.8%	82.3%	185.40	0.16	0.30
56.5%	6.6%	58.6%	231.53	0.13	0.25
48.8%	5.6%	61.1%	295.47	0.13	0.52
55.4%	6.4%	70.5%	322.41	0.13	0.32
55.1%	7.6%	72.5%	288.22	0.12	0.30
51.2%	8.9%	51.8%	281.24	0.15	0.27
58.8%	7.1%	62.4%	314.81	0.14	0.29

Table A.3: Optimality of the solutions without labor-saving

Solution Quality			Computational Time (s)		
Bargaining		Matching	Centralized	Bargaining	Matching
Mean	STD	Mean			
54.9%	11.5%	59.0%	89.85	0.01	0.05
64.6%	8.0%	59.7%	76.26	0.01	0.06
54.9%	14.0%	68.0%	209.45	0.01	0.08
57.7%	13.7%	69.1%	345.94	0.01	0.09
70.0%	7.9%	71.1%	311.40	0.01	0.11
59.2%	7.7%	68.8%	687.93	0.01	0.11
68.2%	5.0%	71.1%	441.67	0.01	0.15
64.9%	9.3%	66.8%	1085.09	0.01	0.16
73.0%	4.0%	75.2%	423.76	0.01	0.20
73.7%	5.2%	75.0%	619.51	0.01	0.21
71.3%	4.6%	76.5%	905.23	0.01	0.24
72.2%	6.7%	80.3%	956.19	0.01	0.30
75.7%	4.1%	72.2%	1138.77	0.01	0.29
69.7%	8.2%	74.3%	1584.62	0.01	0.34
74.6%	7.0%	77.5%	423.84	0.01	0.37
73.6%	4.5%	81.9%	813.43	0.01	0.41
66.7%	8.2%	76.8%	1252.06	0.02	0.45
70.9%	5.1%	72.4%	2085.00	0.01	0.50
68.8%	5.8%	75.0%	2292.65	0.01	0.54

Table A.4: Optimality of the solutions with labor-saving

APPENDIX B

Declaration

Papers have been published based on the materials in this dissertation include:A

- Sun, X., & Yin, Y. (2019). Behaviorally stable vehicle platooning for energy savings. Transportation Research Part C: Emerging Technologies, 99, 37-52.

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