Master's Thesis of Arts

Spatio-Temporal Optimization for Locations and Routes of Mobile Vendors

- The Case of Food Trucks in Seoul, Korea -

이동식 상업의 시공간적 입지와 경로 최적화: 서울시 푸드트럭을 사례로

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Abstract

As the mobility of people increases, the market vendors in urban areas also obtain spatio−temporal dynamics. The enhanced mobility yields the behavioral change, for not only the customers but also the market vendor's business model. The food truck is one of the representative mobile vendors which show the possibility of the mobility of the suppliers. In particular, the deregulation in 2017 enabled food trucks to move to another site. Also, due to the high rent in Seoul, the food truck is considered as a prospective business model for young people. Although there are new characteristics of mobile vendors, such as the food truck, the business model of the mobile vendor when the existing market was already located did not receive academic attention. This research aimed to optimize the locations and routes of the mobile vendor through spatio−temporal analysis.

This research designated three research questions. First, the locating trend of mobile vendors, when the existing competitive market already existed, has different result compared to the traditional mobile vendor's strategy. Second, the value of the multi−objective optimization method is verified to improve the mobile vendor's spatio−temporal optimal location and route sets. Lastly, the potential for improvement of current mobile vendor's strategy through spatio−temporal analysis is examined.

This research makes a model that targeted the current situation of Seoul. To reflect the spatio−temporal population dynamics, the de facto population data in Seoul was applied to this study. The objectives of the research were to reduce the dependency of the occasional festivals, maximizing the profit of food trucks, and minimizing the conflict between the existing markets and the food trucks. This research followed three steps to achieve those goals.

First, based on the descriptive data analysis, it was verified whether the population dynamics existed on the days, time, and region. By analyzing the locations of restaurants, which are

competitors to the food trucks, the relationship between the de facto population and the restaurant's distribution was empirically proved. Also, unifying two factors to compare the weight was conducted during the first step.

The spatial optimization method was applied to find the spatio-temporal optimal locations for food trucks in the second phase. After selecting the feasible area, the optimal food truck locations were found at each time period. To minimize the conflict between the existing restaurants and the food trucks, this research used the multi-objective optimization and made multiple scenarios depending on the weight factor α. As a result, as the α increases, the more food trucks are gathered into the CBDs in Seoul.

In the final step, the food truck's spatio-temporal routes were calculated, the minimal distance set of distance was composed, and the results were visualized. The data mining method, K-Means, was applied to capture the spatio-temporal clusters of mobile food trucks. The minimized distance set presented the optimal spatio-temporal locations and routes of food trucks. The results were presented by the 3D mapping method, due to the complexity of the data.

In conclusion, the food trucks showed different optimal locations depending on the α, but, at lunch time, the food trucks tended to gather into the CBDs. The reasons for these spatio-temporal patterns are mostly due to the economic and leisure factors during the weekday and the weekend. On the other hand, the food truck locations need to move at dinner time to follow the residential population in the outskirts of Seoul. The Pareto optimal set of this research showed superior results than the current food trucks location, which means minimizing the conflict and maximizing the capturing of demand.

This research used multiple methodologies of GIS and spatial optimization to analyze the mobile vendor's spatio-temporal optimal locations and routes. This research has significance in that it has built the model to deal with two separated factors, location, and traffic, in an integrated method with spatio-temporal analysis.

Keyword : Mobile vendor, Spatio−temporal analysis, Spatial optimization, Greedy adding algorithm, Multi−objective optimization, Vehicle routing problem,
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Chapter 1. Introduction

In recent years, urban areas in Korea faced totally unprecedented social changes and urban problems. Particularly, the development of urban transportation systems, such as the increase of subway lines, elaboration of bus routes networks, private automobile rate rise, and improved social accessibility of public transportation, contributed to a tremendous change in people's lifestyle in Korea. At the same time, many urban problems appeared and were recognized (e.g., high store rent and the gap between rich and poor). For a full understanding and to close the gap on the social problem, it is essential to acknowledge the urban social situations in Korea.

1.1. Study Background

It is a serious problem that the land price of Seoul has been highly increased both for residential and business purpose. Figure 1.1 demonstrates the temporal trend of land price index of residential buildings to compare with Seoul and South Korea when the land price index of 1987 is assumed to be 100. The slope of Seoul's land price index is steeper than the slope of South Korea. Particularly, from 2010, the difference of land price value index between Seoul and Korea has become serious. It means the land price of Seoul has been increased more rapidly than the global land price change trend in South Korea.

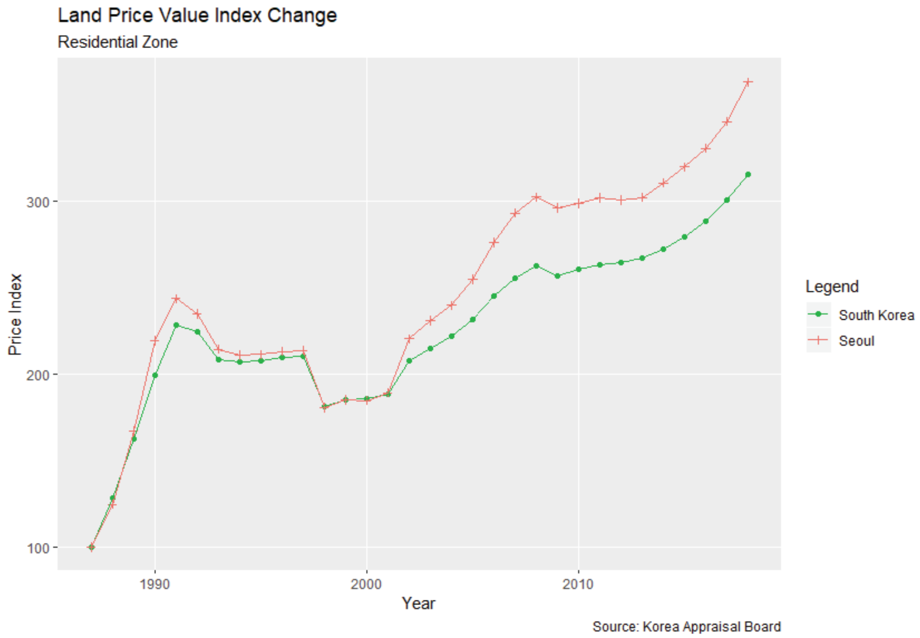

Figure 1.1. Land price value index change in Seoul

The median house price in Seoul was 434,850,000 KRW in 2016, which was similar to New York's median house price. Especially, the 'period of availability via savings'① in Seoul is 9.2 years (Statistics Korea, 2016), which means that young people in Korea have to save more than 20 years to buy their own house. So more and more, young people have tended to live with their parents and cannot establish their own companies in Seoul. Not only is Seoul the capital city of Korea, but it also has a lot of job opportunities for young people with over 47% of the companies located in the Seoul metropolitan area (Statistics Korea, 2016), so most of the young people want to live and work in Seoul.

High house prices also affect the rise of rent in the business district. The office rent price in Seoul has been the most expensive than any other 7 *Gwangyeok-si*② (Metropolitan City). Figure 1.2 shows that office rent per 1㎡, and office rent in Seoul is more than

① Period of availability via savings means the term that is needed to buy house with the person's own income savings without any expense.
② The biggest metropolitan city level in Korea

double than that of other cities. That is the main reason why young people in Korea cannot start their own businesses. On the contrary, starting up a mobile vendor does not require many funds for young people, such as office rent, purchase of office goods, and labor costs. For example, the average food truck purchase cost is about 20,000,000 KRW.③ It is relatively affordable for young people who have low investing power than the average person.

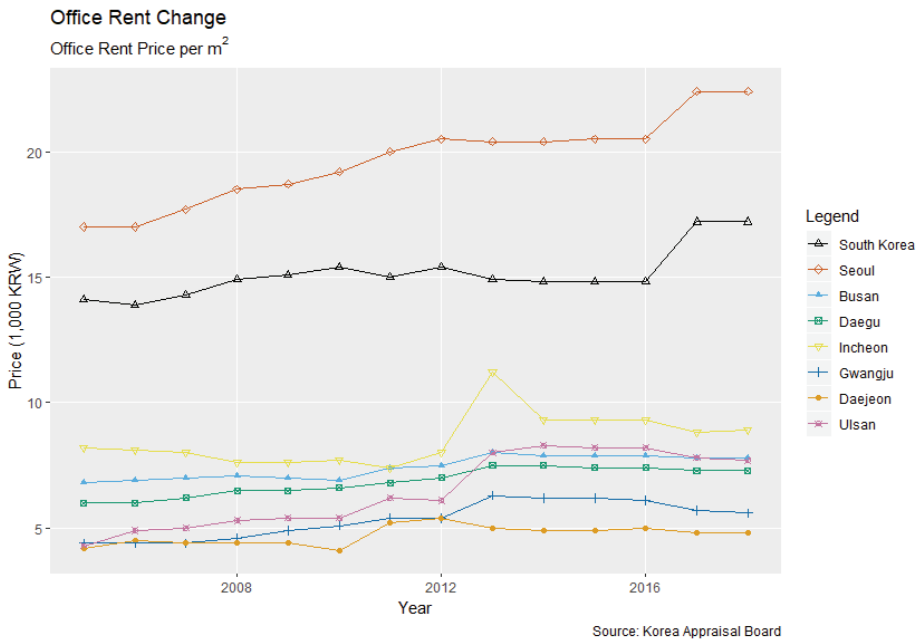

Figure 1.2. Office rent increase in Seoul

At the same time, the mobility of people has increased as transportation technologies have developed. Population distribution changes vividly, especially, in the urban (Bhaduri *et. al.*, 2007), people's commuting pattern and movement dynamic are so high due to the development of transportation in the city (Song Gao, 2014; Thomas *et al.*, 2014). On the other hand, increased mobility has made both the consumer and the supplier easier to move globally. The

③ It included the fee to tune a truck. The truck needs to be renovated to be converted as the food truck. The food trucks should equip gas cooking and safety system to follow the regulation.

dynamics of population distribution yielded spatio−temporal fluctuation of demand from the population. Therefore, capturing demand by following the population hotspots would be more profitable.

Furthermore, the spread of social media made it easier to get the food truck’s location and information. The locations of food trucks and their menu were provided on their own social media channels, such as Tweeter and Instagram. Unlike the fixed market’s advertisement, traditionally, unknown location and menu is the biggest problem for the food truck customers. The social media helped to connect the potential food truck customers and the food truck workers who have the mobility to access the location.

Food trucks have two advantages in the mobile age. First of all, mobile vendors can cover more demand if they follow the population flow well. The fixed stores can only cover the population without movement, but mobile vendors can cover maximum population by following the population flows. Second, the relatively low cost of purchasing the food truck makes it easy to be a food truck owner for the young generation. Due to the expensive price of fixed store fee, it is hard for the young generation have their own business. However, by operating the food truck, young people can make their own money and improve their economic situation.

Recently, the Seoul Metropolitan Government held a special conference on food truck management and finding new candidate areas for food trucks (Seoul Metropolitan Government, 2017). According to the result of the meeting, there were two major deregulations on food trucks. The first change is moving one spot to another spot in one day is now permitted for food truck workers. Before the amendment of the city ordinance, food trucks were only permitted to work in the authorized zones and could not move to other zones on the same day. This change enabled food truck workers to open their food truck and move to other places with registration to the city government in one day.

The second outcome of the meeting is enacting into law by categorizing possible food trucks working zones. Also, after the discussion, the city hall announced that the principles of food truck zoning will consider two factors; they want to find new food truck zones as “not only making high profits but also avoiding competition from the existing restaurant service area (Seoul Metropolitan Government, 2017).” According to the city hall and the food truck worker’s consensus, the demand to find the food trucks optimal locations that can capture maximum profits and minimum interference on the existing commercial district. So, in this analysis, using a multi-objective optimization model for maximizing profits and minimizing conflicts with the existing restaurants will work to solve this problem.

Before the meeting, the food truck workers operated their food trucks on the open space, and most of their income was made from temporal festivals. For example, *Seoul Bamdokkaebi Night Market* was their primary income opportunity. During the Seoul Bamdokkaebi Night Market, many food truck workers parked their trucks and did not move to another place. The food truck workers said that they do not know a feasible area to operate their food trucks. They used many social media, such as Instagram (refer to Fig 1.4), Facebook, and Twitter, but it was hard to find the expected demand hotspots. Therefore, they parked their food trucks in the market and abandoned the food truck’s mobility (refer to Fig 1.3).

Figure 1.3. Fixed food trucks in Seoul Bamdokkaebi Night Market

Even though the food trucks earn sufficient income from Seoul Bamdokkaebi Night Market, the market is an occasional event. Finding the food trucks' stable operating site is needed to improve the food truck worker's economic status in the long term. The social need to find the spatio−temporal food trucks hotspot is increasing.

Figure 1.4. The food truck's social media advertisement

1.2. Purpose of Research

In these social backgrounds, this research aims to analyze the optimal spatio−temporal locations of food trucks to improve social benefits. This research aims to improve the current food truck's situation. The actors who utilize this multi−objective optimization decision supporting system are the decision makers, such as law makers, stationary restaurant owners, and food truck owners. Specifically, this study has three objectives.

A primary objective of this research is to develop a competitive mobile vendor's location and route models in Seoul, particularly when the traditionally fixed stores already located. Although most of the Seoul area was covered by facilities, it is hard to cover all the maximum demand on each day. With the supply of fixed stores, mobile vendors will have different optimal locations and routes for each vendor. Former studies were focused on the mobile vendor's behavior, when the field was not covered by fixed stores. This study will figure out the unique characteristics of mobile vendor's location and route model, when the competing fixed stores were already located.

The second purpose of this study is to make spatio−temporal multi−objective optimal location scenario sets change, with the base competing stores. The mobile vendors of this research should consider both maximizing profit and minimizing competition. Particularly, the relation between profit and competition of the mobile vendor is inverse. Variety of models applying different weight factors helps to find out the difference between spatio−temporal optimal locations of the mobile vendors. Various sets of the vendor locations and routes will lead support stakeholders' spatial decision−making process.

The last objective is improving the business model of the mobile vendors in Seoul. This study will suggest the spatio−temporal optimal locations and routes sets of the food trucks. The results of this study shows the multiple scenarios of food truck's model. The multi−objective optimization based scenarios can improve the current food truck's situation by reforming the locations and routes. The results will show the improved business model of the food trucks and present the way with an effective mapping method. Due to the complexity of the spatio−temporal data, new mapping method is needed to support spatial decision model to improve the current food truck's situation. Therefore, this study will show the reformed business sites with effective visualization methods.

To achieve the three objectives of this research, I used GIS and spatial optimization methodologies. To analyze the competing aspects of mobile vendors and existing restaurants, spatial interpretation is required. Particularly, the spatial optimization method offered a change in the competing market range. Also, mobile vendors have the mobility to access another site in one day. So network−based distance calculation and spatio−temporal movement analysis can be achieved by applying GIS and spatial optimization methods.

This research designed three research questions to analyze the optimal locations and routes of mobile vendors. And spatio−temporal analysis and mapping method are suggested. The major research questions are as follows.

First, what is the distinct mobile vendor's optimal location when the existing market is already structured?

Second, can it be possible to apply multi−objective optimization to build the mobile vendor's spatio−temporal business location model scenarios?

Third, can spatio−temporal analysis improve the mobile vendor's current business model about locations and routes and present the results effectively?

1.3. Organization of Chapters

Based on the research purposes, this research is organized as follows (refer to Fig 1.5). In Chapter 2, the literature review is presented. Both traditional periodical market model theory and competitive location model are reviewed in Chapter 2. Notably, the food truck location research and routing problems are combined with the research about mobile vendors and competitive location models. Thus two kinds of academic achievements are reviewed. The research methodology and research area information are discussed in Chapter 3. This chapter presents the definition of research keywords and analyzing methodologies. To clarify the process of the research, the methodology is divided into three parts, location analysis, spatial optimization, and vehicle routing problem (VRP). The result is yielded in Chapter 4. In this chapter, three scenarios of multi-objective results are presented. In particular, data mining, VRP, and space-time cube are also shown with the interpretation. In Chapter 5, the thesis is concluded with a summary, and further proposal is discussed.

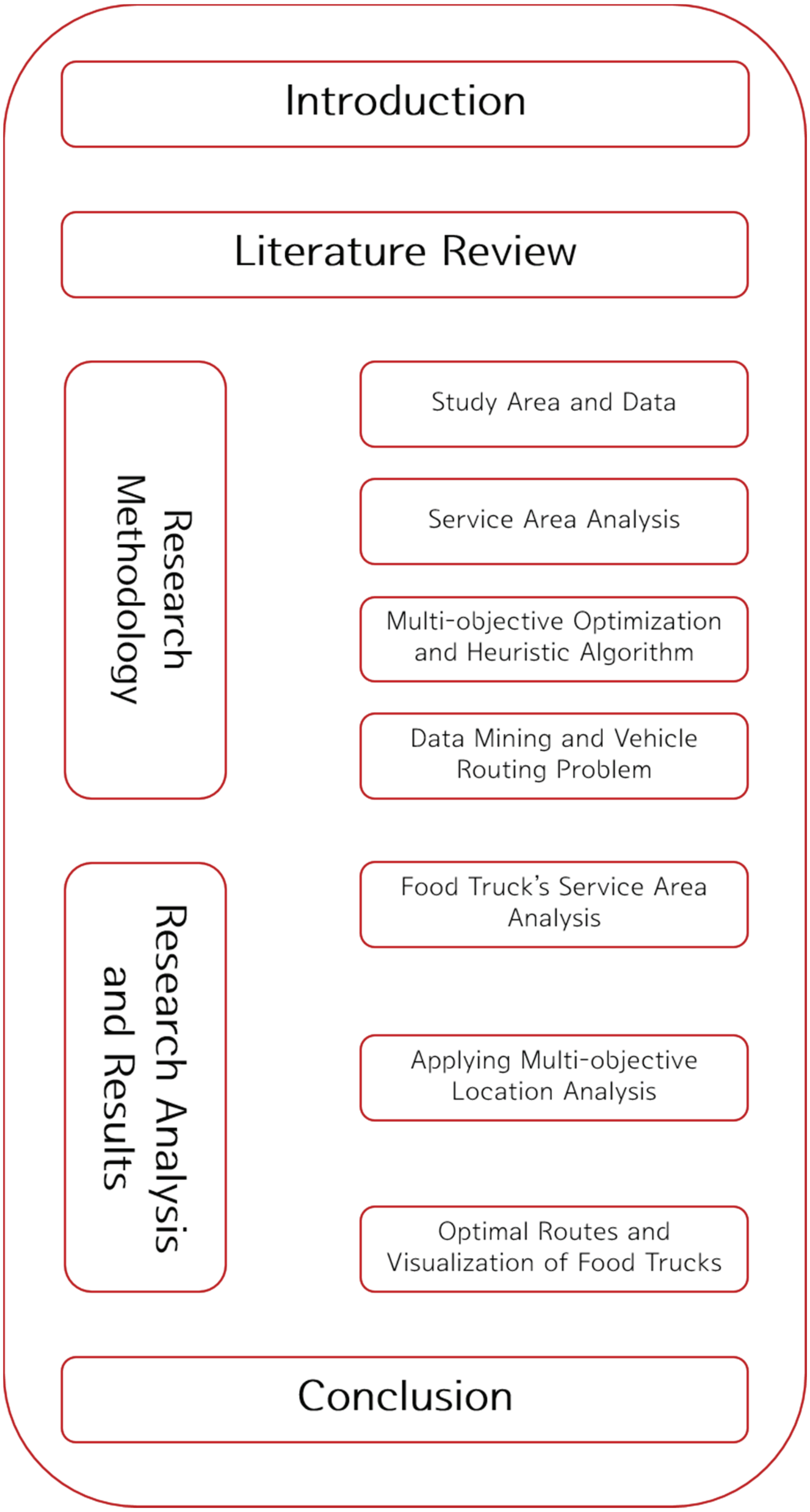

Figure 1.5. Research Flow

Chapter 2. Literature Review

2.1. Periodic Market Model

Traditionally, periodic market research has been widely developed from the seminal book of J. H. von Thunen (1826). He looked at evolving the periodic market from the development of communication and transportation in the farmland. The farmer's markets, which are the representative periodic market, have grown over the past 30 years (Brown, 2004).

Christaller (1932) also dealt with the periodic market as a developing step to constructing permanent market structures. Due to the lack of demand in the range, the suppliers need to move to capture sufficient demand. Therefore, if the demand in the area reaches the threshold of the supplier, then the supplier would settle down in the area. And he explained the Central Place Theory to show the steps of constructing the market structure.

Stine (1962) studied the periodic markets in Korea. He analyzed the workers of periodic markets and searched their routes. By studying the periodic market workers, he explained the periodic market's characteristics based on the concepts of range and threshold of the Central Place Theory. Stine argued that if the range of the goods is smaller than the threshold, then the trader becomes a mobile vendor.

Gosh (1982) developed the research to make a mathematical model. He aims to study the locational behavior of the itinerant trader. He analyzed how to maximize the profit of the periodic market workers by applying the optimization approach. He focused on the locational strategy and the consequent spatio−temporal pattern of the periodic market system.

The past researches focused on the development and characteristics of the periodic market. The periodic market was considered as an intermediate stage to construct the permanent market structure. However, some novel business models, such as food trucks, also have high mobility. Therefore, the mobile vendor model would be one of the models of market structure, not of the intermediate stage. So the completeness of the periodic market model needs to be considered in the recent study.

In addition, the past research considered the periodic market without the permanent market structure. With the increasing mobility of the stores, there are both fixed and mobile stores in the same area. For example, the food trucks and the traditional restaurants exist in the same area. To analyze the realistic problem, the fixed competing stores need to be considered as one of the factors to locate the mobile vendor.

Though the impressive researches about the periodic markets were introduced, there is scant published work to date and almost no scholarly discussion regarding modern markets (Brown, 2002). The research of the periodic markets can be rediscovered with the current situation of increasing mobility. So, the periodic market's research has to be re−considered with a more significant social value.

2.2. Competitive Location Model

Traditionally, competitive location models pose two major questions: locating new facilities among already existing competing facilities and allocating customers to a specific facility (Lee, 2008). The first study of spatial economics and industrial organization is Hotelling's (1929) seminal paper. Since Hotelling's (1929) work published, a variety of economic assumptions and location equilibrium has been applied in location analysis, And the competitive location problem has a clear interdisciplinary benefit to a variety of fields of study (Eiselt *et al.*, 1993).

Lee (2008) presents three components of competitive location model's backgrounds: spatial competition, location theory, and customer behavior theory (refer to Fig 2.1.). The location theories and customer behavior theories are dealt with in the next part.

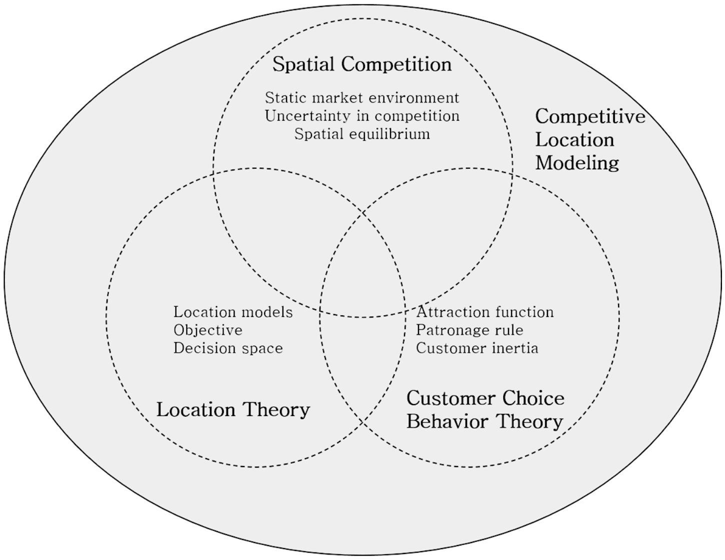

Figure 2.1. Major components in competitive location modeling (Lee, 2008)

Deterministic choice-based competitive location models are assumed that customers choose the nearest of the most attractive facility. This model's supposed people to keep their behavior reasonable. When the deterministic choice-based competitive location models are applied to allocate the customers to the facilities, the large number of feasible facilities and the customer significantly increases the computational burden to solve the location analysis (Church, 2002).

This research used discrete space as a research area. Also, if the two market range overlaid, the market area was shared with the Break-Even Distance method. Drezner (1994) introduced the BED and circle geometry. The market will capture the demand which is closest to the market core. By dividing the demand based on the distance, the demand is allocated to the nearest market.

Prior studies analyzed the deterministic choice-based competition model for the fixed market. It means the suppliers are fixed at their location, and the demand is divided to allocate the nearest supplier. Due to the computation burden and the lack of mobility of suppliers, the research on the mobile vendor's deterministic choice-based competitive location model is hard to study. However, with the development of analyzing tools, such as CPU and GPU, the traditional obstacles for the research were waned. Therefore, the research on the mobile vendor's competitive model considering the existing competitors is recently enabled. The food trucks location and allocation problems are not well recognized as a social and academic problem. There were some studies about the restaurants market area or a food desert concept (Widener *et al.*, 2012; Simons, 1992). Food trucks shared some characteristics of the regular market and the traveling salesman problem.

2.3. Multi−objective Spatial Optimization

Spatial optimization developed a variety of competitive location models. A *p*−median problem is one of the earliest formulations of a location−allocation model (Cooper, 1963; Hakimi, 1964; Teitz and Bart 1968). The *p*−median problem based on the allocation process that the consumers are assigned to the closest facility. Because of the objective function in the *p*−median problem that minimizes the sum of the distance between the customers and facilities, the problem usually applied to the problem that only concerns the distance.

Maximum capture problem and a *p*−center problem are also widely used spatial optimization approaches. ReVelle (1986) proposed the maximum capture problem, particularly, considering the Maximal Covering Locations with minimal facilities problem (MCLP). The maximum capture problem's objective is capturing as many customers as possible who are allocated to the nearest facility. The objective of the *p*−center problem is minimizing the maximum distance between the demand and the nearest facilities (Daskin, 1995). The *p*−center model aims to cover all the demand by the facilities' range. Both models are well applied on spatial analysis, however, the food truck's demand capturing characteristic does not match the assumptions of the models.

Due to the conflicting factors, such as demand and competition in the location analysis, problems of reality need to consider multiple scenarios. Pareto optimum is proposed by Pareto (1906). The Pareto optimum suggests the non−inferior solution sets, Pareto front. Multi−objective optimization is based on the Pareto optimal concept that defines the set of solutions that were not inferior to any other feasible solutions. There were several types of research on spatial multi−objective optimization. Cao *et al.* (2011) used the spatial multi−objective optimization method on the land use part. To make diverse scenarios and spatial decision support systems, the researchers also applied a genetic algorithm to the land use model. Likewise, Zielinska *et al.* (2008) applied the spatial multi−objective method on land use allocation. Kuby *et al.* (2005) made a trade−off curve of dam removal scenarios with the multi−objective optimization method. Czyzak and Jaszkiewicz (1998) developed a simulated annealing algorithm for the metaheuristic method of multi−objective optimization. By using simulated annealing, the calculation time of the Pareto optimal set decreased.

Due to the multiple scenarios and Pareto optimal sets, the computation burden to solve the multi−objective problem is huge. Also, the spatial optimization problem has larger data and computation size than the non−spatial optimization problem. Therefore, many heuristic algorithms were developed and applied to the optimization problem. Simulated annealing, Genetic algorithm, and Greedy algorithm are popular heuristic algorithms.

The above studies are based on urban planning aspects. There was almost no study using the multi−objective method on the more micro scale issues both in terms of spatial and economic considerations. This study is focusing on the mobile vendor’s location and routes problem which are emerging social and economic problems in Seoul.

2.4. Research on Food Trucks

The food truck is a newly emerging business model, so there were few limited types of research about the food trucks. Most of the researches about the food truck focused on the food truck's business model as a restaurant. Particularly, the menu of the food trucks is studied (Lee, 2018; Joo, 2018; Oh, 2019). Lee (2018) and Oh (2019) studied which factors are important for the consumers to visit the food trucks. The price, taste, and emotional satisfaction are the dominant factors of the choice. Joo (2018) showed which element affects the consumer's visit to the same food truck. Those researches figured out the importance of menu development and consumer's experience in the food trucks. However, these researches are only concerned with food trucks as a kind of restaurant business model, the same as a traditional fixed restaurant.

Secondly, the research on the regulations of food trucks is done. Kim (2014) discussed the restricted conditions of food trucks in Korea. He argued that the regulations in Korea suppressed the operation of the food trucks. Park (2015) reviewed the regulations of the food trucks by comparing the foreign regulations. Also, Moon (2017) analyzed the food truck's utilization to enhance social values. After the deregulation of Seoul in 2017, the situation that the food trucks face has totally changed, so the new research has to consider the current change in Seoul.

The food truck researches are prolific in other countries. Food truck's utility is analyzed with health and nutrition covering methods. The food trucks can deliver and cover marginalized areas of food supply (Acho-Chi, 2002). Particularly, the developing countries can obtain more social benefits from operating food trucks to cover the food deserts. Not only in the developing countries but also developed countries applied food trucks as the supplement of the traditional restaurant's menu. Wallace (2012) argued that the food trucks could have a role in enhancing public health. In the regional scale, the food trucks can be healthy nutrition suppliers for the residents (Lassere, 2013). Those researches already recognized that the food truck's unique characteristics can boost the social values in the region.

In addition, some studies analyzed the food truck's routes problem. Liu (2013) formulated the linear network system of food trucks in San Francisco. And Bhandawat (2018) made a model to maximize the benefits of the food trucks in the New York metropolitan area. Also, Wessel *et al.*, (2015) suggested the method of using Twitter to promote and maximize the profits of the food trucks. Although these researches suggested how to optimize the food truck's operation, the spatial analysis is needed to compensate for the results as one of the most important factors in the restaurant selection is proximity in Korea (Lee and Sul, 2014).

Reviewing the past research made the objectives of this research clearer. Due to the radical change of social and legal situation, the new research has to reflect the deregulation and existing market structures in Seoul. And the food truck's location and allocation problem will be solved by multiple methodologies. Because of the complexity of the problem, it should consider both location analysis and routes finding the problem. In Chapter 3, the appropriate methods are introduced to analyze the food truck's location problem.

Chapter 3. Research Methodology

This study integrated multiple spatial analysis techniques. In this chapter, a brief introduction to the study area is presented in the first part. Also, the characteristics of the de facto population and the existing food trucks operation status are discussed in this part. In the second part, the method that the service area defined is discussed regarding social and legal conditions. The multi-objective spatial optimization and heuristic algorithm is discussed in the third part. Due to the huge dataset and calculation time, this research applied heuristic algorithm instead of using exact solution solver. In the final part, data mining and Vehicle Routing Problem (VRP) is presented to define food trucks routing set. By incorporating those methods, the food truck locations and routing problem can be solved.

3.1. Study Area and Data

3.1.1. Research Area

In this study, the research area is Seoul, South Korea. Seoul consists of 25 *Gu*, 424 *Dong*, and 19,153 *Jipgyegu*[④]. This research determined Seoul as the research area due to three reasons. First of all, the business districts and residential area is significantly separated (Byun and Seo, 2011; Eun, 2011). Due to the segregation between business districts and residential area, there was tremendous dynamic population flow on Seoul. Dynamics of population distribution yielded a spatial change of demands that were derived from people. These spatial dynamics of population distribution showed the results of the research model more obviously.

Since 2017, Seoul Metropolitan Government has provided the de facto population at every hour using the jipgyegu scale. By applying this data, it is enabled to capture spatio-temporal population

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④ Jipgyegu is the minimum census unit in South Korea. Mean residential population and area per jipgyegu is 643 and 0.03㎢.

distribution and high demand spots. Because of the sensitiveness of food trucks location on demand, it is significant to analyze the real-time population flow on the research area, particularly, the Seoul government's various datasets, such as road networks, population characteristics, and legal regulations, to support research. This research environment helped to construct and verify the robust model.

Finally, the Seoul Metropolitan Government considered food trucks' poor locations problem as an important issue and held the meeting with food truck workers. As a result of the consensus, Food trucks in Seoul have been enabled to move one location to another location on the same day. So the 500 existing food trucks in Seoul (refer to the right map of Fig 3.1) got mobility to follow population flow.

Before the meeting, six months after starting the business, 35% of the food trucks were out of business (Seoul Metropolitan Government, 2017). Particularly, the lack of sites to operate the food truck made it hard for the workers to capture optimal population, due to the opposition of the existing restaurants and regulation. However, due to the amendment of regulation, the food trucks can find the optimal locations at each time period. And this spatial study can detect the spatio-temporal niche of the existing restaurants. Due to the dynamics of the population distribution, the site that had low attraction at the prior time can be the competitive site at the next time period with the low competition.

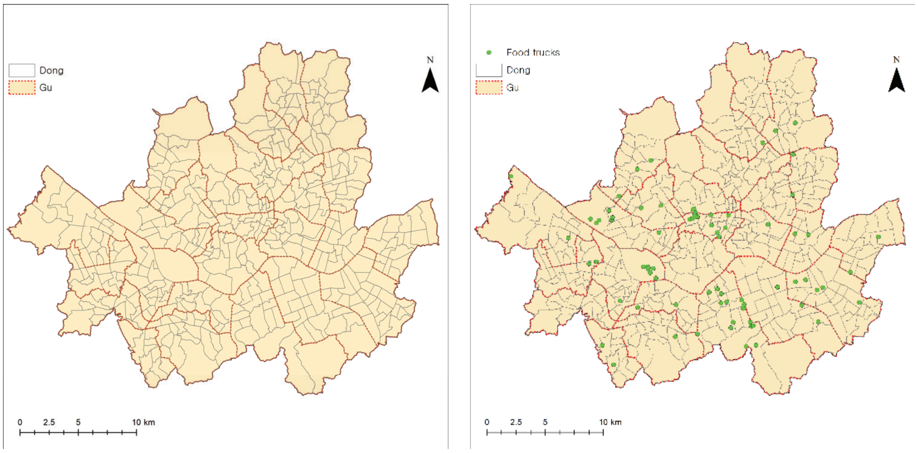


Fig 3.1. Research area and existing food truck locations

3.1.2. Data Description

Main data applied in this research is the de facto population. De facto population in Seoul is calculated with KT telecommunications big data and building data. The data contains five items (refer to Table 3.1), and Seoul Metropolitan Government and KT [⑤] constructed de facto population in Seoul. Applying jipgyegu ID to each spatial coordinate enabled geo-referencing the de facto population spatially. Telecommunication data made it possible to represent the de facto population in Seoul (Lee & Kim, 2016).

Even though floating population on the roadside has high correlation to the food truck's daytime sales, the potential demand of food trucks is not only on the road, but also includes the people who stay inside while the office hours. Also, the de facto population can represent the population dynamics in the city. So this research analyzed the de facto population data to explore the dynamics and change of population in Seoul.

⑤ Telecommunication company in South Korea

Table 3.1. The data description

Item	Explanation
Date	The day the population was measured
Time	The time the population was measured
Jipgyegu ID	The unique ID of jipgyegu that contains a population
Age	The population's age information
Sex	The population's sex information

Following the spatio−temporal change of de facto population in Seoul, the demand, de facto population, in the range fluctuated at each time period. The time period is divided into four categories. That time span is the usual meal time in Korea (Jin, 2017). In addition, weekdays and weekends have different population dynamics, so time periods are defined to those four categories: Weekday lunchtime, Weekday dinner time, Weekend lunchtime, and Weekend dinner time (refer to Table 3.2). The period demand is calculated by aggregating the de facto population at each time span. This research used the de facto data in Seoul at 13^{th} and 16^{th}, June 2018. Two dates are selected to represent the normal phenomenon of the population dynamics in Seoul. 13^{th} June in 2018 was Wednesday, and there was not an extreme event in Seoul. The other day, 16^{th} June in 2018, is Saturday. These two days represented ordinary weekdays and weekends' population flow in Seoul.

Table 3.2. Time periods

	11:00−13:00	17:00−20:00
Weekday	Weekday lunchtime	Weekday dinner time
Weekend	Weekend lunchtime	Weekend dinner time

In addition, a spatial data set was used in this research. Road network data was applied to analyze network distance in Seoul. To represent the competitive market model, the existing restaurant points were obtained from the Ministry of the Interior and Safety in Korea.

3.2. Service Area Analysis

Service area analysis follows three steps: calculating profit with population, analyzing competition index by the existing restaurants, and unifying two variables to Z−score. To produce the unit area, Seoul is divided into 100*100m square. The total number of unit area is 61,650.

3.2.1. Calculating Profit of Each Food Trucks

The competitive location problem has been studied since the finding of Hotelling (1929). Competitive location models were developed into two kinds, deterministic choice, and probabilistic choice models. In this study, food trucks' demand is defined with a deterministic model, because of two assumptions that probabilistic models have (Huff, 1964; Stanley and Sewall, 1976; Nikanishi and Cooper, 1974). First of all, the probabilistic model assigned different effect of distance. However, the range of the food truck is only 200m, under 5 minutes walking distance, it is very short distance especially when the workers tried their lunch (Embrain, 2012). The short range of food trucks made it redundant to use the probabilistic model in a competitive model. Second, most of the probabilistic models assumed that each competing facility has different characteristics or attraction factors, but most of the food trucks are indifferent to people who need to eat fast. Due to these two reasons, this study utilizes a deterministic choice based competitive location model.

The square grid, as known as Fishnet grid, was formed to calculate the range of food trucks. Food truck captures all of the population in the range (black circle in Fig. 3.2). The range of food truck is defined as 200m from the centroid of the grid. Because of the low attracting impact on the field and limited meal time, people tend to spend less than 5 minutes to visit the food truck (Jin, 2017). Therefore, the range of food truck is defined as 200m from the location where they are located.

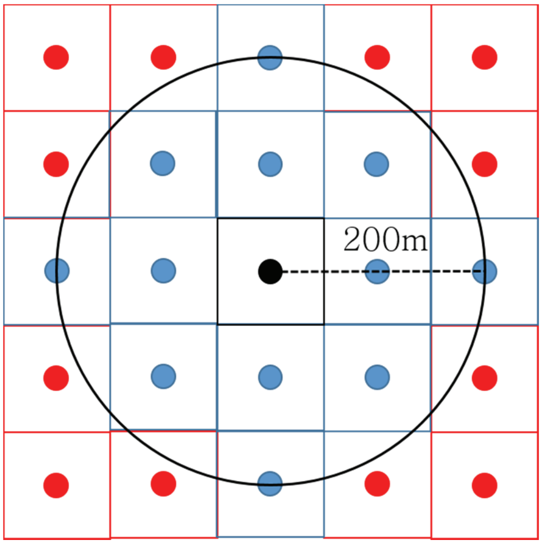


Figure 3.2. The range of food truck

The competitive market model shares demand when each facility's range conflicted. In this study, the food trucks have a range and attractive factor. Therefore, when two food trucks' range overlapped, the overlapped range was allocated into the near food truck. Refer to Fig. 3.3, the overlapped area can be divided into two parts. If the food truck is located on O_i and the range of O_n overlapped, the demand in range, P_n, is allocated as following:

$$P_n = (A + (\frac{d_{in}}{2} * sin(cos^{-1}(\frac{\frac{d_{in}}{2}}{r}))) * r - \left(\pi r^2 * 2\,cos^{-1}\left(\frac{\frac{d_{in}}{2}}{r}\right) * \frac{\frac{180}{\pi}}{360}\right) / A) * P_n \tag{1}$$

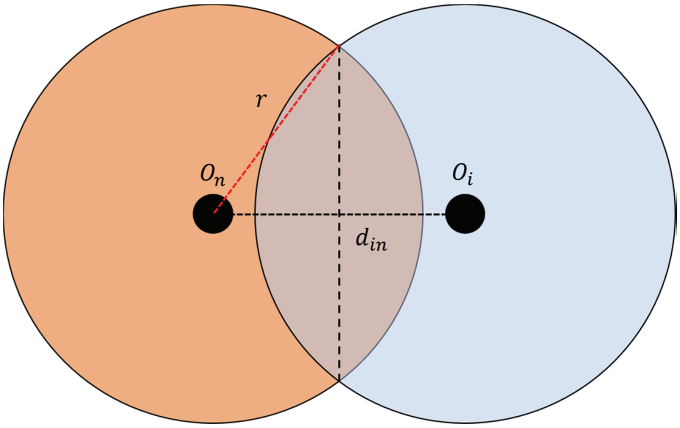


Figure 3.3. Overlapped food trucks range allocation

, where A is the original area of the range of food truck n, d_{in} is the distance between two food trucks, r is the range diameter of a food truck.

After calculating and allocating the demand in each food truck range, it is possible to analyze the expected profit on their range.

3.2.2. Analyzing Competition of Existing Restaurants

To analyze the expected competition between food trucks and the existing restaurants, collecting and joining restaurants location data is the pre-requisition. The restaurants in Seoul were intensively distributed in business districts, such as Gangnam and Yeouido (refer to Fig. 3.4.).

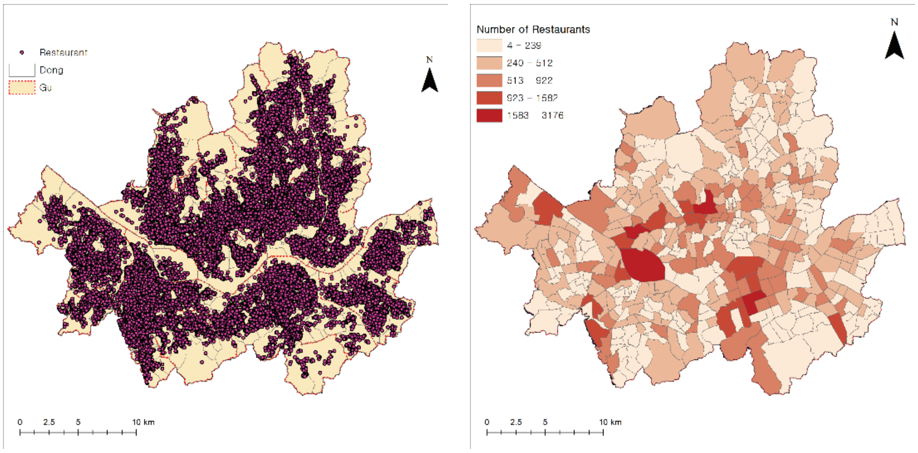


Figure 3.4. The distribution of restaurants in Seoul

The restaurants located in the range of each food truck are counted at the food truck's attribute. If many restaurants located in the range of the food truck, it means there was high competition for the food truck. Even if there was high demand in the range, it would be not an optimal site to operate the food truck for two reasons. The existing restaurants are the competitors to the food truck, and their complaints can make decision makers unwilling to allow that place as an operating site.

3.2.3. Unifying Two Variables

Due to the different data scale and unit, demand, represented by population, and competition, applying the number of restaurants, have to be unified to the same scale. In this study, normalization was used for unifying two variables to the same scaled factor. The normalized Z−score demand and competition index is the following:

$$Z_i = \frac{x_i - \mu}{\sigma} \tag{2}$$

, where Z_i is the normalized value, and x_i means the original value of the profit or competition

After the normalization, two factors are enabled to be compared by Z−score. As a result, the service area's demand and competition index were calculated on the deterministic choice based competitive market. With these two unified spatial indexes, the spatial decision would be achieved.

3.3. Multi-objective Optimization and Heuristic Algorithm

Multi−objective optimization is applied when the two factors have to be considered in one problem. Particularly, if two considered objectives are conflicting or competing, then the multi−objective optimization can yield the tradeoff effect between two conflicting factors (Daskin, 1995). In this study, the greedy adding heuristic algorithm was applied to the multi−objective spatial optimization problem. Although greedy adding algorithm could be stuck in the local optimum, the food truck's market range is small enough to be considered as an independent solution, there would be no interruption from the former selected set of solution. And the competitive market model prevents the interruption effect, so the results would not be stuck in the local optimum.

3.3.1. Multi−objective Spatial Optimization

The multi−objective optimization usually applied two conflicting objectives. In this study, there are two objectives in location decision; maximizing profit and minimizing competition. The profits of each food truck is represented by Z−score of the de facto population on their range, and capturing maximum de facto population is the first objective in this study. Simultaneously, the competition between food trucks and the restaurants which share the range has to be minimized. The second objective is minimizing the Z−score of the existing market in the range. Figure 3.5 presents the example of the multi−objective non−inferior solution sets.

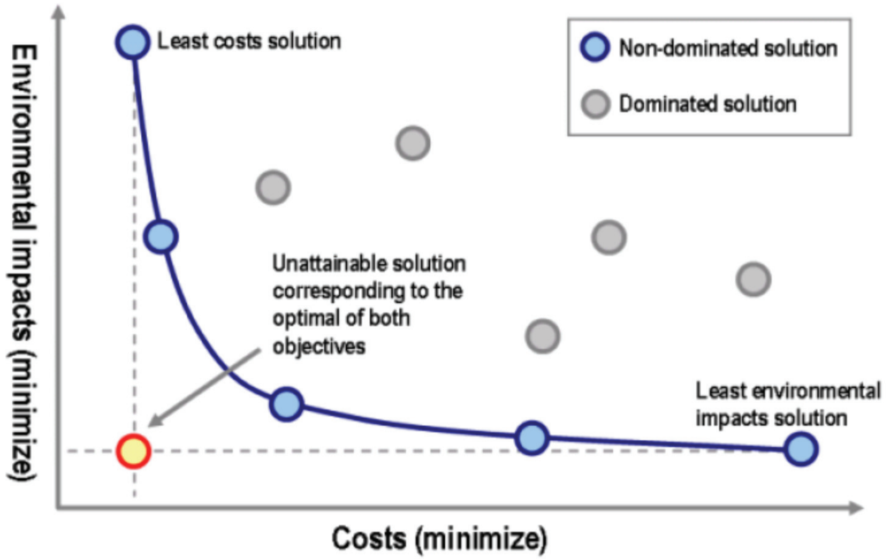


Figure 3.5. Example of tradeoff diagram (Kuby, 2018)

In this study, the feasible area is defined by regulation of the Seoul Metropolitan Council[6]. The act prescribed food trucks possible operating sites, feasible area in this problem. The act designated nine categories of legal land use as a possible area for operating the food truck. And those nine categories are incorporated into seven practical land use categories (see Table 3.3). As a result, filtering out the feasible area from the whole area reduced the computational load to solve the problem.

[6] The law was enacted at 2017.
Source: http://www.law.go.kr/LSW/ordinInfoP.do?ordinSeq=1302944

Table 3.3. Feasible area categories

Category
Festival place
Public facility
Plaza or attached open space
Public or enterprise property
Public parking lot
Traditional market
Roadside

Even though the feasible area decreased the computational load, the grid in Seoul is still numerous. The number of the original square grid is 61,650, and the decreased number of the square grid is 44,714. Unless the number of the grid is decreased, the computational load is still huge enough to find the exact solution. The exact solving computational load is still impossible to calculate, $\binom{44{,}714}{500}$, so heuristic algorithm needs to be applied in this problem.

3.3.2. Heuristic Algorithm

Location-allocation problems usually have large mathematical complexity. For example, the p-median problem is difficult to solve, due to the computational load (Eiselt, H. A., 2011). Kariv and Hakimi (1979) showed it as a NP-hard problem, and Megiddo and Supowit (1984) also discovered it in a continuous case. In this study, the mathematical complexity of this problem is about $O(n^n)$. Due to this high complexity, the heuristic algorithm is required in the food trucks location-allocation problem.

There are many classical heuristic methods, such as Cooper (1963, 1964), Maranzana (1964), and Teitz and Bart (1968), in spatial optimization. Those models developed the basis of the heuristic methods and how to define the distance on the field. After the advent of the classical heuristic methods, many recent heuristic algorithms also developed, such as taboo search, genetic algorithm, and simulated annealing. However, due to the food truck's short-range distance and mobility, the greedy adding algorithm can reach the global optimal solution.

The exact solving method's computational load was about 8.30 E+1189. This high computing load contains two major problems. The huge computation time cost is the first point that made it hard to achieve spatial optimization results. To get the result of this spatial problem, the research needs to spend enormous time. The second problem is that the complexity, $O(n^n)$, was increasing as the size of the problem became larger. So, the methodology is hard to apply to other huge size problems. The greedy adding algorithm decreased the complexity of the problem to 500, and it enhanced the versatility of the research methodology.

The greedy adding algorithm is searching the optimal solution at each step, and it iterates this process to find the optimal solution set. The greedy adding algorithm found the best location for the food truck, and then shared the demand near the location. After selecting the most suitable location, it iterates until the number of food trucks reaches the condition, in this study 500. The greedy adding algorithm is presented in Fig 3.6.

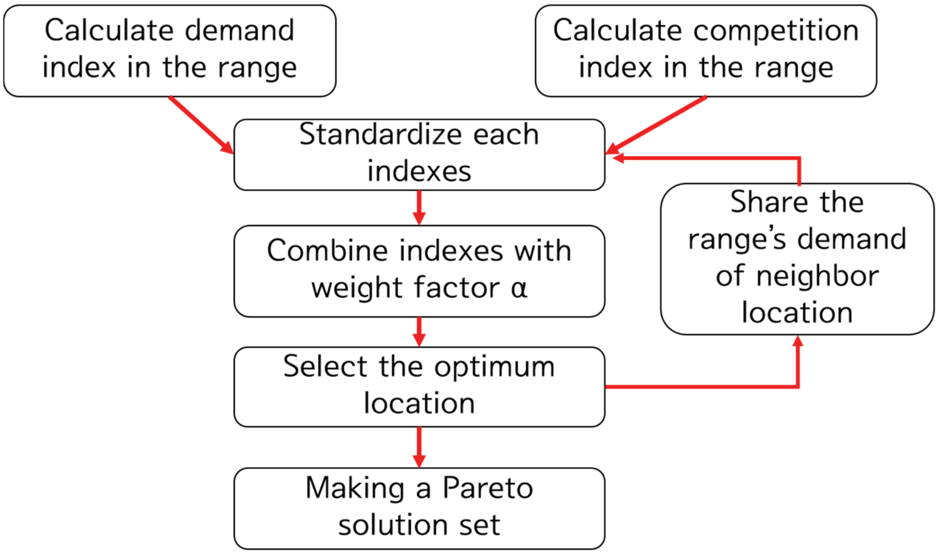


Figure 3.6. Greedy adding algorithm research flow

After applying the greedy adding algorithm, the food trucks' Pareto optimal location set would be founded. Including all the optimal location sets the finding the process, the multi−objective model can be designed with one multi−objective function and four constraints. The optimal location and route seeking multi−objective function are conducted as below. The multi−objective model of this study formulated:

$$\text{Maximize Z} = \alpha Z_1 - (1-\alpha)Z_2 \tag{3}$$

$$Maximize\ Z_1 = \sum_i I_i P_{ti} X_{ti} \qquad \forall t \tag{4}$$

$$Minimize\ Z_2 = \sum_i N_i X_{ti} \qquad \forall t \tag{5}$$

Subject to:

$$\sum_i X_{ti} = 500 \qquad \forall t \tag{6}$$

$$P_n = (A + (\frac{d_{in}}{2} * \sin(\cos^{-1}(\frac{\frac{d_{in}}{2}}{r}))) * r - \left(\pi r^2 * 2\cos^{-1}\left(\frac{\frac{d_{in}}{2}}{r}\right) * \frac{180}{\frac{\pi}{360}}\right) / A) * P_n * X_i \tag{7}$$

$$X_{ti} \geq 0 \quad \forall t,\ i \tag{8}$$

Where:

$X_{ti} =$ The number of food trucks at period t in grid i

$I_i =$ 1 if grid i is a feasible area, 0 otherwise

$P_{ti} =$ The de facto population at period t in grid i

$N_i =$ The number of restaurants in the range of i

$d_{ot} =$ The distance of route o, at period t

$r =$ The radius of the food truck's service range

$A =$ The initial service area of food trucks

$d_{in} =$ The distance between two food trucks which shared the service area

3.4. Data Mining and Vehicle Routing Problem

Han (2011) defined that the data mining is often used to refer to the entire knowledge discovery process (KDD). Data mining is the process of discovering patterns and knowledge from huge data. Finding expected flow is a kind of difficult process, due to its high complexity of data. In this part, the research methodology used in this research for finding the mobile food trucks' clusters and routes are presented.

3.4.1. Clustering the Mobile Food Trucks

This part follows three steps. First, filtering out the food trucks that need to move. Second, Silhouette score that was applied to designate the number of clusters is explained. Lastly, the data mining method used to find the clusters of mobile food trucks is presented.

Due to the population flow dynamics, the demanding population in each food truck's range changed every time periods. For example, unless the food truck's location at weekday lunchtime period is superior to other sites, the site would be the inferior location site at weekday dinner time period, due to the off work of employees who returned to their house. This transition to the inferior location needs to be detected with a definite condition. The food trucks that need to move can be defined by two conditions.

$$X_{it} - X_{it+1} > 0 \tag{10}$$

$$0.8 * P_{it} > P_{it+1} \tag{11}$$

In an inequality (10), the originally selected optimal site (X_{it}) is a no longer the optimal site (X_{it+1}) to locate the food truck. For example, to satisfy the condition, the result of location analysis shows the X_i is the optimal location at the weekday lunch time period but not the optimal location at the weekday dinner time period. Simultaneously, the condition (11) have to be satisfied. An inequality (11) presented the demand decrease at the period $t+1$. The decrease rate is defined as 80%. According to the interview with food truck workers, they avert to move other site, because of the cost, such as fuel cost, efforts to convert their food truck as a mobile form. They tend to keep their original site, and it means that without a significant reduction of demand, they will not move (Moon, 2017). So a 20% reduction of the population represents the threshold value of the food truck worker's movement.

The result of clustering varies the number of cluster parameter changes (Kodinariya and Makwana, 2013). Because the cluster parameter, particularly the number of clusters, affects the result, there are many approaches to select the right number of clusters. *Elbow method* is the oldest method for determining the number of clusters. This method compares cost and K (the number of clusters) and detecting the elbow point of the clustering function. Elbow method is a visual method, however, it cannot choose the right number of the cluster when it is hard to capture the rapid change point.

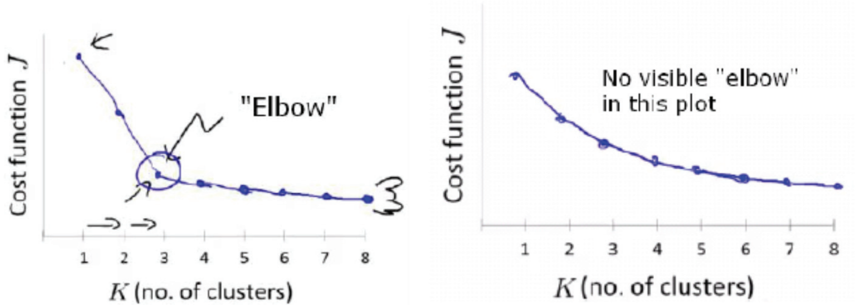


Figure 3.7. Elbow method's well-determined one (left); the ambiguous result (right) (Kodinariya and Makwana, 2013)

Kaufman and Rousseeuw (1990) proposed the *silhouette* statistic, for assessing clusters and exploring the optimal number of clusters (Tibshirani *et al.*, 2001). Equation (12) contains two factors, minimizing the average distance the point (a(i)) and other points in the same cluster and maximizing the average distance between the point and the points in other cluster ($b(i)$). The silhouette statistic ranges from −1 to +1, where a high value indicates that the cluster is well organized. This study applied a silhouette statistic to find the optimal number of clusters, because it can eliminate the arbitrariness of selecting the number of clusters.

$$\mathrm{s(i)} = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{12}$$

Cluster analysis is a kind of exploratory data mining and machine learning. Clustering has many kinds of cluster analysis methods. Density−based analysis (DBSCAN) is one of the representative methods in clustering. DBSCAN apply two parameters, radius and minimum points, and cluster three classes, core points, reachable points, and outliers. DBSCAN does not require the pre−determined the number of clusters and robust to outliers. However, the threshold distance (ε) affects the result of DBSSAN. And the border points are assigned as an outlier point. Due to the lack of information for the threshold of food truck clusters, it is hard to apply DBSCAN in this study.

Secondly, Affinity Propagation (AP) based on the concept of message passing between the points (Frey and Dueck, 2007). AP assigns exemplar points, representative points of clusters, and makes clusters that connected points. AP is faster than K−means clustering, but it needs to assign preferences as a parameter. Like DBSCAN's limitation, it is hard to define the right preferences on AP in this study.

Finally, K−means clustering is used in this study. K−means method is a simple and fast clustering technique (Kodinariya and Makwana, 2013). K−mean clustering is one of the unsupervised learning algorithms. K−means clustering aims to minimize the variance within the cluster (refer equation (13)), maximizing the variance between the clusters. With the predetermined number of clusters, it aggregates all the points to the clusters. The difficulty when using K−means clustering is defining the predetermined number of clusters. By using the silhouette score, the objective number of cluster is founded. As a result, to find the clusters of the food trucks that need to be moved, the K−means clustering method is applied in this study.

$$arg\min_{s}\sum_{i=1}^{k}\sum_{x\in S_i}\|x-\mu_i\|^2 = arg\min_{s}\sum_{i=1}^{k}|S_i|VarS_i \tag{13}$$

3.4.2. The Spatio−temporal Vehicle Routing Problem

VRP can be described as the problem of designing optimal delivery or collection routes from several points to a number of scattered sites (Laporte, 1992). Dantzig and Ramser (1959) first presented the VRP with truck dispatching problem. In this study, the VRP considered the capacity of the carrier and the points where they have to visit. As a result, the original VRP defined the objective function with the capacity of the truck and deliveries (refer to simultaneous inequalities (14)).

$$\sum_{i=1}^{t} q_i \leq C \ and \ \sum_{i=1}^{t+1} q_i > C \tag{14}$$

In this study, the food trucks capacity is unlimited, so it can be generalized by only imposing the distance condition. The objective function is formulated with a different form. Travelling Salesman Problem (TSP) is the routing problem that considers the shortest path visiting all the points and returning to the origin. The TSP analyzed the shortest routes for operating the optimal sites. The origin point and the destination point is the same in the TSP (Fig 3.8). The TSP was mathematically formulated by W. R. Hamilton in 1800s.

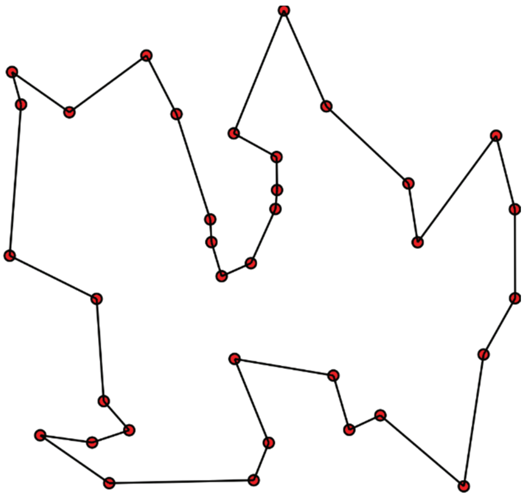


Figure 3.8. TSP graph

The TSP can be formulated as an integer program. The TSP was formulated by Miller–Tucker–Zemlin (1960). The objective function follows:

$$\text{Minimize} \sum_{0 \le i \ne j \le n} \sum d_{ij} x_{ij} \tag{15}$$

Subject to:

$$\sum_{\substack{i=0 \\ i \ne j}}^{n} x_{ij} = 1 \tag{16}$$

$$\sum_{\substack{j=0 \\ j \ne i}}^{n} x_{ij} = 1 \tag{17}$$

$$u_i - u_j + p x_{ij} \le p - 1 \tag{18}$$

While the TSP is the NP−complete problem, metaheuristic methods are usually applied. However, this research used the clustering method, so the computing complexity is dramatically reduced. The number of original food trucks is decreased to the number of clusters. The exact solving approach can be applied to this problem. The exact solving method needs to calculate the distance between the points. Using the exact solving method leads to the global optimal result of the analysis.

To calculate the distance between the points, the Dijkstra algorithm is applied. The Dijkstra algorithm is an algorithm for finding the shortest paths between the nodes. The Dijkstra algorithm can be used with the road network in Seoul. The efficiency to find the shortest path between two nodes is the Dijkstra algorithm's characteristic. This iterates the process to calculate the nearest node from the candidates. Even though the order of complexity is $O(n^2)$ time, the small dataset requires negligible time to apply it. As a result, the Dijkstra algorithm is well fitted to find the shortest network distance between the food trucks clusters in this study.

The result of food trucks routing problem has two different characteristics from other TSP. The TSP only concerns the shortest routing for one vehicle. However, the food truck routing problem has multiple points that have to move. The multiple food trucks are moving simultaneously, so the number of feasible solutions is $n!^t$, when the number of clusters is n, and the number of time periods is t. The enormous calculation complexity made it hard to solve than the TSP.

The second unique characteristic of food trucks routing problem is that the food trucks routing problem has a time axis. The movement of food trucks' cluster made temporal trajectories in the spatial field. Time geography was introduced by Hagerstrand (1970), and has been developed. The temporal routes of food trucks require collaborative research using space and time axis.

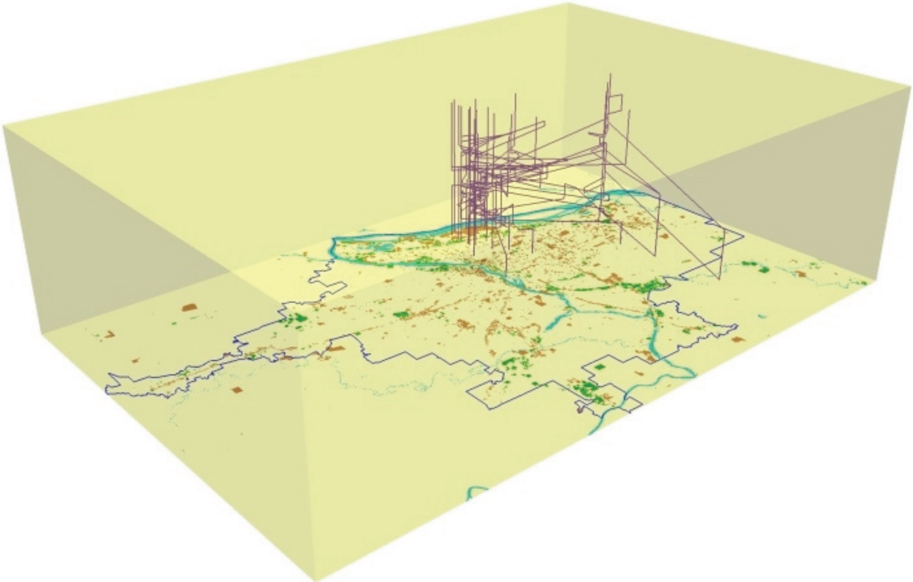


Figure 3.9. Space-time path in the Portland Activity-Travel survey (Kwan, 2004)

Many space-time path and prism research were developed by Miller (1999), Forer (1998), Kwan and Hong (1998). Space-time prism visualizes the spatio-temporal flow. In this study, the space-time prism would represent the trajectories of the food trucks clusters regarding both space and time and capture the spatio-temporal patterns of moving clusters.

This research used multiple tools to apply those methodologies. ArcGIS 10.5 and QGIS 2.18 were the main GIS tools that have advantages in analyzing spatial phenomena. The service area, range calculation, and visualization were analyzed by two professional GIS programs. Data wrangling, clustering the food trucks points, and optimizing the food trucks' spatio-temporal location were analyzed by R 3.5.3 and Python 3.7.1. The greedy adding algorithm was coded by the R language.

In Chapter 3, the study area and data's brief explanation was introduced There were three steps in this research, During the first phase, classical service area analysis was introduced to preprocess the data and define the range of food trucks. Secondly, multi-objective spatial optimization was introduced using heuristic methods. By applying the multi-objective optimization, minimizing the conflict between the food trucks and the restaurants can be achieved. Lastly, the food trucks that need to move routing approach was introduced. To find the shortest path and minimizing the food trucks routes, the Dijkstra algorithm and the TSP method is applied. In Chapter 4, the results of applying those methodologies on the food trucks problem are presented.

Chapter 4. Research Analysis and Results

In this chapter, the results of the food trucks' location are presented with three parts, as was in Chapter 3. In the first part, the traditional location analysis and explorative research are presented. Spatio−temporal dynamics of the population in Seoul is shown in this part. The multi−objective model results are presented with three scenarios in the second part. The multi−objective spatial optimization process is conducted in the part. The third part shows the results of the routing problem and spatio−temporal patterns analysis. Finally, the last part summarized this part's analysis.

4.1. Food Truck's Service Area Analysis

First of all, examining the existence of population distribution's dynamics has to be done. In this part, the existence of population distribution dynamics in Seoul is analyzed by temporal analysis. This analysis showed the temporal difference of population dynamics in a single day and between the weekday and the weekend. After analyzing the temporal dynamics of population, the spatio−temporal aspects of population flow are presented. In the last part, Z−scored choropleth maps are shown with the interpretation.

4.1.1. Global Trend of the De Facto Population

In Seoul, the weekday's de facto population trend shows population dynamics by the time change in one day (refer to Fig 4.1). The graph presents the peak and the minimum time of the de facto population. Seoul shows the peak de facto population over 10,950,000, and the minimum de facto population is lower than 10,650,000. Because of the clustered business districts in Seoul, the de facto population follows the commuting and working pattern of people. After 22:00, most of the people who commuted into Seoul go back to their home, so only the resident population remains. Globally, Seoul showed the temporal population difference in a single day.

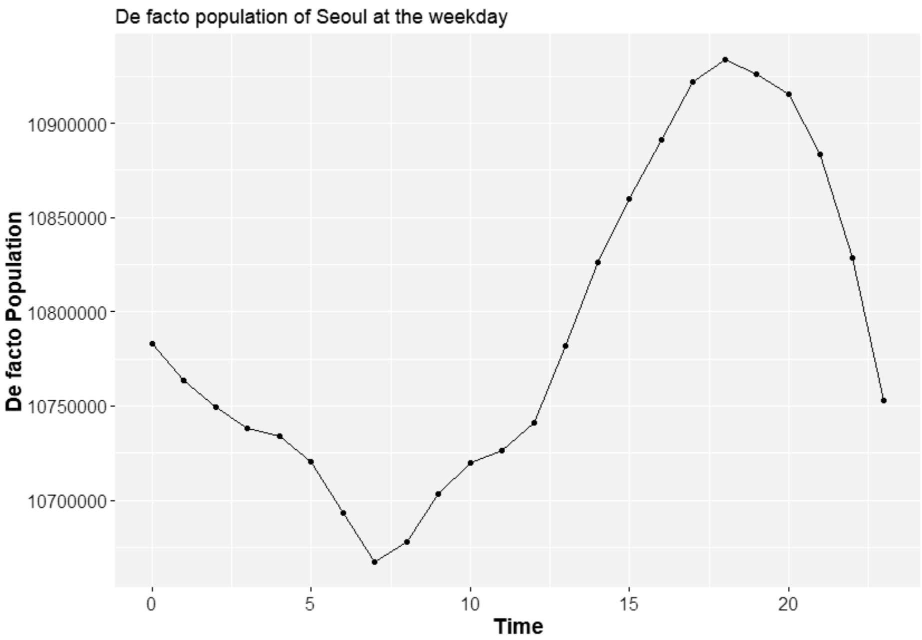


Figure 4.1. De facto population change at the weekday

On the other hand, the temporal de facto population aspect is different during the weekends. Due to the low number of workers and the different lifestyle in the weekend, the de facto population trend (Fig 4.2) presents a different shape compared to Fig 4.1. First, the steep slope at 5:00 means the starting time of public transportation, such as bus and metro systems. The peak time of de facto population in the weekend is 14:00. It represents people flowing into Seoul to have their leisure time or visiting the place that is not related to their business. So the main reason to move into Seoul in the weekend is not for the productive or official activities, such as commuting and business trip.

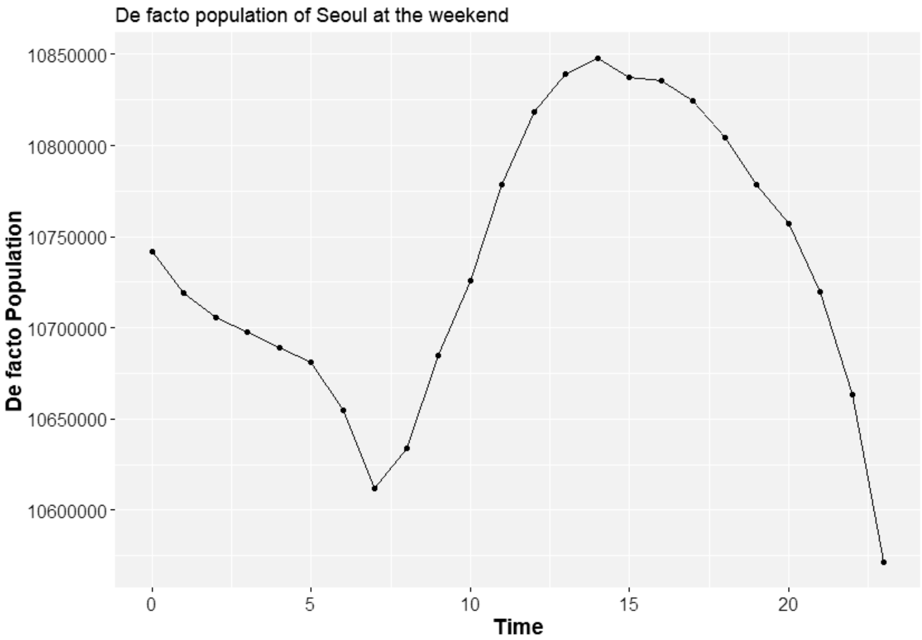


Figure 4.2. De facto population change at the weekend

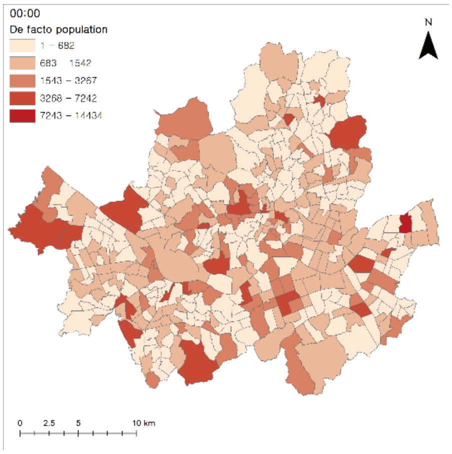
The different de facto population value and the slope between the time periods clarified two distinct points between the weekday and the weekend's trend of the de facto population flow. First, after the peak time: 18:00 at the weekday and 14:00 at the weekend, the slope of the weekend is more moderate than the weekday's same time period. Because of the low commuting flow, the graph shows a moderate slope between the peak point and the lowest point at the weekend. On the other hand, the stiff slope between the time zone made a rush hour at the weekday in Seoul. It can be deduced that the private movement affects more the de facto population trend in the weekend (Byun, 2011; Eun, 2001).

The second difference distinguished point between the weekday and the weekend is the different peak time. The de facto population peak time is about four hours later during the weekday. Due to the off work time in the company, after 20:00 in the weekday, the workers who lived outside of Seoul went back to their residential area. The main working hour, about from 09:00 to 18:00, made the primary flow and peak point in a single day.

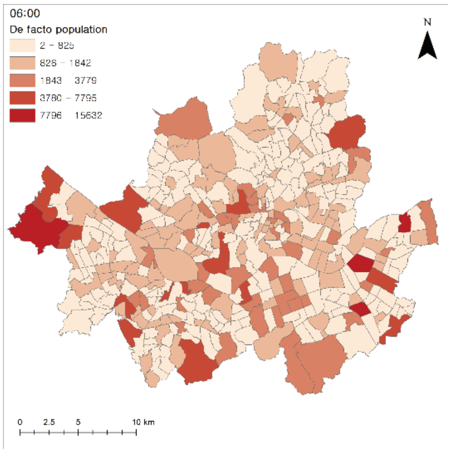
These differences between the weekday's trend and the weekend's trend only showed the temporal fluctuation of the de facto population and the flow, both outbound and inbound flows. To specify the population dynamics, spatial analysis is inevitable.

4.1.2. Spatial Heterogeneity of Population Distribution

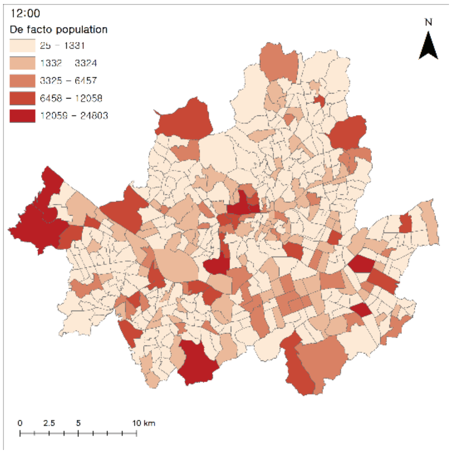
The spatial distribution of the de facto population is analyzed by choropleth mapping. Though the jipgyegu is the finest spatial unit, to visualize and detect spatial patterns of the population distribution, dong unit is used for the choropleth mapping. To compare the difference between the time periods, the interval of four−time is six hours. In Fig 4.3, the de facto population at 00:00 and 08:00 shows the residential population in Seoul. Particularly, the weekday distribution of the de facto population presents the spatial separation between the residential area and the business districts. The central business districts (CBD) located at the center, *Jongro*, and south area, *Gangnam*. During the weekday, there are hotspots on the CBD at 12:00 and 18:00. The hotspots occurred at the ordinary business hours. And the CBDs are already constructed in their own market structure (Goodchild, 1984). So the hotspots presented the most crowded and competitive area in Seoul.



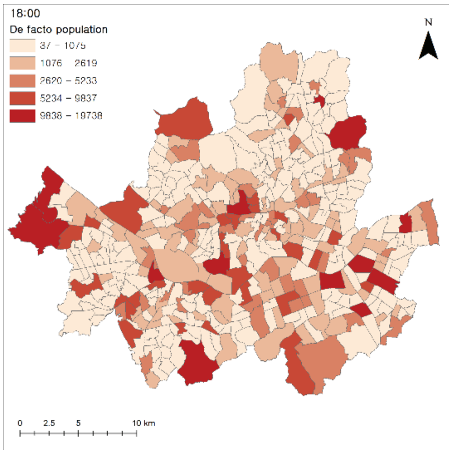
De facto population at 00:00



De facto population at 06:00



De facto population at 12:00

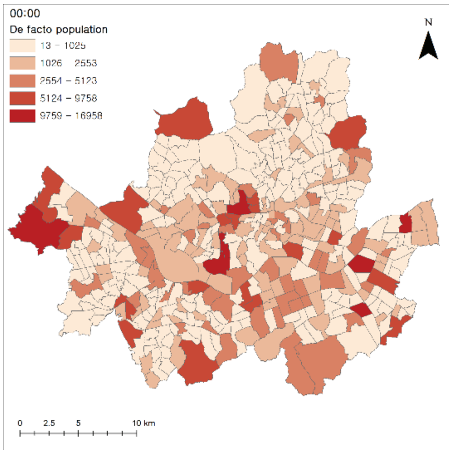


De facto population at 18:00

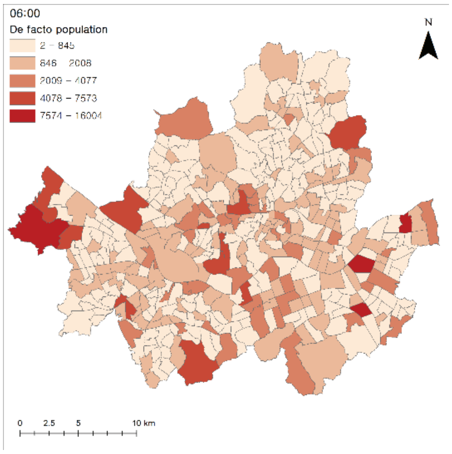
Figure 4.3. The de facto population at the weekday

On the contrary, the choropleth maps of weekend represent different population distribution in Seoul (refer to Fig 4.4). Due to the decrease of workers in Seoul, the de facto population at CBD reduced at 18:00. Particularly, the Gangnam business district shows less population than the weekday. Instead of crowding the business districts, the de facto population around the Gangnam districts and *Itaewon*'s population is concentrated. Also, there is Friday night's impact on Saturday's de facto population distribution. On Saturday at 00:00, the population hotspots are presented in the residential area and "hip space", such as Itaewon and Gangnam. Those people spent the time from Friday night, so it shows the connectivity and behavioral patterns of people with spatial representation.

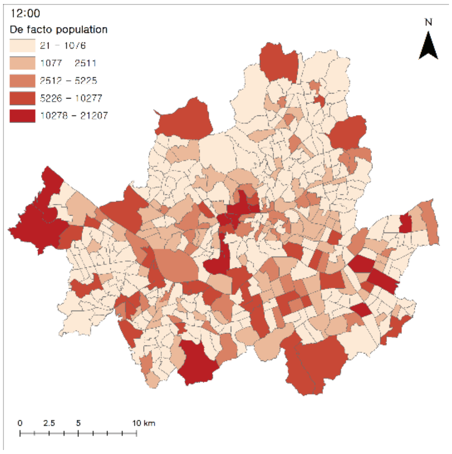
The primary factor that made a serious difference in spatial population distribution is economic activities. The commutes from the outskirt or outbound of Seoul to the CBDs made the CBDs crowded during the working hours in the weekday. However, in the weekend, the hip space is the most attractive place to the population. And more people gathered in the residential area. So there was a significant difference of de facto population distribution in Seoul depending on each time period and whether it is the weekdays or weekend. Therefore, to optimize capturing the food truck's demand, the food truck locations have to be changed depending on the fluctuation of the population distribution.



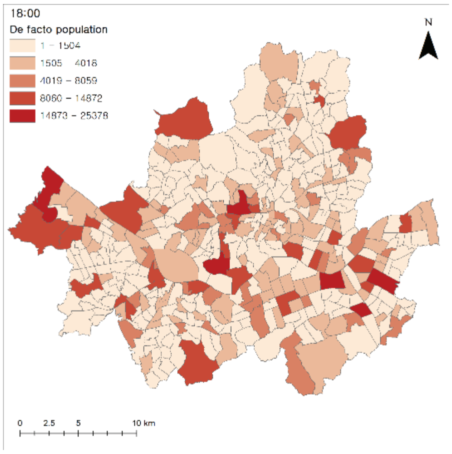
De facto population at 00:00



De facto population at 06:00



De facto population at 12:00



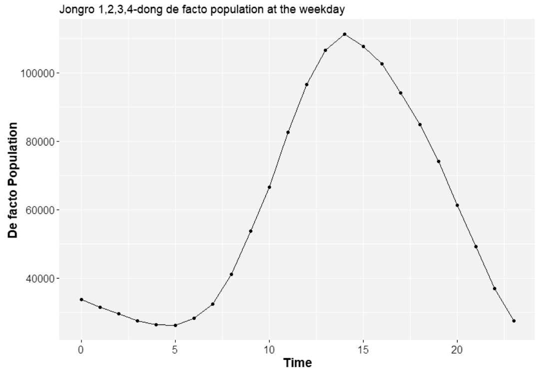
De facto population at 18:00

Figure 4.4. The de facto population at the weekend

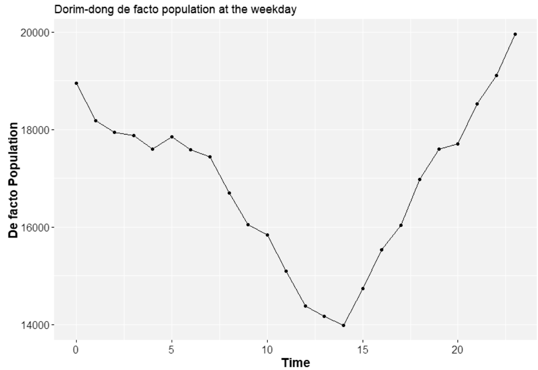
The local de facto population also varies depending on the time periods. The CBDs and the residential areas show the different trend of de facto population graph. In the weekday, *Jongro 1 · 2 · 3 · 4* dong, the typical CBD in Seoul, presented the bell-shaped de facto population trend. The population gathered into Jongro 1 · 2 · 3 · 4 dong during the working hour and diffused after the work off time. On the other hand, the de facto population trend of the residential area made a U shaped graph. *Dorim* dong is the apartment clustered area, so most of the people commuted to the other area at the daytime, and the settled population came back to Dorim dong. The settled population came back to their dwelling area. So the main factor to each dong's population fluctuation is the economic facilities in the area.

On the weekends (refer to Fig 4.6), the local factors that made a different trend of the number of people are distinct from the weekday's economic facility factor. *Yangjae 2* dong has Ynagjae Citizen forest, the leisure space during the daytime. This leisure place attracts people from another area in the daytime: 10:00 to 20:00. On the other hand, Itaewon dong is one of the transnational and hip places in Seoul. There are many global restaurants, pubs and night clubs. These amusing places attract people especially at night time, so the number of de facto population increased after 15:00 in Itaewon dong and reduced after 23:00.

Following the findings from the de facto population by dong scale, the importance of time axis and the population change is verified. If it is to find the spatial optimization problem for the traditional fixed store, detecting dong that contains maximum total population would be sufficient. However, the food trucks have the mobility to move to another location on the same day. Therefore, the food trucks can choose both of the optimal dongs, such as Jongro 1 · 2 · 3 · 4 dong and Dorim dong, on the same day as their optimal site each period. This research allocated the population on the grids that were overlapped by each dong.

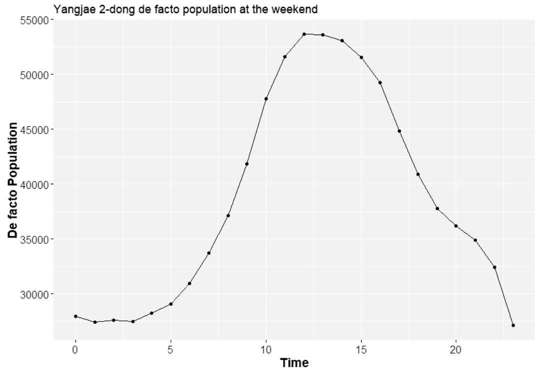


The de facto population at Jongro 1 · 2 · 3 · 4 dong

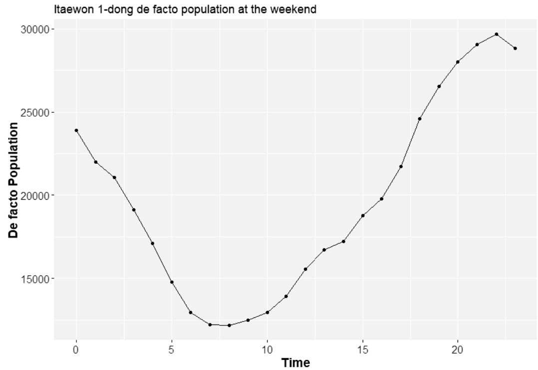


The de facto population at Dorim dong

Figure 4.5. The local de facto population at the weekday



The de facto population at Yangjae 2 dong



The de facto population at Itaewon dong

Figure 4.6. The local de facto population at the weekday

This study divided four time periods; the weekday lunch time (11:01 – 13:00), the weekday dinner time (17:01 – 20:00), the weekend lunch time (11:01 – 13:00), and the weekend dinner time (17:01 – 20:00). Those time periods are typical meal time to the residents (Kim, 2017).

4.1.3. Integrating Indexes and Descriptive Analysis

To compare with the restaurants and the de facto population, the de facto population at each time period converted to the Z-score. The Z-score of each jipgyegu's de facto population is calculated by the de facto population per 10,000㎡. It refers to the temporally summed de facto population per grid. The statistics of the restaurants and the de facto population at each time follows table 4.1. Due to the difference in time span, the dinner time demand of jipgyegu is higher than the lunch time's one

Table 4.1. Statistics of competition and demand

Category		Mean	Standard Deviation
Competition	The number of restaurants	7.76	25.59
Demand	Weekday lunch	871.78	775.38
	Weekday dinner	1277.78	1140.78
	Weekend lunch	858.80	789.92
	Weekend dinner	1010.32	1244.58

In Figure 4.7, the Z-scored map of competition, the number of restaurants in jipgyegu, shows that the restaurants are intensively located at the CBDs. The outskirt of Seoul is out of the supply of the restaurant's service. So, if the food trucks want to minimize the competition between the existing restaurants, the food trucks need to settle in the outskirts of Seoul, residential area.

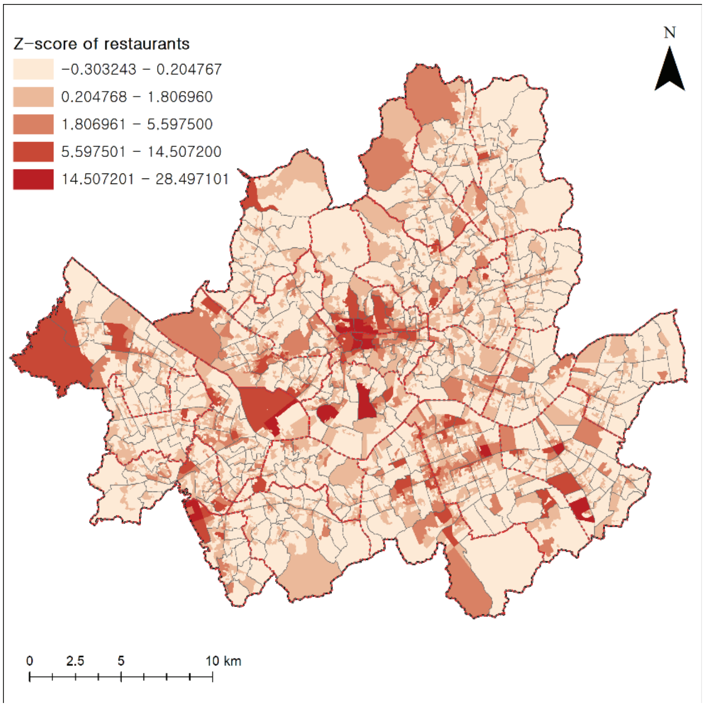
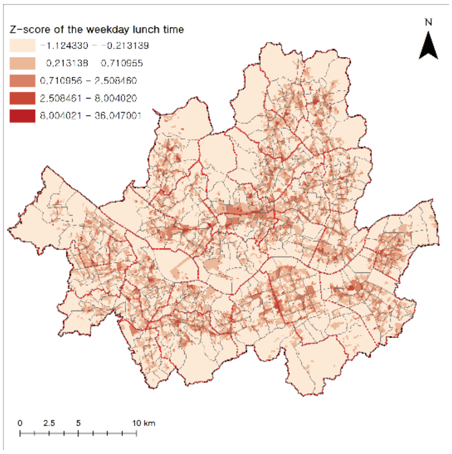
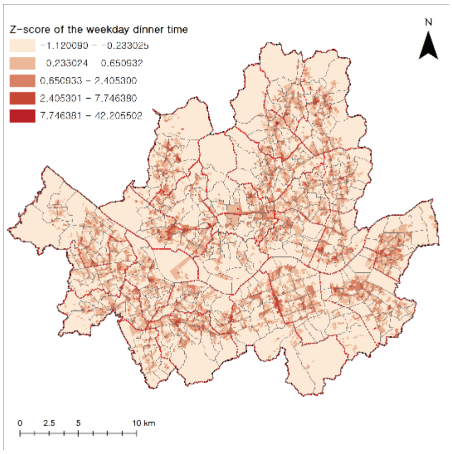


Figure 4.7. The Z-score of the number of restaurants

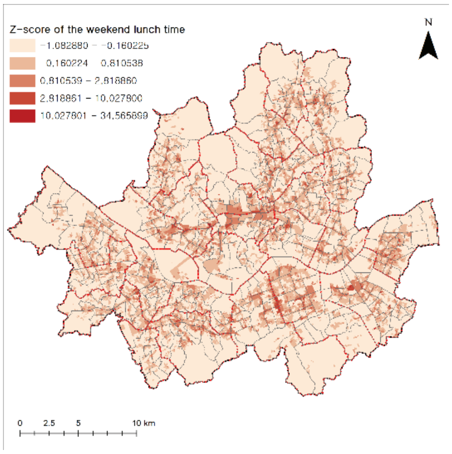
As Figure 4.7, Figure 4.8 partly showed that same spatial hotspots in Seoul. The CBDs show the high de facto population, especially, during the weekday lunch time. The overlapped area where the number of restaurants and the de facto population is simultaneously high contains both high competition and demand index. Some jipgyegu contains temporally relative high demand, the de facto population, and low supply, which means that the jipgyegu is a temporal niche of the existing restaurants.



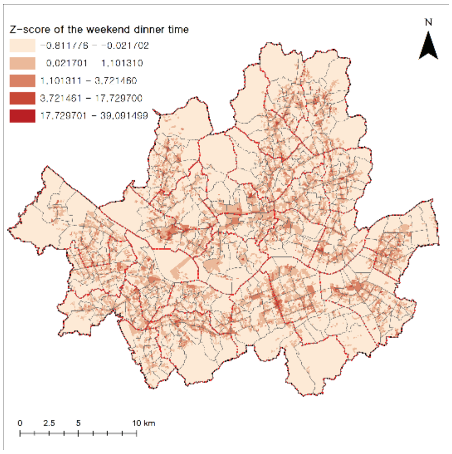
The weekday lunch time



The weekday dinner time



The weekend lunch time



The weekend dinner time

Figure 4.8. The Z−score of the de facto population

To solve the conflict between the demand and competition, the food trucks location analysis needs to apply multi−objective optimization to find the multi−objective solution set. During the next part, the results of spatial multi−objective optimization will be shown.

4.2. Applying Multi-objective Location Analysis

In this part, the results of multi−objective location analysis are presented following these three steps. The first step is selecting feasible grids in Seoul. Unfeasible grids, following the regulation, are eliminated from the potential food trucks site from the research area. After processing the greedy adding algorithm, the results of Pareto optimal tradeoff curve and the statistics are presented in the second step. In the last step, three scenarios are concerned depending on the three weight factor, α, and the interpretation is provided.

4.2.1. Filtering Feasible Area

According to the deregulation, refer to Chapter 3., the Seoul Metropolitan Council enacted conditions for the food trucks feasible operating site. There are seven categories of the feasible area, and those categories can be divided into two kinds; land use data and road data. The land use data contains six categories: festival place, public facilities, plazas, enterprise properties, public parking lots and traditional markets. Those kinds of data are areal data, so it contains the unit grids of the research. The second type of data is the line. The road network is a typical line data. So the grids that touch the line are selected for the feasible area. The possible food trucks locating grids have to contain the affordable land use area or the roadside to follow the regulation (see Fig 4.9.).

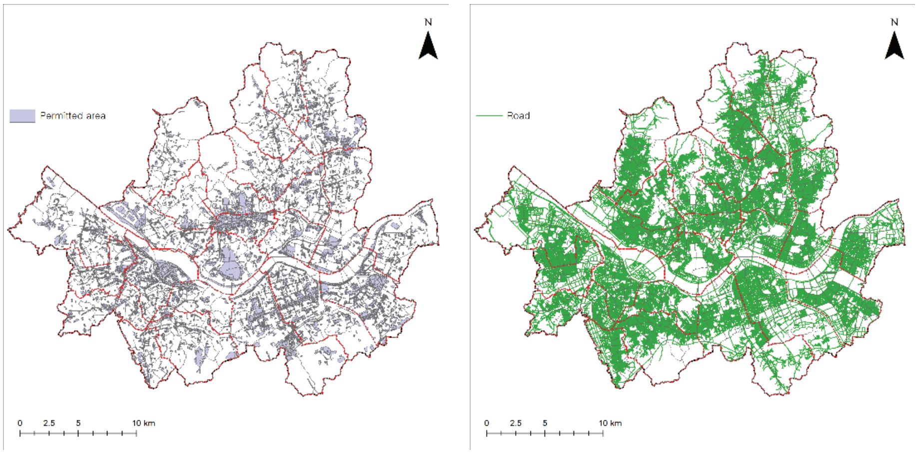


Figure 4.9. The feasible area depending on the land use (left) and the road (right)

As a result of filtering out the feasible sites, Figure 4.10. shows the result of the selected grids that are defined as feasible sites. After eliminating the restricted area, 16,936 grids were deleted from the feasible area. So the sky blue area in Fig 4.10. shows the feasible sites for operating the food trucks in Seoul.

In this research, the regulation is used for the binary conditions to find the optimal solution. Eliminating 27.4% of grids from the possible area reduces the computational load of this research. With the reduced calculation load, the greedy adding algorithm is applied to find the optimal food trucks operation sites.

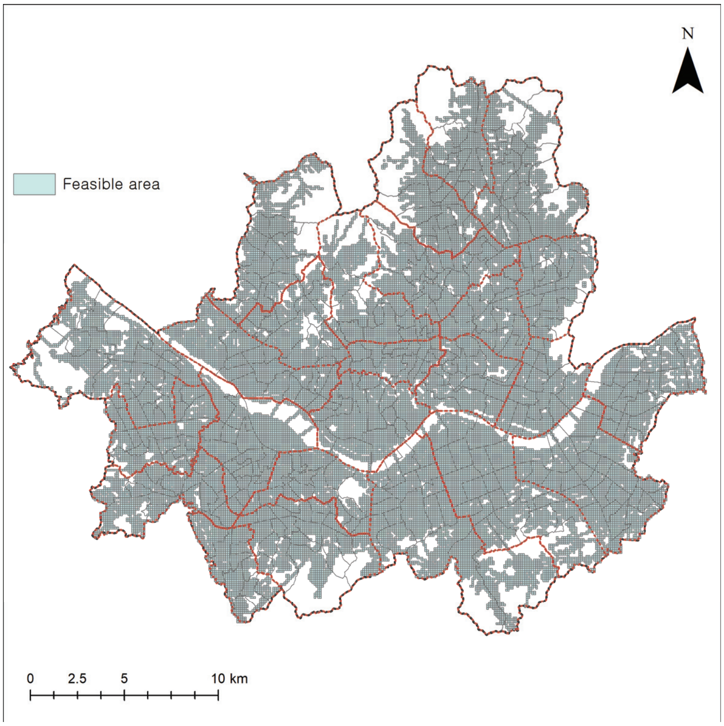


Figure 4.10. The feasible area of the food truck's operation

4.2.2. Pareto Optimal Set

This part shows the global trend of Pareto optimal solutions to the food trucks location problem. Pareto optimal tradeoff curve (Fig 4.11.) means the interrelationship of two variables, the de facto population and the number of restaurants, depending on the weight factor change. The red line and black points mean the feasible non-dominated and non-inferior solution sets. The left area of the red line is the inferior solution sets compared to the Pareto optimal solution, red line. And the right area of the red line is impossible to achieve without the additional resources. The red star point is the ideal point, as known as a *utopian objective point*, that is an infeasible solution.

In this study, the objectives of the research are maximizing the capturing de facto population and minimizing the competition from the existing restaurants. Due to the positive proportional effect between the demand and the competition index, the Pareto optimal tradeoff curve shows onwards and upwards trend. As the Pareto optimal tradeoff curve presented, the optimal solution is maximizing the demand (X−axis) and minimizing the competition (Y−axis). Because of the matured commercial structure, to increase the captured de facto population, the competition to the existing restaurants is inevitable on the global scale.

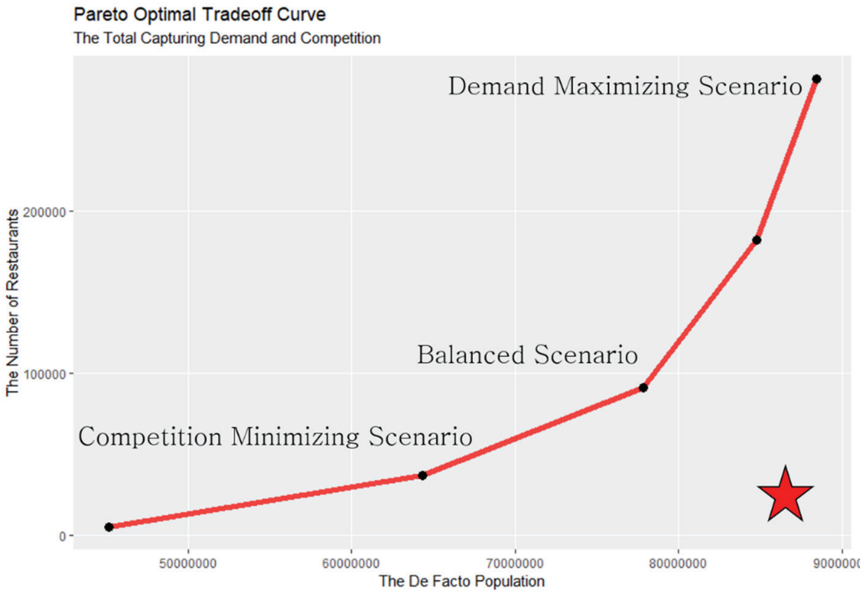


Figure 4.11. The Pareto optimal tradeoff curve

The specific statistics of the change in the competition and the demand is provided at Table 4.2. The number of restaurants and the de facto population are summed up at all the time periods. As the weight factor α increased, the number of de facto population in the food truck's range also added. When the α is 0.1, a competition minimizing scenario, each food truck only covers 90,366 people, but less competition than any other scenarios. However, if the α increased to 0.9, a demand maximizing scenario, then the covering de facto population almost double. On the other hand, the number of restaurants in each food truck's range skyrocketed by more than 60 times. When the α is 0.5, the competition and the demand was dealt with the same weight factor, so it is a balanced scenario.

Table 4.2. The basic statistics of the Pareto optimal tradeoff curve

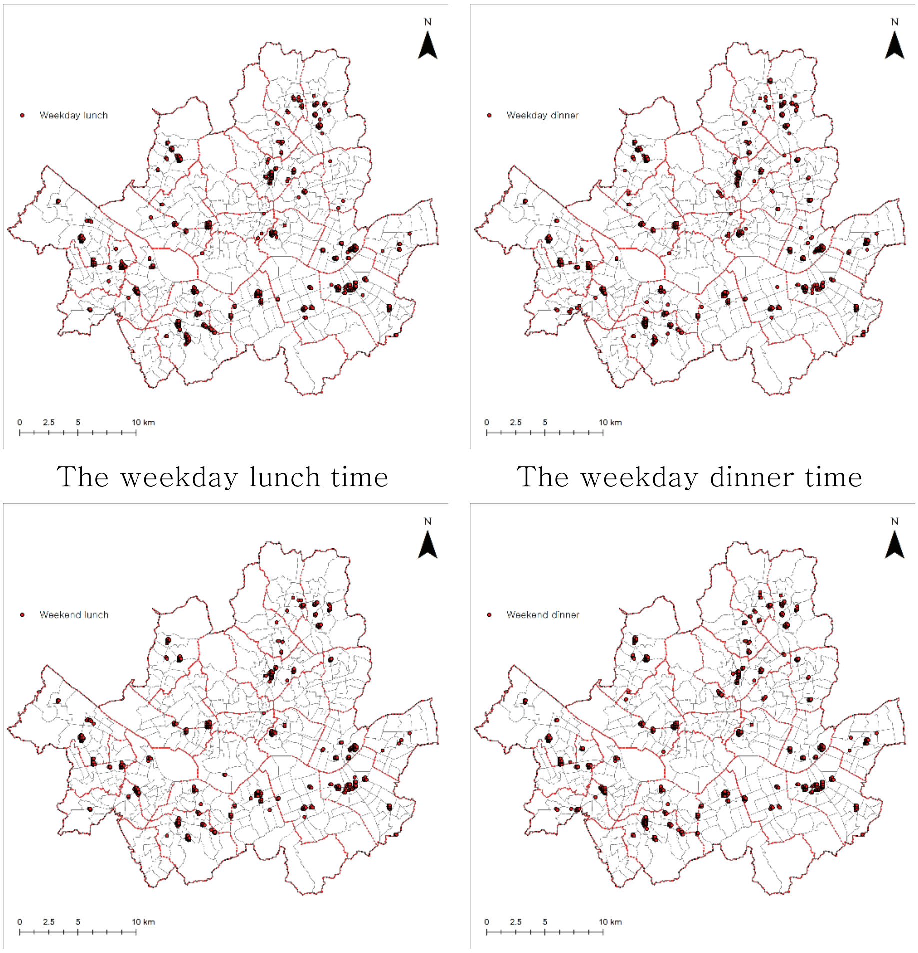
Weight Factor (α)	The number of Restaurants	The Mean Number of Restaurants	Covering De Facto Population	The Mean Covering De Facto Population
0.1	4,644	9.288	45,183,106	90,366
0.3	36,933	73.866	64,315,346	128,631
0.5	91,040	182.08	77,816,843	155,634
0.7	182,525	365.05	84,741,657	169,483
0.9	281,730	563.46	88,420,654	176,841

The Pareto optimal tradeoff curve and the basic statistics support spatial decision making. If the stakeholders consider that the high competition index from the existing restaurants is not a significant problem, then the weight factor will be defined as more than 0.9. To keep the balance between maximizing the food truck's profit and minimizing the existing restaurant's loss, the stakeholders will make spatial optimization results regarding the proper α in their society.

4.2.3. Exploring three multi−objective scenarios

To compare the effect of α, three scenarios are provided by the maps. Three weight factors are applied to the scenarios, and each α is 0.3, 0.5, and 0.7. To suppose the moderate stakeholder, the extreme weight factors are excluded in this part. At each scenario, the results are shown at each time period. So, the results present the spatio−temporal location change of food trucks depending on the weight factor replacement.

At the competition minimizing scenario, I supposed the stakeholders are reluctant to permit food tucks in the existing market area. The weight factor that means the importance of assuring maximum demand for food trucks is 0.3. Due to the weight factor, the spatio-temporal change of de facto population does not significantly affect the food trucks location. So the results map shows only a slight difference depending on the change of time periods. Because the fixed restaurant's location is not varied, there is not a noticeable change in positions of food trucks even with time. The results of multi-objective optimization show that the food trucks need to settle at the low competitive grids. There exist many restaurants than the average number of restaurants in Seoul. Therefore, the food trucks are located on the outskirts of Seoul to evade the competition between the existing restaurants.

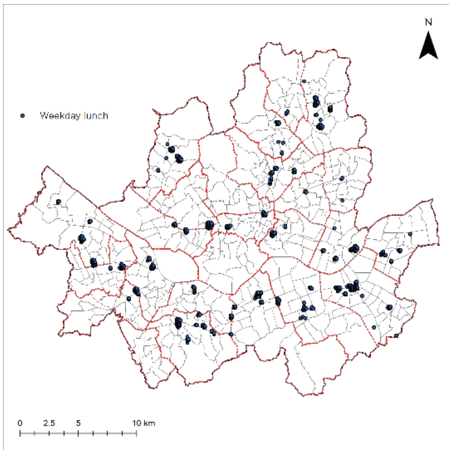


The weekday lunch time The weekday dinner time

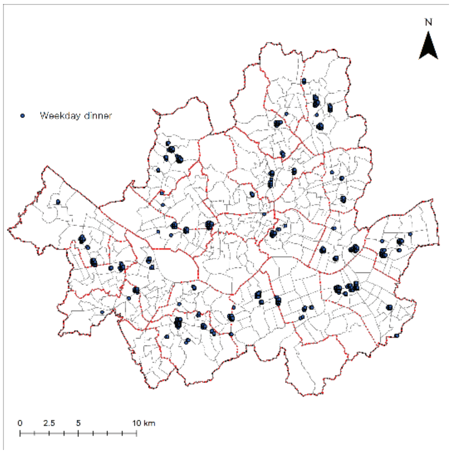
The weekend lunch time The weekend dinner time

Figure 4.12. Food trucks location when α is 0.3

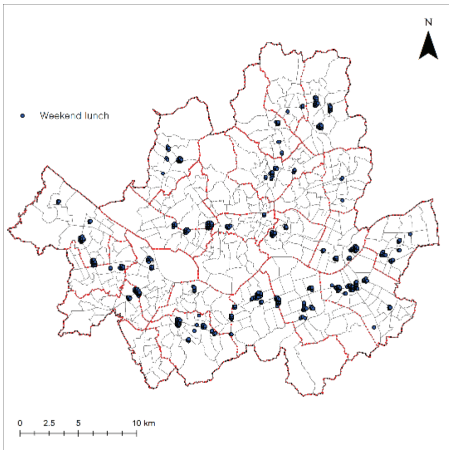
The balanced scenario defined α as 0.5. This scenario assumed that the weight between the competition and the demand. Compared to the scenario of α =0.3, the food trucks are located near the CBD at the weekday lunch time period. Also, more food trucks located on the Gangnam districts at the weekend. By the way, the food trucks can capture more population from the CBDs and nonresidential area, even though they need to compete with the existing market.



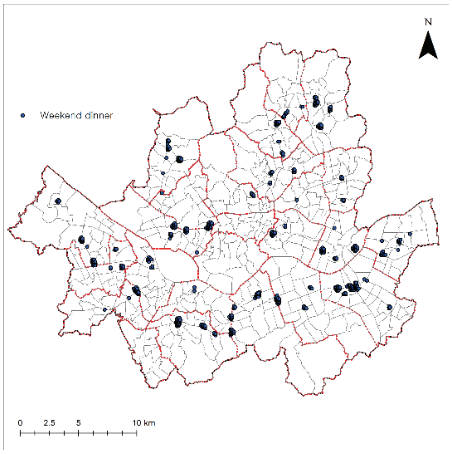
The weekday lunch time



The weekday dinner time



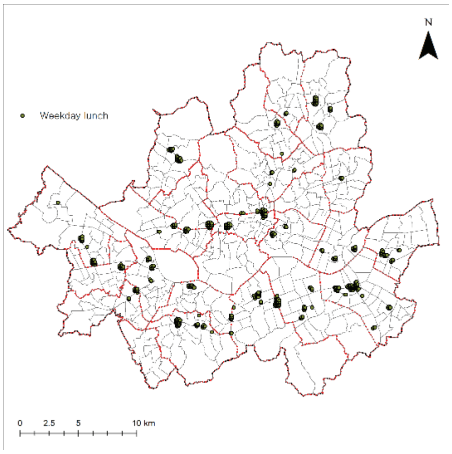
The weekend lunch time



The weekend dinner time

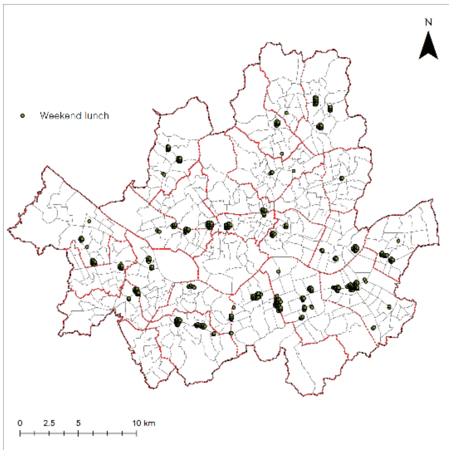
Figure 4.13. Food trucks location when α is 0.5

At the demand maximizing scenario, the α is defined as 0.7. More food trucks gathered into the CBDs at the weekday lunch time, and the spatio–temporal fluctuation increases. The locations that food trucks operate change significantly at each period to capture the de facto population. Particularly, at lunch time, food trucks settled on Jongro and Gangnam districts and move to other sites at dinner time.

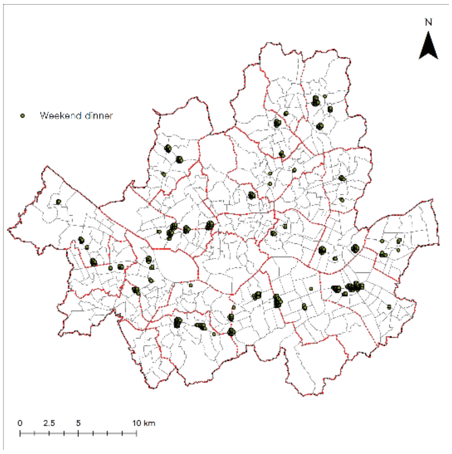


The weekday lunch time

The weekday dinner time



The weekend lunch time



The weekend dinner time

Figure 4.14. Food trucks location when α is 0.7

The results of food trucks optimal location depending on the different weight factor α presented whole food trucks set of the optimal location. There was a significant difference between the scenarios. However, the distinctive location change among the time period was not detected due to the fixed food trucks. Though the spatio−temporal dynamics of the population existed in Seoul, some food trucks did not need to move to the other site. To select the food trucks that may move and clarify the food trucks location pattern, the food trucks routing problem preprocessing and results will be shown in the next part.

4.3. Optimal Routes and Visualization of Food Trucks

In this part, the balanced scenario was selected to show the results of routes and visualization of food truck's improved model. The food trucks that fulfill conditions of the mobility are selected in this chapter. The conditions are defined by the temporal de facto population change. After selecting the food trucks that need to move, clusters are made to clarify the food trucks mobile trend. The clusters show the change of food trucks locations depending on the time periods. In the last part, calculating the distance between the clusters and making an Origin-Destination (O-D) Matrix to find the optimal routing set are conducted. Also, the space-time trajectories are presented at this part.

4.3.1. Conditions of the Mobile Food Trucks

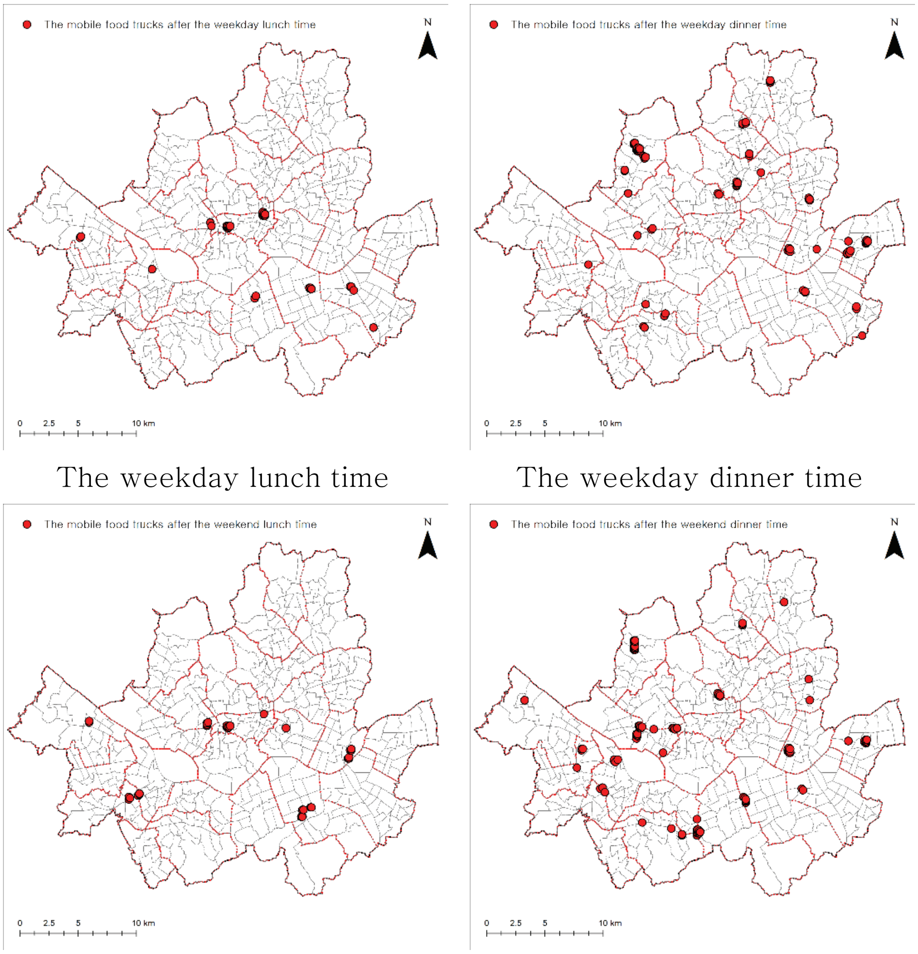
Although the de facto population changes depending on the time periods, the food truck workers are reluctant to move to another site. Due to the price that they have to spend and inconvenience, the food truck workers hesitated to move other sites in one day. Also, the uncertainty that another site is more superior for the food truck operation made them settle down in one site. To reflect the behavioral habits of the food truck workers, this research used a threshold to move to another site.

In this research, the mobile food trucks that need to move other site are defined with three conditions, as mentioned in Chapter 3. The most important condition that used in this research is that population decrease. The threshold of population decrease, in this research, is 20%. 20% is a significant population decrease for each food truck's range, so if one site's de facto population decreased over 20%, then the food truck's profit would be seriously damaged. Following to three conditions, the optimal site at the prior time period, the inferior locational site at the next time zone, and the significant population decrease, the number of food trucks that are recommended to move is referred to in Table 4.3.

Table 4.3. The number of food trucks that need to move

Time Periods	The Number of Food Trucks
After the weekday lunch time	31
After the weekday dinner time	78
After the weekend lunch time	32
After the weekend dinner time	95

Due to the different dynamics between the time periods, the number of mobile food trucks is varied. Because there is a totally different population distribution between the weekday and the weekend, the number of mobile food trucks after the weekend dinner time shows the biggest value upon all the time periods. And the mobile food trucks which moved at each time was partially different due to the inferior location distribution changed.



The weekday lunch time The weekday dinner time

The weekend lunch time The weekend dinner time

Figure 4.15. The mobile food trucks after each time period

Four−time periods show that the mobile food trucks that have to move after the time period. At the weekday lunch time, the food trucks which are located at CBDs need to change their operation site during the break time between the lunch and dinner time. Similarly, the food trucks that was near from Seoul Train Station, Sindorim, and Gangnam metro station is better to move their location to other sites at the break time. Such food trucks' flow shows that the food trucks need to move from the CBDs to the relative outskirts of Seoul.

On the other hand, the food trucks gather into the CBDs, when they finished their sales at dinner time. Because of the intense residential area at the outskirts of Seoul, the food trucks operate in the residential area at dinner time to capture the residential population. These results show the spatio-temporal mobile food trucks in Seoul. However, due to the difference in the number of food trucks at each time period, it is hard to recommend the optimal routing set for the mobile food trucks. To solve the routing problem, in the next part, the K-means clustering method is applied to represent the food trucks' change.

4.3.2. K-Means Clustering

As mentioned in Chapter 3., the number of clusters has a significant influence on the results of making the clusters. To select the appropriate number of the clusters, the Silhouette score is applied to detect the precision of making the clusters. Figure 4.16. shows the overall Silhouette scores depending on the number of clusters. According to the graph, the Silhouette score means the global optimum number of the clusters is nine.

This optimal number of clusters means that maximizing the demand and minimizing the competition on the balanced scenario. The Silhouette score recommended the optimal number of clusters from the whole food truck's benefit regarding the competition. So the decision-makers who use this number of clusters are the government officer or the food truck association's leader.

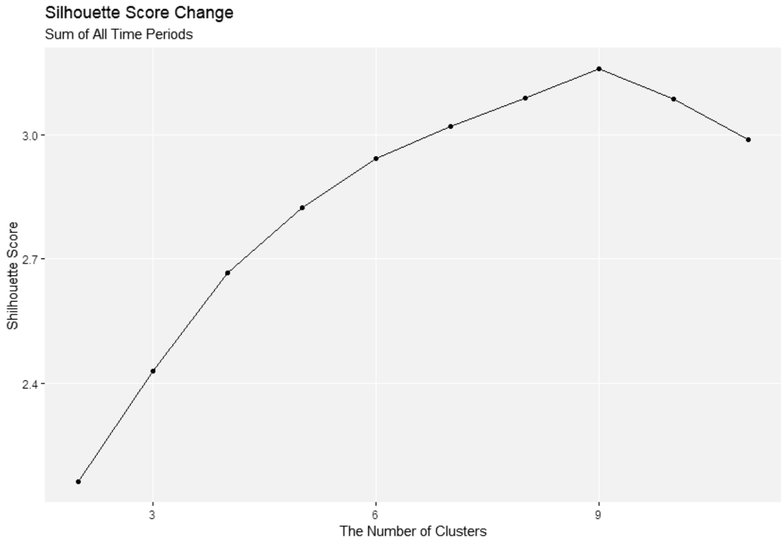
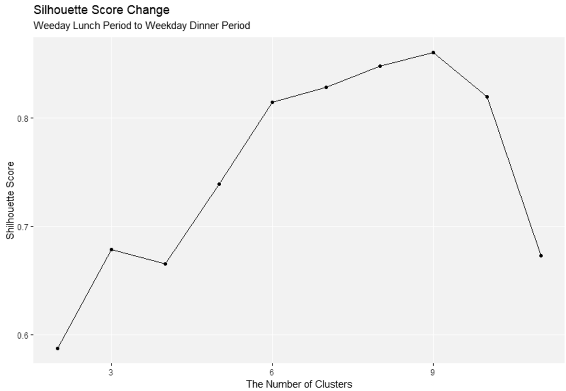


Figure 4.16. Sum of the Silhouette scores

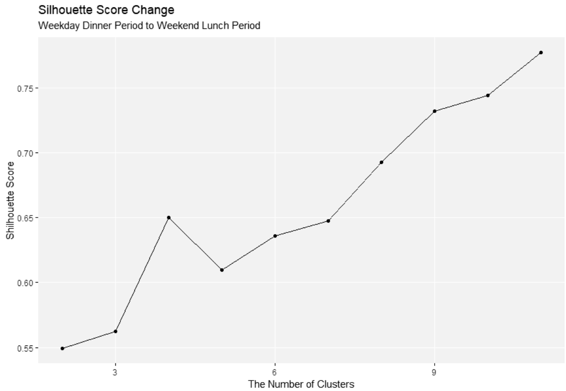
Figure 4.17 presented the Silhouette scores of each time period to detect the optimal number of the clusters. Although each time showed the different highest values of the Silhouette scores, the average Silhouette score shows nine as the optimal number of clusters (refer to Table 4.4.). When the Silhouette score is nine, all of the Silhouette scores at each time period shows a score of over 0.72, and the average Silhouette score is bigger than any other number of clusters. The average Silhouette score over 0.71 means a strong structure has been found (Berkeley, 2007). Therefore, all of the clusters have a strong structure of clustering.

Table 4.4. The Silhouette scores of each number of clusters

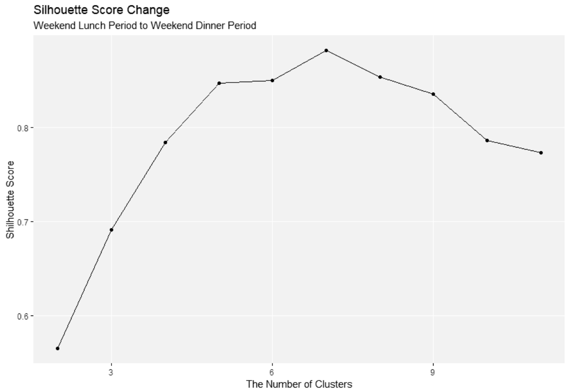
The Number of Clusters	Weekday Lunch to Weekday Dinner	Weekday Dinner to Weekend Lunch	Weekend Lunch to Weekend Dinner	Weekend Dinner to Weekday Lunch	Average
2	0.587413	0.549152	0.565154	0.460827	0.540636
3	0.678766	0.562594	0.691747	0.496800	0.607477
4	0.665690	0.650228	0.784016	0.566014	0.666487
5	0.738902	0.609865	0.847619	0.626476	0.705716
6	0.814435	0.635809	0.850513	0.641360	0.735530
7	0.828683	0.647485	0.882054	0.661343	0.754891
8	0.848029	0.692410	0.854300	0.692924	0.771916
9	**0.860424**	**0.732112**	**0.835830**	**0.729559**	**0.789481**
10	0.819596	0.744382	0.786431	0.736051	0.771615
11	0.672914	0.777163	0.773306	0.763219	0.746651



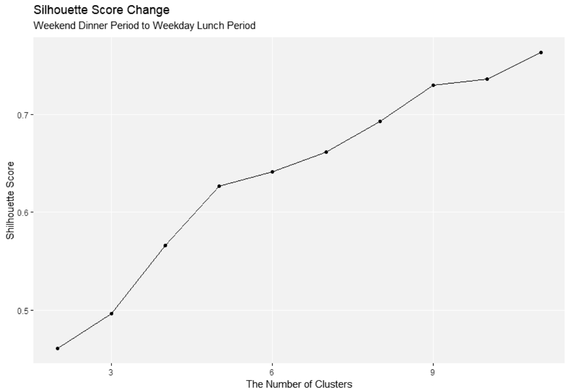
After the weekday lunch time



After the weekday dinner time



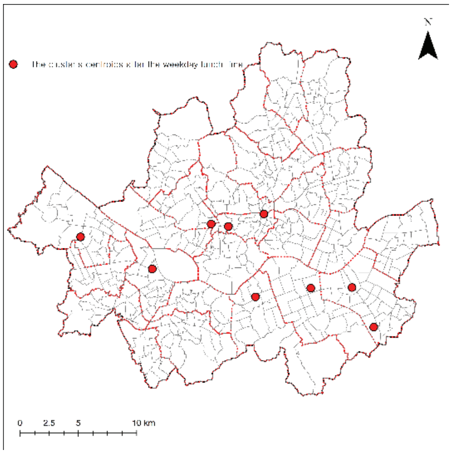
After the weekend lunch time



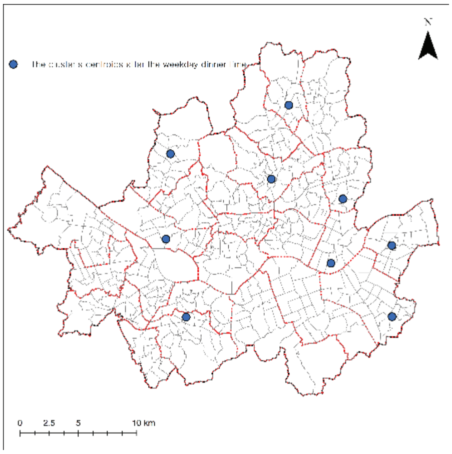
After the weekend dinner time

Figure 4.17. The Silhouette scores at each time period

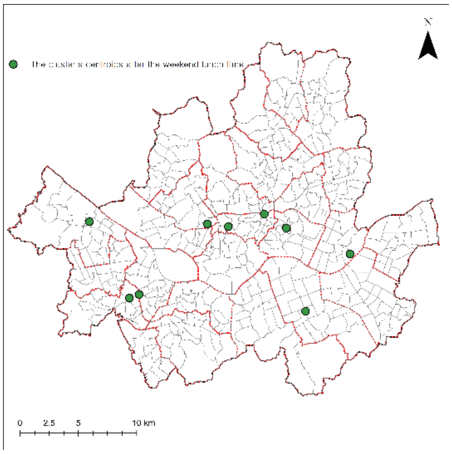
After applying nine clusters to divide the food trucks, the centroids of each cluster can represent the food trucks of the cluster. Figure 4.18. represents the food trucks cluster centroids at each time period. The results present that the clusters of the food trucks get farther away from the center of Seoul at dinner time, and shrinking into the CBDs at lunch time. The same pattern happened when the food trucks and the de facto population were analyzed. In the next part, the routing problem from the centroids of the cluster is dealt with.



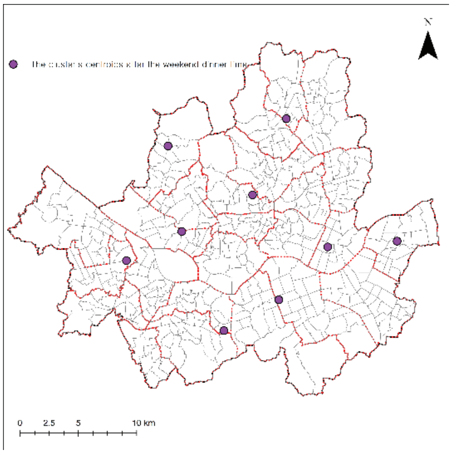
The weekday lunch time



The weekday dinner time



The weekend lunch time



The weekend dinner time

Figure 4.18. The cluster centroids of mobile food trucks after each time period

4.3.3. Optimal Routes for Food Trucks

To solve the optimal routes problem of the network distance, this research used the Dijkstra algorithm and the Hungarian algorithm. The Dijkstra algorithm is applied to calculate the shortest distance between the cluster centroids at each period. By using the Dijkstra algorithm, it is possible to calculate O–D matrixes efficiently. The O–D matrixes are formed at each period, so four O–D matrixes are created.

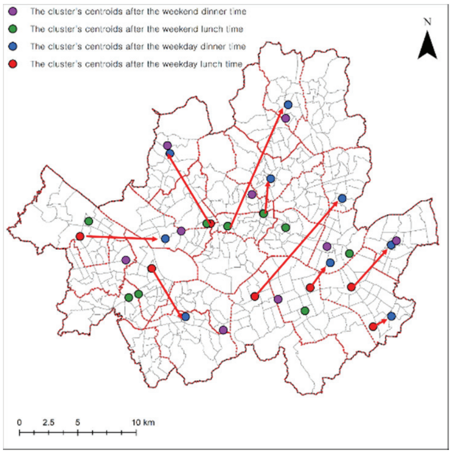
After creating the O–D matrixes, selecting the shortest routing set is performed to allocate previous time's centroids to the next step's centroids. Originally, the time complexity of finding the minimum sum of the matrix is $O(4 * 9!)$, but the Hungarian algorithm, known also as the Kuhn–Munkres algorithm, has $O(n^3)$ time complexity. As a result of applying the Hungarian algorithm, the shortest routing set is calculated as of Table 4.5.

Table 4.5. The optimal routes of the food trucks

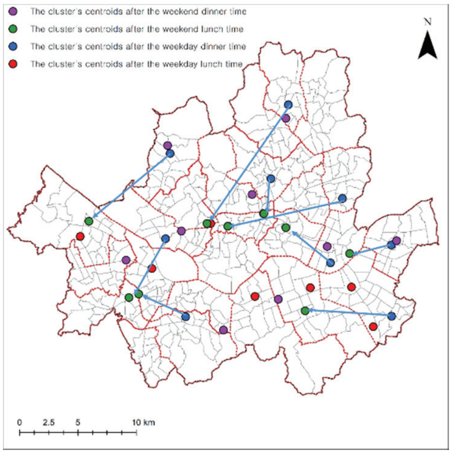
Weekday Lunch Time (t_1)	Weekday Dinner Time (t_2)	Weekend Lunch Time (t_3)	Weekend Dinner Time (t_4)	Weekday Lunch Time (t_1)
$Gangseo_1$	→$Mapo_2$	→$Guro_3$	→$Yangcheon_4$	→$Gangseo_1$
$Joong1_1$	→$Dobong_2$	→$Seodaemun_3$	→$Mapo_4$	→$Yeongdeungpo_1$
$Gangnam_1$	→$Gwangjin_2$	→$Seongdong_3$	→$Seongdong_4$	→$Songpa2_1$
$Joong2_1$	→$Seongbuk_2$	→$Joong1_3$	→$Dobong_4$	→$Joong1_1$
$Seocho_1$	→$Joongrang_2$	→$Joong2_3$	→$Jongro_4$	→$Joong2_1$
$Songpa1_1$	→$Gangdong_2$	→$Gwangjin_3$	→$Gangdong_4$	→$Songpa1_1$
$Yeongdeungpo_1$	→$Gwanak_2$	→$Yeongdeungpo_3$	→$Dongjak_4$	→$Seocho_1$
$Songpa2_1$	→$Songpa_2$	→$Gangnam_3$	→$Seocho_4$	→$Gangnam_1$
$Seodaemun_1$	→$Eunpyeong_2$	→$Gangseo_3$	→$Eunpyeong_4$	→$Seodaemun_1$

The names of clusters were designated by gu scale as of Table 4.5. Traditional CBDs were located near Joong–gu, Gangnam–gu, and Yeongdeungpo–gu, and the suburban areas were located on the outskirt of Seoul. The optimal routes of the food trucks showed the routes of food truck's cluster movement according to the sequence of time periods.

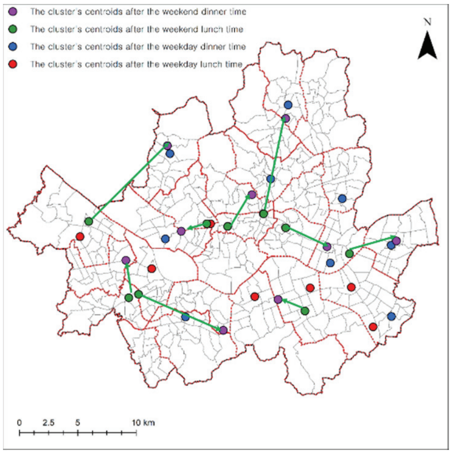
Figure 4.19 shows directions to the next optimal sites from the previous optimal food trucks' sites. The food trucks are allocated to the near feasible sites, to accomplish the global optimum, however, the food trucks are not always going to the nearest optimal sites. Although the distance between the centroids is calculated by the network distance, Fig 4.19 just presents the direction of the food trucks' routes. This mapping method has two disadvantages. First, this representation distorted the true network optimal routes of the food trucks. Euclidean direction between two points overlooks the road network between the points. Therefore, people can confuse the nearest optimal sites, due to the difference between the Euclidean distance and the network distance.



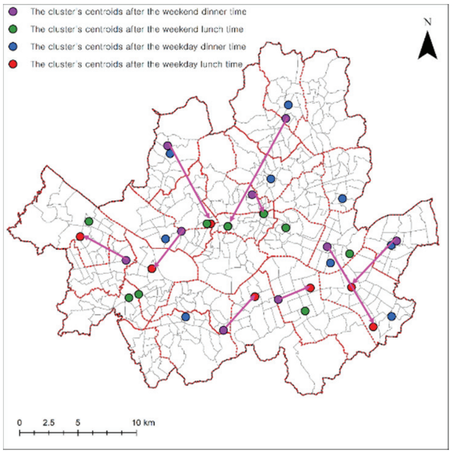
The weekday lunch time



The weekday dinner time



The weekend lunch time



The weekend dinner time

Figure 4.19. Directions of the mobile food trucks

Second of all, visualizing the routes all over the time period makes it hard to recognize the pattern. Figure 4.20 presents the food truck's moving direction sequentially. Four colors, red, blue, green, and purple, are used to mean the sequence of the routes. However, because the line was clotted by the overlapping, it is hard to recognize and follow the patterns of the routes sequence. Particularly, if there are more cluster centroids or time periods, then finding the patterns, known as the data mining, would be harder to achieve. To solve these problems, the network distance based spatio-temporal mapping is needed.

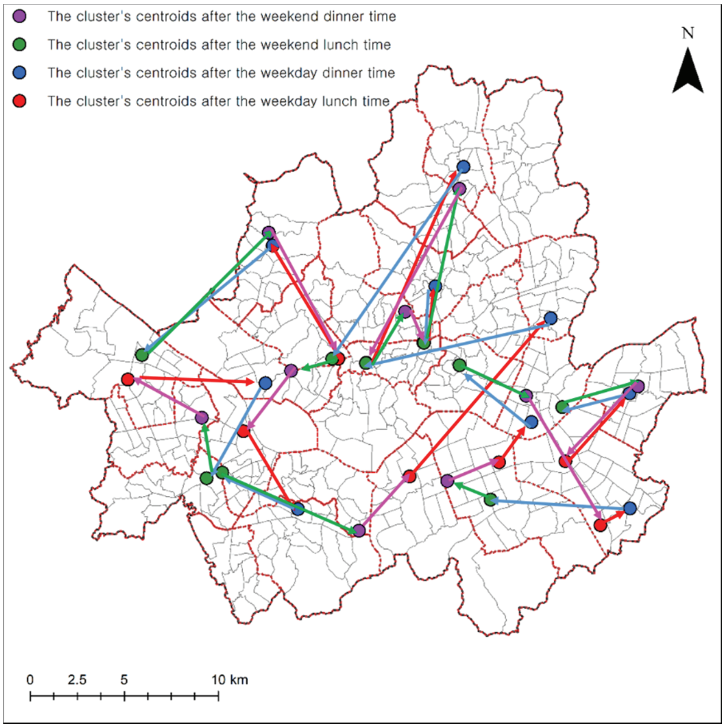
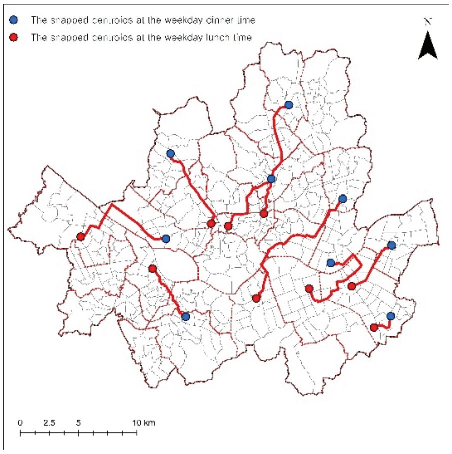
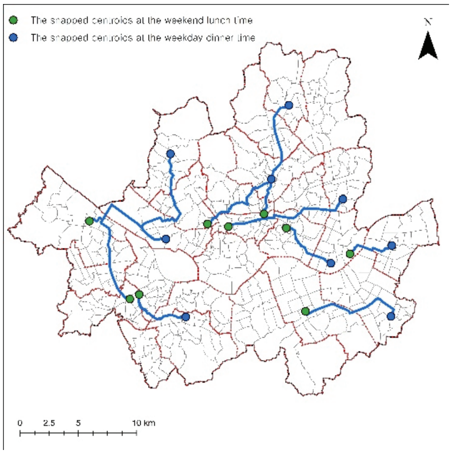


Figure 4.20. Overlapped directions of the mobile food trucks

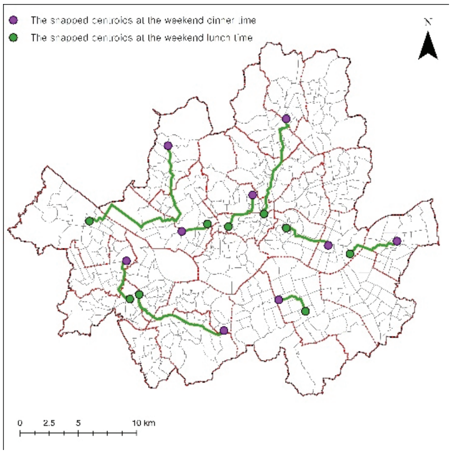
The network distance–based mapping between the centroids shows the real routes of food trucks. Particularly, due to the lack of the roads between the Northwest of Seoul and the Southwest of Seoul, they spent more time and distance to access the optimal locations at the next time period. Some food trucks are not allocated to the adjacent sites, due to the road network.



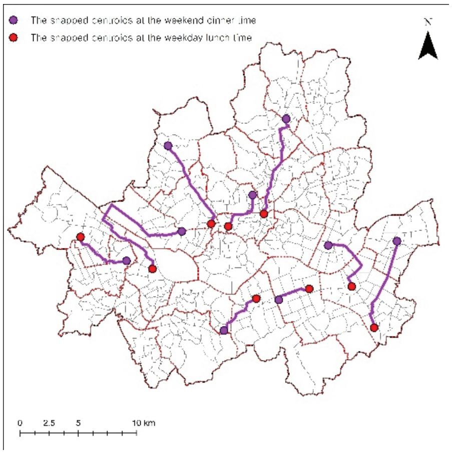
The weekday lunch time



The weekday dinner time



The weekend lunch time



The weekend dinner time

Figure 4.21. Optimal network optimal routes of mobile food trucks

To apply the network distance, the centroids were snapped to the nearest roadside. The snapped distance is less than 500m, so there was a negligible difference after snapping the food trucks to the roadside. Only one centroid is snapped to the northern area of Seoul, because of the absence of roads. Fig 4.22 shows more practical food trucks routes than Fig 4.20. However, line clotting still happens due to the overlaid selected roads.

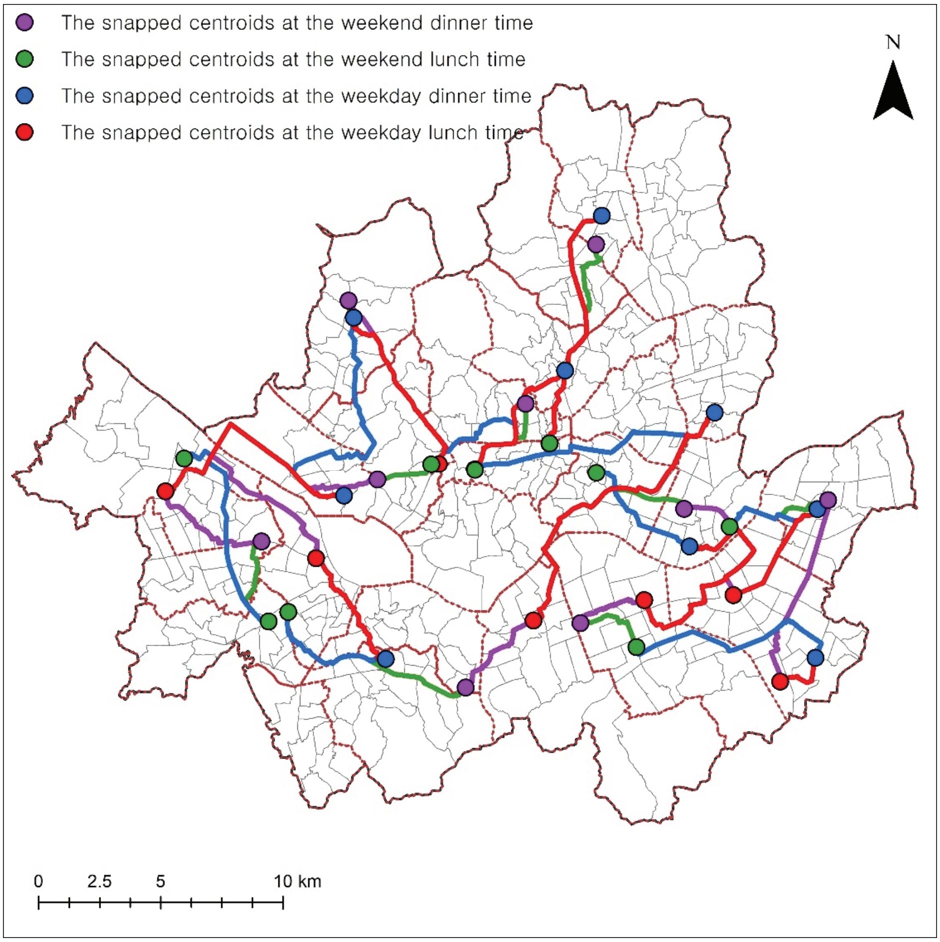


Figure 4.22. Network optimal routes of mobile food trucks

To solve the clotting problem, this research used 3D mapping for spatio−temporal analysis. By applying the spatio−temporal mapping, also known as space−time prism, the stakeholders can understand the routes patterns and amend the results to use their tacit knowledge. Because of un−recognized human behavioral patterns and the region's situation, sometimes the results would recommend the rational but not practical solutions. Preventing this problem can be possible with the stakeholder's decision and adjustment to reality.

3D map of Fig 4.23 and the interactive video helps to enhance the food truck's current situation, by showing each time period. Following to the distinguished four periods and coming back to the original points, the map contains five layers on Fig 4.23. Dividing layers according to time periods made it easy to interpret and share the stakeholders' idea. Therefore, the spatio−temporal locations and routes mapping need to be presented as overlaid maps or interactive videos.[7]

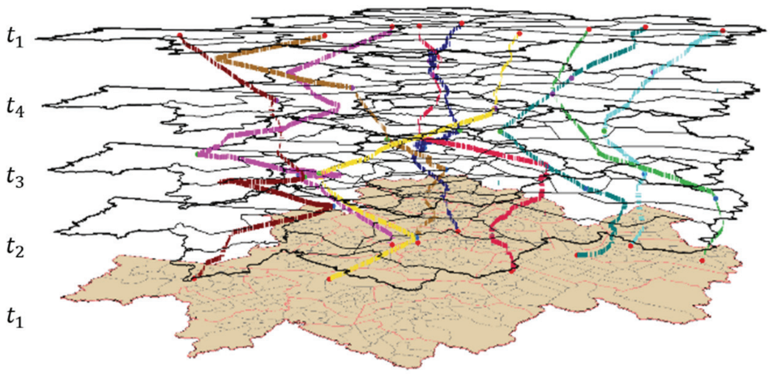


Figure 4.23. Spatio−temporal optimal network routes of food trucks

To clarify the routes of food trucks, Fig 4.24 presents the five characteristic routes. Fig 4.24 shows the food truck's centroids moved to the outskirt of the Seoul and back to the CBDs at each time zone (t_1 to t_2 and t_2 to t_3).

[7] The video can be accessed at the following address (https://drive.google.com/file/d/15nQ5gNbkHRzaxOQEqjaYwjmJVno1RTSo/view?usp=sharing).

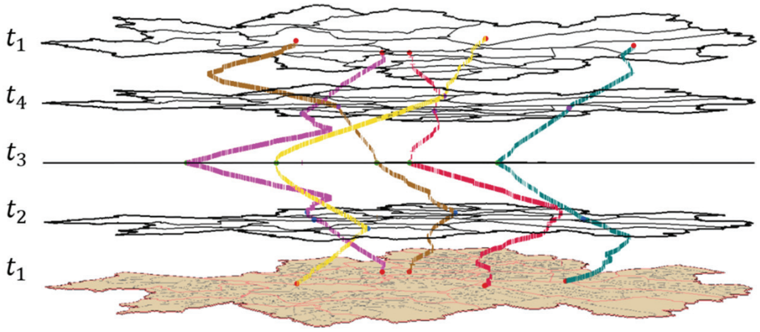


Figure 4.24. Simplified spatio-temporal optimal network routes of food trucks

4.4. Summary and Discussion

In this chapter, three steps were processed to achieve the research goals. In the first part, the spatio-temporal dynamics of the population was analyzed. In Seoul, either space or time, caused an important difference of de facto population distribution. Also, by unifying two factors, the demand and the competition index, Z-score is applied to progress the research.

In the second part, the Pareto optimal locations were derived. Selecting the feasible area, defining the weight factor, and showing the global and local Pareto optimal set were completed at this part. The Pareto tradeoff curve empirically presented that there was a tradeoff effect between the demand and the competition index. By completing this part, the spatio-temporal optimal sites for food trucks were selected.

The routing problem and space-time trajectories were shown in the last part. The mobile food trucks, which met the conditions of the site change were selected, and the clusters were made by the K-means clustering method. The number of the clusters is defined with the Silhouette score. As a final result, the routes of the food trucks during the time change were presented. The results of the spatio-temporal sites change were presented by the traditional mapping and the 3D mapping.

Although the results of the food trucks' optimal location showed a reasonable problem solution, they should be compared with the comparative group to verify the results' excellence. The existing food trucks' locations are used to compare the research results. The Pareto Optimal tradeoff curve shows a red line in Fig 4.24. The blue point means the present food trucks' conflicting restaurants and the capturing de facto population. The blue point is located upper left part of the Pareto set, so it is inferior to other feasible site sets on the Pareto frontier line. Therefore, the results of the research suggest a superior situation compared to the current situation.

Even though the covered de facto population was not shared to the adjacent food trucks, the current food truck's location is inferior than the scenario which supposed the demand weight factor as 0.1. The low covered population and the restaurants imply that the stake holders who permitted the current food truck's locations tended to lessen the conflict between the food truck workers and the restaurant owners. However, the Pareto optimal tradeoff curve shows that the food trucks can obtain more profit by changing the locations and moving at the break time. Otherwise, the stakeholders can decide the food trucks to operate on the less competitive and more productive sites than now, following the scenario with the weight factor as 0.1. Both of the methods can be beneficial ways for the food trucks and the restaurant owners.

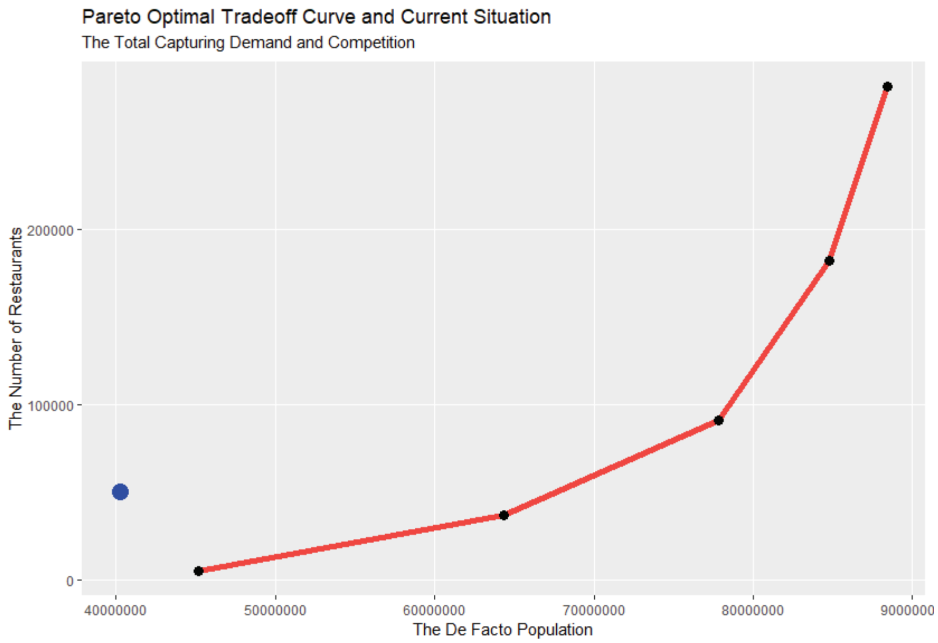


Figure 4.25. Comparison between the Pareto optimal tradeoff curve and the current situation

The result of this research, Pareto optimal sets, shows non-inferiority than the current situation. If the weight factor for the demand is the same or less than 0.3, the number of restaurants in the food trucks' service area is smaller than the current situation. The de facto population in the food trucks' service area overwhelmed the number of de facto population in the current service area of food trucks. It shows that the conflict between the food trucks and the existing market can be reduced by increasing the profit of the food trucks. For instance, the scenario with weight factor 0.1 can decrease 90% of the number of competing restaurants and increases the covered population 10% at the same time.

Table 4.6. Comparison between the current situation and the Pareto optimal results

The Current Situation		The Pareto Optimal Results		
The number of competing restaurants	The captured de facto population	Weight factor (α)	The number of competing restaurants	The captured de facto population
50,375	40,276,752	0.1	4,644	45,183,106
		0.3	36,933	64,315,346
		0.5	91,040	77,816,843
		0.7	182,525	84,741,657
		0.9	281,730	88,420,654

At Chapter 5., the conclusion and the research meaning is shown. Also, complementary points of the research are presented with the resulting review.

Chapter 5. Conclusion

5.1. Summary of Thesis

Chapter 1 introduces the social situation and conditions of Seoul and the motivation of this research. High rent price, recent deregulation, and the spatio−temporal dynamics of the population enabled the food trucks to move to the other site in one day. Also, three purposes of the research are mentioned in Chapter 1. First, the existing fixed stores, the competition index in this research, affected the locations of mobile vendors to prevent the cover maximizing the profit. Second, the Pareto optimal tradeoff curve and the scenarios show the methods of how to support spatial decision−making process. Lastly, the multi−objective results present the improvement from the current situation. Three objectives of the research are explained in Chapter 4.

Chapter 2 reviews the precedent research. From the traditional periodical market models, the traditional theory supposed mobile vendors and the periodical market as a step that did not develop. To incorporate the competitive market model to the mobile vendors, the competitive location models, and multi−objective spatial optimization models are also reviewed. By studying this research, methodologies and the necessity of this research are reinforced.

Chapter 3 suggests the methodologies of the research. This research applied multiple methodologies, such as GIS, spatial optimization, and scenario−based modeling, to construct the appropriate model for the food trucks. Also, the competitive model is calculated, when the range of food trucks have the same distance. In addition, the brief introduction of the research area and the de facto population data are presented.

The results of this research are suggested in Chapter 4. The spatio−temporal dynamics of the population is verified. Location analysis is applied with the greedy adding algorithm. The routing problem is also soling with the data mining, the Dijkstra algorithm, and the Hungarian algorithm. These multiple methodologies are applied and strengthen the research process and the results.

In summary, this research will support the economic minority's operation of food trucks by recommending a suitable area. Hopefully, this research enhances the social benefit, particularly for the person who does not have the ability to pay the high rent. In addition, the spatio−temporal population dynamics are reflected in this research. By applying the population distribution's change, this research provides more practical and situation−based results. And the different methodologies are combined to analyze the spatial problem in this research.

5.2. Discussion

This research combined the traditional location analysis by GIS, spatial optimization, spatio-temporal analysis, and 3D mapping to solve the research question and visualize the results effectively. The possibility of combining interdisciplinary methods is presented in this research. Particularly, location analysis and the minimizing transportation research are combined into the food truck's optimal business sets research. Two major topics are explored at the same time in this research. In addition, this study extended a view of the combined location and routes modeling by considering the spatio-temporal data.

Second, the recent spatio-temporal problems have huge computational complexity, so the optimization methods, such as the heuristic approach, would improve the spatial analysis. In this research, the modified greedy adding algorithm significantly decreased the computational complexity and load, $O(n^n)$ to $O(n)$. With small computational complexity, the research algorithm can be applied to other spatial problems to solve the multi-objective conflicting situation.

Proposing the spatio-temporal 3D mapping is one of the strong points in this research. Particularly, the web-based 3D interactive spatio-temporal mapping is enabled. Due to the complexity of the data dimensions, also known as the curse of the dimensionality, spatio-temporal data analysis requires more calculation loads. The results contain more data, so it is hard to be recognized by the traditional mapping methods. Therefore, the interactive 3D mapping is appropriate when representing the spatio-temporal data analysis.

5.3. Future Research Directions

Although the studies in this thesis extended our understanding of location and routes problem, several limitations remain for future research. First, this study aims to solve the location and routes problem for the food trucks in Seoul. For the generalized formulization of the mobile vendor's location and routes problem, this model needs modification to fit exactly on each case. Some parameters, like the mobile vendor's range, feasible area, or the number of mobile vendors, have to be adapted to the specific problem's situation. Therefore, it is recommended to finish the pilot survey to understand the characteristics of the mobile vendor.

Not only the parameters but also methods may change at the specific problem situation. The most representative method used in the study may change is the greedy adding algorithm. The greedy adding algorithm was applied to solve the location problem efficiently. Due to the narrow range and the deterministic market share assumption, the greedy adding algorithm performed well in this research. However, if the range of the mobile vendor is affected by other mobile vendors, then the interaction between the mobile vendors will distort the optimal solution from this model. So, the model might seek the local optimum as the global optimum in some problems. Therefore, the characteristics of the problem have to be considered discreetly.

This research assumed the single structured market model of food trucks. Assumptions that were applied in this research are the homogeneous food trucks' characteristics of their service distance, the equal hierarchy, and the absence of aggregation effect. If the food trucks have different service distance and threshold, due to the difference in their characteristics, the results will need to consider the uniqueness of the food trucks. In addition, the hierarchy of food trucks is not assumed in this research, so all of the food trucks are in the same competitive stage. The aggregation effect increases the attraction to the food trucks group than the distributed individual food trucks, such as food truck festivals. In this research, the food truck's aggregation effect was not considered. The market share model would be changed when the aggregation effect occurred in the food truck business model.

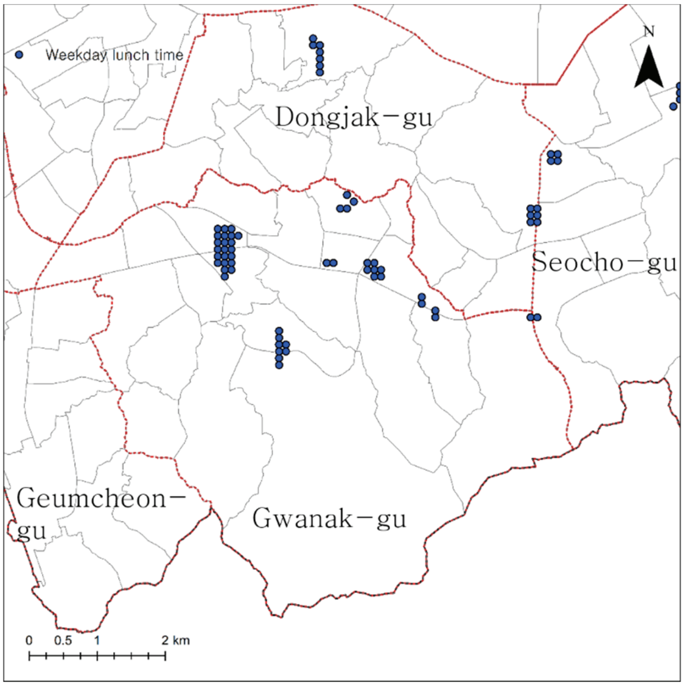


Figure 5.1. Extremely clustered food trucks

The concentrated distribution of the food trucks also needs to be studied in more depth. Because of the absence of the regulation that restricted the food truck's proximity, the food trucks are gathered at the de facto population hotspots (refer to Fig 5.1.). Although the food trucks share the demand of those sites, the extremely high density of population leads to the gathering many food trucks around the hotspots. If the regulation is enacted to keep the distance between the food trucks, then the food truck's concentration will be alleviated than the current situation.

Bibliography

Acho□Chi, C. (2002). The mobile street food service practice in the urban economy of Kumba, Cameroon. *Singapore journal of tropical geography*, *23*(2), 131-148.

Berkeley. (2007). *Performing and Interpreting Cluster Analysis*. Available at: https://www.stat.berkeley.edu/~spector/s133/Clus.html (accessed March 30th 2019)

Bhaduri, B., Bright, E., Coleman, P., & Urban, M. L. (2007). LandScan USA: a high-resolution geospatial and temporal modeling approach for population distribution and dynamics. *GeoJournal*, *69*(1-2), 103-117.

Bhandawat, R. (2018). *Location Optimization for a Mobile Food Vendor Using Public Data* (Doctoral dissertation, State University of New York at Buffalo).

Brown, A. (2002). Farmers' market research 1940–2000: An inventory and review. *American Journal of Alternative Agriculture*, *17*(4), 167-176.

__________ (2004). Periodic Markets Now and Then. In *WorldMinds: Geographical Perspectives on 100 Problems* (pp. 267-270). Springer, Dordrecht.

Byun, Miree. & Seo, U-Seok. (2011). How to Measure Daytime Population in Urban Streets?. *Survey Research*, 12(2), 27-50.

Cao, K., Batty, M., Huang, B., Liu, Y., Yu, L., & Chen, J. (2011). Spatial multi-objective land use optimization: extensions to the non-dominated sorting genetic algorithm-II. *International Journal of Geographical Information Science*, *25*(12), 1949-1969.

Christaller, W. (1966). *Central places in southern Germany*. Prentice Hall.

Church, R. L. (2002). Geographical information systems and location science. *Computers & Operations Research*, *29*(6), 541-562.

Cooper, L. (1963). Location-allocation problems. *Operations research*, *11*(3), 331-343.

___________ (1964). Heuristic methods for location-allocation problems. *SIAM review*, *6*(1), 37-53.

Dantzig, G. B., & Ramser, J. H. (1959). The truck dispatching problem. *Management science*, *6*(1), 80-91.

Daskin, M. S. (2011). *Network and discrete location: models, algorithms, and applications*. John Wiley & Sons.

Drezner, T. (1994). Locating a single new facility among existing, unequally attractive facilities. *Journal of Regional Science*, *34*(2), 237-252.

Eiselt, H. A., & Marianov, V. (Eds.). (2011). *Foundations of location analysis* (Vol. 155). Springer Science & Business Media.

Embrain. (2012). Lunch time analysis for the workers. Kyobo.

Eun, Ki-Soo. (2001). Social Stratification of the Great Seoul Area. *Korea Journal of Population Studies*, 24(1), 41-65.

Forer, P. (1998). Geometric approaches to the nexus of time, space, and microprocess: implementing a practical model for mundane socio-spatial systems. *Spatial and temporal reasoning in geographic information systems*, 171-190.

Frey, B. J., & Dueck, D. (2007). Clustering by passing messages between data points. *science*, *315*(5814), 972-976.

Huff, D. L. (1964). Defining and estimating a trading area. *Journal of marketing*, *28*(3), 34-38.

Gao, S. (2015). Spatio-temporal analytics for exploring human mobility patterns and urban dynamics in the mobile age. *Spatial Cognition & Computation*, *15*(2), 86-114.

Ghosh, A. (1982). A model of periodic marketing. *Geographical Analysis*, *14*(2), 155-166.

Goodchild, M. F. (1984). LACS: A Location-Allocation Mode for Retail Site Selection. *Journal of Retailing*, *60*, 84-100.

Hägerstraand, T. (1970). What about people in regional science?. *Papers in regional science*, *24*(1), 7-24.

Hakimi, S. L. (1964). Optimum locations of switching centers and the absolute centers and medians of a graph. *Operations research*, *12*(3), 450-459.

Han, J., Pei, J., & Kamber, M. (2011). *Data mining: concepts and* *techniques*. Elsevier.

Hotelling, H. (1990). Stability in competition. In *The Collected Economics Articles of Harold Hotelling* (pp. 50–63). Springer, New York, NY.

Joo, Sung–Min. (2018). Impacts of Service Quality of Food Truck to Customer Satisfaction and Revisit Intention. *Journal of Foodservice Management Society of Korea*, 21(4), 291–308.

Kariv, O., & Hakimi, S. L. (1979). An al gorithmic approach to network location problems. I: The p–centers. *SIAM Journal on Applied Mathematics*, *37*(3), 513–538.

Kim, Yong Gyeom. (2014). An Exploratory Research on the Food Truck. (Master dissertation, Kyonggi University).

Kodinariya, T. M., & Makwana, P. R. (2013). Review on determining number of Cluster in K–Means Clustering. *International Journal*, *1*(6), 90–95.

Kuby, M. J. (2018). Lecture note.

Kuby, M. J., Fagan, W. F., ReVelle, C. S., & Graf, W. L. (2005). A multiobjective optimization model for dam removal: an example trading off salmon passage with hydropower and water storage in the Willamette basin. *Advances in Water Resources*, *28*(8), 845–855.

Kwan, M. P. (2004). GIS methods in time□geographic research: Geocomputation and geovisualization of human activity patterns. *Geografiska Annaler: Series B, Human Geography*, *86*(4), 267–280.

Kwan, M. P., & Hong, X. D. (1998). Network–based constraints–oriented choice set formation using GIS. *Geographical Systems*, *5*, 139–162.

Laporte, G. (1992). The vehicle routing problem: An overview of exact and approximate algorithms. *European journal of operational research*, *59*(3), 345–358.

Lasserre, M. R. (2013). Location, Location, Location–The Food Truck's Battle for Common Ground. *Cumb. L. Rev.*, *44*, 283.

Lee. Eun–Yong. (2018). An Exploratory Study of Selection Attributes of Food Trucks through Revised IPA. *International*

Journal of Tourism and Hospitality Research, 32(3), 227-239.

Lee, Eun-Yong. & Park, Kyu-Eun. (2018). An Analysis of Customers' Price Sensitivity to Food Truck Menus. *International Journal of Tourism and Hospitality Research*, 32(12), 19-34.

Lee, Gunhak, & Kim, Kamyoung. (2016). Estimating de facto Population Using Spatial Statistics. *Journal of the Korean Cartographic Association*, 16(2), 71-93.

Lee, In-Suk. & Sul, Hoon-Ku. (2014). A Study of Location Preferences Factors of Foodservice Enterprises. *Journal of Tourism and Leisure Research*, 9(88), 161-177.

Ligmann□Zielinska, A., Church, R. L., & Jankowski, P. (2008). Spatial optimization as a generative technique for sustainable multiobjective land□use allocation. *International Journal of Geographical Information Science*, *22*(6), 601-622.

Liu, J. L. (2013). *Analysis of Mobile Food Facility Locations in San Francisco City* (Doctoral dissertation, UCLA).

Louail, Thomas, Maxime Lenormand, Oliva G. Cantu Ros, Miguel Picornell, Ricardo Herranz, Enrique Frias-Martinez, José J. Ramasco, and Marc Barthelemy. "From mobile phone data to the spatial structure of cities." *Scientific reports* 4 (2014): 5276.

Maranzana, F. E. (1964). On the location of supply points to minimize transport costs. *Journal of the Operational Research Society*, *15*(3), 261-270.

Megiddo, N., & Supowit, K. J. (1984). On the complexity of some common geometric location problems. *SIAM journal on computing*, *13*(1), 182-196.

Miller, C. E., Tucker, A. W., & Zemlin, R. A. (1960). Integer programming formulation of traveling salesman problems. *Journal of the ACM (JACM)*, *7*(4), 326-329.

Miller, H. J. (1999). Measuring space□time accessibility benefits within transportation networks: basic theory and computational procedures. *Geographical analysis*, *31*(1), 187-212.

Moon, Byungchan. (2017). Study on the Food-truck Consumer

Behavior and Selection Attributes by Types of the Food-related Lifestyle. (Master dissertation, Kyunghee University).

Nakanishi, M., & Cooper, L. G. (1974). Parameter estimation for a multiplicative competitive interaction model—least squares approach. *Journal of marketing research*, *11*(3), 303-311.

Oh, Ji-Hun. (2019). Effect of Food Truck's Selection Attributes on Customer Satisfaction. (Master dissertation, Pukyong National University).

Pareto, V. (2014). *Manual of political economy: a critical and variorum edition*. OUP Oxford.

Park, Doohee. (2015). A Research of Efficient Implementation of Food Truck Policy. (Master dissertation, Korea University).

Rousseeuw, P. J., & Kaufman, L. (1990). Finding groups in data. *Hoboken: Wiley Online Library*.

Seoul Metropolitan Government. (2017). Meeting on expansion of food truck business site. Available at: http://tv.seoul.go.kr/new/src/onair/vod_about.asp?cid=119178 (accessed February 5th 2019)

Stanley, T. J., & Sewall, M. A. (1976). Image inputs to a probabilistic model: predicting retail potential. *Journal of Marketing*, *40*(3), 48-53.

Stine, J. H. (1962). Temporal aspects of tertiary production elements in Korea. *Urban System and Economic Development*, 68-88.

Statistics Korea. (2016). The median house price in Seoul is over 400 million won. Available at: http://www.seoul.co.kr/news (accessed February 6th 2019)

Suhua Jin. (2017). Meal Structure of Korean employees. (Master dissertation, Seoul National University).

Teitz, M. B., & Bart, P. (1968). Heuristic methods for estimating the generalized vertex median of a weighted graph. *Operations research*, *16*(5), 955-961.

Tibshirani, R., Walther, G., & Hastie, T. (2001). Estimating the number of clusters in a data set via the gap statistic. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *63*(2), 411-423.

Thunen, J. V. (1826). Der Isolierte Staat in Beziehung auf Landwirtschaft und Nationaldkonomie (The isolated state with reference to agriculture and national economy. *Readings in Economics, edited by KW Kapp and LL Kapp*, 299.

Wallace, E. V. (2012). Can Mobile Food Truck Vendors Contribute to the Accessibility of Nutritious Foods in Vulnerable Communities?: An Analysis of Public Health Policy. *The Journal of Race & Policy*, *8*(1), 87.

Wessel, G., Ziemkiewicz, C., & Sauda, E. (2016). Revaluating urban space through tweets: An analysis of Twitter-based mobile food vendors and online communication. *New Media & Society*, *18*(8), 1636-1656.

Abstract in Korean

도시 내 인구 역동성이 증가하면서, 상업 활동의 수요 역시 시공간적 역동성을 보인다. 도시 내 수요자의 이동성(mobility)이 증가하면서 공급자 역시 수요자의 공간적 변동을 따라 이동할 필요성이 높아진다. 본 연구에서는 이동성을 갖춘 상업시설을 이동식 상업시설(mobile vendor)로 정의하는데, 푸드트럭이 대표적인 이동식 상업시설이다. 푸드트럭은 수요자의 시공간적 핫스팟이 변함에 따라 공급자도 이동할 수 있다는 특성을 대표적으로 보여준다.

중앙정부는 2017년 푸드트럭 규제를 완화하였고 서울시는 관련 조례를 제정하였다. 이 조례에 의거하여 푸드트럭은 기동성을 활용할 수 있게 되었고, 대표적인 청년 창업의 수단으로 각광받고 있다. 기존의 연구들은 이동식 상업시설의 입지에만 주목하면서 고정식 상업이 기입지한 상태에서의 이동식 상업시설 입지 양상을 연구하지는 않았다. 수요의 역동성이 증가하는 현대 사회에서 이동식 상업시설의 시공간적 입지와 이동에 대한 연구도 부족하였다. 본 연구는 기존 상권이 존재하면서, 수요가 시공간적으로 변동하는 상황에서 푸드트럭의 입지와 이동 경로를 최적화하는 방안에 대해 살펴보았다.

본 연구는 세 가지 연구 질문을 제기하고 이에 대한 해답을 찾았다. 첫 번째로 상업 구조가 이미 형성된 상태에서 이동식 상업시설의 입지와 경로의 최적화 모형은 어떠한지 연구하였다. 두 번째로 다목적 최적화 기법이 이동식 상업시설의 최적 입지와 경로 선정 시나리오 구축에 적용 가능한지도 살펴보았다. 마지막으로 시공간적 최적 입지 탐색과 경로 최적화가 현재의 이동식 상업시설의 운영을 개선할 수 있는지도 탐구하였다.

위와 같은 연구 질문에 답하기 위해, 본 연구는 서울시의 현재 상황과 동일하게 500대의 푸드트럭이 운영되는 모델을 구축하였다. 서울시의 생활인구 자료를 활용하여 모델에서의 수요를 대표하는 인구 역동성을 측정하였다. 위 과정을 통해, 현재 푸드트럭의 일회성 축제 매출 의존성을 낮추고, 일상적 상황에서의 수요 포획을 극대화하면서도 기존 상권과의 마찰을 최소화하는 방안을 도출하였다. 연구 목적 달성을 위해 다음 세 가지 단계를 통해 연구를 진행하였다.

첫 번째로는 기술적 자료 분석을 토대로, 인구 역동성이 요일, 시간, 지역적 스케일에서 각각 존재하는지를 검증하였다. 또한, 푸드트럭과

경쟁 업체들의 입지를 검토하여, 서울시의 평일 생활인구와 음식점의 입지 사이의 상호관계를 실증적으로 규명하였다. 각 단위 구역 내의 생활인구와 음식점 수를 가중치로 변환해서 비교하기 위해, 수치를 정규화하고 수요와 경쟁의 지표로 정의하였다.

두 번째로 다목적 공간 최적화 기법을 토대로, 가중치에 따른 시나리오별 푸드트럭 최적 입지를 탐색하였다. 공간 최적화 기법을 적용하기 위해 푸드트럭의 입지 가능 지역을 선택하고, 각 시간대별 푸드트럭 최적 입지를 선정하였다. 푸드트럭 운영자의 수익 보장을 위한 수요 포획 극대화와 기존 상권과의 갈등 최소화라는 두 가지 목적 하에, 다목적 함수를 설계하고 푸드트럭의 시공간적 다목적 공간 최적화 결과를 각각의 수요 가중치 시나리오에 따라 도출하였다. 그 결과, 푸드트럭의 배후지 내 수요 포획 극대화에 높은 가중치를 부여할수록, 도심지에 푸드트럭이 더 많이 입지함을 확인할 수 있었다.

마지막으로 각 시간대별 이동 푸드트럭을 정의해서, 네트워크 이동 거리를 최소화하는 조합을 도출하였고, 이를 시각화 하였다. 푸드트럭의 이동 경향성을 파악하기 위해 데이터 마이닝 기법인 K-Means 클러스터링을 활용하여 클러스터를 구축했고, 각 시공간별 클러스터의 이동 경로를 도출하였다. 그 후 시공간 클러스터들의 이동 거리 합을 최소화하는 방법을 통해, 푸드트럭의 시간대별 입지와 이동 경로를 계산하였다. 이렇게 도출된 시공간 입지, 경로 분석 결과물을 3D 지도로 재현하였다.

연구 결과, 푸드트럭은 목적식의 가중치에 따라 서로 다른 최적 입지를 보이지만, 점심 시간에는 도심 지역에 입지하는 공통점을 보이고 있다. 이는 주중에는 경제활동인구가, 주말에는 여가활동을 즐기는 인구가 도심에 집중되기 때문으로 해석된다. 반면 푸드트럭이 저녁 시간에는 상주인구의 밀집 지역을 따라 서울시 외곽으로 이동하는 경향이 나타난다. 본 연구 성과를 현재의 푸드트럭 입지와 비교한 결과, 기존 상권과의 마찰을 현재보다 감소시키면서도, 수요를 추가 포획할 수 있는 파레토 균형의 달성이 가능함을 확인할 수 있었다.

본 연구는 GIS와 공간 최적화의 다양한 기법을 활용하여, 이동식 상업시설과 기존 상권이 병존할 때의 입지와 이동 양상을 시공간적으로 분석하였다. 본 연구의 의의는 기존의 입지와 교통이라는 두 가지 주요 요소를 시공간적으로 고려하며 통합적으로 다루는 모델을 구축하였다는 점에 있다.