Optimization of platoon formation center location for truck platooning

Master's Thesis

OPTIMIZATION OF PLATOON FORMATION CENTER LOCATION FOR TRUCK PLATOONING

March 2022

Graduate School of Marine Science and Technology

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Content

Abstract

In Road Transportation, truck transportation is commonly being categorized into Less Than Truckload (LTL), Partial Truckload and Full Truckload (TL). The standard LTL transportation is carried out by means of consolidated freight at optimized depots of designation, in the form of single or multiple assignment. Nowadays, freight transportation industry is now facing a serious problem of scarce labor force and environmental concerns. One solution for that is truck platooning. Truck Platooning is a grouping of freight vehicles into connected vehicle convoys using electronic coupling as an application in automated driving technology with the aim of saving fuel, reducing travel costs, and improving infrastructure efficiency. Truck platooning has been researched since the 1940s and a reasonable amount of platooning trials are being carried out in developed countries. So far, the focus area has been on the vehicle connection and sensor technology. Platooning technology still needs a lot of infrastructure development and legal maturity for large-scale business operation and spontaneous platoon formation. There are still compatibility challenges existing for platoon creation among different truck makers. Hence, platoon planning is required to obtain the best results of platooning. Therefore, the objective of this study is to find the optimal locations of PFC for (de)formation truck platoons by using discrete mathematical optimization. PFC location optimizing problems can be considered as hub location problems (HLPs). Considering discrete optimization scheme, truck platooning can be modelled by using inter-PFC travel, which has travel cost efficiency, due to fuel saving and aerodynamic drag reduction. The objective is to minimize the total transportation cost for each origin-destination pair via two PFCs. Unlike commonly used discount factor calculation due to economies of scales in most facility location studies, we will consider the benefits solely thanks to the platooning process. Three different types of locational data, which represent different distribution patterns across the interest region, are used for optimization analysis. In addition, three different platooning scenarios—(i) all manually-driven platooning trucks, (ii) one manually-driven leading truck and the following automated trucks, and (iii) all fully automated trucks are considered for the optimization process. The aim is to find the general characteristics of truck platooning process with respect to the different distribution patterns and different platooning scenarios. All the trucks from a certain origin are assigned to single or multiple PFCs for (de)formation of platoons. Moreover, the number of platooning trucks is hypothetically varied from 3 to 10 for optimization to consider the impact of optimized location of PFC. In addition, the number of PFCs is also varied for analysis in all respective datasets. All these aforementioned methods are aimed to analyze the impact on the total transportation cost, from which we can conclude the general characteristics of the platooning optimization. Specifically for PFC planning, not only PFC location, but also the characteristics of the travel routes between PFC and non-PFC nodes, based on automation level change and different number of PFCs, are worth being deep dived for better recommendation of PFC planning purpose.

Acknowledgement

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1. Introduction

1.1. Truck Platooning in Freight Transport

Freight transport is considered as the essential part of this modern era. Road transport occupies a vital role of this transport system. There are a lot of advantages of road transport in comparison with the other modes of transport. The capital investment of road infrastructure is not as high as in other transport modes. Road transport is best applicable for serving far-flung areas which cannot be accessible via other transport modes. It has high flexibility in trip scheduling, allowing a more frequent freight transport service. Road transport can be served as the initial and final transport phase in supply chain process, thus serving a bridge to connect with other transportation modes.

When a great amount of freight are transported on road transport, truck transportation is used. Truck transportation is commonly being categorized into Less Than Truckload (LTL), Partial Truckload and Full Truckload (TL). The standard procedure of LTL transportation is carried out by means of consolidated freight at optimized depots of designation and the multiple destinations are served by respective depots (Tolga et al. 2017). Depot designation can also be considered as single assignment or multiple assignment. Single assignment is that all the origins and destinations must be connected to not more than a single depot while multiple assignment allows multiple depot connections to origins and destinations. Such consolidation-based transport system is in the form of hub-and-spoke network (Tolga et al. 2017).

Nowadays, freight transportation industry is now facing a serious problem of scarce labor force while, on the other hand, the transportation demand is growing very rapidly (Watanabe et al. 2021). Moreover, air pollution and global warming have become top concerns in freight transportation. To tackle such challenges, truck platooning technology has been adopted. A truck platoon is a convoy of electronically connected vehicles, and this can be achieved by using Cooperative Adaptive Cruise Control (CACC), which has a huge potential in reducing fuel emission and to relax rest hour restrictions. In fact, truck platooning is not a novel technology, and it has been reasonably researched since the 1940s (Rune et al. 2019). Nowadays, there are a reasonable amount of truck platooning trials being carried out in United States, European countries, and Japan (Watanabe et al 2021). So far, the focus area has been on the vehicle connection and sensor technology. It can be noted that platooning technology is reasonably operational, which is almost ready to be materialized in the freight transport.

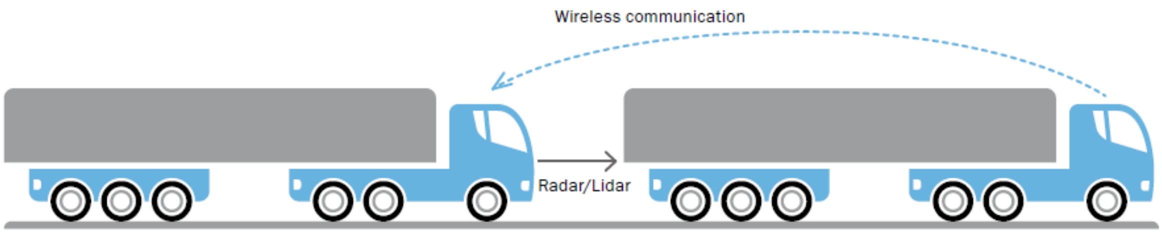

Fig. 1.1 Truck Platooning (source: Vision Truck Platooning 2025, TNO and Rijkswaterstaat, 2016 and Janssen et al"Truck Platooning", TNO, 2015)

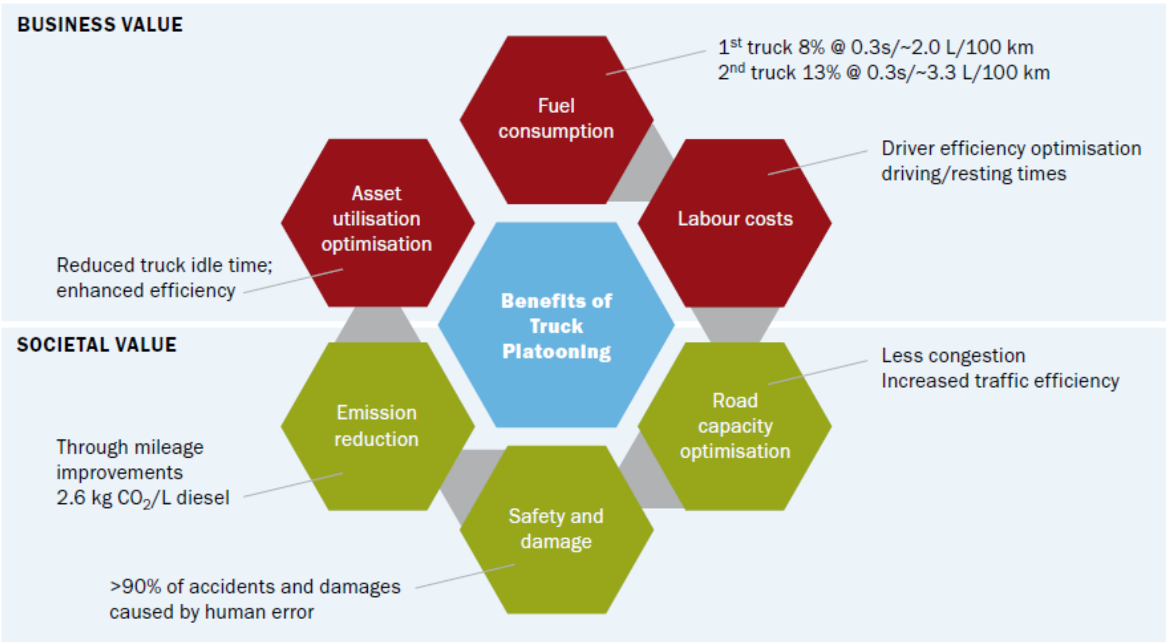

Fig. 1.2 Truck Platooning Benefits (source: Janssen et al"Truck Platooning", TNO, 2015)

1.2. Characteristics of Truck Platooning

Truck platooning scenario can be different depending upon trip information management. Trip information of each truck generally includes at least an origin node, a destination node, an earliest departure time and a latest arrival time. A platoon plan generally requires (1) which trucks will form a platoon, (2) where and when the platoons will be created, (3) which routes they will travel, and (4) what is the order of the trucks in that platoon. Nevertheless, based on truck platooning management and trip information, three platoon formation scenarios have been mainly considered as follows (Janssen et al. 2015).

(1) Scheduled platooning: Trip information is obtained before travel and platoon management is made in advance. Therefore, this is also known as off-line or static planning.
(2) Opportunistic platooning: Platoons are formed spontaneously on the road between the trucks travelling at a proximity. This type of platoon planning does not require much trip information early or before departure. Since this platooning system does not need prior platoon planning, it is called spontaneous or on-the-fly platooning.
(3) Orchestrated Platooning: It is a platooning managed by Platooning Service Providers (PSPs). Platoon Formation Center (PFC) for (de)formation of platoons plays a vital role in this platooning technology.

It should be noted that platooning technology is still at its early stage, and it still needs a lot of infrastructure development and legal maturity for large-scale business operation and spontaneous platoon formation. There are still compatibility challenges existing for platoon creation among different truck makers. In addition, a simulation study by Liang et al. 2014 showed that there can be tremendous amount of economic and environmental benefits due to precise planning of platoons before their departure. Therefore, it can be concluded that some of platooning management is required to obtain the best results of platooning. PFC run by PSP has the following functional benefits as below.

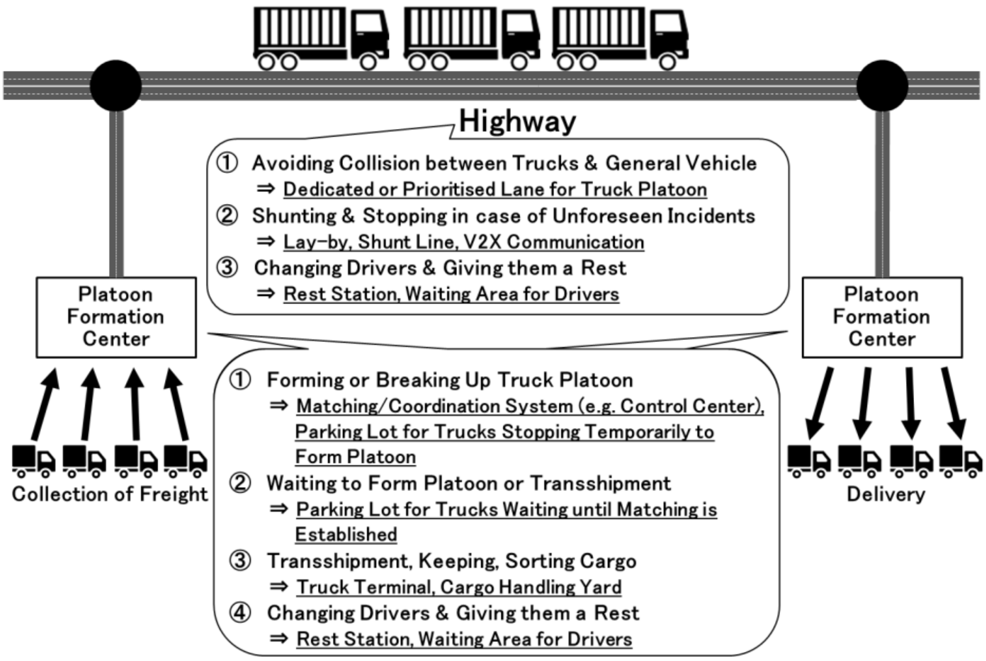

Fig 1.3 Infrastructure Development for Truck Platooning (source: Watanabe, D., Kenmochi, T. and Sasa, K.: An Analytical Approach for Facility Location for Truck Platooning-A Case Study of Unmanned Following Truck Platooning System in Japan-, Logistics, 5(2), 27, https://doi.org/10.3390/logistics5020027, 2021.)

1.3. Objectives

Although the main focus of the truck platooning research has been on vehicle communication and sensor technology (Rune et al. 2019), the objective of this study is to find the optimal locations of PFC for (de)formation truck platoons by using discrete mathematical optimization. Although this study is a branch of hub locational analysis, the discount factor calculation is different from other classical hub locational analysis. Most of the hub locational problems consider discount factor based on economies of scales due to a large, consolidated freight at designated hubs. However, this study mainly considers discount factor which arises during inter-PFC travel by platooning, and therefore, discount factor variation is highly affected by number of trucks in each platoon, and the driving system of trucks in that platoon. In addition to the discount factor variation, variations in the number of PFCs and different types of assignment patterns to PFCs will also be considered to analyze their impacts on total travel cost.

Hub location problems are NP-hard (Campbell et al. 2012). In addition, hub locational optimization problems are computationally difficult to solve and can give optimal solutions only for a small amount of nodes (O'Kelly et al. 1998). Therefore, in our study, we only consider the data size of up to 45 nodes as maximum for three different types of datasets of different distribution patterns across the interest region.

1.4. Thesis Structure

In this study, chapter 1 highlights how important the road transportation is for the whole logistics industry and what kind of benefits truck platooning can bring to the future road freight logistics. In addition, the current available technology and the challenges in truck platooning are also discussed.

Chapter 2 focuses on the history and future trend of the hub location research, especially related to the different optimization modelling. In addition, the fact that how PFC location optimization can be integrated into hub location modelling problems is also discussed, along with some particular assumptions for platooning optimization.

Chapter 3 explains the computational process applied in this study. This chapter mainly covers the areas related to optimization process together with the modelling assumptions, the computational environment such as optimization software and the computational parameters.

In chapter 4, findings from the optimization process are mainly discussed. The analysis is made scenario by scenario based on different parameters, from which the general characteristics are concluded with regard to the respective dataset of different distribution patterns.

Chapter 5 provides a summarized conclusion about the finding from this study. Moreover, future improvements which can be made in the future research are also discussed.

2. Literature Review

2.1. Hub Locational Research

One of the important factors in hub location problems is that how the nodes will be represented (Daskin et al. 2013). In planar distribution, demands can arise anywhere on a plane, and they are described using a spatially distributed probability distribution. In this case, facilities can be located at anywhere on the plane. This type of locational concept contradicts with network location models, where the demands and potential hubs are only considered on a network or graph composed of origin, destination, and potential hub nodes. It is normally assumed that demands only occur on the origin or destination nodes whereas there are some considerations that demands can occur anywhere on the links of the network (Daskin et al. 2013). Therefore, discrete location models allow for the use of arbitrary distances between nodes and as a result, a broader range of locational problems can be modelled. Discrete locational problems are normally formulated as mixed integer programming problems. The focus of this literature will be discrete location models.

Optimized PFC location problem can be considered as hub location problem because there have been a lot of research related to hub location for logistics operation (Laporte et al. 2015). Hub location problem involves locating hub facilities and assigning demand nodes to hubs for freight service between origin-destination (Kara et al. 2009). In a hub-network structure, there are two basic types of assignment pattern— single assignment and multiple assignment. All origin and destination nodes are connected to hubs via either one of these two systems. Single assignment is that all demand nodes are connected to only a single hub while multiple assignment is that all demand nodes are connected to more than one hub. Basically, while single assignment can give the simple assignment pattern from the freight management perspective, multiple assignment can give more freedom of choice for the allocated hubs, thereby reducing system-wise total transportation cost more.

Hub locational analysis research was started by O'Kelly (1986). O'Kelly (1987) presented first quadratic hub locational model. His formulation is well-known as single allocation *p*-hub median problem, because each demand node is allocated to only a single hub, there are *p* number of hubs to be assigned and the main objective is to minimize the total transportation cost between each origin-destination pair. Later, to make the optimization become relatively easy, several linearization of that quadratic model were introduced. In addition to that, researchers also considered multiple allocation, which allows the demand nodes to be assigned to more than one hub.

Hub location problem generally includes the location of hub facilities through which the flow (passenger or freight) must be routed between origin-destination pairs (Campbell et al. 2012). Freight flow from origin-destination can directly travel without any stop or can pass through one or two hubs. Figure 2.1 shows the possible travel between origin-destination pairs. Path 1 shows the direct travel between origin and destination without any stop. Path 2 includes one-hub stop to where origin and destination nodes are allocated. Path 3 includes inter-hub travel through which the freight from origin to destination flows.

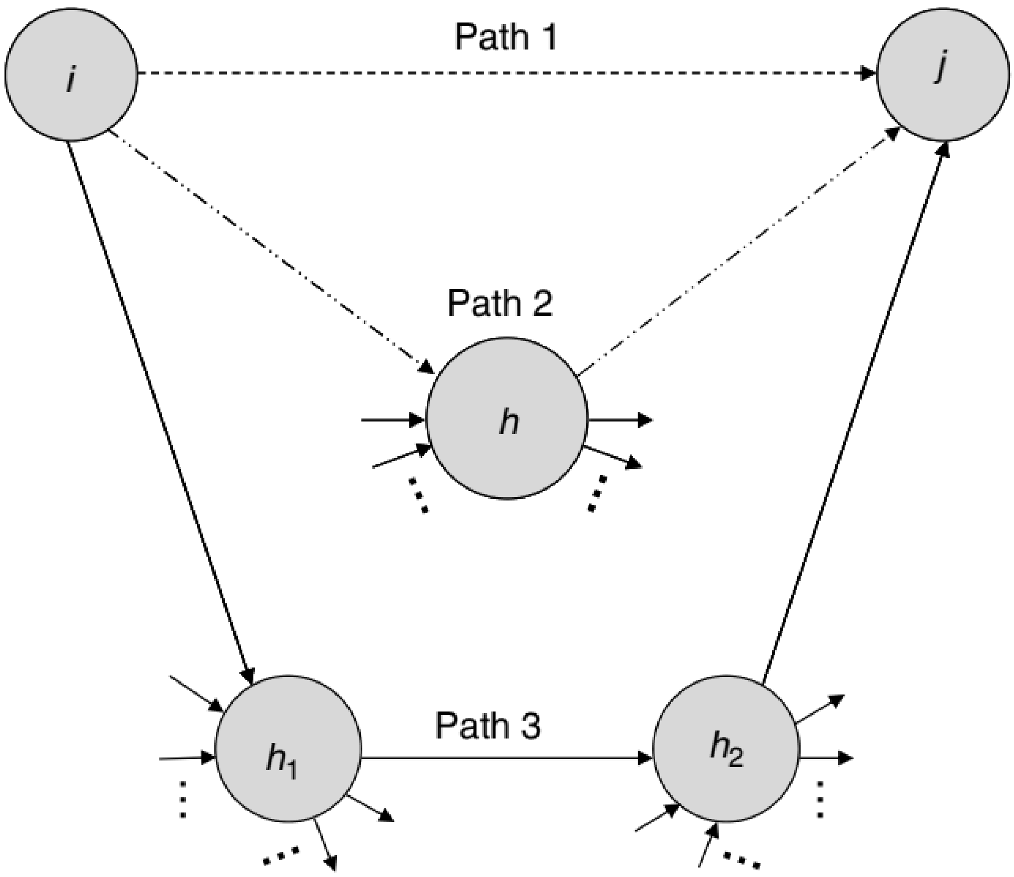

Fig 2.1 Possible paths between origin i and destination j (source: Campbell et al. 2012)

2.2. Different Features of Hub Locational Problems

Even though there are a different number of hub locational problems based on their different scenarios, the following can be considered as the common characteristics of the hub location research.

(a) There is a freight flow between each origin-destination pair
(b) Freight is to be flowed via hub facilities.
(c) Hubs are facilities to be located.
(d) There is an incentive (in the form of economic benefit) or requirement for the freight to flow between hubs.
(e) There is an objective function which depends on the hub location and flow routing.

Although more general problems include the features (a)–(e), fundamental hub locational problems defined by Campbell (1994b) includes two more following features.

(f) Freight flow between each origin-destination pair must travel at most two hubs.
(g) There is no direct flow between each origin-destination pair.

These problems also assume single assignment or multiple assignment. In reality, both assignments can be utilized depending upon the industry. For example, in the case of passenger airline travel, non-hub cities can be assigned to multiple hub airports, whereas for logistics industry, LTL network will have its freight consolidated at a single hub for ease of managerial perspective.

More commonly, hub location problems consider a complete graph with $G=(V,E)$ with a common node set of $V= \{1,2,...,N\}$, which belongs to all origin, destination, and hub nodes. It is also possible to have a particular set of hub nodes separate from origin/destination nodes. The distance between each origin-destination pair is denoted as d_{ij} and the amount of freight flow as W_{ij}. From now on, we assume d_{ij} as Euclidean distance and thus satisfies the triangle inequality.

The network of the graph is considered based on tree-network and more general (fully connected) graph. A tree is a network which has at most one path from any node to any other node (Daskin et al. 2013). Figure 2.2 illustrates possible different types of trees and graphs.

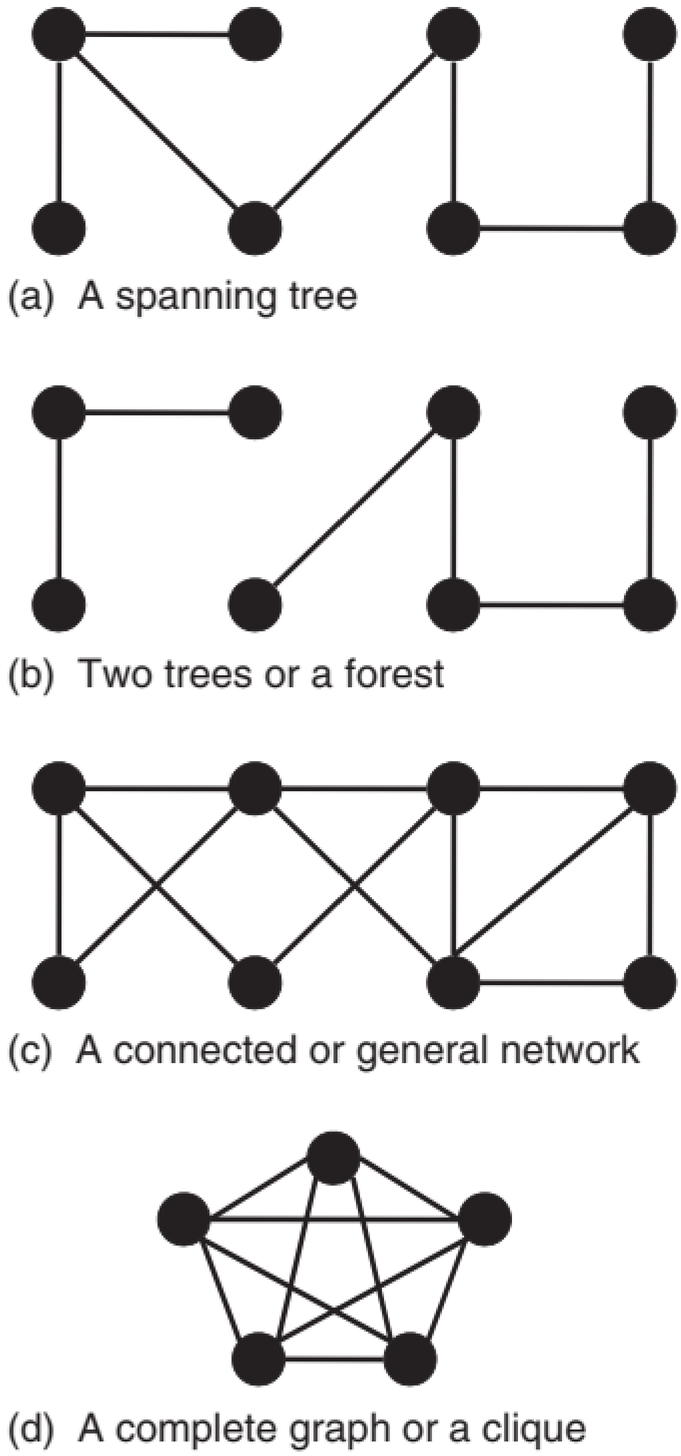

Fig 2.2 Example trees and graphs (source: Daskin et al. 2013)

There are various types of hub location problems and research depending upon their objectives. Hakimi el al. (1964) first published a paper on hub location and subsequent paper was not published until the next two decades. After that, Toh et al. (1985) published a paper on hub location for airlines and airports. Therefore, we can assume that the hub location problems has been first discussed since 1980s (Marzie et al. 2009).

The hub location models proposed by O'Kelly (1987) played a major role in progressing hub location research. His first two optimization models– single hub location and *p*-hub location problems (O'Kelly et al. 1987) and *p*-hub median location problem with fixed costs (O'Kelly et al. 1992) are very popular in hub location research. After that, Campbell (1994) also contributed to the completion of hub location model. He proposed famous hub location problems such as *p*-hub median, uncapacitated hub location, *p*-hub center, and hub covering.

There were also development of several heuristics and optimal solution algorithms. Some major early research include the continuous location hub model of Aykin and Brown (1992), the tabu search heuristics of Skorin-Kapov and Skorin-Kapov (1994) for single allocation, and Lagrangean relaxation of models with hub capacities by Aykin (1994).

The problem with the hub location model is that the number of assignment variables can be extremely large. Therefore, researchers approach tighter formulations, to solve large problems such as preprocessing methods and new tighter constraints (e.g., Skorin-Kapov, Skorin-Kapov, O'Kelly 1996; Boland et al. 2004) and application of polyhedral results (e.g., Hamacher et al. 2004; Labbe, Yaman, and Gourdin 2005; Marin, Canovas and Landete 2006) to provide much tighter LP bounds.

2.3. Truck Platooning and Hub Locational Research

Hub Location is a fertile area for multi-disciplinary research such as operation research, transportation, geography, network design, telecommunications, regional science, economics etc. (Campbell et al. 2012). Therefore, hub location research can also be applied to logistics industry in order to solve various economical and sociological problems. The main focus of truck platooning research has been on communication and sensor technology and few research has been carried out for truck platoon planning. Truck platoon planning plays a very important role because the planning stage will follow every technological development.

There is a need to locate the PFC for the formation of truck platooning to run unmanned operation in platoon (Watanabe et al. 2021). Larsen et al. (2019) presents a model for optimizing truck platoons formed at a PFC at a fixed location using a dynamic programming based local search heuristics. PFC optimizing problem can be considered as hub location problems (HLPs) and there are a lot of related studies for hub location optimization for logistics operation (Laporte et al. 2015).

Considering discrete optimization scheme, truck platooning operation can be modelled by using inter-hub travel (inter-PFC in the case of truck platooning). There will be cost efficiency benefit for inter-PFC travel, due to fuel saving and reduction in aerodynamic drag between trucks. There have been a lot of research about discount factor calculation in hub location research. Almost all researchers consider discount factor calculation on the grounds of economies of scale, i.e. the more freight we can transport or consolidate along the arc or at a certain hub, the more reduction in total transport cost we can enjoy. When we model truck platooning scenario, it will be reasonable to consider the discount factor calculation due to other factors rather than freight consolidation. The factors that can reduce the cost in truck platooning can be the number of trucks in a platoon and the driving system of the truck platooning and so on. So far, there has been almost no research which discusses about truck platooning discount factor except a recent study by Watanabe et al. (2021) about unmanned platooning system in Japan. He considered discount factor calculation based on the number of trucks in a platoon and the vehicle driving system such as manual or automated. Apart from that, there has been very few research about PFC optimization for truck platooning.

3. Methodology

3.1. Consideration of Platooning Scenario

There are certain different types of platoon planning process depending upon their characteristics. Based on them, there can be different consideration of platooning objectives and constraints. In our study, we consider a platooning service provider (PSP) which provides platooning management service based on trip information which is obtained from different trucks. Based on this platooning plan, trucks can form platoons enroute or at a designated area.

Basically, trucks can be managed to wait for each other at a designated location or PFC to form truck platooning. This can be done by sharing origin-destination data, arrival, and departure time data among different trucks. This type of management can mainly aim to maximize the travel distance by truck platooning in order to enjoy the cost saving and emission reduction benefit as much as possible while at the same time, considering within the arrival-departure time window.

There will also be two types of assignment consideration depending upon their trade freight capacity or destination nodes. When PSP obtains information from the trucks incoming to PFC early enough for managerial aspect, it can be more time-efficient to arrange a truck platoon without much delay, which in turn can avoid any possible congestion at a certain PFC. By this way, one can rule out capacity restriction at PFCs, which, otherwise, can have a huge impact on the assignment pattern of the whole transport scenario. When the capacity of a PFC cannot meet all of their demands assigned to it, it will be reasonable to assign partial of demands to another PFC, leading to multiple assignment.

In addition to it, when we pay more attention to individual trucks information, especially their individual freight flow and their individual destination nodes, rather than just the collective information about their total freight which leaves the same origin node, multiple allocation can possibly bring down the total travel cost more than single assignment. However, single allocation can provide much easier trip management procedures than multiple assignment from a managerial perspective.

Trucks can also form platoons enroute simultaneously by sharing their instant telematics data and other related data to form platoons without prior planning. Obviously, this platoon formation system needs speed and distance adjustment until the participant trucks match their speed at a certain equal distance between them. Without a beforehand planning, it makes sense to consider that this driving system needs a driver in each participant truck, who has to perform instant formation and deformation of platoons at any time. There can be multiple (de)formations of platoons en-route without the need of PFCs. It is true that drivers in the following trucks can take a rest when only the leading driver takes the driving actions such as steering, braking and so on. However, this cannot save more labor costs than fully-automated driving system, where the following drivers are not needed. In fact, this simultaneous platoon formation system is known as "On-the-fly Platooning", which needs complicated optimization modelling and advanced information sharing system. Even though it does not need a designated PFC, it still needs a specific infrastructure for safe, efficient, and successful truck platooning.

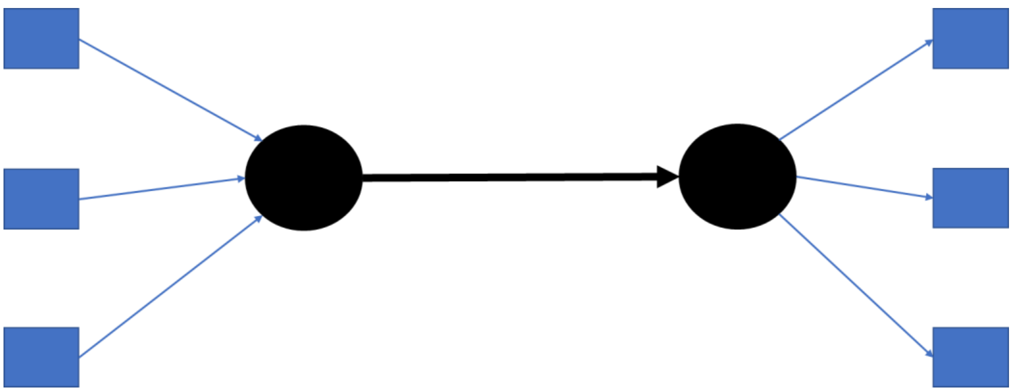

Fig 3.1 Truck Platooning with inter-PFC travel

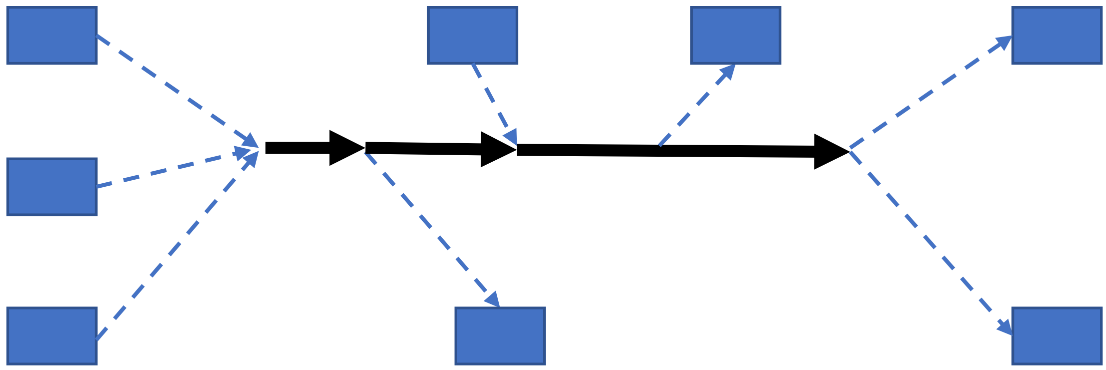

Fig 3.2 Truck Platooning with spontaneous multiple platoon formation en-route

In this analysis, we consider single and multiple PFC assignment with inter-PFC travel as in Fig 3.1. It is assumed that the trucks from each origin must form their platoons at a PFC, and must travel by platooning to another PFC, where the trucks will deform their platoons and go to their respective destinations.

3.2. Consideration for Optimization

For optimization process, there are several distinct features which are to be added for consideration of modelling process.

(a) For optimization of truck platooning, the network structure can be either on a network or a plane. The former case is called discrete hub location problem and the latter is continuous hub location problem. In this study, we will consider discrete PFC location and its problem will include a given set of nodes, which will perform as origin-destination pairs. There will also be a finite number of potential PFC location nodes. For the case of continuous hub location analysis, PFCs can be located at anywhere on a plane and not from a specific set of location, which is different from our study.

(b) The freight flow from each origin to destination node is associated with a non-negative value. PFC node set can be considered separately or from the same set as the other nodes such as origin and destination nodes. If we consider all nodes from the same set, we are looking for which origin and destination nodes will be activated as PFC nodes, which is the consideration used in our study.

(c) For optimization model of truck platooning scenario, we will set a constraint which will eliminate the direct travel of trucks from each origin to each respective destination node. In other words, the trucks will go through two PFCs in order to enjoy the discounted costs for inter-PFC travel. There can also be different considerations for connections between the nodes based on underlying network structure, but in our study, we will consider a complete graph, where PFCs are interconnected with each other.

(d) Every origin-destination link has a unit shipping cost, which can be described in terms of distance, time, or actual travel cost. In our analysis, it will be in terms of distance travelled between each two nodes, which will increase as the travelled distance becomes greater. There will be a cost-saving benefit for using inter-PFC link, which basically implies that the unit travel cost between two PFCs will always be less than that between every other node and a PFC. This benefit can be achieved by using a discount factor.

(e) Unlike other hub location problems, the discount factor which benefits from the truck platooning depends upon its way of driving and the number of platooning trucks. There is a potential to reduce the travel cost when we have a large number of trucks in a platoon because of reduction of aerodynamic drags among the trucks. However, there can be a limitation defined by regulations in each country for the allowed number of trucks in each platoon because of the infrastructural constraint. Likewise, there must also be consideration for the driving system of the whole platooning trip. We can have three scenarios for each platooning travel such as fully manual, semi-automated and fully automated driving. Fully manual driving needs all the trucks to have drivers for platoon formation process. Semi-automated driving is where we need a driver only in the leading truck when we perform inter-PFC travel. Fully-automated driving is, as its name suggests, that there will be no human intervention at all for inter-PFC travel. Quite clearly, we can save labor costs when we can adopt automated driving rather than manual driving. In this study, we will consider all these driving environments and conditions which will have an impact on the discount factor.

(f) There will be two types of assignment— single assignment and multiple assignment and both of these two scenarios will be covered in our analysis.

(g) Hubs are facilities which normally have the capacity limits that can handle a certain amount of freight. The origin and destination nodes assigned to the hubs need to consider the hub capacity limits. This is the common consideration in the hub location problems whether the problems will be capacitated or not. Obviously, we do not need to consider hub capacity when its handling capability is far greater than its incoming freight flow, leading to uncapacitated problems. In this study about truck platooning operation, it is reasonable to consider that PFCs will not have any difficulty or congestion for truck platoon planning because the way how PFCs can handle truck platoons can take less time than the freight consolidation and processing in normal hubs or facility centers in other hub location problems.

(h) Objective function is the most important part of the whole optimization process because this is where our main goal is to be decided. Based on the objective of the optimization function, we need to consider our modelling process about what kind of constraints we will add and what is the data we will use for optimization. Even for the same dataset, one objective cannot be reasonable for another different objective. For example, when we consider cost reduction of the whole transport system, which is known as mini-sum problem, this can cause some nodes to detour very long distance or take very long time to bring down the total cost, thus impacting the arrival time. When we need to give very much attention to the departure-arrival time window, this is more suited with the objective of minimizing the maximum cost, which, however, can slightly increase the total system-wise cost. There are also considerations that adopt multi-objective functions to find the optimal solution which can satisfy multiple objectives at best. In this study, we will consider mini-sum problem, where we will bring down the total transportation cost of the trucks by considering platooning travel.

(i) One can add more constraints to better grasp the situation as realistic as possible. However, it should always be noted that there is no evidence that too many constraints will always give the better optimal solution. In most cases, they can complicate the model, make the constricts conflict with each other and even give less reasonable solution. Therefore, in addition to mathematical modelling knowledge, a researcher also needs to have knowledge in the background problem so that he can always check the feasibility of the optimization result by using his common sense without relying excessively on the solution given by optimization process. Likewise, in the optimization for truck platooning, one can add more constraints such as PFC location cost, arc link cost and so on. However, in this study, we will only consider the shipment cost from each origin and destination, and the discounted cost between PFCs.

(j) The number of PFCs can be determined endogenously or exogenously. Being exogenous means that the user needs to input his desired number of PFCs into the optimization process. However, if there will be consideration of PFC location cost, instead of inputting the number of PFCs exogenously, one may expect the minimum number of PFCs as the output from optimization in order to minimize the PFC location cost. In this case, the number of PFCs will be an optimal solution output from optimization process, which is known as endogenous method. However, in this study, we will decide our desired number of PFCs exogenously and analyze the impact on the total cost due to the change in number of PFCs.

3.3. Optimization Model

The hub location model has started gaining its popularity since O'Kelly (1987) adopted a single allocation P-hub location problem. Almost all later hub location models and heuristics algorithms are developed based on this model. In this model, it is necessary to locate exact number of hubs exogenously. This is a discrete mathematical model problem where the number of participant nodes is finite. As the model's name suggests, each non-hub node is allocated to exactly one hub node out of p nodes. This model assumption is also based on complete graph in which there is a complete connection between each and every hub node. There is also a constraint that travelling between two non-hub nodes needs to go through two hubs at most, i.e. there is no direct connection between non-hub nodes. The fixed cost of locating hubs is not considered. There is no consideration of capacity limit of the hubs as well. All decision variables of the model are binary variables.

The hub location problem is defined on a graph $G=(V,E)$, where the node set $V=\{1,2,\ldots n\}$ includes all origin, destination and possible hub nodes. If V_d is termed as destination node set and V_h is hub node set, this optimization model considers $V_h = V_d = V$, implying that hubs can be located at any node that belongs to the common set V.

The set of connection is defined as E, between nodes $i \in V$ and $j \in V\setminus\{i\}$ and each connection has a positive unit shipping cost termed as c_{ij}. Here, the direction of the shipping cost will not be considered and therefore, the same arc is used for the shipment of goods, leading to $c_{ij}= c_{ji}$ for all $i, j \in V, i \neq j$. If the direction matters, i.e. if the unit shipping costs c_{ij} and c_{ji} are not same for a given link $\{i,j\}$ in the set E, or when the freight flow depends strictly on the explicit ordering of nodes, then the problem needs to be defined on a direct graph $G=(V,A)$, where A is the set of arcs. A total freight volume of w_{ij} units is transported from origin $i \in V_d$ to destination $j \in V_d, i \neq j$. There will be a discount factor effect α applied to the inter-hub shipment costs, where $0 \leq \alpha \leq 1$.

O'Kelly (1987) considers the objective as mini-sum problem, which will bring down the overall shipping cost of the whole transport system. Considering aforementioned points, it is formulated as follows.

Minimize

$$\sum_{i,j \in V_d; i \neq j} w_{ij} (\sum_{k \in V_h} c_{ik} X_{ik} + \sum_{m \in V_h} c_{jm} X_{jm}) + \sum_{i,j \in V_d; i \neq j} w_{ij} (\sum_{k,m \in V_h} \alpha c_{km} X_{ik} X_{jm}) \quad (3.1)$$

subject to

$$\sum_{k \in V_h} Y_k = P \quad (3.2)$$

$$\sum_{k \in V_h} X_{ik} = 1 \ \forall i \quad (3.3)$$

$$X_{ik} \leq Y_k \ \forall i \in V_d, k \in V_h \quad (3.4)$$

$$Y_k = [0,1] \ \forall k \quad (3.5)$$

$$X_{ik} = [0,1] \ \forall i,k \quad (3.6)$$

The objective function is defined by the equation 3.1, which includes two parts. The first part accounts for the cost of shipment from the origin $i \in V_d$ to the first hub $k \in V_h$, plus the cost of shipment from the second hub $m \in V_h$ to the destination $j \in V_d$. That first part is added by the second part, which includes the shipment cost between two hubs $k \in V_h$ and $m \in V_h$. It is also possible that $k=m$, meaning that there can be no inter-hub travel if it cannot satisfy the cost-saving objective.

Constraint (3.2) states that the model needs to define the desired number of hubs which is *P*. Since the model is single-assignment model, constraint (3.3) ensures that each node *i* to be allocated to exactly one hub. Constraint (3.4) allows the assignment of origin node *i* to hub *k* only if a hub has been located at *k*. Finally, constraints (3.5) and (3.6) determine the standard integrity constraints for assignment variables.

In the above optimization model, it is easily noticeable that the objective function is quadratic due to the product of two decision variables, $X_{ik} X_{jm}$. This product value will be equal to one if and only if there is a freight flow in the form of the path *i-k-m-j*, and the inter-hub shipment cost αc_{km} is included in the overall calculation.

Moreover, the formulation assumption that allows two-hub travel at most can be serious restriction for some transportation systems which need to travel more than two hubs for their optimal solutions. However, if the travel costs have the property which can satisfy the triangle inequality $c_{ij} + c_{jk} \geq c_{ik}$, for any set of three nodes *(i,j,k)* through which the transportation flows, one can always find a path which has the optimal cost by only passing two hubs at most. This kind of assumption can be illustrated as follows.

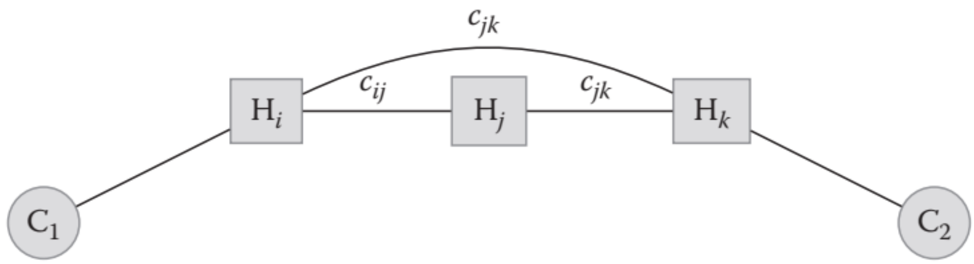

Fig 3.3 Triangle inequality assumption

The problem with the above formulation is that there is a quadratic term $X_{ik}\, X_{jm}$, which makes the optimization relatively difficult to be solved. Since O'Kelly (1987) first introduced such discrete hub location problem, there were rapid advances in mathematical models which attempted to locate the exact solutions in several hub location networks. A large number of research was also carried out and an example of this was that Campbell (1994) reviews over 70 papers on hub network optimization. O'Kelly and Miller (1994) also identified several prototype models for hub network design analysis. The two most well-known versions of design networks are based on completely connected hubs, with two types of spoke-hub connectivity— single allocation and multiple allocation. In both assignments, the hubs are assumed to be completely connected and all flow must be through hubs. A linearization developed by (Skorin-Kapov et al., 1995) gives an effective method of finding solutions especially in case of small hub and spoke network models.

3.3.1 Multiple Allocation

As the name suggests, all the origin and destination nodes are assigned to more than one PFC node. There can be multiple network assumptions based on how PFC nodes are connected with each other, as discussed in Fig 2.2. In our analysis, we will consider the complete connection among all PFC nodes as shown in the following figure.

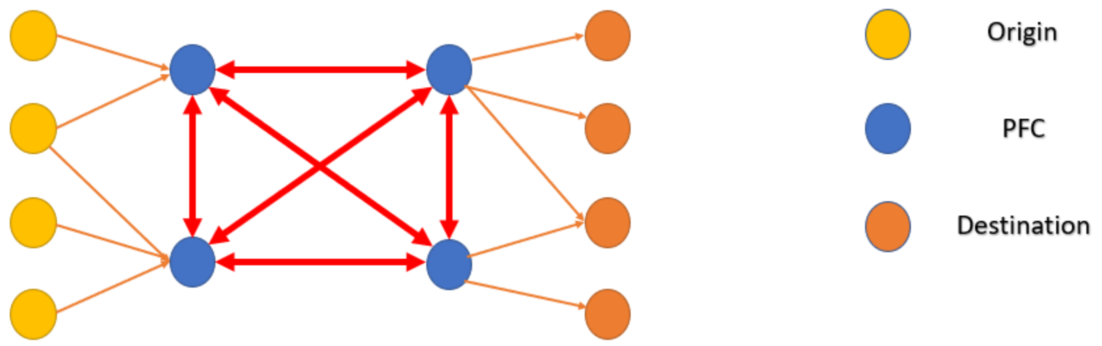

Fig 3.4 Complete Connection among PFC nodes (Multiple Assignment)

In Fig 3.4, all the yellow nodes serve as origin, blue as PFC and orange as destination. The thick red arrows represent the complete connection among PFC nodes without any detour.

In the multiple assignment hub location (Campbell, 1994), each origin-destination pair is allowed to utilize the hub that will give the lowest travel cost, independent of how this flow can produce a large amount of interaction. As a result, the objective function can minimize the total travel cost for the system. A compact formulation of that model, known as HUBLOC (Skorin-Kapov et al. 1997) is as follows, which is used in our analysis.

Minimize $\sum_{i,j} \sum_{k,m} t_{ij} c_{ij}^{km} z_{ij}^{km}$, where $c_{ij}^{km} = c_{ik} + \alpha c_{km} + c_{mj}$ *(3.7)*

Subject to

$\sum_k X_k = P$ *(3.8)*

$\sum_{k,m} z_{ij}^{km} = 1 \;\; \forall i, j$ *(3.9)*

$\sum_m z_{ij}^{km} - X_k \leq 0 \;\; \forall i, j, k$ *(3.10)*

$\sum_m z_{ij}^{km} - X_m \leq 0 \;\; \forall i, j, m$ *(3.11)*

$X_k = [0,1] \; \forall k$ *(3.12)*

Let's consider the transportation networks modelled by complete graphs *G=(V,E)*, where the node set $V = \{1, 2, \ldots, n\}$ represents the origin, destination and possible hub locations. Let t_{ij} be the number of trucks (the total flow in the classical model) travelling from node *i* to node *j*. The cost c_{ij}^{km} is a total cost of c_{ik}(from origin i to PFC k), αc_{km} (discounted inter-PFC cost) and c_{mj}(from PFC m to destination j). Constraint (3.8) ensures that the number of PFCs *(P)* is determined exogenously. Constraint (3.9) ensures that all flow be routed via exactly one path. Constraints (3.10) and (3.11) prevent flow from being routed via a non-PFC node. All flow must travel through at least one PFC. Constraint (3.12) ensures the integrity of the decision variable.

3.3.2 Single Allocation

Similar to multiple allocation, the complete connection among the PFC nodes is assumed as in the following figure.

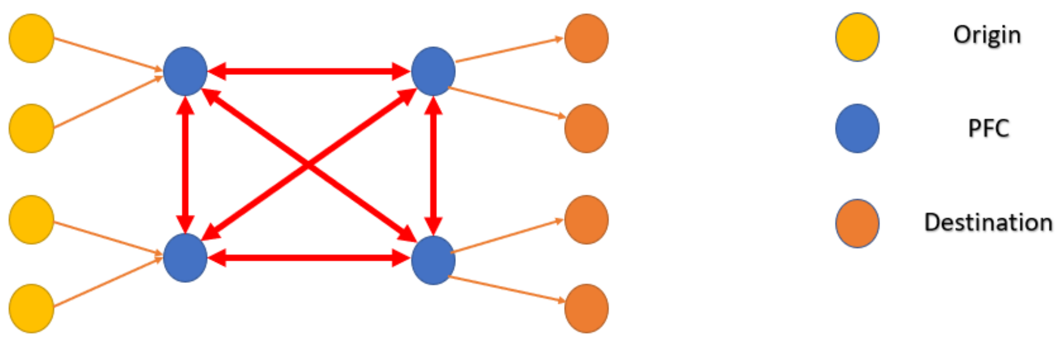

Fig 3.5 Complete Connection among PFC nodes (Single Assignment)

It can be noted that in Fig 3.5, all origin and destination nodes are connected to each respective PFC node via a single link, unlike in Fig 3.4.

From the modelling perspective. the following model by Skorin-Kapov (1996) is used for single assignment in our study. This model is a LP relaxation of Campbell (1996b).

Minimize $\sum_{i,j}\sum_{k,m} t_{ij} c_{ij}^{km} z_{ij}^{km}$, where $c_{ij}^{km} = c_{ik} + \alpha c_{km} + c_{mj}$ *(3.13)*

Subject to

$\sum_k X_{kk} = P$ *(3.14)*

$\sum_k X_{ik} = 1 \ \forall i$ *(3.15)*

$X_{ik} \leq X_{kk} \ \forall i, j$ *(3.16)*

$\sum_m z_{ij}^{km} = X_{ik} \ \ \forall i, j, k$ *(3.17)*

$\sum_k z_{ij}^{km} = X_{jm} \ \ \forall i, j, m$ *(3.18)*

$z_{ij}^{km} \geq 0 \ \forall i,k$ *(3.19)*

$X_{ik} = [0,1] \ \forall i,k$ *(3.20)*

Constraint (3.14) ensures that the number of PFCs, which is *P*, is determined exogenously. Constraint (3.15) forces single assignment. Constraint (3.16) ensures that no node is assigned to a location unless it is a PFC. Constraints (3.17) and (3.18) determine that there must be only one flow through the link *i-k-m-j*. Constraints (3.19) and (3.20) determine the decision variables. The objective is to minimize the total transportation cost for the trucks travelling through the *i-k-m-j* link.

The following figures show some examples of the single assignment pattern with the blue lines as the single assignment connections between origin/destination nodes (green nodes) and red lines as the interconnection between PFCs (yellow nodes).

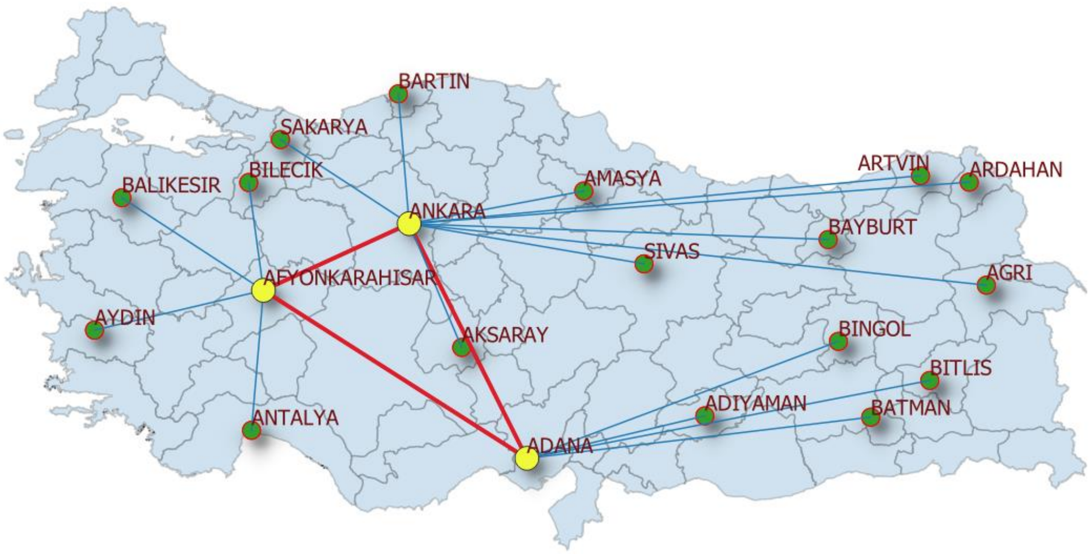

Fig 3.6 Single Assignment Pattern of Turkish Dataset

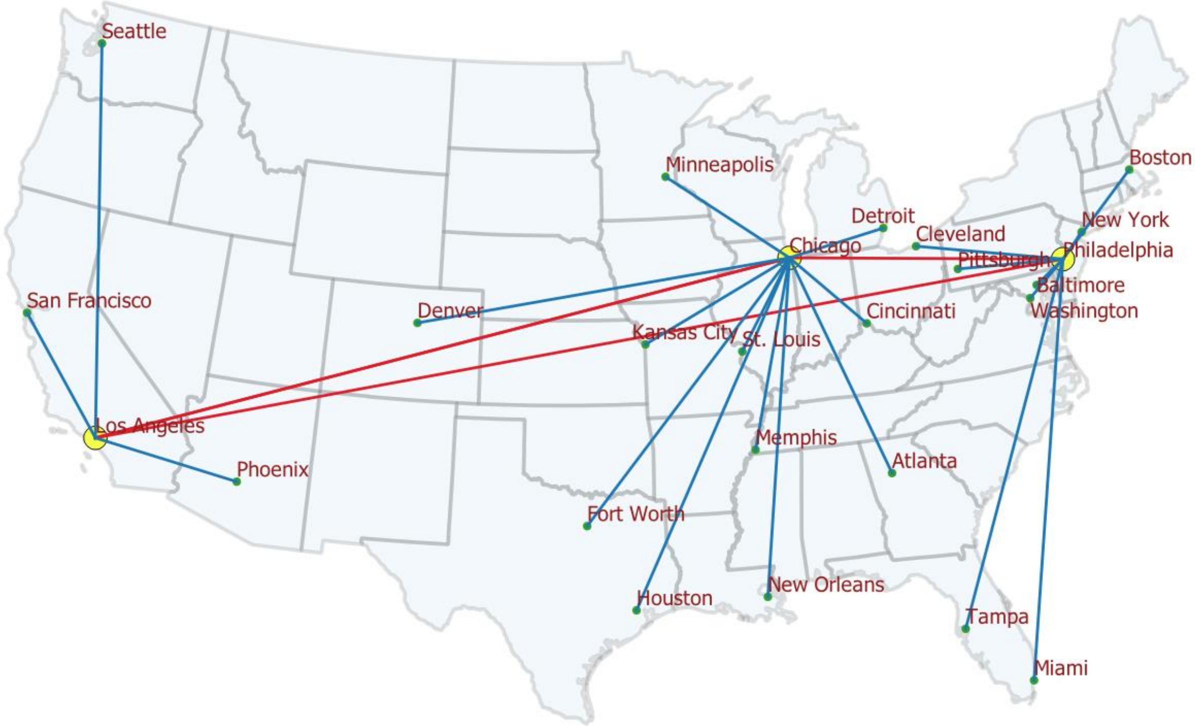

Fig 3.7 Single Assignment Pattern of USA Dataset

3.4. Discount Factor Estimation for Platooning

Watanabe et al. (2021) considers the discount factor calculation thanks to truck platooning. The discount factor calculation in truck platooning should be different from the traditional calculation of discount factor which highly depends on trade flow due to economies of scale. Truck platooning mainly benefits from the platoon in which trucks travel together, which must be included in the discount factor calculation. Driving at a close distance between trucks reduces the aerodynamic drag between them, which leads to the reduced fuel emission and cost saving.

The normal truck travel costs without platooning can be calculated as follows.

$$T_s = sn \qquad (3.21)$$

The truck travel costs without platooning (T_s) can be calculated as the single truck travel cost *(s)* multiplied by the number of trucks *(n)*. In the case of platooning, there will be two different types of truck travel costs— the first leading truck travel cost and the following truck travel costs because these two types of costs are different due to aerodynamic properties. The truck travel costs in the case of platooning can be calculated as follows.

$$T_p = a + (n-1)b \qquad (3.22)$$

The platooning truck travel cost is calculated by the leading truck travel cost *(a)*, the following trucks travel cost *(b)* and the number of vehicles *(n)*. We will always assume that $s>a$, $s>b$ *and* $a>b$. The discount factor (α) is simply the ratio of the platooning truck travel costs (T_p) to the normal traveling truck costs (T_s), which can be calculated as follows.

$$\alpha = \frac{T_p}{T_s} = \frac{a+(n-1)b}{sn} \qquad (3.23)$$

From the equation (3.23), it is obvious that the discount factor (α) is highly dependent on platooning trucks travel costs (a and b) and the number of platooning trucks (n). If we can decrease a and b, and increase n; we can hypothetically assume that we can enjoy more of the benefits of the platooning discount factor (α).

3.5. Platooning Scenario

In this section, we will consider the parameter settings for calculating discount factor (α). Watanabe et al (2021) assumes that based on Japan condition, the ratio of the labor costs in the trucking industry is around 40 % , which implies the cost difference between unmanned and manned driving. When it comes to the fuel saving due to platooning, leading vehicle can enjoy around 10% and the following vehicles around 20%. Although our analysis uses three different datasets for Turkey, USA and Japan; we assume the same parameter settings based on aforementioned Japan condition for all datasets. As a result, three platooning scenarios can be considered as follows.

Table 3.1 Three platooning scenarios based on different driving systems

No	Scenario	s	a	b
I	Platoon with all manned vehicles	1	0.9	0.8
II	Platoon with unmanned following vehicles	1	0.9	0.4
III	Platoon with all fully automated vehicles (FAVs)	1	0.5	0.4

In the table 3.1, for scenario I, when there are all manned trucks in a platoon, there will be cost saving benefit solely due to the platooning. When the trucks are unmanned in the scenario II and III, the platooning benefits can be added by the labor cost saving benefits, leading to more saving in total travel cost. Therefore, in scenario II, the cost saving for the following trucks becomes 60% (20% + 40%), leading to the discount value 0.4. In the case of unmanned scenario III, not only the leading vehicle has the discount value benefit of 50% (10% + 40%), but also the following vehicles have the discount value benefit of 60% (20% + 40%). The number of platooning trucks is restricted depending upon each country's regulation requirement. For example, the number of platooning trucks is restricted to 3 in case of Japan. However, in our analysis, the number of platooning trucks is hypothetically varied from 3 to 10 in order to provide a wide range of discount factor value, which can be analyzed for its impact on total travel cost in both single and multiple assignments. As a result, the following table 3.2 is obtained.

Table 3.2 Three different platooning scenarios based on the number of platooning trucks

<table>
<tr><th colspan="2">Scenario</th><th>s</th><th>a</th><th>b</th><th>n</th><th>α</th></tr>
<tr><td>I</td><td>Platoon of all manned vehicles</td><td>1</td><td>0.9</td><td>0.8</td><td>3—10</td><td>0.8</td></tr>
<tr><td rowspan="2">II</td><td rowspan="2">Platoon with unmanned following vehicles</td><td rowspan="2">1</td><td rowspan="2">0.9</td><td rowspan="2">0.4</td><td>3</td><td>0.6</td></tr>
<tr><td>4—10</td><td>0.5</td></tr>
<tr><td>III</td><td>Platoon of all fully automated vehicles (FAVs)</td><td>1</td><td>0.5</td><td>0.4</td><td>3—10</td><td>0.4</td></tr>
</table>

In the above table 3.2, for platooning scenario I, although the number of platooning trucks is hypothetically varied from 3 to 10, α value does not change much and stays around 0.8. Therefore, we assume the average α value as 0.8 in manned platooning scenario, for all number of platooning trucks from 3 to 10. For unmanned following vehicles in scenario II, the number of platooning trucks from 4 to 10 provides α value around 0.5. For almost all the instances at which our optimization are made, α values 0.6 and 0.5 give the same PFCs except very few exceptional instances in single assignment for CAB data. Similarly, the platoon of all automated vehicles gives the α value of around 0.4. Therefore, it can be summarized that in each platooning scenario, the discount factor value does not change very much for a range of number of platooning trucks from 3 to 10 and hence, it gives almost the same optimal PFCs for each instance in each scenario. In other words, the number of platooning trucks do not have much impact on discount factor for each different platooning scenario.

3.6. Platooning Scenarios with Driving Hours Restriction Included

Each country legally adopts driving hours limitations for truck drivers. For example, in Japan, the basic upper driving hour limit set by government is 293 hours per month. In EU, the driving hours are limited to 9 hours per day. However, we need to bear in mind that there are still a lot of legal complexity to extend or adjust aforementioned driving hours permission from legal perspective. To better reflect reality, it can be more sensible to include driving hours limitation to our modelling process as well, especially for platooning scenarios I and II, where drivers are needed for platoon operation. If this will be the case, there may occur some changes to our discount factor values in platooning operations and also to the objective function. Starting from scenario I, since all human drivers are needed, we must consider their driving hours constraints as the time diameter concept, which implies that the distance they can travel will be restricted by a certain coverage area of travelling distance which cannot exceed their driving hours permission constraint. In this case, our objective value will simply change to minimization of number of PFCs because we are limiting the driving distance based on driving hours permitted and within that time circle, we need to consider how many PFCs at least we can have. Since we are not freely optimizing but limiting ourselves to the maximum driving distance/time that truck drivers can drive, we cannot simply expect the minimum total cost from optimization, because that driving hours constraint will somehow hinder us from reaching that purpose. In this case, if we want to achieve cost minimization target at best while including driving hours constraint, we can opt to multi-objective optimization, where we will try to minimize the total travel cost while still considering the number of PFCs suggested by driving hours constraint.

Scenario II can be slightly complicated and there can be a couple of options for consideration of driving hours constraint. Since only one driver is needed for leading truck while other following trucks can be remotely controlled, we can consider the driver change scenario after reaching one's driving hours limitation, without the need to impact much negatively on overall transportation time. If this can be the solution, how we will make the driver change can depend on the gross vehicle tonnage. For example, for medium-duty segment extending from about 7 to about 13 tons, this may possibly be carried out along the infrastructure, but for heavy-duty segment which includes tractor-trailers with a certain gross combined vehicle weight rating (GCWR), long-hauls, and so on, they definitely need a specific parking area to carry out driver change. This parking area availability can be a challenging issue because even developed countries such as Japan still cannot provide many parking areas as expected to facilitate such platooning operation. However, this parking area availability can be considered as a maximum driving coverage constraint as well, similarly as scenario I, which definitely must be less than or equal to the driving hours limitation coverage. If so, the same logic can be applied to scenario II as discussed above in scenario I. However, for medium duty vehicles, which may not need a specific parking area depending upon their body types, vehicle tonnage and the road types on which they will travel, they may be able to perform driver change by just stopping vehicles for a while in the sideways along the road, for replacing the leading driver with the following drivers who already took their relaxation hours in the following trucks until the leading driver reaches his maximum driving hour permission. Such driver replacing system can lead to confusion in setting driver wage during relaxing hours from legal perspective because those drivers will somehow be in the following trucks while resting. However, considering datasets used in this study, since we are simply considering long-haul distance between prefectures, states or large cities, we will definitely need to consider parking area availability in our modelling scenario.

The scenario III will be the best solution as there will be no need to consider driving hours restriction or parking area availability because all the trucks will be operated without the need of human. However, this scenario still theoretically exists because in reality, there are a lot of challenges from technical or infrastructure or legal perspective to achieve all-truck autonomic driving and the best technological breakthrough which can be tested or acheived so far is scenario II until now and still needs at least a human driver in the leading truck.

However in our study, for the sake of simplicity, we will not consider driving hours restriction in our modelling scenario.

3.7. Computational Environment

All optimization instances are carried out by using XpressIVE 8.11 commercial optimizer. Regarding the device specification, Intel Xeron Bronze 1.9 GHz (16 CPUs) computer with 32768 MB RAM, and 1 MB Cache was used for data analysis. Computation time highly depends upon computational complexity. It was found out that single assignment takes a wide range of duration, ranging from half an hour to even more than 12 hours in rare cases. In addition, more PFC node assignment also lead to more computational duration, regardless of single and multiple allocation. Multiple assignment generally takes about 2-3 hours as an average.

4. Analysis on Optimization Results

4.1. Three Different Datasets

The first dataset is USA CAB dataset, which is produced from the Civil Aeronautics Board Survey of 1970 passenger data in the United States of America. It includes passenger flows and distances between 25 USA cities and is considered as the common benchmark dataset for hub locational analysis.

The second dataset is Turkish network dataset by Kara, which includes 81 cities as demand nodes. This includes different data for travel distance, travel times, freight flow and fixed link costs for Turkish 81 cities. As a benchmark size, we took 20 cities which represent uniform distribution across the region. For the simulation of truck platooning, we took the freight flow and travel time data.

The third dataset is Japanese freight flow dataset for 45 prefectures. In fact, Japan has 47 prefectures in total, but we did not consider Hokkaido and Okinawa Prefectures because these two isolated islands do not have direct road networks with the other prefectures. The Japanese dataset used in our analysis has two aspects– freight data and distance data matrix. The origin-destination freight data is obtained from Net Freight Volume (ton) 2015 Census data, which is a survey result of "National Freight Transport Survey". That survey is, in fact, National Census for Logistics Sector, which surveys nationwide cargo flow throughout the whole of Japan, conducted every 5 years by Japanese government- Ministry of Land, Infrastructure, Transport and Tourism (MLIT), supported by NX Logistics Research Institution and Consulting Inc. (NXLRIC). Regarding distance matrix, the dataset is the direct distance matrix between prefectural government offices provided by Geospatial Information Authority of Japan (GSI), which is calculated as the shortest distance (geodesic lengths) on a rotating ellipsoid (GRS80).

Each of these datasets has their respective spatial patterns. For example, Turkish dataset has more uniform distribution pattern than USA CAB dataset. Japan dataset, as it includes 45 prefectures in our analysis, represents denser spatial distribution pattern. Optimizing such different dataset with different distribution pattern allows us to have a better overall picture of how spatial distribution can have an impact on platooning process with different PFC assignment systems.

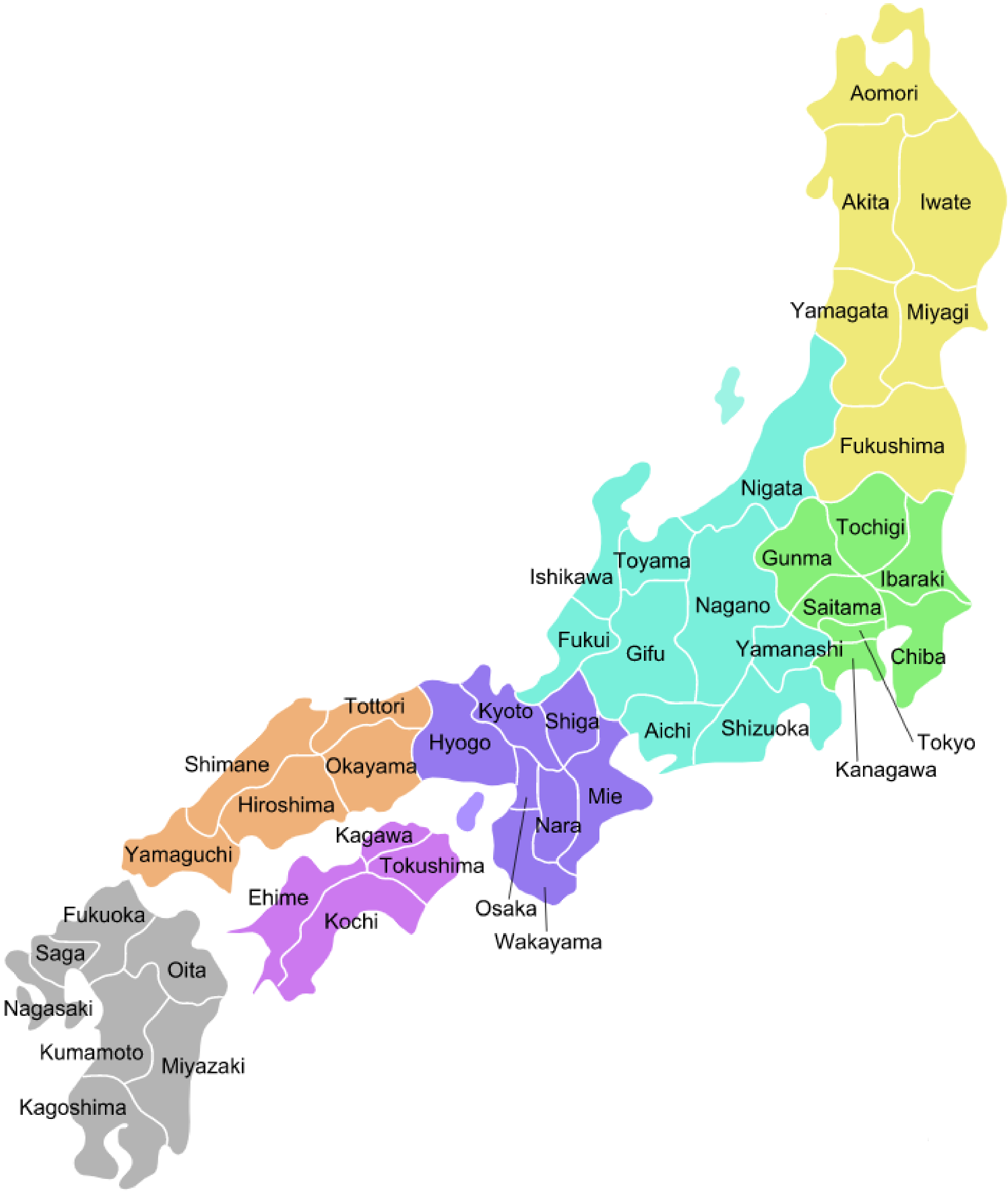

Fig 4.1 Japanese Dataset Spatial Distribution Pattern

Fig 4.2 USA Dataset Spatial Distribution Pattern

Fig 4.3 Turkish Dataset Spatial Distribution Pattern

4.2. Optimization Result

We do the optimization for these three datasets based on three platooning scenarios and the different number of PFCs, which provide the following results.

Table 4.1 Turkish Dataset Optimization Result

Scenario	Number of trucks	Discount factor (α)	Number of hubs	Single Allocation		Multiple Allocation	
				Hub Nodes	Obj Value	Hub Nodes	Obj Value
I	3—10	0.8	2	ANKARA, SİVAS	2,759,303,532	ADANA, ANKARA	2,589,307,800
			3	ADANA, AFYON, ANKARA	2,547,442,578	ANKARA, ADIYAMAN, ANTALYTA	2,369,305,475
			4	ADANA, AFYON, SİVAS,ANKARA	2,377,738,261	ADANA, ANKARA, AFYON, BİNGÖL	2,220,060,861
			5	ADANA, AFYON, SİVAS,ANKARA, ANTALYA	2,282,294,932	ADANA, ANKARA, ANTALYTA, BİNGÖL, BALIKESİR	2,132,414,815
			6	ADANA, AFYON, SİVAS,ANKARA, ANTALYA, ADIYAMAN	2,200,313,562	ADANA, ANKARA, ANTALYTA, BALIKESİR, BATMAN, SİVAS	2,053,389,149
			7	ADANA, AFYON, SİVAS,ANKARA, ANTALYA, ADIYAMAN, AYDIN	2,155,565,136	ADANA, ANKARA, AFYON, ANTALYTA, BALIKESİR, BATMAN, SİVAS	2,005,900,581
			8	ADANA, AFYON, SİVAS,ANKARA, ANTALYA, ADIYAMAN, AYDIN, BALIKESİR	2,101,729,477	ADANA, ANKARA, AFYON, ANTALYTA, BALIKESİR, BATMAN, SİVAS, AĞRI	1,971,293,141
II	3	0.6	2	ANKARA, SİVAS	2,647,480,436	ADANA, ANKARA	2,530,526,026
			3	ADANA, AFYON, ANKARA	2,355,566,516	ADANA, ANKARA, AFYON	2,248,377,060
			4	ADANA, AFYON, ANKARA, BİNGÖL	2,115,305,184	ADANA, ANKARA, AFYON, BİNGÖL	2,012,367,928
			5	ADANA, AFYON, ANKARA, BİNGÖL, ANTALYA	1,992,319,559	ADANA, ANKARA, ANTALYTA, BİNGÖL, BALIKESİR	1,883,598,193
			6	ADANA, AFYON, ANKARA, BİNGÖL, ANTALYA, SİVAS	1,882,774,965	ADANA, ANKARA, ANTALYTA, BALIKESİR, BATMAN, SİVAS	1,784,650,846
			7	ADANA, ANKARA, BİNGÖL, ANTALYA, SİVAS, AYDIN, BALIKESİR	1,811,319,139	ADANA, ANKARA, AYDIN, ANTALYTA, BALIKESİR, BATMAN, SİVAS	1,706,506,550
			8	ADANA, AFYON, ANKARA, BİNGÖL, ANTALYA, SİVAS, AYDIN, BALIKESİR	1,733,874,877	ADANA, ANKARA, AYDIN, ANTALYTA, BALIKESİR, BATMAN, SİVAS, AĞRI	1,647,132,247
	4—10	0.5	2	ANKARA, SİVAS	2,591,568,888	ADANA, ANKARA	2,488,547,120
			3	ADANA, AFYON, ANKARA	2,259,628,486	ADANA, ANKARA, AFYON	2,180,015,664
			4	ADANA, AFYON, ANKARA, BİNGÖL	1,969,649,901	ADANA, ANKARA, AFYON, BİNGÖL	1,895,815,239
			5	ADANA, AFYON, ANKARA, BİNGÖL, ANTALYA	1,831,619,300	ADANA, ANKARA, ANTALYTA, BİNGÖL, BALIKESİR	1,738,024,975
			6	ADANA, AFYON, ANKARA, BİNGÖL, ANTALYA, SİVAS	1,712,797,675	ADANA, ANKARA, ANTALYTA, BALIKESİR, BATMAN, SİVAS	1,637,798,365
			7	ADANA, ANKARA, BİNGÖL, ANTALYA, SİVAS, AYDIN, BALIKESİR	1,620,134,410	ADANA, ANKARA, AYDIN, ANTALYTA, BALIKESİR, BATMAN, SİVAS	1,549,711,145
			8	ADANA, AFYON, ANKARA, BİNGÖL, ANTALYA, SİVAS, AYDIN, BALIKESİR	1,538,472,343	ADANA, ANKARA, AYDIN, ANTALYTA, BALIKESİR, BATMAN, SİVAS, AĞRI	1,476,443,992
III	3—10	0.4	2	ANKARA, BİNGÖL	2,499,447,095	ADANA, ANKARA	2,444,275,718
			3	ANKARA, BİNGÖL, AFYON	2,160,059,659	ANKARA, AFYON, BİNGÖL	2,089,356,165
			4	ANKARA, BİNGÖL, AFYON, ADANA	1,823,994,617	ADANA, ANKARA, AFYON, BİNGÖL	1,769,749,459
			5	ADANA, AFYON, ANKARA, BİNGÖL, ANTALYA	1,670,919,040	ADANA, ANKARA, ANTALYTA, BİNGÖL, BALIKESİR	1,586,388,530
			6	ADANA, AFYON, ANKARA, BİNGÖL, ANTALYA, SİVAS	1,542,820,385	ADANA, ANKARA, ANTALYTA, BALIKESİR, BİNGÖL, SİVAS	1,476,686,330
			7	ADANA, ANKARA, BİNGÖL, ANTALYA, SİVAS, AYDIN, BALIKESİR	1,428,949,681	ADANA, ANKARA, AYDIN, ANTALYTA, BALIKESİR, BİNGÖL, SİVAS	1,377,719,836
			8	ADANA, ANKARA, BİNGÖL, ANTALYA, SİVAS, AYDIN, BALIKESİR, SAKARYA	1,340,835,100	ADANA, ANKARA, AYDIN, ANTALYTA, BALIKESİR, BATMAN, SİVAS, AĞRI	1,297,886,158

Table 4.2 USA CAB Dataset Optimization Result

Scenario	Number of trucks	Discount factor (α)	Number of hubs	Single Allocation		Multiple Allocation	
				Hub Nodes	Obj Value	Hub Nodes	Obj Value
I	3—10	0.8	2	Pittsburgh, LA	11,086,701,110	Pittsburgh, LA	10,112,632,930
			3	Baltimore, Chicago, LA	9,928,394,350	LA, Philadelphia, Chicago	8,766,822,298
			4	Atlanta, Philadelphia, Chicago, LA	9,349,117,426	LA, Chicago, New York, Atlanta	8,187,484,416
			5	Atlanta, Philadelphia, Chicago, LA, Dallas-Fort Worth	8,896,530,276	LA, Chicago, New York,Tampa, Dallas-Fort Worth	7,833,704,320
			6	Atlanta, Philadelphia, Chicago, LA, Dallas-Fort Worth, Cleveland	8,503,570,972	LA, Pittsburgh, New York, Chicago, Dallas-Fort Worth, Miami	7,557,637,014
			7	Atlanta, Chicago, Dallas-Fort Worth, Cleveland, New York, LA, Washington DC	8,226,020,204	Pittsburgh, New York, Chicago, Dallas-Fort Worth, LA, Miami, San Francisco	7,349,885,831
			8	Atlanta, Chicago, Dallas-Fort Worth, Cleveland, New York, LA, Washington DC, Denver	7,962,783,700	Pittsburgh, New York, Chicago, Dallas-Fort Worth, LA, Miami, San Francisco, Denver	7,191,653,802
			9	Atlanta, Chicago, Dallas-Fort Worth, Cleveland, New York, LA, Washington DC, Denver, San Francisco	7,729,597,964	Pittsburgh, New York, Chicago, Dallas-Fort Worth, LA, Miami, San Francisco, Denver, Atlanta	7,046,625,372
			10	Atlanta, Chicago, Dallas-Fort Worth, Cleveland, New York, LA, Washington DC, Denver, San Francisco, Miami	7,501,621,147	Washington DC, LA, New York, Chicago, Atlanta, Cleveland, Miami, Dallas-Forth Worth, San Francisco, Denver	6,938,782,154
II	3	0.6	2	Pittsburgh, LA	10,293,329,780	Pittsburgh, LA	9,745,890,602
			3	Baltimore, Chicago, LA	8,858,627,953	LA, Philadelphia, Chicago	8,157,181,036
			4	Atlanta, Philadelphia, Chicago, LA	8,101,410,264	LA, Chicago, New York, Atlanta	7,459,019,617
			5	Chicago, Philadelphia, Dallas-Fort Worth, Miami, LA	7,578,755,771	New York, Miami, Chicago, Dallas-Fort Worth, LA	6,931,515,226
			6	Cleveland, New York, Chicago, Dallas-Fort Worth, Miami, LA	7,114,524,038	Pittsburgh, New York, Chicago, Dallas-Fort Worth, Miami, LA	6,570,185,322
			7	Cleveland, New York, Chicago, Dallas-Fort Worth, Miami, LA, San Francisco	6,833,035,794	San Francisco, Pittsburgh, Chicago, Dallas-Fort Worth, LA, Miami, New York	6,322,459,263
			8	Cleveland, New York, Chicago, Dallas-Fort Worth, Miami, LA, San Francisco, Washington DC	6,562,154,039	San Francisco, Pittsburgh, Chicago, Dallas-Fort Worth, LA, Miami, Denver, New York	6,085,584,796
			9	Atlanta, Washington DC, New York, Chicago, Cleveland, Dallas-Fort Worth, LA, Miami, San Francisco	6,291,781,547	San Francisco, Pittsburgh, New York, Chicago, Atlanta, Dallas-Fort Worth, Denver, Miami, LA	5,884,577,953
			10	Atlanta, Washington DC, New York, Chicago, Cleveland, Dallas-Fort Worth, Denver, Miami, San Francisco, LA	6,028,915,420	Washington DC, LA, New York, Chicago, Atlanta, Cleveland, Miami, Dallas-Fort Worth, San Francisco, Denver	5,707,997,230
	4—10	0.5	2	Pittsburgh, LA	9,872,931,686	Pittsburgh, LA	9,485,303,158
			3	Baltimore, Chicago, LA	8,323,744,755	Philadelphia, LA, Chicago	7,789,289,190
			4	Atlanta, New York, Chicago, LA	7,459,179,506	New York, LA, Chicago, Atlanta	7,013,643,908
			5	Chicago, New York, Dallas-Fort Worth, Miami, LA	6,851,031,800	New York, Miami, Chicago, Dallas-Fort Worth, LA	6,406,114,469
			6	Cleveland, New York, Chicago, Dallas-Fort Worth, Miami, LA	6,391,945,043	Pittsburgh, New York, Chicago, Dallas-Fort Worth, LA, Miami	6,019,057,656
			7	Cleveland, New York, Chicago, Dallas-Fort Worth, LA, Miami, San Francisco	6,089,248,778	San Francisco, Pittsburgh, New York, Chicago, Dallas-Fort Worth, Miami, LA	5,735,208,745
			8	Atlanta, New York, Chicago, Cleveland, Dallas-Fort Worth, LA, Miami, San Francisco	5,813,546,371	San Francisco, Pittsburgh, New York, Chicago, Dallas-Fort Worth, Miami, LA, Denver	5,486,558,109
			9	Atlanta, New York, Chicago, Cleveland, Dallas-Fort Worth, LA, Miami, San Francisco, Denver	5,547,634,963	San Francisco, Pittsburgh, New York, Chicago, Atlanta, Dallas-Fort Worth, Denver, Miami, LA	5,266,271,986
			10	Atlanta, New York, Washington DC, Chicago, Cleveland, Dallas-Fort Worth, LA, Miami, San Francisco, Denver	5,282,479,469	Washington DC, LA, New York, Chicago, Atlanta, Cleveland, Miami, Dallas-Fort Worth, San Francisco, Denver	5,067,339,203
III	3—10	0.4	2	Pittsburgh, LA	9,442,748,342	Pittsburgh, LA	9,194,195,483
			3	Chicago, Philadelphia, LA	7,764,038,638	New York, LA, Chicago	7,400,411,097
			4	Atlanta, New York, Chicago, LA	6,804,125,455	Tampa, New York, Chicago, LA	6,502,347,636
			5	Chicago, New York, Dallas-Fort Worth, LA, Miami,	6,122,523,270	New York, Miami, Chicago, Dallas-Fort Worth, LA	5,835,442,965
			6	Cleveland, New York, Chicago, Dallas-Fort Worth, Miami, LA	5,669,366,048	Pittsburgh, New York, Chicago, Dallas-Fort Worth, LA, Miami	5,432,675,254
			7	Cleveland, New York, Chicago, Dallas-Fort Worth, LA, Miami, San Francisco	5,345,461,762	San Francisco, Pittsburgh, New York, Chicago, Dallas-Fort Worth, Miami, LA	5,112,382,233
			8	Atlanta, New York, Chicago, Cleveland, Dallas-Fort Worth, LA, Miami, San Francisco	5,064,604,925	San Francisco, Pittsburgh, New York, Chicago, Dallas-Fort Worth, Miami, Denver, LA	4,868,553,648
			9	Atlanta, New York, Chicago, Cleveland, Dallas-Fort Worth, LA, Miami, San Francisco, Denver	4,796,676,947	San Francisco, Pittsburgh, New York, Chicago, Dallas-Fort Worth, Miami, Denver, LA, Atlanta	4,637,317,660
			10	Atlanta, Washington DC, New York, Chicago, Cleveland, Dallas-Fort Worth, LA, Miami, San Francisco, Denver	4,531,368,188	Washington DC, LA, New York, Chicago, Atlanta, Cleveland, Dallas-Fort Worth, Denver, San Francisco, Miami	4,414,060,846

Table 4.3 Japanese Dataset Optimization Result

Scenario	Number of trucks	Discount factor (α)	Number of hubs	Single Allocation		Multiple Allocation	
				Hub Nodes	Obj Value	Hub Nodes	Obj Value
I	3—10	0.8	2	Saitama, Osaka	2,174,245,686	Saitama, Osaka	2,027,437,825
			3	Saitama, Shiga, Fukuoka	1,847,780,272	Saitama, Shiga, Fukuoka	1,662,693,343
			4	Saitama, Osaka, Aichi, Fukuoka	1,624,463,980	Saitama, Hyogo, Aichi, Fukuoka	1,460,368,961
			5	Saitama, Osaka, Aichi, Fukuoka, Fukushima	1,503,341,432	Fukuoka, Hyogo, Miyagi, Saitama, Aichi	1,320,554,305
			6	Saitama, Osaka, Aichi, Fukuoka, Fukushima, Okayama	1,417,475,260	Fukuoka, Okayama, Miyagi, Saitama, Aichi, Osaka	1,249,812,756
			7	Saitama, Osaka, Aichi, Fukuoka, Fukushima, Shizuoka, Okayama	1,354,441,410	Fukuoka, Okayama, Miyagi, Tochigi, Tokyo, Osaka, Aichi	1,202,329,840
			8	Saitama, Osaka, Aichi, Fukuoka, Fukushima, Shizuoka, Okayama, Gunma	1,315,967,447	Fukuoka, Okayama, Miyagi, Tochigi, Tokyo, Aichi, Osaka, Toyama	1,177,342,236
			9	Osaka, Aichi, Fukuoka, Fukushima, Shizuoka, Okayama, Hiroshima, Gunma, Saitama	1,283,933,769	Fukuoka, Hiroshima, Miyagi, Tochigi, Toyama, Tokyo, Aichi, Osaka, Okayama	1,156,380,585
			10	Osaka, Aichi, Fukuoka, Fukushima, Shizuoka, Okayama, Tochigi, Gunma, Tokyo, Hiroshima	1,253,618,690	Fukuoka, Hiroshima, Miyagi, Ibaraki, Gunma, Tokyo, Toyama, Aichi, Osaka, Okayama	1,136,158,853
II	3—10	0.5 (assumed collectively as 0.5, instead of 0.6)	2	Saitama, Osaka	2,029,368,040	Saitama, Osaka	1,971,369,318
			3	Saitama, Shiga, Fukuoka	1,655,004,188	Saitama, Shiga, Fukuoka	1,578,763,214
			4	Saitama, Osaka, Aichi, Fukuoka	1,422,092,886	Fukuoka, Osaka, Saitama, Aichi	1,347,608,558
			5	Saitama, Osaka, Aichi, Fukuoka, Fukushima	1,268,752,341	Fukuoka, Osaka, Fukushima, Saitama, Aichi	1,189,493,470
			6	Saitama, Osaka, Aichi, Fukuoka, Fukushima, Okayama	1,166,764,075	Fukuoka, Okayama, Fukushima, Saitama, Aichi, Osaka	1,099,210,360
			7	Saitama, Osaka, Aichi, Fukuoka, Fukushima, Shizuoka, Okayama	1,101,140,682	Fukuoka, Okayama, Miyagi, Tochigi, Tokyo, Aichi, Osaka	1,040,646,961
			8	Miyagi, Tokyo, Shizuoka, Aichi, Okayama, Fukuoka, Osaka, Gunma	1,055,065,245	Fukuoka, Okayama, Miyagi, Tochigi, Tokyo, Aichi, Osaka, Nagano	1,001,334,449
			9	Miyagi, Ibaraki, Tokyo, Shizuoka, Aichi, Okayama, Fukuoka, Osaka, Gunma	1,005,184,943	Fukuoka, Okayama, Miyagi, Tochigi, Tokyo, Aichi, Osaka, Nagano, Shizuoka	962,813,170
			10	Miyagi, Ibaraki, Tokyo, Shizuoka, Aichi, Okayama, Fukuoka, Osaka, Gunma, Hiroshima	966,512,837	Fukuoka, Hiroshima, Miyagi, Tochigi, Tokyo, Nagano, Aichi, Shizuoka, Osaka, Okayama	928,169,721
III	3—10	0.4	2	Saitama, Osaka	1,981,075,491	Saitama, Osaka	1,949,018,831
			3	Saitama, Shiga, Fukuoka	1,590,745,493	Saitama, Shiga, Fukuoka	1,538,741,090
			4	Saitama, Osaka, Aichi, Fukuoka	1,354,635,854	Fukuoka, Hyogo, Saitama, Aichi	1,299,703,405
			5	Yamagata, Saitama, Osaka, Aichi, Fukuoka	1,188,608,758	Fukuoka, Hyogo, Fukushima, Saitama, Aichi	1,132,520,274
			6	Yamagata, Saitama, Osaka, Aichi, Fukuoka, Okayama	1,081,244,787	Fukuoka, Okayama, Fukushima, Saitama, Aichi, Osaka	1,038,310,647
			7	Yamagata, Saitama, Osaka, Aichi, Fukuoka,, Shizuoka, Okayama	1,014,810,995	Fukuoka, Okayama, Miyagi, Tochigi, Tokyo, Aichi, Osaka	976,375,573
			8	Miyagi, Tochigi, Tokyo, Shizuoka, Aichi, Okayama, Fukuoka, Osaka	962,509,871	Fukuoka, Okayama, Miyagi, Tochigi, Tokyo, Shizuoka, Aichi, Osaka	930,642,871
			9	Miyagi, Ibaraki, Gunma, Tokyo, Aichi, Shizuoka, Osaka, Okayama, Fukuoka	910,618,100	Fukuoka, Okayama, Miyagi, Ibaraki, Gunma, Aichi, Shizuoka, Osaka, Tokyo	887,687,773
			10	Miyagi, Ibaraki, Gunma, Tokyo, Aichi, Shizuoka, Osaka, Okayama, Fukuoka, Hiroshima	869,590,828	Fukuoka, Hiroshima, Miyagi, Ibaraki, Gunma, Tokyo, Shizuoka, Aichi, Osaka, Okayama	847,545,118

4.3. Characteristics of Optimization

4.3.1 Number of Platooning Vehicles and Platooning Scenarios

It was found out that the main contributing factor to bring down the total travel cost for the truck platooning is not the number of trucks in the platoon. In other words, increasing the number of trucks in a platoon cannot reduce the total travel cost considerably.

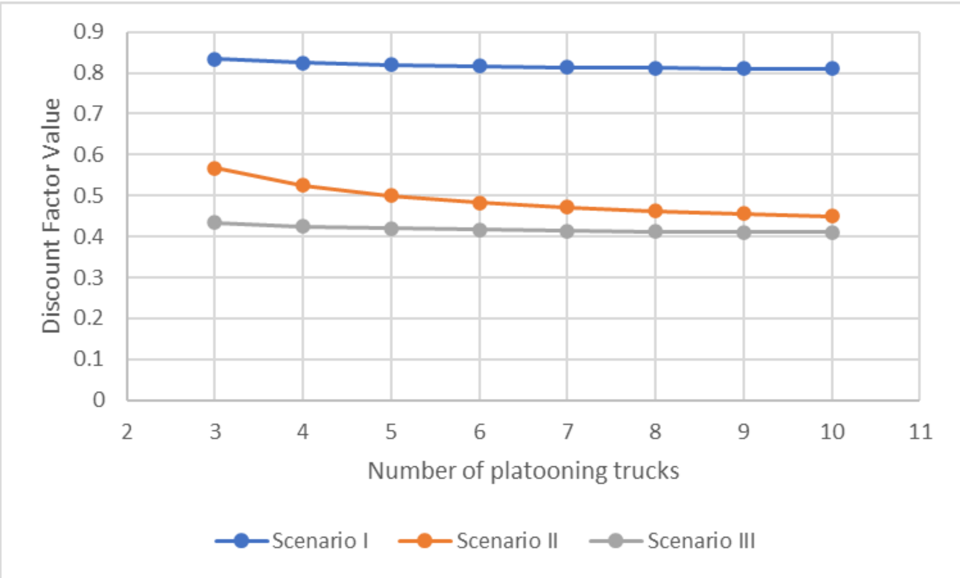

Fig 4.4 The relationship between the number of platooning trucks and discount factor (α)

As shown in the figure 4.4, the discount factor value (α) tends to remain flat for all numbers of platooning trucks ranging from 3 to 10 in each platooning scenario except scenario II which shows a slightly steeper downward trend, compared with the other two scenarios. Because of this reason, in our study, α value 0.8 is commonly considered for all number of platooning trucks in platooning scenario I and 0.4 for scenario III. However, for scenario II, α value 0.6 is considered for three platooning trucks and 0.5 for the rest of the number of platooning trucks for Turkish and USA dataset as shown in the table 4.1 and 4.2. When it comes to the Japanese dataset, since the dataset is relatively large at least for the optimizer used, and for the sake of the time, just a single α value 0.6 is considered for the whole platooning scenario II as shown in the table 4.3.

This finding can be very important from the legislation perspective because the large number of platooning trucks in a platoon is relatively difficult to be accomplished in the real world scenario. The infrastructure must be made able to withstand such a great combined load from many platooning trucks travelling together. The road signs on the transport infrastructure also need to be adapted for platooning technology. Although the truck platooning makes the transportation process safe theoretically by utilizing the transport infrastructure effectively, there can easily arise public concerns for safety if there are many platooning trucks on the road. It can also be difficult to handle many platooning trucks, especially at platoon forming and (de) forming period on the road. From the regulation perspective, for many countries, it is not yet feasible to have a large number of platooning trucks, such as ten platooning vehicles used in our analysis. For example, Japan regulation permits only three vehicles for platooning process. Therefore, our analysis highlights that there should not be much focus on having a large number of platooning trucks with the aim of reducing total travel cost.

Here, it is noteworthy that there is a huge cost saving between platooning scenario I (all manned vehicles) and scenario II (only one manned leading vehicle). The finding is self-explanatory because the labor cost saving can be more considerable when the number of unmanned vehicles grows larger. α value gap is very small between platooning scenario II and III because scenario II needs only one driver just for the leading truck. Therefore, instead of increasing the number of trucks in a platoon, it can be more effective to introduce semi-auto driving or fully-auto driving system into platooning technology in order to reduce travel cost considerably.

4.3.2 Single Assignment and Multiple Assignment

In addition to platooning scenarios related to manned and unmanned driving, multiple PFC allocation can also reduce the travel cost considerably. Below are the graphs which show the total travel cost of the different datasets in cases of single and multiple assignment with respect to the number of PFCs.

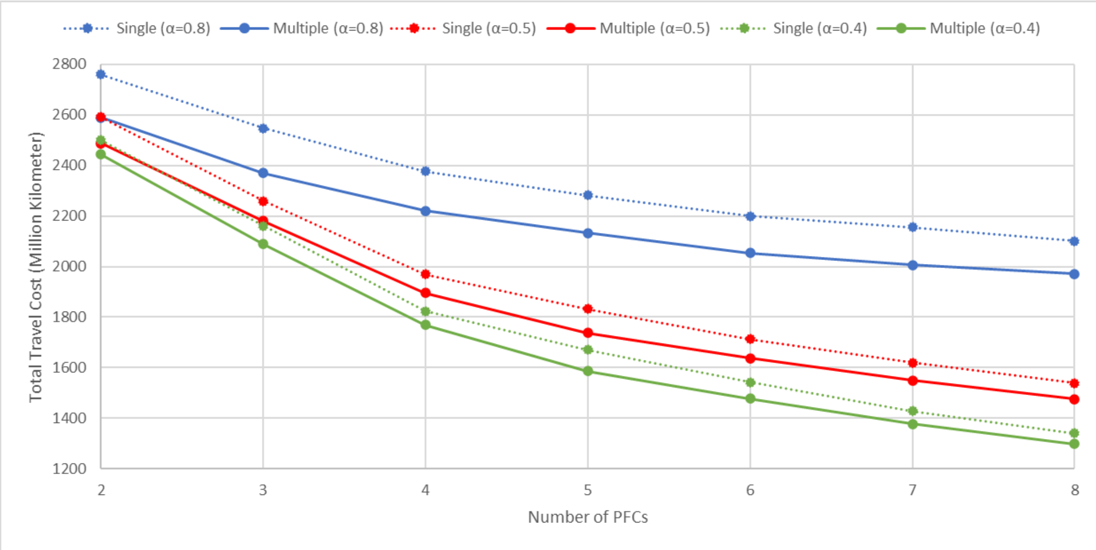

Fig 4.5 Travel Cost with respect to the number of PFCs (Turkish Dataset)

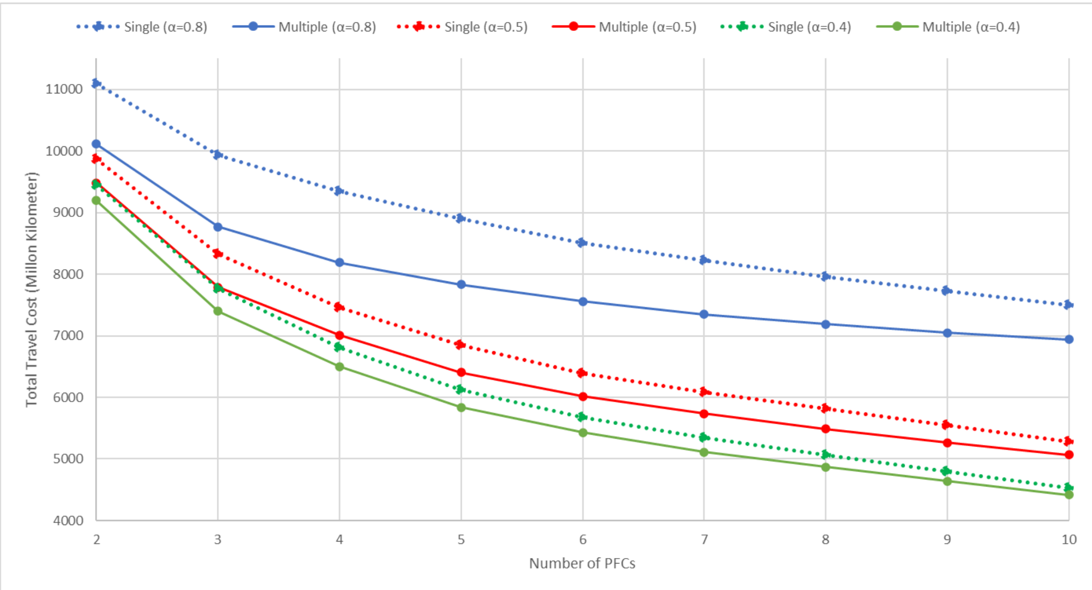

Fig 4.6 Travel Cost with respect to the number of PFCs (USA CAB Dataset)

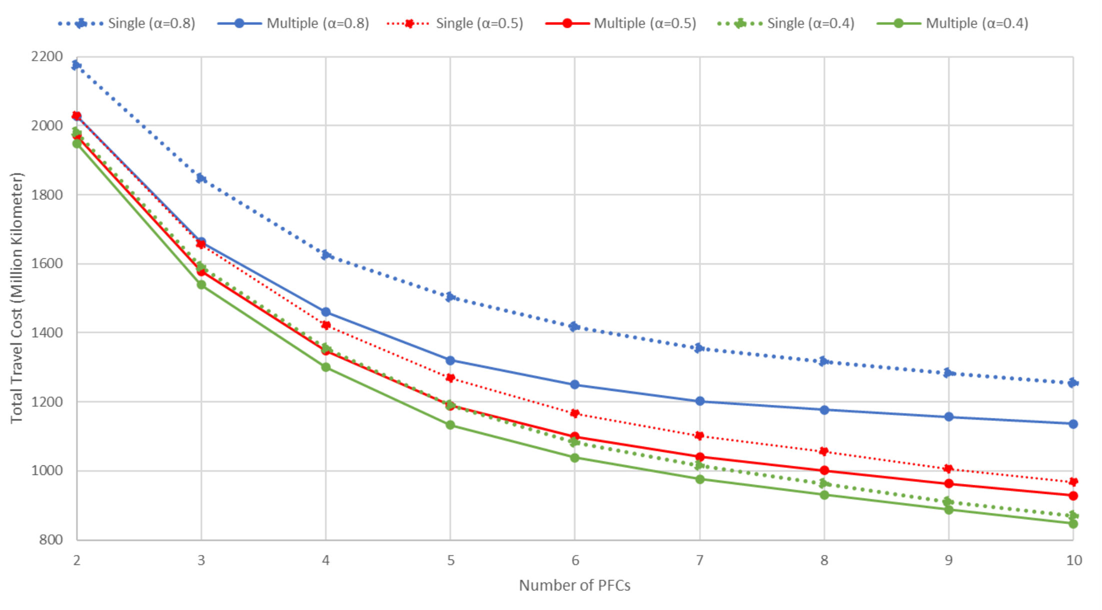

Fig 4.7 Travel Cost with respect to the number of PFCs (Japan Dataset)

The optimization of all these datasets represents more or less similar trends in cost reduction with respect to the number of PFCs. It is quite clear that for the platooning scenario I (manned platooning system), the cost gap between the single and multiple allocation is quite large compared to platooning scenario II and III. It is implying that if we cannot yet achieve the driverless platooning system due to certain technological and regulation constraints, multiple PFC allocation option can be adopted to bring down the total travel cost. However, when we can adopt the driverless platooning system such as in the case of platooning scenario III, the cost gap between single and multiple allocation tends to become narrow. In other words, there is not much cost saving result between single and multiple PFC allocation when we can reduce the driver's role in platooning scenario.

4.3.3 Number of Platoon Formation Centers (PFCs)

For all platooning scenarios, increasing the number of PFCs can significantly reduce the total travel cost, no matter whether the PFC assignment pattern is single or multiple allocation. However, the decline rate of the cost becomes less steep when the number of platooning trucks becomes larger. For example, the travel cost reduction rate is quite noticeable from two to five platooning trucks but becomes less significant when the number of PFCs becomes larger.

4.3.4 Trade Flows

For all optimization instances, the nodes with the larger trade flows mostly serve as PFCs. The trade flow here is defined by the total value of incoming and outgoing flows. Incoming trade flow of a node is the total value of the trade flows coming to that node from the other nodes. Outgoing trade flow of a node is the total value of the trade flows going out of that node to the other nodes. Therefore, trade flow value of a node shows how much trade is flowing through that certain node and how strategically important that node can be in terms of trade volume for the whole transport system.

Table 4.4 Decreasing Order of Trade Flow of Turkey Dataset

City	Outflow	Inflow	Total
Ankara (PFC)	737202	704085	1441286
Adana (PFC)	389583	389236	778819
Antalya (PFC)	364921	365405	730326
Balikesir (PFC)	236571	239346	475917
Aydin (PFC)	210361	213233	423594
Afyon (PFC)	181059	183908	364967
Adapazari (PFC)	169016	171817	340833
Sivas (PFC)	168785	171585	340369
Adiyaman (PFC)	140386	142986	283372
Ağri (PFC)	119571	121949	241520
Batman (PFC)	103664	105833	209497
Aksaray	90174	92138	182312
Bitlis	88521	90458	178979
Amasya	83279	85129	168408
Bingöl (PFC)	58180	59563	117744
Bilecik	44689	45788	90477
Artvin	44144	45231	89375
Bartin	42377	43425	85801
Ardahan	30852	31636	62488
Bayburt	22497	23080	45576

Table 4.5 Decreasing Order of Trade Flow of USA CAB Dataset

Cities	Outflow	Inflow	Total
New York (PFC)	1447732	1447732	2895464
Chicago (PFC)	857239	857239	1714478
Los Angeles (PFC)	624183	624183	1248366
Boston	516949	516949	1033898
Washington DC (PFC)	488406	488406	976812
Miami (PFC)	472710	472710	945420
San Francisco (PFC)	432156	432156	864312
Detroit	365160	365160	730320
Philadelphia (PFC)	305516	305516	611032
Cleveland (PFC)	305482	305482	610964
Dallas-Fort Worth (PFC)	262417	262417	524834
St. Louis	247845	247845	495690
Pittsburgh (PFC)	242947	242947	485894
Atlanta (PFC)	242873	242873	485746
Minneapolis	213516	213516	427032
Denver (PFC)	207827	207827	415654
Houston	205557	205557	411114
Baltimore (PFC)	193417	193417	386834
Kansas City	169964	169964	339928
Seattle	164136	164136	328272
Tampa (PFC)	158904	158904	317808
New Orleans	157816	157816	315632
Cincinnati	132671	132671	265342
Phoenix	126634	126634	253268
Memphis	98327	98327	196654

Table 4.6 Decreasing Order of Trade Flow of Japan Dataset

Prefectures	**Outflow**	**Inflow**	**Total**
Aichi (PFC)	605548	567033	1172581
Saitama (PFC)	488190	573437	1061628
Tokyo (PFC)	382879	575567	958446
Osaka (PFC)	445850	424955	870806
Kanagawa	396405	364482	760887
Chiba	383823	298187	682010
Hyogo (PFC)	343592	289466	633058
Ibaraki (PFC)	305157	304782	609939
Shizuoka (PFC)	273343	238651	511995
Tochigi (PFC)	278300	174638	452939
Fukuoka (PFC)	240761	180339	421099
Mie	250524	158984	409508
Gunma (PFC)	196537	184776	381313
Gifu	170888	190370	361258
Okayama (PFC)	203352	107860	311211
Miyagi (PFC)	128581	176056	304637
Hiroshima (PFC)	79475	176148	255623
Fukushima (PFC)	134830	109655	244485
Shiga (PFC)	103670	135809	239479
Nagano	81667	136154	217821
Niigata	126866	80390	207255
Kyoto	89845	109591	199436
Nara	31943	136363	168306
Yamaguchi	92271	65375	157647
Ehime	104955	49718	154673
Saga	47918	95741	143659
Yamanashi	35846	99130	134977
Toyama (PFC)	52832	78177	131010
Kumamoto	60980	66602	127582
Ishikawa	75113	42521	117634
Kagawa	67491	48390	115881
Iwate	57601	56400	114001
Wakayama	55061	35615	90676
Oita	45037	41908	86945
Fukui	32520	53391	85911
Yamagata	39202	39022	78224
Kagoshima	31183	44460	75643
Miyazaki	32135	37886	70022
Aomori	35927	29824	65751
Tokushima	34081	29705	63786
Shimane	38066	22611	60677
Tottori	21366	37678	59044
Nagasaki	19598	34206	53804
Akita	22420	31021	53441
Kochi	9888	20444	30331

In the above tables, all nodes which appear as PFCs in optimization instances are described as PFC besides their names. The above tables are sorted in decreasing order of trade flows, i.e. the nodes in the top positions have a larger trade flow than the ones in the bottom positions. It is easily noticeable that the nodes with the larger trade flows mostly appear as PFCs in most optimization instances with some exceptions. Moreover, most of the nodes with the lower trade flows never appear as PFCs as well. Therefore, it can be reasonably concluded that the nodes which have greater importance in terms of trade flow have high possibility to become PFCs in all platooning scenarios and assignment systems.

4.3.5 Discount Factor Value (α)

As discussed above, the platoon driving system has high impact on α value. That α value, in turn, has a certain degree of impact on PFC location. The lower α value makes PFC locate at a far distance between two PFCs. The reason is that when there is much inter-PFC benefit, the trucks have much interest to travel by platooning for a larger distance. Therefore, in other words, unmanned platooning scenarios tend to have further PFCs than manned platooning scenario.

Fig 4.8 Turkish dataset PFC location (yellow-colored) when α value is 0.8 and the number of PFCs is 4 with single assignment

Fig 4.9 Turkish dataset PFC location (yellow-colored) when α value is 0.5 and the number of PFCs is 4 with single assignment

From the above figures 4.8 and 4.9, when α value is 0.8, PFCs tend to locate closely, with not much great distance between them. When it comes to α value 0.5, even for the same number of PFCs which is 4, PFCs tend to locate at a far distance. The PFC location at Sivas from figure 4.8 shifts towards Bingöl in figure 4.9. This same characteristic can also be found in USA CAB dataset and Japan dataset as well.

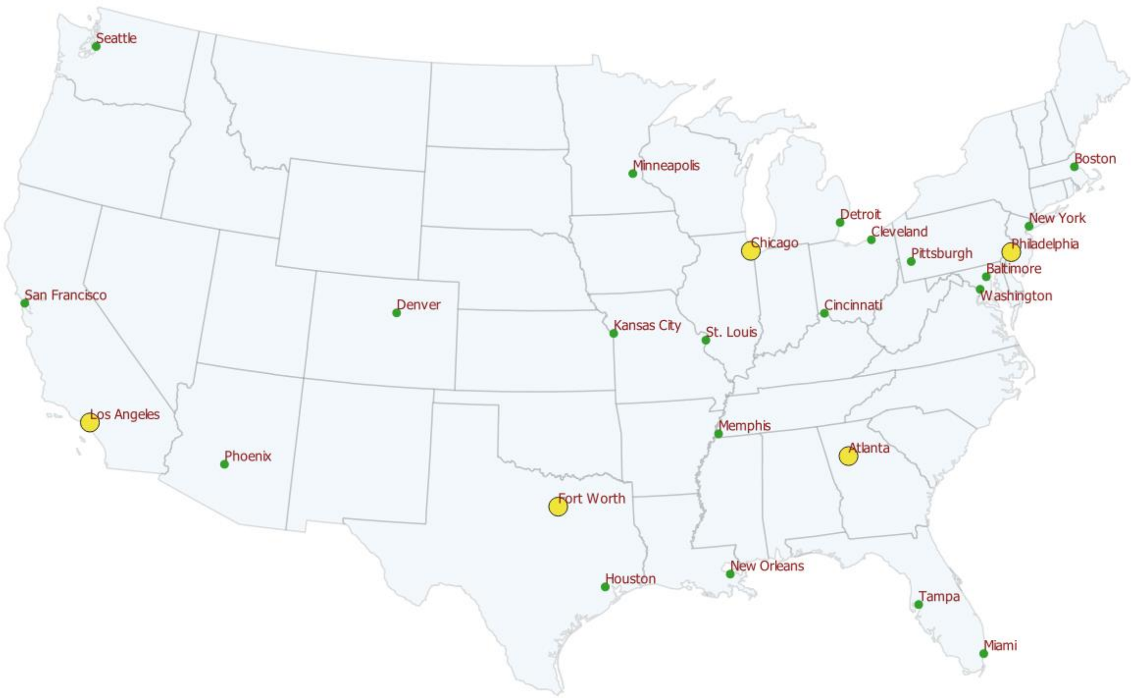

Fig 4.10 USA CAB dataset PFC location when α value is 0.8 and the number of PFCs is 5 with single assignment

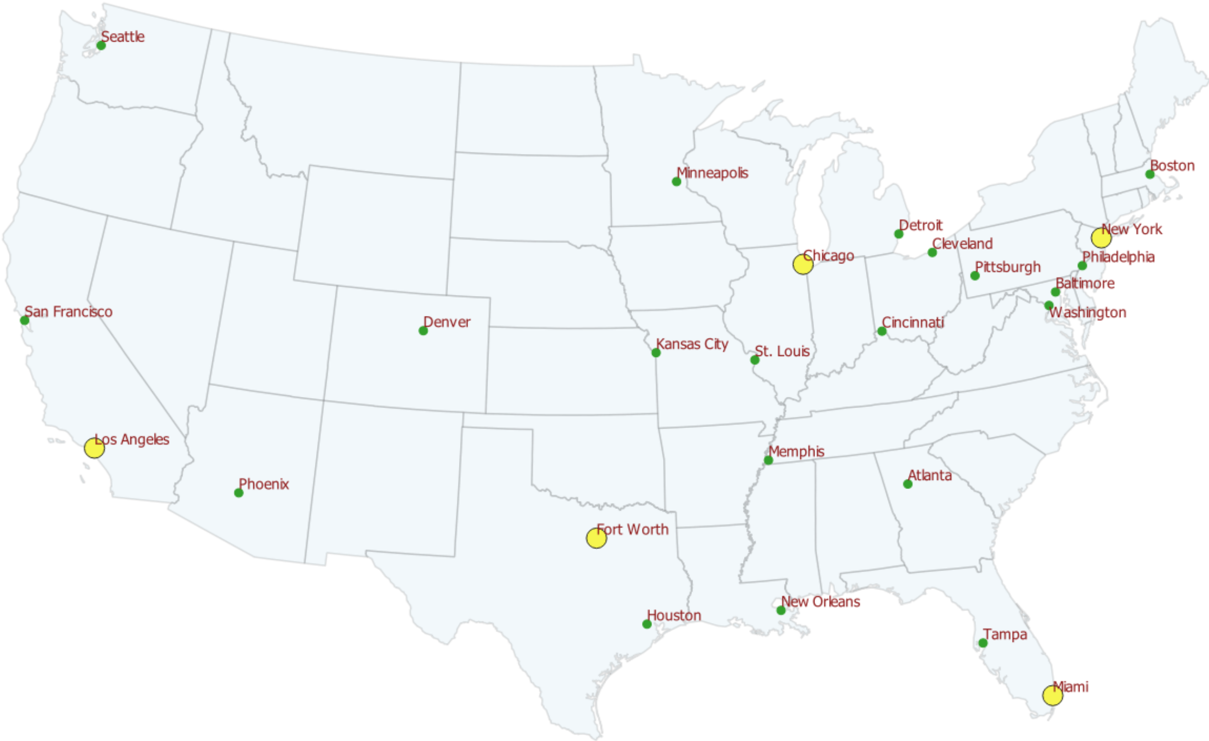

Fig 4.11 USA CAB dataset PFC location when α value is 0.5 and the number of PFCs is 5 with single assignment

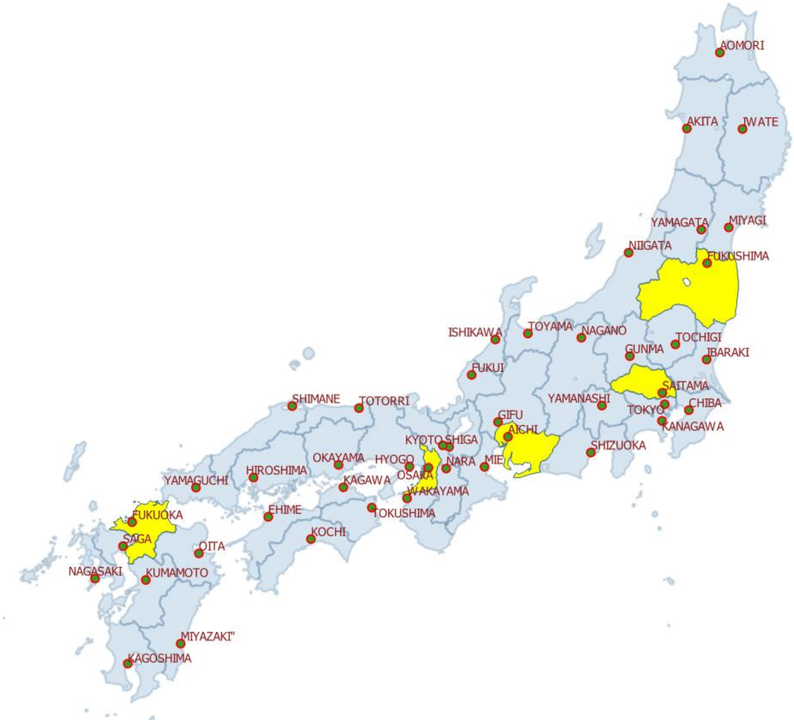

Fig 4.12 Japan dataset PFC location when α value is 0.5 and the number of PFCs is 5 with single assignment

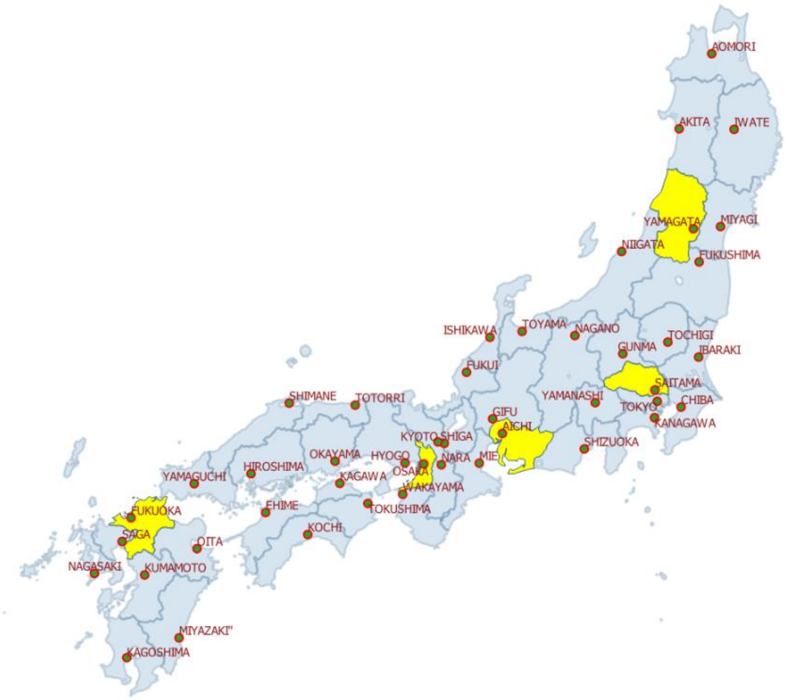

Fig 4.13 Japan dataset PFC location when α value is 0.4 and the number of PFCs is 5 with single assignment

When it comes to multiple assignment, PFCs do not change a lot depending upon α value, at least as frequently as what it happens in single assignment. For example, when we will decide to assign four PFCs in multiple assignment, the same four PFCs appear no matter what α value is, which in other words, no matter what the platooning scenario is. This finding is same for all these three datasets. So, it can generally be concluded that multiple assignment is less sensitive to platooning scenario variation which can lead to different α values.

4.3.6 Infrastructure Planning

When we discuss about the infrastructure, it is much needed to emphasize its long-term usefulness. Infrastructure is not something which can be relocated, modified, or even demolished very easily at low cost and therefore, it needs to be strategically important since the early phase of planning, regardless of the usage scenarios change in the future. Therefore, from locational analysis perspective, it is critically important to figure out which nodes appear frequently as hubs in most optimization instances, which should stay top in the priority list for infrastructure building. Specifically for PFC planning, not only PFC location, but also the characteristics of the travel routes between PFC and non-PFC nodes, based on automation level change and different number of PFCs, are worth being deep dived for better recommendation of PFC planning purpose. Having said that, based on Table 4.1, Table 4.2 and Table 4.3, there can be a lot of deep analysis as per the specific number of PFCs and the driving automation level, from which one can make a proper infrastructure planning idea, given financial, locational and some other constraints as further research.

The example analysis for Japanese dataset can be made as follows. In the single assignment, as the number of PFCs increases, the optimal location stays along the Pacific Coast and there is no significant difference between different automation scenarios in terms of optimal PFC locations with the change in number of PFCs. The following figure 4.14 shows the common results of three different automation levels for single assignment scenario when the number of PFCs is equal to 3.

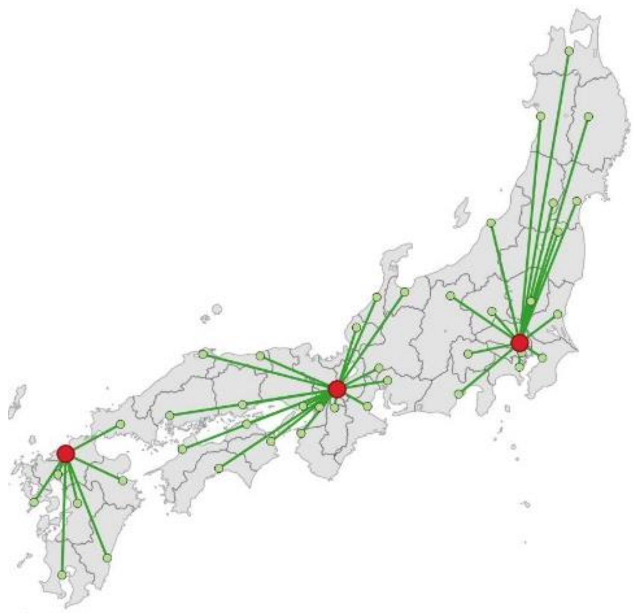

Fig 4.14 Common results of all automation levels for single assignment of 3 PFCs

When number of PFCs becomes higher, PFCs tend to accumulate along the Pacific Coastal Regions as per following figures.

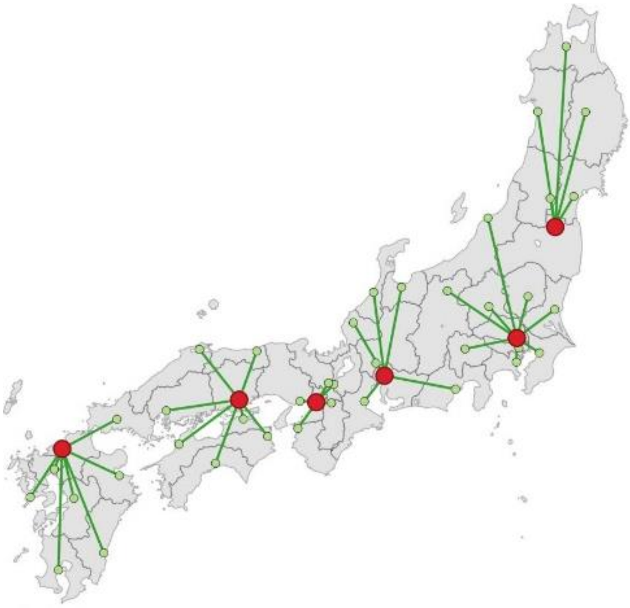

Fig 4.15 6 PFCs location in single assignment scenario I and II

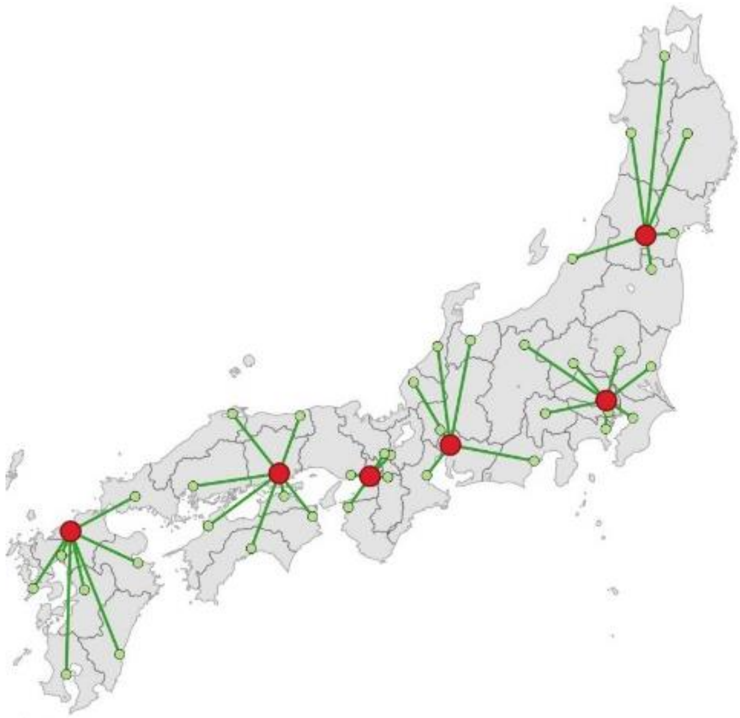

Fig 4.16 6 PFCs location in single assignment scenario III

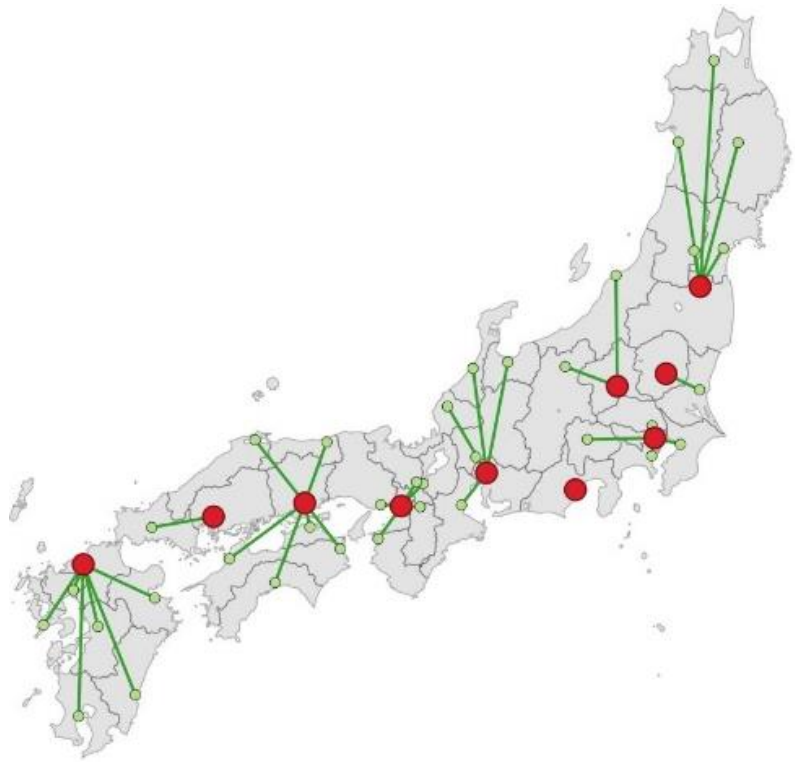

Fig 4.17 10 PFCs location in single assignment scenario I

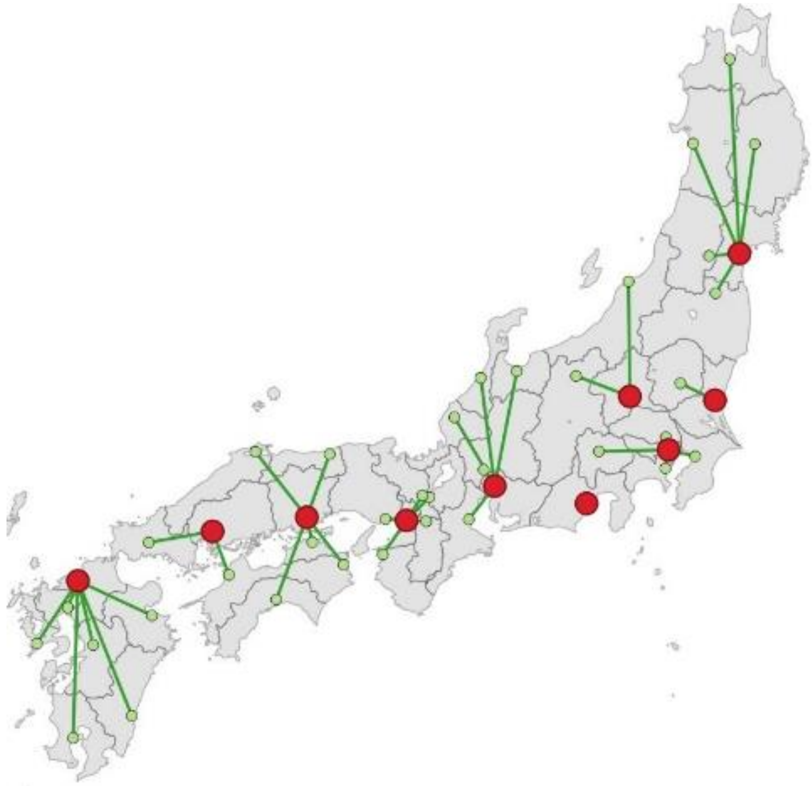

Fig 4.18 10 PFCs location in single assignment scenario II and III

When it comes to multiple assignment, for optimal location in case of 10 PFCs, it can be noted that change in the automation scenarios leads to decrease of allocation links between origin/destination nodes and PFC nodes, shown as green lines in the following figures. Consequently, the allocation is more concentrated to neighboring PFCs. As a common result of the scenarios, the locations in Tohoku, South Kanto, Chukyo, Sanyo, and Northern Kyushu on the Pacific coast are highly likely to be utilized even if there is a change in the situation of the level of automation after the early development of the PFCs. As a result of the difference between the scenarios, the location in the Chubu region shifts from Hokuriku to the North Kanto region, where transportation demand is high.

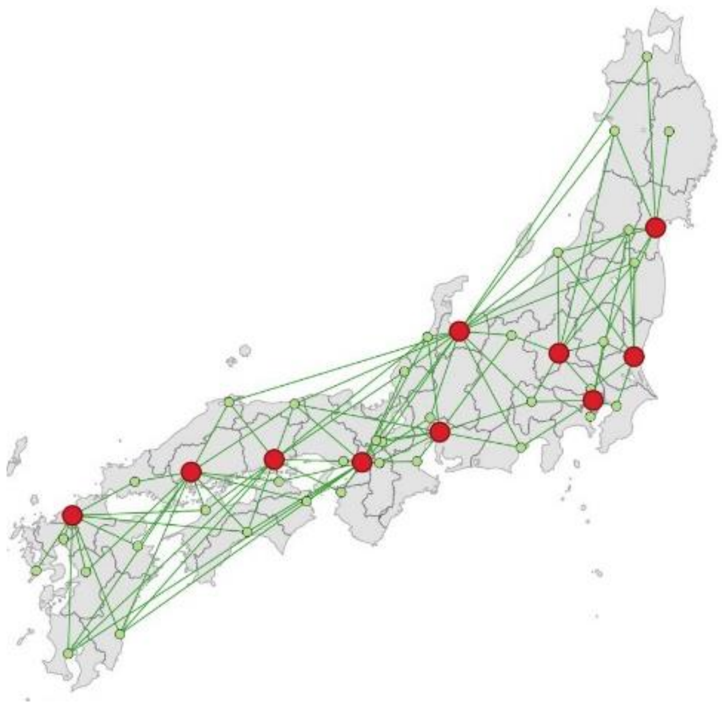

Fig 4.19 10 PFCs location in multiple assignment scenario I

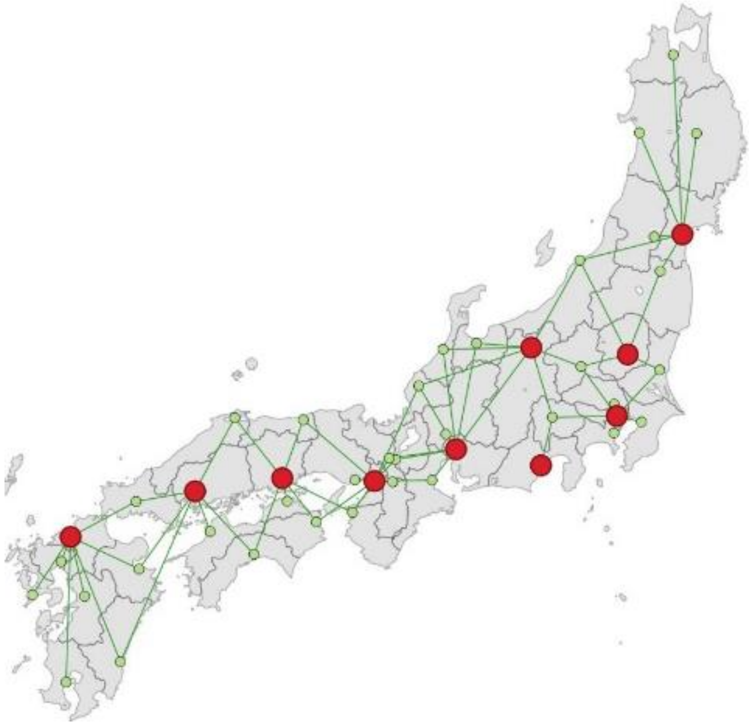

Fig 4.20 10 PFCs location in multiple assignment scenario II

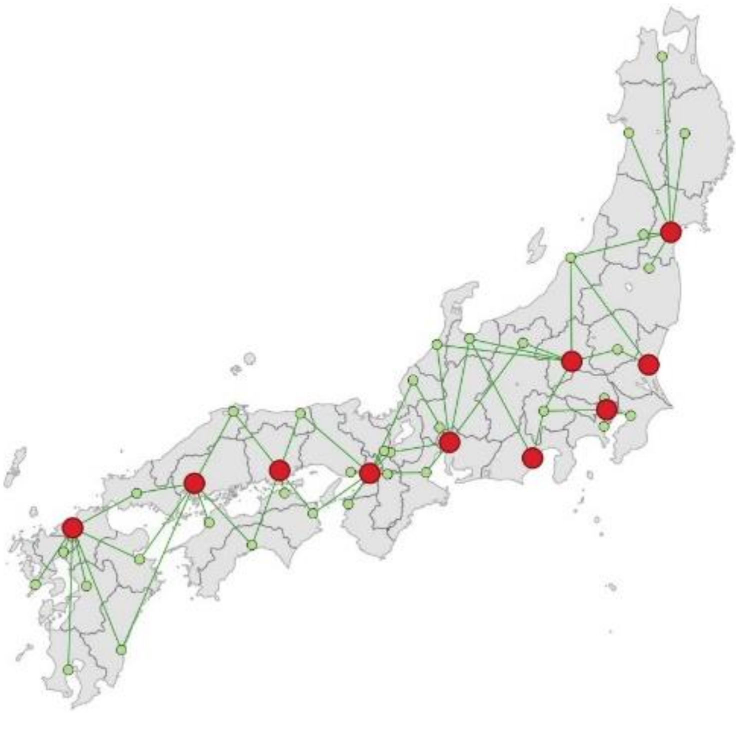

Fig 4.21 10 PFCs location in multiple assignment scenario III

5. Conclusion

5.1. Conclusion

For platooning operation, it is very important to strategically locate PFCs for several objectives and one of which includes reduction in total transportation cost, just like any other hub location problems. However, for PFC location problem, it is also very important to include the assumption of cost reduction due to platooning in our PFC location model to better reflect the realistic benefit of the truck platooning, unlike economic scales in other normal hub location models. From our analysis, the conclusions including the following points but not limited to, can be made.

(i) Increasing the number of platooning trucks in each platoon cannot significantly bring down the inter-PFC travel cost between two platooning hubs. Changing the platooning system from completely manned driving to semi-unmanned or totally unmanned driving system can reduce the inter-PFC travel reasonably.

(ii) If trucks from a specific origin can be assigned to more than one single PFC, it can reduce the total travel cost considerably as well. Therefore, it can be summarized that increasing the number of PFCs or allowing multiple PFC assignment system can reduce the total travel cost more than increasing the number of platooning trucks in a platoon.

(iii) Lower inter-PFC discount factor means that truck platoons can enjoy more of the platooning benefit. Therefore, lower inter-PFC discount factor can generally lead to larger inter-PFC distance. This characteristic is more commonly found for single assignment. In other words, optimal PFC location in multiple assignment is less sensitive to discount factor variation or different platooning scenarios.

(iv) Nodes with the larger trade flows tend to appear as PFCs repeatedly in almost all optimization instances, regardless of the spatial distribution pattern of the dataset. Most of the nodes with lower trade flows never appear as PFCs in all optimization instances.

5.2. Further Research

In the real world, there are a lot of factors needed to be considered for the optimization process. There is no single such simple objective as total transportation cost minimization because there are some other concerns need to be included such as maximum coverage, latest arrival time and so on. In addition, the objectives can be different depending upon the types of goods to be transported. To better reflect the reality, future research should be done, with multi-objectives rather than standalone single objective done in this research.

Moreover, the capacity of the PFCs may need to be considered when it comes to the platoon formation at the platooning hubs. The congestion in PFCs can have a huge impact on total transportation cost as a whole. The platoon formation in PFC can be really complicated depending upon a lot of factors such as by when the trip information from the participant trucks is obtained, the assignment system and so on. The reason is the fact that even though multiple assignment is more cost efficient than single assignment, there are a lot of complexities because even from a single departure node has different assignment patterns to different PFCs based on their respective destination nodes and their respective trade flow. Just changing the trade volume to the destination nodes can change the assigned PFCs. Therefore, multiple PFC assignment may take longer platoon formation time than single PFC assignment, which is the fact to be included in the later research to investigate whether multiple PFC assignment really saves more cost than single PFC assignment, considering different managerial perspectives.

In addition, several fixed costs can be integrated to our modelling process. The biggest proportion of that fixed cost will go to truck insurance cost, PFC locating cost, PFC development cost, land price and so on. From the location cost perspective, it will not be sensible enough if we will locate PFC at an expensive location even though it will be technically and strategically important to bring down the cost. In order to persuade the truck industry about the platooning technology, a researcher carefully needs to pay attention to the business case as this will be one of the main promising incentives to the key stakeholders. There are also some other variable costs which can be considered such as toll cost, arc link cost and so on. However, it has to be noted that too many constraints may not reflect the reality better every time. In some cases, it can even lead to less reasonable optimized values.

Therefore, a researcher should always rely on his common sense and background knowledge rather than model alone.

In addition, it is also recommended to try other optimizers such as Gurobi, as Xpress IVE solver used in this study can only optimize for around 50 nodes as maximum as far as our analysis goes. It is not recommended to use LocalSolver optimizer because its optimizable dataset is not as large as XpressIVE and it can even take longer optimization hours than XpressIVE according to our experience. There can be more optimizers available which can effectively optimize a larger dataset, so it is recommended for a researcher to try as many optimizers as possible and use the most efficient one for optimizing a large dataset in future research. However, we need to bear in mind that optimization problems are NP hard, so no matter which optimizer is used, it cannot optimize a very big dataset. In this aspect, heuristics solutions are viable for optimizing big data. Moreover, the dataset optimized in our analysis represents more or less benchmark size, which is the solvable extent for an optimizer. Our optimizing algorithm will serve as the skeleton model, which can be applied to any dataset regardless of the distribution pattern. Therefore, we can optimize other countries' dataset as well, not just limited to the dataset used in our analysis but as discussed earlier, if the dataset is too big, we need to reduce the data size to a benchmark size to reach optimality or otherwise, we need to find heuristics solution if we will not compromise the data size. Here, there is no standard definition about the bigness of the data size, which will determine the threshold level from where heuristic solution should start to be considered. As long as chosen optimizer can optimize the dataset, we do not need to consider the heuristics method. Therefore, it is highly important that a researcher needs to adopt a proper optimization method based on the dataset and the optimizer which will be used in optimization process.

Last but not least, it is recommended to carry out deep analysis about the allocation analysis for infrastructure planning as discussed in 4.3.6, as this is quite helpful for the infrastructure policy recommendation. From allocation pattern, one can easily notice the long-term usefulness of the PFCs, which can be prioritized in terms of the frequency of their occurrence as PFCs. Similar allocation can be mapped regardless of datasets for regional planning purpose. The process can be made more realistic by adding more financial and locational constraints into modelling process for better realistic allocation visualization.

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