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An Algorithm for Searching Optimum Path using Car-hailing as Transit Feeder

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이 논문을 공학석사 학위논문으로 제출함

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Abstract

An Algorithm for Searching Optimum Path using Car-hailing as Transit Feeder

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Promoting the use of transit helps alleviate many problems caused by excessive use of private autos, such as traffic congestion, parking problems and air pollution. In Seoul, the modal split of transit has declined in the past five years and that of private autos has increased. This means that transit is less competitive than private autos, and in order to enhance transit competitiveness, it should first evaluate its competitiveness. Most of the studies evaluating transit focused on the accessibility of transit, which can be measured using factors such as travel time, distance and fare. This study compares the two modes by using five-weekday smart card data in Seoul to obtain the passengers of transit, and by acquiring the travel time of auto and transit through application programming (API) services. Not only travel time is compared, but the number of transit passengers is considered to define transit vulnerable ODs (Origin and Destination) in Seoul. The travel occurred during the morning peak hours where traffic is concentrated is analyzed, and the OD is selected as the transit vulnerable OD when the difference in travel time between transit and auto is more than 5 minutes and the number of passengers of transit is more than 500 in 5 days. By using four multimodal integrated route generating algorithms of each vulnerable OD, combined paths between transit and car-hailing service were generated and compared with existing unimodal paths to identify how the transit competitiveness has improved. Among the multimodal paths generated by the algorithm, the optimum path is selected by calculating the generalized cost, and the optimum paths selected by each algorithm are compared. As a result, the second algorithm, which replaces the bus with the car-hailing service and selects the transfer points before and after the transfer stations of transit path as the origin and the destination of the car-hailing service, is found to find multimodal paths most efficiently. Although the multimodal paths have the shortest travel time at a specific OD in a certain time period, at the majority of the ODs, the multimodal paths have about 30% of the travel time between the car-hailing only and the transit paths. Also, the competitiveness of multimodal path was low for ODs with short travel distance, and the competitiveness of multimodal paths was high at ODs with long travel distance. It is most effective to use the car-hailing service as transit feeder where the access time is long.

keywords : Transit, Car-hailing service, Smart card data, API service, Multimodal integrated path generation
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Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Background

Countless major cities have been having problems such as traffic congestion, air pollution and parking problems recently. These problems are caused by the increase of private autos, and it is necessary to replace the traffic of private auto with transit in order to solve them. Over the past five years, the modal split of transit in Seoul has fallen from 65.9% to 65.0%, while that of auto has increased from 22.9% to 24.4%. This means that the competitiveness of transit is falling against auto, and the problems mentioned above are getting worse. Therefore, in order to increase the modal split of transit in many high-density metropolitan areas, it is necessary to evaluate the competitiveness of current transit, to select vulnerable areas or origin-destination (OD) pairs, and to improve the transit system.

Many studies have tried to assess transit. Various indicators of different values such as accessibility, mobility and equity were developed and applied, and the transit vulnerable social groups or areas were selected. Of the many important concepts, accessibility, which is the most direct indicator to both operators and users, is most widely used to evaluate transit all over the world. However, due to the differences in the situation and transit system faced by country and region, it is important to assess transit by choosing appropriate indicators, which suit the situation in the region, and carefully suggest the solution to improve it.

Indicators that evaluate transit consist of travel information such as travel time, distance, fare, number of transfers, and socioeconomic indicators. This information is obtained primarily from surveys or government data. Recently, however, due to the development of technology, travel information of actual users can be easily obtained.

Automated fare collection (AFC) systems are widely applied to large cities such as Seoul, Hong Kong and Singapore where transit is active, so these data can be analyzed to understand the actual travel patterns of people. In addition, due to the popularization of navigation application, aggregated actual travel information of many autos can be easily accessed through application programming interface (API) services.

To increase the modal split of transit, a comparison is needed with competing modes, and if the comparison shows that the transit is considered inferior to other modes in certain areas or OD pairs, the transit service or infrastructure in these regions should be improved. However, in cities where transit is already well equipped, such as Seoul, it is difficult and less effective to improve existing transit services or infrastructure. Previous studies have devised many methods to improve transit, but the solution by such methods has reached its limits, and now there is a need for a new solution that fits the current situation.

With the recent introduction of mobility as a service (MaaS), it has become possible to increase the modal split of transit by integrating transit with other modes. MaaS is a service that integrates various modes of transportation and allows planning, booking and payment in a single platform (Jittrapirom et al., 2017). New modes are also being introduced such as car–hailing service or ride–hailing service, car–sharing and bike–sharing recently. Car–hailing service literally means a service in which a passenger, who needs to move, hail a car and rides to the desired destination. When a passenger enters the desired OD using a smartphone, the service operator catches it and forwards it to the drivers, and the driver near the origin takes the order (Wang et al., 2017). Using car–hailing service as a transit feeder, it is possible to increase the modal split of transit.

In order to operate this integrated mode, it is necessary to generate the multimodal optimum path and compare it with existing modes. Since there has not been much research done to generate the optimum path of integrated modes that combines transit and car–hailing service or taxi, algorithms, which find the optimum path of integrated modes efficiently should be developed.

1.2 Objectives

The objectives of this study are to develop multimodal integrated path generation algorithms (MIPG) and to generate multimodal integrated paths to evaluate how much more competitiveness has been improved compared to the existing transit. This study consists of two stages. The first step is to develop MIPG algorithms using several travel data and the second step is to select transit vulnerable ODs based on several rules and generate the multimodal integrated paths by using developed algorithms for the selected ODs, and analyze the effect of the introduction of integrated mode.

In the first stage, four algorithms that generate multimodal integrated paths were developed applying different criteria. Integrated paths were generated using transit and auto route guidance API services.

In the second stage, the OD matrix of the traffic analysis zones (TAZ) in Seoul at the morning peak hours was created. Travel information such as travel time, distance, number of transfer and transit line between TAZs, and the corresponding travel information of autos is obtained using API services. The transit passenger volume between TAZs at morning peak hours was obtained through smart card data. Considering the difference in travel time between auto and transit, and the number of transit passengers, the transit vulnerable ODs at morning peak hours were selected. Using the algorithms developed in the first step, integrated paths were generated for transit vulnerable ODs and compared with the existing paths of transit and auto to analyze the effect of introducing the integrated mode.

Chapter 2. Literature Review

2.1 Transit Accessibility

The definition of transit accessibility varies from study to study. This means mainly access to transit facilities, or access to employment or leisure activities using transit. Many existing studies have evaluated transit in terms of mobility. However, the ultimate goal of most transportation is accessibility, and mobility is one of the ways to improve accessibility (Litman, 2003 and 2018). It is important to assess the overall accessibility because various factors, such as mobility and connectivity, affect accessibility (Litman, 2003). In this context, most studies evaluating transit defined accessibility and developed indicators to evaluate transit. These papers did not simply evaluate the accessibility of transit in a particular region but analyzed whether all regions or ODs were provided with equivalent transit services in terms of equity.

Schoon et al. (1999) defined accessibility and developed accessibility indices. They argued that the measured actual travel time and cost are important factors in the accessibility indices. Also, accessibility indicators can identify the characteristics of different modes and facilitate cross-measuring comparisons in specific ODs. They developed accessibility indicators (AI) using transit, car travel time and cost. AIs using travel cost were defined in the same way as AIs using travel time.

$$\text{Car travel time AI} = \text{time by car}/(\text{time by car} + \text{time by bus})/2 \tag{2.1}$$

$$\text{Bus travel time AI} = \text{time by bus}/(\text{time by car} + \text{time by bus})/2 \tag{2.2}$$

They selected 15 pairs of important ODs using land use and the types of modes available and compared the accessibility of transit, autos and cycle between 7 AM and 9 AM.

Mamun and Lownes (2015) combined existing three transit accessibility indicators to quantify transit accessibility using each positive feature and to reflect the views of various users such as transit planner, provider and property developer, etc. They calculated the indicators using data obtained from the transit provider and the 2001 National Household Travel Survey (NHTS). The first indicator they used was the local index of transit availability (LITA), which measures the transit service intensity of an area. The second indicator was transit capacity and quality of service manual (TCQSM) that measures service coverage. The last indicator was a time-of-day tool. It measures the accessibility of transit service using the daily travel demand distribution and provides the relative value of transit service provided for each specific time period.

Karner (2018) developed indicators of accessibility and equity for robust transit equity analyses. He estimated travel times for departures occurring during a morning peak hour (7:00-9:00 AM) using transit route and schedule information in the general transit feed specification (GTFS) format. Resident worker and job locations by wage categories were also considered in this study. They used the gravity model formulation of accessibility with demographics and travel times.

$$AT_i^w = \sum_j E_j^w e^{-\beta t_{ij}} \tag{2.3}$$

$$AW_i^w = W_i^w \frac{AT_i^w - \overline{AT^w}}{\sigma_{AT^w}} \tag{2.4}$$

where, AT_i^w = Territorial accessibility at stop i for resident workers with wage level w

AW_i^w = Worker – weighted accessibility at stop i for resident workers with wage level w

E_j^w = Jobs in service area silver j with wage level w

W_i^w = Resident workers in service area at stop i with wage level w

$\overline{AT^w}$= Mean territorial accessibility for resident workers with wage level w

σ_{AT^w}= Standard deviation of territorial accessibility for resident workers with wage level w

t_{ij}= Average peak period travel time (minutes) by transit between stop i and service area sliver j

β= empirically derived impedance term

He conducted analysis at the transit stop level to measure transit accessibility with high spatial resolution.

Saghapour et al. (2016) developed transit accessibility index using access time, service frequency and population density. They analyzed Melbourne's transit accessibility using timetable at the morning peak hours (7:00–9:00 AM) and government–provided open–source transit stations and routes data.

Wu (2017) compared the accessibility of transit and auto, which are dominant modes of transportation in most cities. He used the ratio of transit/auto travel time as an accessibility index. The travel times of transit and auto between activity centers were calculated by using Google Maps API.

2.2 Transit Path Searching Algorithm

Many existing studies have developed algorithms that efficiently navigate optimal paths in networks based on links and nodes.

Shin and Noh (2004) presented a method to selectively navigate through a loopless path (Loopless Path; Simple Path; Node Loopless Path) where there is no overlap of nodes or links on the path of the Path Deletion Method based on the existing Graph Theory–based Dijkstra algorithm. Based on this paper, Jo et al. (2006) developed K minimum time path search algorithms by combining departure time constraints considering schedules of transit paths. Shin et al. (2008) developed an algorithm to establish the number of transfers, total transit time, availability of seats, fare constraints, and transit time as constraints, and to reduce the path search conditions to provide a path that reasonably meets the requirements of transit passengers.

Lo et al. (2005) developed a web–based route guidance service and UI combining various transit modes, and developed an algorithm to recommend routes that meet the minimum cost, shortest time and minimum generalization costs. The transit route guidance used a method of finding all stations that could be reached within an acceptable walking time based on their destination, and reverse looking for routes with the lowest generalization cost.

Yang (2018) used RAPTOR, a time–based shortest–path search algorithm with very low computational complexity compared to the previous algorithms that based on graph theory, to calculate the transit travel time in Seoul, and clustered transit stations using DBSCAN to assess transit accessibility.

2.3 Multimodal Path Generation Algorithm

The studies of generating paths using multimodal in a single trip were mainly conducted on the freight side to minimize transportation costs.

Ziliaskopoulos and Wardell (2000) presented a time-dependent intermodal optimum path algorithm for multimodal transportation networks considering delays at mode and arc switching points. They developed a time-dependent intermodal least time path (TDILTP) algorithm. It defines a directed graph with the set of nodes, the set of arcs, the set of the discretized time period and the set of modes. At first, the least-time paths from every origin node, mode and departure time to the destination node were computed and labels were corrected from the destination node.

Khani et al. (2012) developed intermodal optimal path algorithm considering time-dependent auto network and scheduled transit service. This algorithm defined two categories of transportation. Private modes are auto and bicycle, and public modes are public transit. An intermodal path was defined as a combined path of private modes and public modes. Finding the optimal transfer point from auto to transit was the key point of this algorithm. This study focused on the park-and-ride trip, so the transfer points were the park-and-ride lots. From the access points to every transfer point, a multisource time-dependent shortest path (MTDSP) was used to find an optimal transfer point and from the time-dependent shortest path algorithm (TBSP) was used to find the optimal path for transit.

As reviewed, most studies have developed algorithms that recommend reasonable paths for corresponding departure time by combining the method of efficiently guiding transit paths and schedules of modes, and custom paths to meet the requirements of passengers, and applied to actual transit networks. These techniques have already been sufficiently developed and are applied to the aforementioned mobile application, and can be easily received by the public using the several API services.

Therefore, in this study, by using travel information of private autos (car−hailing) from T map API provided by SK telecom and transit travel information from ODSAY API, an algorithm that gets travel information of two modes, and repeatedly combine paths of transit and car−hailing service was developed. The main reason for the failure to apply algorithms such as the existing Graph Theory−based Dijkstra algorithm or the newly emerging RAPTOR that used in existing studies is that it is difficult to obtain both transit and auto travel information in link units, and that information does not reflect real−time traffic information. In other words, the path of a private auto (car−hailing) would be changed depending on the road traffic state that changes in real−time, and if it cannot be reflected, it will provide incorrect information. Therefore, this study used an API that provides route guidance service based on real−time traffic information.

Chapter 3. Data and Study Area

3.1 Data

3.1.1 Smart Card Data

Smart card data is the data gathers travel information when passengers tag in and tag out. It is a big data that records boarding time, alighting time, boarding station, alighting station, transfer count, fare, modes, passenger type, and so on. Because of privacy issue, all transactions are recorded with an encoded card ID, and the ID is maintained for 24 hours from 4 AM to 4 AM the following day. Smart card currently used by more than 99% of passengers was introduced to Seoul in 2004 (Lee et al., 2019). Since almost all transit passengers in Seoul use smart card, analysis of smart card data shows the actual travel patterns of transit passengers. Therefore, the smart card data was used to identify the current situation of transit in Seoul.

The smart card data was collected over one week, i.e., 2017/5/16 – 2017/5/22, and only weekday data was used. 108,311,249 transactions recorded during these five weekdays and the trip chain was configured using encoded card ID. A trip chain is a chain of trips that contain transfer trips. To find the exact origin and destination of passengers, individual trip data should be chained using the encoded card ID, transfer count and boarding time.

As the study area is Seoul and raw data includes transactions in the Seoul metropolitan area, including Seoul, Gyeonggi Province and Incheon, trip chains that occurred only in Seoul were used. Smart card data contains station codes of the passenger's boarding and alighting stations so that geographical information system (GIS) analysis can be performed through matching station-based information which includes station code and latitude and altitude coordinates. Through this method, only Seoul traveled trips were extracted.

Table 3.1 Trip chaining

Card ID	Boarding Time	Alighting Time	Transfer Count	Boarding Station ID	Alighting Station ID
aVW23kw	20170518110322	20170518112234	0	0071661	8000305
aVW23kw	20170518112651	20170518113821	1	8000305	8002155
aVW23kw	20170518114017	20170518115959	2	8002155	8000471

↓

aVW23kw	20170518110322	20170518115959	2	0071661	8000471

After matching the origin and destination of the trip chains to TAZ, the trip chains containing the abnormal trips were removed. The abnormal trip means that does not have an alighting tag or has a negative travel time due to an error on the tag device or card itself. Also, trip chains with extremely short or long travel time, such as those with less than one minute or more than two and a half hours were excluded. The number of transit passengers was obtained by aggregating the trip chains into OD level.

Table 3.2 Smart card data on five-weekdays

Date	Day	Transaction	Trip Chain	In Seoul
17/5/16	Tue	21,457,457	15,949,635	8,985,068
17/5/17	Wed	21,696,673	16,156,617	9,087,375
17/5/18	Thu	21,545,009	16,047,449	9,028,837
17/5/19	Fri	22,559,153	16,918,961	9,567,630
17/5/22	Mon	21,052,957	15,631,204	8,762,993
Total		108,311,249	80,703,866	45,431,903

This study focused on commuting trips, so only the trip chains that occurred at the morning peak hours were used for analysis. Therefore, the trip chains whose last alighting occurred between

8:00 AM to 9:00 AM were used for the analysis of the morning peak hour. As a result, 3,984,955 trip chains in five weekdays were analyzed in this study. In OD level, there were many ODs that had no passenger at the peak hours, and some had very little transit passengers. Therefore, only ODs with more passengers than the median value of all ODs' passengers were used for analysis. The median value of transit passengers at the morning peak hours was 9. There are 424 TAZs in Seoul. Therefore, there are total 179,776 (424 × 424) ODs. As shown in table 3.3, about 30% of ODs were used for analysis.

Table 3.3 The number of ODs used for analysis

Peak hours	Total OD	Traveled OD	# of passengers ≥ median value(9)
Morning	179,776 (100%)	110,082 (61.2%)	56,451 (31.4%)

Table 3.4 The number of passengers at the morning peak hours of transit

Mean (person)	Max (person)	Min (person)	S.D. (person)
69	6,848	9	142

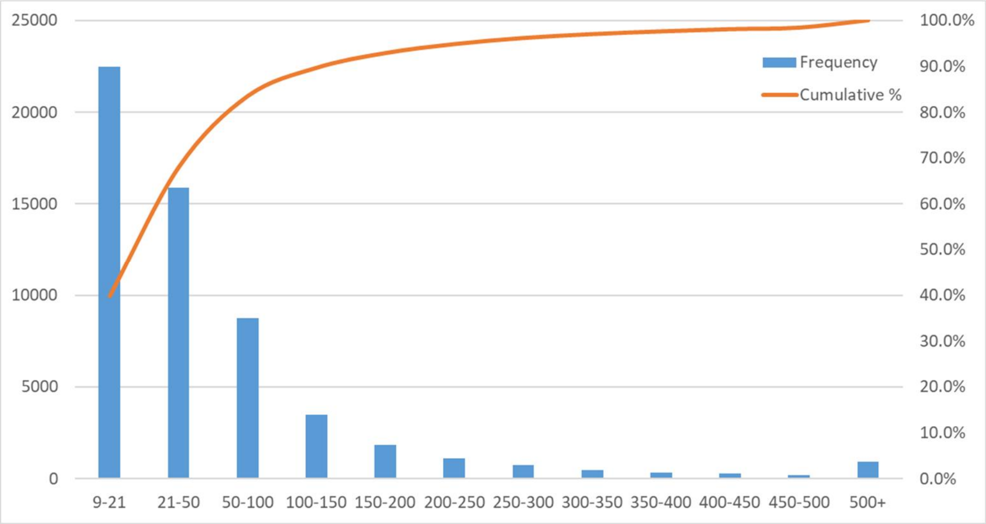


Figure 3.1 Histogram of the number of passengers by OD

3.1.2 API Service

API is literally application programming interface. This makes it easy to use existing functions from other service servers. Among them, the open API is a service that opens up the data and specific functions from government or companies for free and easy access to people. When information is requested using the certain specifications and parameters determined through the API statement, the corresponding information is directly transmitted from server to client. It usually provides the web development environment of JavaScript-based, and can also be used in various programming languages such as python, R and C++. Response parameters are usually sent in JSON or XML format and desired information can be found through parsing.

The Google Maps API is a representative API for transportation services. It offers mapping functions, route guidance service, and so on. Many researches have used Google Maps API to obtain travel information on transit or auto (Wu, 2017; Wang and Xu, 2011). In Korea, however, the Google Maps' route guidance service for auto is not available because the government does not allow foreign companies to take out maps due to the military issue. Only information on transit route is available, but there are restrictions on the use because the travel fare is not calculated, and the map is out of date. For this reason, transit travel information was acquired through another API service. Instead of Google Maps API, travel information of auto was obtained using T map API provided by SK Telecom.

T map is one of the most used navigation applications in Korea. It generates route and forecast traffic state information by using historical data of many users. T map API provides various services such as geocoding, geofencing, map service, real-time traffic state and route guidance. Among several services, time machine auto route guidance service was used to obtain auto travel information. There are several request parameters, payloads and response parameters. The coordinates of origin and destination and departure time or arrival time were used in request payloads and total distance, travel time, fare, taxi fare were used as response parameters.

The travel information of ODs was obtained using API services. For auto, the T map API mentioned above was used, and for transit, ODSAY API was used. It is an API service provided by Arointech that provides data about transit. In the ODSAY API, the optimum transit routes were obtained using the transit route guidance service. The request parameters are the coordinates of origin and destination, and the response parameters are all transit station information including coordinates on the full path, the number of transfers, fare, distance, total travel time, walking distance, mode information. The parameters of each API service are summarized in Table 3.5.

The origin and destination were determined as the centroid of 424 TAZs in Seoul, and the travel that arrives at 9:00 AM on Wednesday was used to analyze travel at the peak of the morning. Just as specific ODs from smart card data were selected, which are considered to have transit demand at that time, auto travel information of the same ODs was used. Besides, of course, intra-zone traveled trips that origin and destination are the same, were excluded.

In the first stage and the second stage, two API services were used to get single modal travel information and generate the integrated paths for car-hailing service and transit. The path of the car-hailing service is the same as the path of auto, which is obtained by using T map API service, and transit path was obtained using ODSAY API.

Table 3.5 Parameters of API services

API service	Operator	Request parameter	Response parameter
Time machine auto route guidance	SK Telecom	• Coordinates of origin and destination • departure time or arrival time	• Travel time • Travel distance • Travel fare • Taxi fare
Transit route guidance	Arointech	• Coordinates of origin and destination	• Travel time • Travel distance • Travel fare • Transit station information • Walking distance • Mode information

3.2 Study Area

Seoul is one of the most densely populated city. In May 2017, about 9.9 million people lived in Seoul. On average, 4,174,677 people used transit per day in 2017. In Seoul, there are 354 bus routes, and 7,405 buses are in operation. The subway comprises 10 routes and 320 stations. As of May 2017, the number of vehicles registered in Seoul was 3,103,657. There are 424 TAZs in Seoul. For GIS analysis, the census boundary data provided by the National Spatial Data Infrastructure Portal was used.

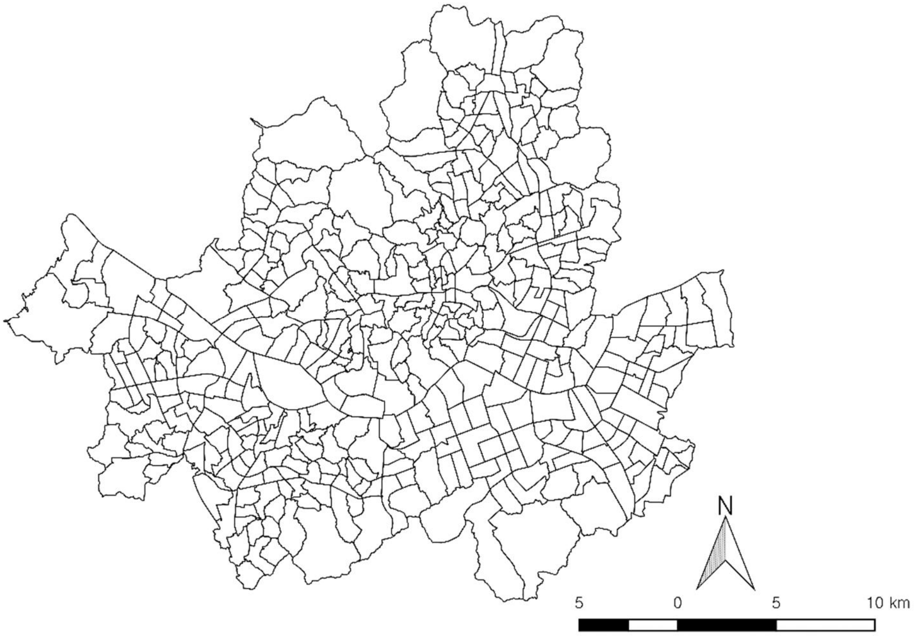


Figure 3.2 424 TAZs in Seoul

As mentioned above, the centroid of TAZ is set as the starting point and destination of car and public transportation. However, each zone contains terrains that are far from the activities of people such as rivers and mountains. If the centroid of each zone is located in a river or a mountain, it causes a serious bias on the traffic information. Therefore, except for natural topography, centroids were recalculated considering only residential areas, commercial areas, industrial areas, and public facilities using land-use data. As shown in figure 3.4, the old centroid was located far from the residential area, but the new centroid is in the middle of the residential area.

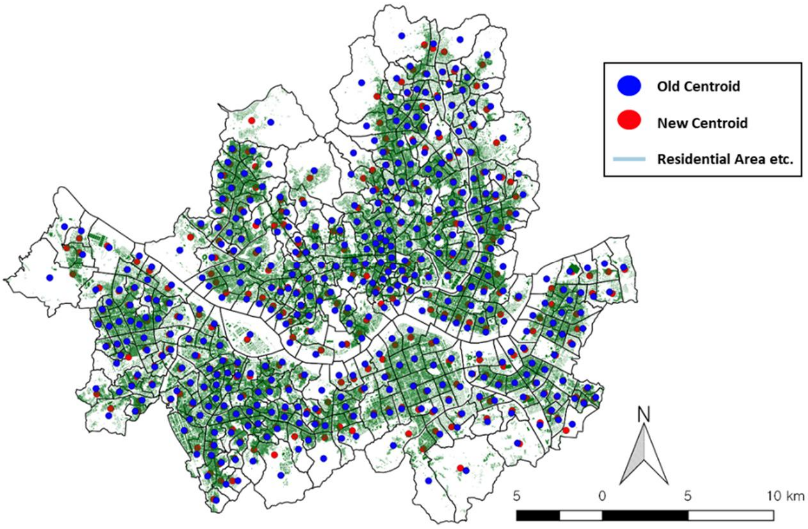


Figure 3.3 Centroids of TAZs in Seoul

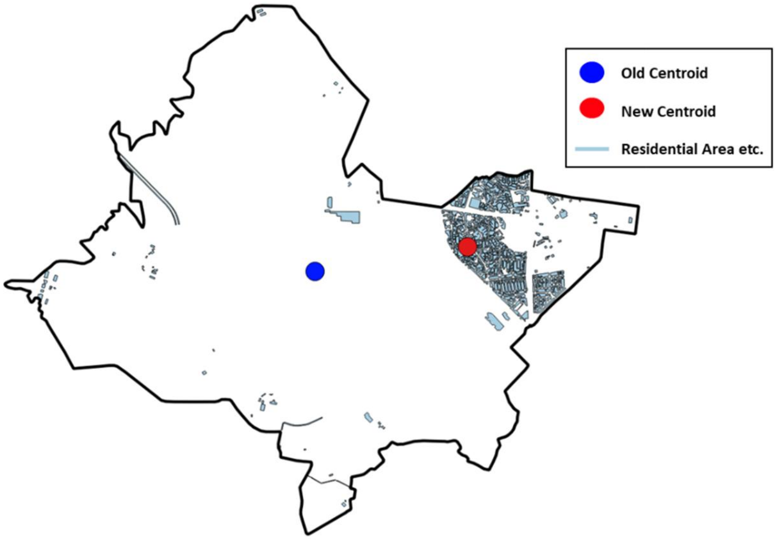


Figure 3.4 Centroids of Gonghang-dong, Gangseo-gu

Chapter 4. Methodology

4.1 Select Transit Vulnerable ODs

Many previous studies developed accessibility indicators for transit and compared them to other modes to evaluate the competitiveness of transit. In particular, studies comparing transit and auto set the travel speed, distance, and time of modes as indicators in terms of mobility. In this study, the transit competitiveness was assessed by calculating the difference of travel time between modes, because travel time is one of the most direct indicators to both user and operator, and is directly interpretable.

Travel time consists of various components according to modes. For example, the total travel time for transit includes access time approaching to the first station from the origin, waiting time for the first mode at the station, in−vehicle time, transfer time, and egress time from the last station to the destination. For auto, access time from the origin to the vehicle, in−vehicle time, parking time, and egress time from the parking lot to destination. Due to a large number of vehicle registrations and lack of parking lots, it takes a long time to find a parking lot and to find a parking space in the parking lot. At the same time, transit in Seoul is well−equipped and there is a transit station located almost every 500m (Kim and Lee, 2017). In this study, it is assumed that the sum of waiting time and transfer time of transit is the same as the sum of access time, parking time, and egress time of auto.

$$TT_{ij}^{T} = AT_{ij}^{T} + WT_{ij}^{T} + IVT_{ij}^{T} + TRT_{ij}^{T} + ET_{ij}^{T} \tag{4.1}$$

$$TT_{ij}^{A} = AT_{ij}^{A} + +IVT_{ij}^{A} + PT_{ij}^{A} + ET_{ij}^{A} \tag{4.2}$$

$$WT_{ij}^{T} + TRT_{ij}^{T} = AT_{ij}^{A} + PT_{ij}^{A} + ET_{ij}^{A} \tag{4.3}$$

$$\Delta TT_{ij} = TT_{ij}^{T} - TT_{ij}^{A} = AT_{ij}^{T} + IVT_{ij}^{T} + ET_{ij}^{T} - IVT_{ij}^{A} \tag{4.4}$$

where, TT_{ij}^{T} = Total travel time of transit from zone i to zone j
AT_{ij}^{T} = Access time of transit from zone i to zone j
WT_{ij}^{T} = Waiting time of transit from zone i to zone j
IVT_{ij}^{T} = In−vehicle time of transit from zone i to zone j
TRT_{ij}^{T} = Transfer time of transit from zone i to zone j

ET_{ij}^{T} = Egress time of transit from zone i to zone j
TT_{ij}^{A} = Total travel time of auto from zone i to zone j
AT_{ij}^{A} = Access time of auto from zone i to zone j
IVT_{ij}^{A} = In−vehicle time of auto from zone i to zone j
PT_{ij}^{A} = Parking time of auto from zone i to zone j
ET_{ij}^{A} = Egress time of auto from zone i to zone j

Using the ΔTT_{ij} defined above, travel times of transit and auto during the morning peak hours were calculated for each OD.

As shown in table 4.1, at the morning peak hours, the average transit travel time was longer than that of auto. At the morning peak hours, a large number of cars were on the road for commuting, causing traffic congestion, which led to longer travel time for private autos, but the walking time of transit is much longer than that of auto. Therefore, the total travel time of transit would be longer that auto.

Table 4.1 Travel time at the morning peak hours of transit and auto

Mode	Mean (min)	Max (min)	Min (min)	S.D. (min)
Transit	45.23	121.00	9.00	17.30
Auto	39.43	111.65	1.82	19.92

As mentioned above, more than 99% of transit passengers use smart card, so the transit travel volume for each OD can be known by analyzing smart card data. However, in the case of ODs with low travel volume on a smart card data, it is difficult to judge whether there is no transit demand for the corresponding OD or whether there was demand, but the competitiveness of transit was low so that other modes were used instead of transit. Therefore, this study considered the number of passengers of transit and determined that there was a demand for transit in OD, where there was a certain amount of transit passengers. Therefore, OD is selected as the transit vulnerable OD when the difference in travel time between transit and auto is more than 5 minutes and the number of passengers of transit is more than 500 in 5 days.

4.2 Multimodal Integrated Path Generation Algorithms

Paths for a particular OD were acquired using the ODSAY API for transit and T map API service for car–hailing service that is generally the same as private autos. Paths by modes were stored separately for comparison, and multimodal integrated paths were generated based on unimodal paths that stored earlier.

In this study, four MIPG algorithms were developed. Each algorithm generates a path that uses car–hailing service and transit once each and differs in how the transfer points of the two modes are selected. Among the multimodal paths generated by each algorithm, the path with the lowest generalized cost was selected as the optimum path. The generalized cost was calculated using the value of travel time estimated in the R&D study related to MaaS.[1] The components of the generalized cost include in–vehicle time, walking time, the number of transfers, and the time values of each component. The details are as follows.

$$GC_{ij}^{M} = IVT_{ij}^{M} \cdot VOIVT + WKT_{ij}^{M} \cdot VOWKT + TR_{ij}^{M} \cdot VOTR + TF_{ij}^{M} \quad (4.5)$$

where,

GC_{ij}^{M}	Generalized cost of mode M from zone i to zone j in won
IVT_{ij}^{M}	In–vehicle time of mode M from zone i to zone j in hour
$VOIVT$	Value of in–vehicle time 8,686.57 won per hour
WKT_{ij}^{M}	Walking time of mode M from zone i to zone j in hour
$VOWKT$	Value of walking time 11,641.79 won per hour
TR_{ij}^{M}	Transfer count of mode M from zone i to zone j
$VOTR$	Value of transfer count 853.73 won per count

---

1) 스마트 모빌리티 서비스 지원을 위한 통합결제 기술개발 및 시범운영, 국토교통과학기술진흥원

TF_{ij}^{M}	Travel fare of mode M from zone i to zone j in won

The first algorithm selects all stations of transit and every 500m point of the path of the car-hailing service as transfer points and combines unimodal paths of transit and car-hailing into one, calculate the generalized cost, and select the path with the lowest generalized cost as the optimum path. The detailed steps of the first algorithm were as follows.

Step 1. Obtain each path of transit and car-hailing from origin i to destination j, $(Path^{Ch}(O_i, D_j),\ Path^{PT}(O_i, D_j))$.

Step 2-1. List all stations' coordinates of transit path, $(ST_{ij}^{(1,1)}, \cdots, ST_{ij}^{(n,m)})$.

Step 2-2. List coordinates of every 500m points of the car-hailing path, $(P_{ij}^{1}, \cdots, P_{ij}^{l})$.

Step 3-1. **For** every station $(a,b) = [(1,1), \cdots, (n,m)]$, **do the following**:

$[Path^{PT}(O_i, ST_{ij}^{(a,b)}),\ Path^{Ch}(ST_{ij}^{(a,b)}, D_j)]$

$[Path^{Ch}(O_i, ST_{ij}^{(a,b)}),\ Path^{PT}(ST_{ij}^{(a,b)}, D_j)]$

Step 3-2. **For** every point $k = 1, \cdots, l$, **do the following**:

$[Path^{PT}(O_i, P_{ij}^{k}),\ Path^{Ch}(P_{ij}^{k}, D_j)]$

$[Path^{Ch}(O_i, P_{ij}^{k}),\ Path^{PT}(P_{ij}^{k}, D_j)]$

Step 4. **For** every path, **do the following**:

Compute the generalized cost.

Step 5. Select the path with lowest generalized cost as optimum multimodal path.

where,

$ST_{ij}^{(n,m)}$	mth station of nth mode in transit path from i to j
P_{ij}^{l}	lth points of car-hailing path from i to j
$Path^{Ch}(x,y)$	Path of car-hailing service from x to y
$Path^{PT}(x,y)$	Path of transit from x to y
O_i	Origin zone i

D_j Destination zone j

For transit paths, the ODSAY API searched ten or more paths, and for the path of auto, the T map API searched just one optimal path. For transit, only one mode can be used or two to three modes can be used in one route. The transit modes include bus and subway. Thus, if the number of transit stations becomes too large, the number of multimodal paths using all ten transit paths results in huge combinations $\approx (10 \times n \times m \times 10 \times 2 + 1 \times l \times 10 \times 2)$. To avoid such a situation, this study used only the path whose travel time is within 5 minutes compared to the minimum travel time among ten transit paths in every algorithm. In the case of multimodal paths based on the car-hailing path, it is possible to extract a large number of transfer points as well, and thus many multimodal paths can be generated. Therefore, the points were extracted every 500m of the car-hailing path and set as the transfer points. As mentioned above, transit stations in Seoul are located at an average interval of 500m, so 500m is a sufficient interval.

More specifically, in Step 3-1, the intermediate stations of the transit path were selected as the transfer points, and in Step 3-2, the points of every 500m of the car-hailing path were selected as the transfer points. The multimodal paths consist of the car-hailing path from origin i to transfer point and transit path from transfer point to destination j in the first part of Step 3-1 and 3-2. In the second part of Step 3-1 and 3-2, the multimodal paths consist of transit path from origin i to transfer point and car-hailing path from transfer point to destination j.

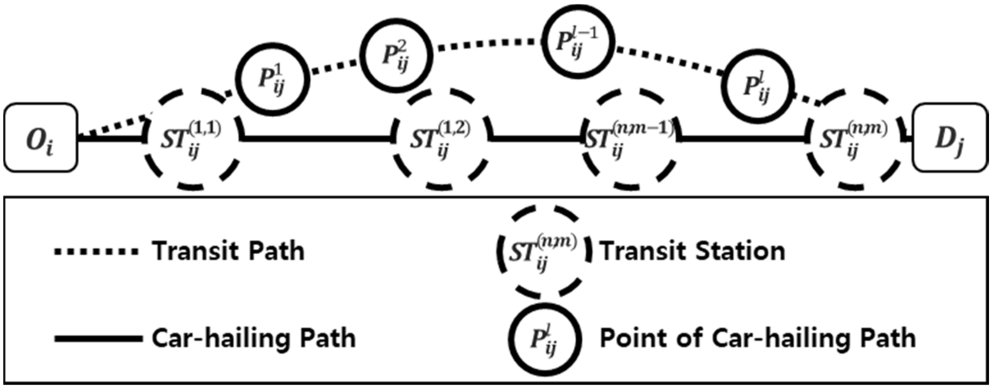


Figure 4.1 Paths of transit and car-hailing

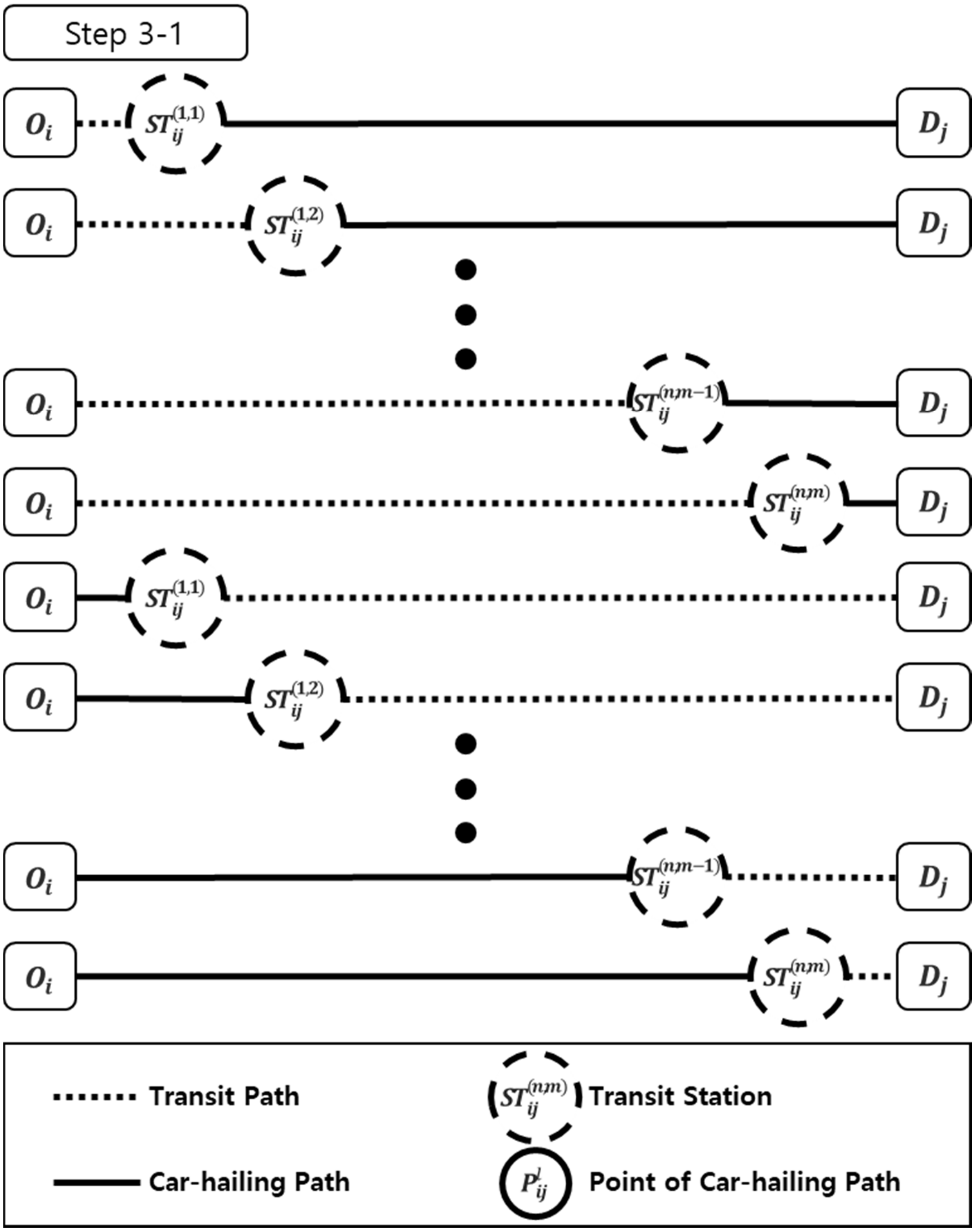


Figure 4.2 Multimodal paths of Step 3-1 in the first algorithm

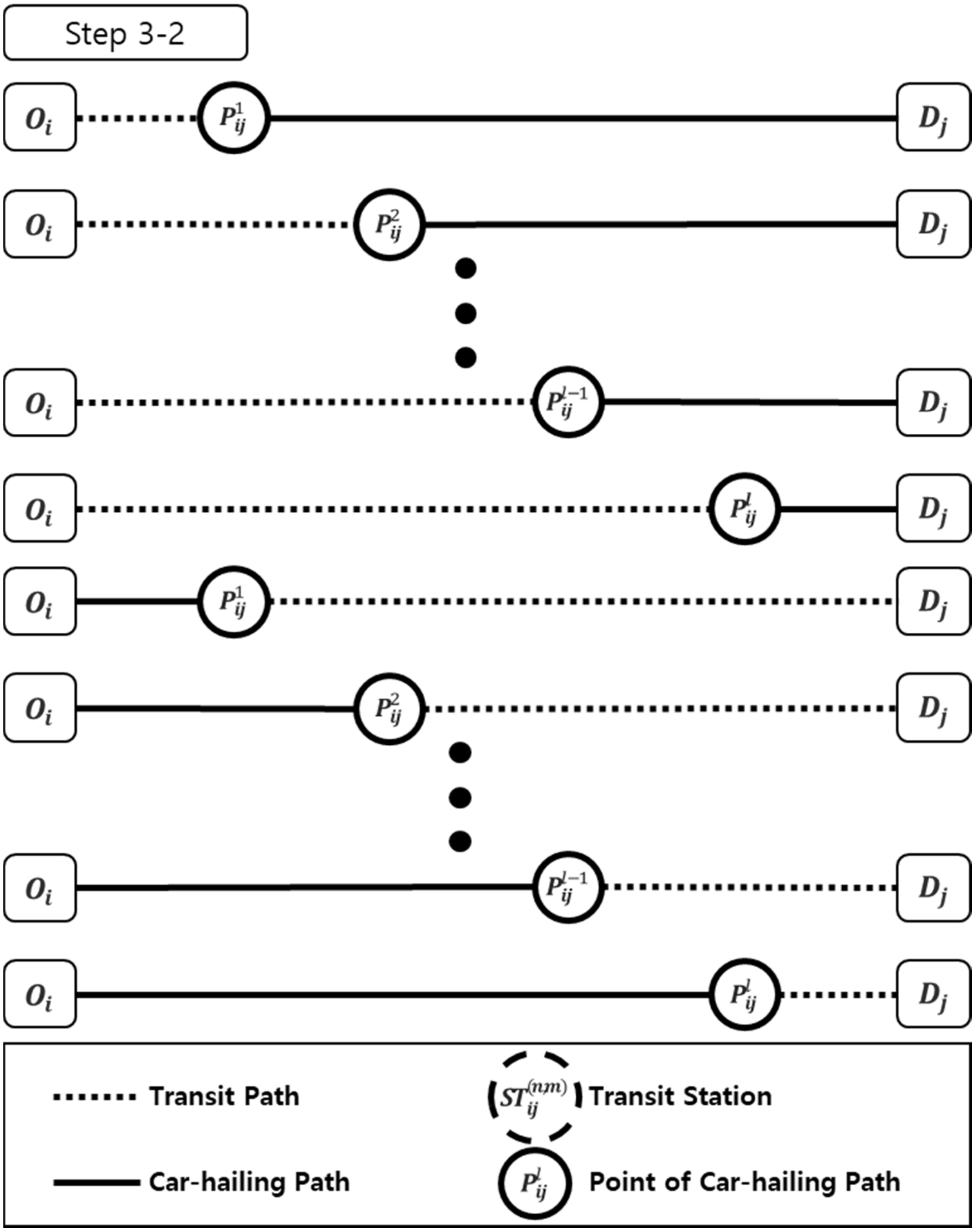


Figure 4.3 Multimodal paths of Step 3-2 in the first algorithm

The results of the first algorithm showed that multimodal paths based on the car–hailing unimodal path were less competitive than those based on the transit path were. Therefore, from the second algorithm, the multimodal paths were generated based on the transit paths only.

Because the multimodal paths using subway were faster than the paths using the bus in the result of the first algorithm, the second algorithm applied the rule of replacing the bus with car−hailing in the path using only transit. Also, when the transfer occurred in the transit path, the paths that transfer to car−hailing near the transfer points of the transit path were selected as the optimum multimodal path. Therefore, the transfer points were selected near the transfer points of the path using only transit.

```
Step 1. Obtain each path of transit and car−hailing from origin i to destination j, ($Path^{Ch}(O_i, D_j)$, $Path^{PT}(O_i, D_j)$).
Step 2. List all stations' coordinates of transit path, ($ST_{ij}^{(1,1)}$,⋯, $ST_{ij}^{(n,m)}$).
Step 3−1. If $TR_{ij}^{PT} \neq 0$, go to Step 3−2; otherwise, do the following:
    If $m \geq 7$ $(n = 1)$, select the first three stations and the last three stations as transfer points and do the following:
        For stations $(a, b) = [(1,1),(1,2),(1,3),(1,m-2),(1,m-1),(1,m)]$, do the following:
            $[Path^{Ch}(O_i, ST_{ij}^{(a,b)}),\ Path^{PT}(ST_{ij}^{(a,b)}, D_j)]$
            $[Path^{PT}(O_i, ST_{ij}^{(a,b)}),\ Path^{Ch}(ST_{ij}^{(a,b)}, D_j)]$
        otherwise, for every station $(a, b) = [(1,1),\cdots,(1,m)]$, do the following:
            $[Path^{Ch}(O_i, ST_{ij}^{(a,b)}),\ Path^{PT}(ST_{ij}^{(a,b)}, D_j)]$
            $[Path^{PT}(O_i, ST_{ij}^{(a,b)}),\ Path^{Ch}(ST_{ij}^{(a,b)}, D_j)]$
Step 3−2. If $TR_{ij}^{PT} \neq 1$, go to Step 3−3; otherwise, do the following:
    Select the last three stations of the first modes and the first three stations of the second modes as transfer points and do the following:
        If the first mode is subway and the second mode is bus, do the following:
            For stations $(a, b) = [(1,m-2),(1,m-1),(1,m),(2,1),(2,2),(2,3)]$, do the following:
                $[Path^{PT}(O_i, ST_{ij}^{(a,b)}),\ Path^{Ch}(ST_{ij}^{(a,b)}, D_j)]$
        If the first mode is bus and the second mode is
```

```
        subway, do the following:
            For stations $(a,b) = [(1,m-2),(1,m-1),(1,m),(2,1),(2,2),(2,3)]$, do the following:
                $[Path^{Ch}(O_i, ST_{ij}^{(a,b)}),\ Path^{PT}(ST_{ij}^{(a,b)}, D_j)]$
            otherwise, for stations $(a,b) = [(1,m-2),(1,m-1),(1,m),(2,1),(2,2),(2,3)]$,
            do the following:
                $[Path^{Ch}(O_i, ST_{ij}^{(a,b)}),\ Path^{PT}(ST_{ij}^{(a,b)}, D_j)]$
                $[Path^{PT}(O_i, ST_{ij}^{(a,b)}),\ Path^{Ch}(ST_{ij}^{(a,b)}, D_j)]$
Step 3-3. Do the following:
    If $m < 5\ (n = 2)$, select the last two stations of the first mode, all stations of the second mode and the first two stations of the third mode as transfer points and do the following:
        For stations
        $(a,b) = [(1,m-1),(1,m),(2,1),\cdots,(2,m),(3,1),(3,2)]$,
        do the following:
            $[Path^{Ch}(O_i, ST_{ij}^{(a,b)}),\ Path^{PT}(ST_{ij}^{(a,b)}, D_j)]$
            $[Path^{PT}(O_i, ST_{ij}^{(a,b)}),\ Path^{Ch}(ST_{ij}^{(a,b)}, D_j)]$
        otherwise, select the last two stations of the first mode, the first two and the last two stations of the second mode and the first two stations of the third mode as transfer points and do the following:
        for stations $(a,b) = [(1,m-1),(1,m),(2,1),(2,2)$
        $(2,m-1),(2,m),(3,1),(3,2)]$, do the following:
            $[Path^{Ch}(O_i, ST_{ij}^{(a,b)}),\ Path^{PT}(ST_{ij}^{(a,b)}, D_j)]$
            $[Path^{PT}(O_i, ST_{ij}^{(a,b)}),\ Path^{Ch}(ST_{ij}^{(a,b)}, D_j)]$
Step 4. For every path, do the following:
    Compute the generalized cost.
Step 5. Select the path with lowest generalized cost as optimum multimodal path.
```

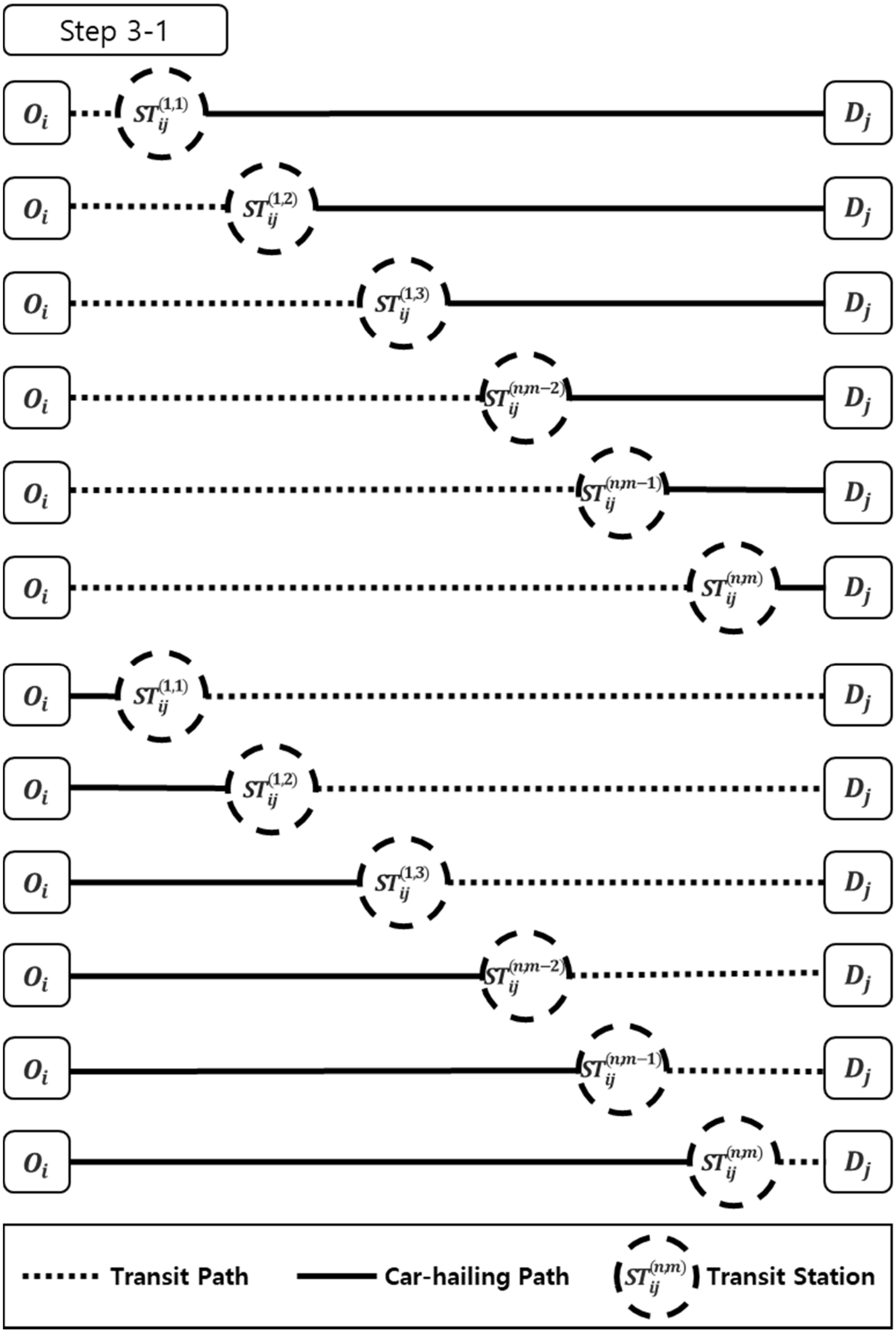


Figure 4.4 Multimodal paths of Step 3-1 in the second algorithm

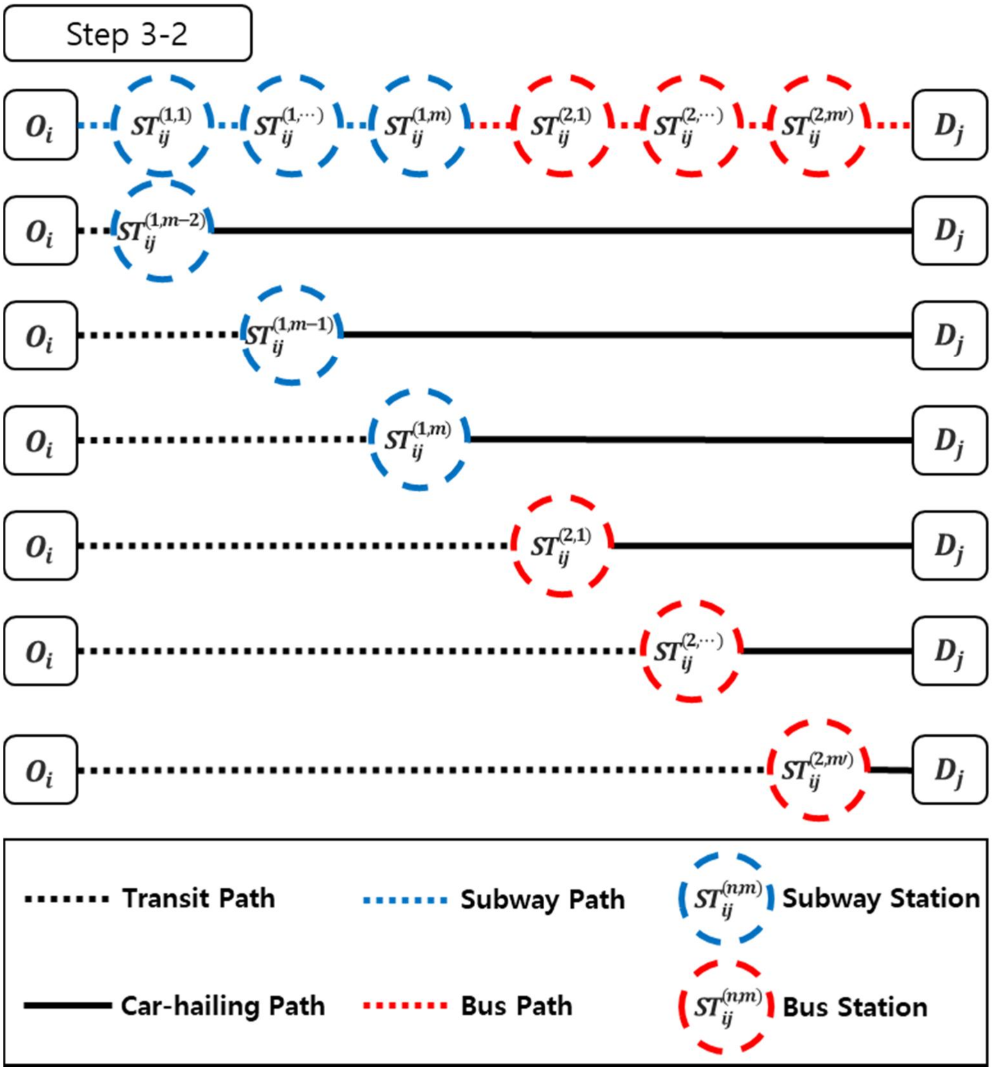


Figure 4.5 Multimodal paths of Step 3-2 in the second algorithm
(If the first mode is subway and the second mode is bus)

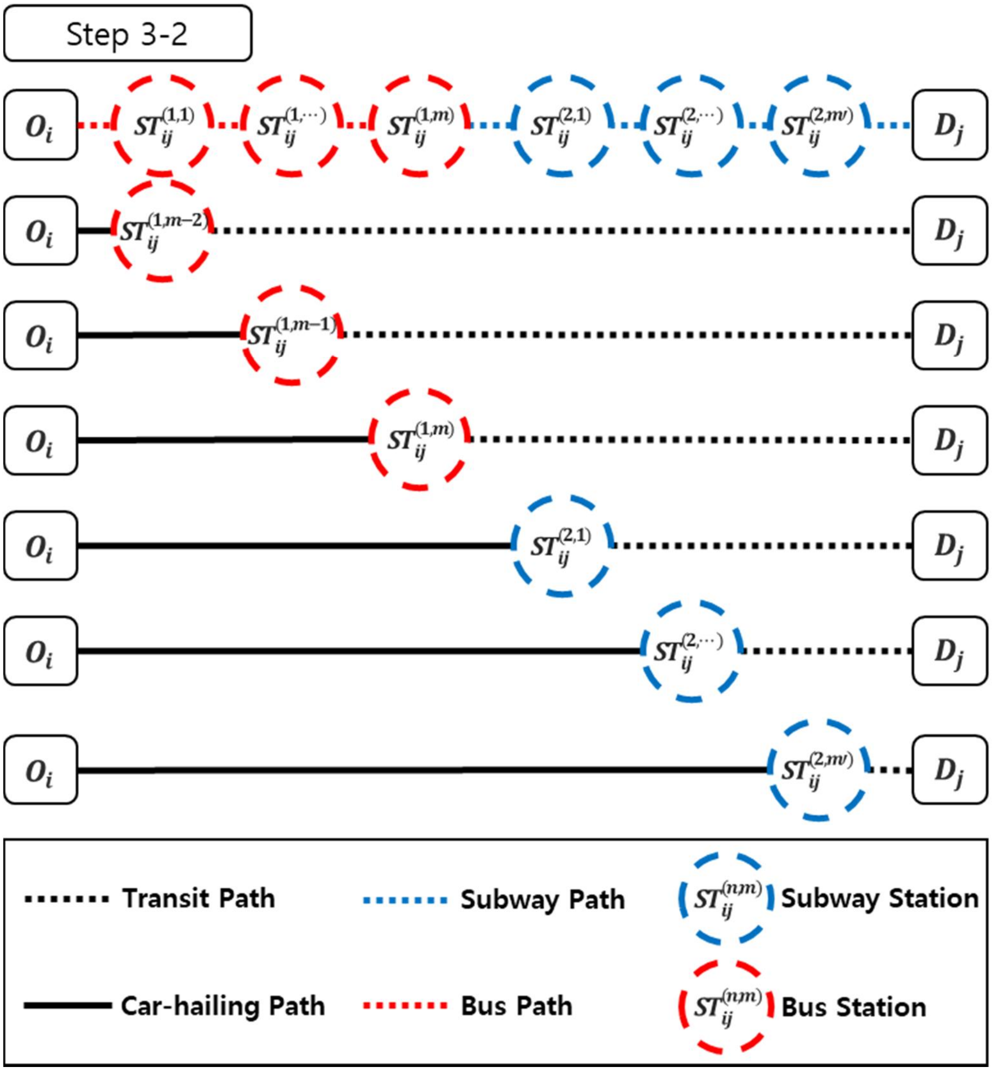


Figure 4.6 Multimodal paths of Step 3-2 in the second algorithm
(If the first mode is bus and the second mode is subway)

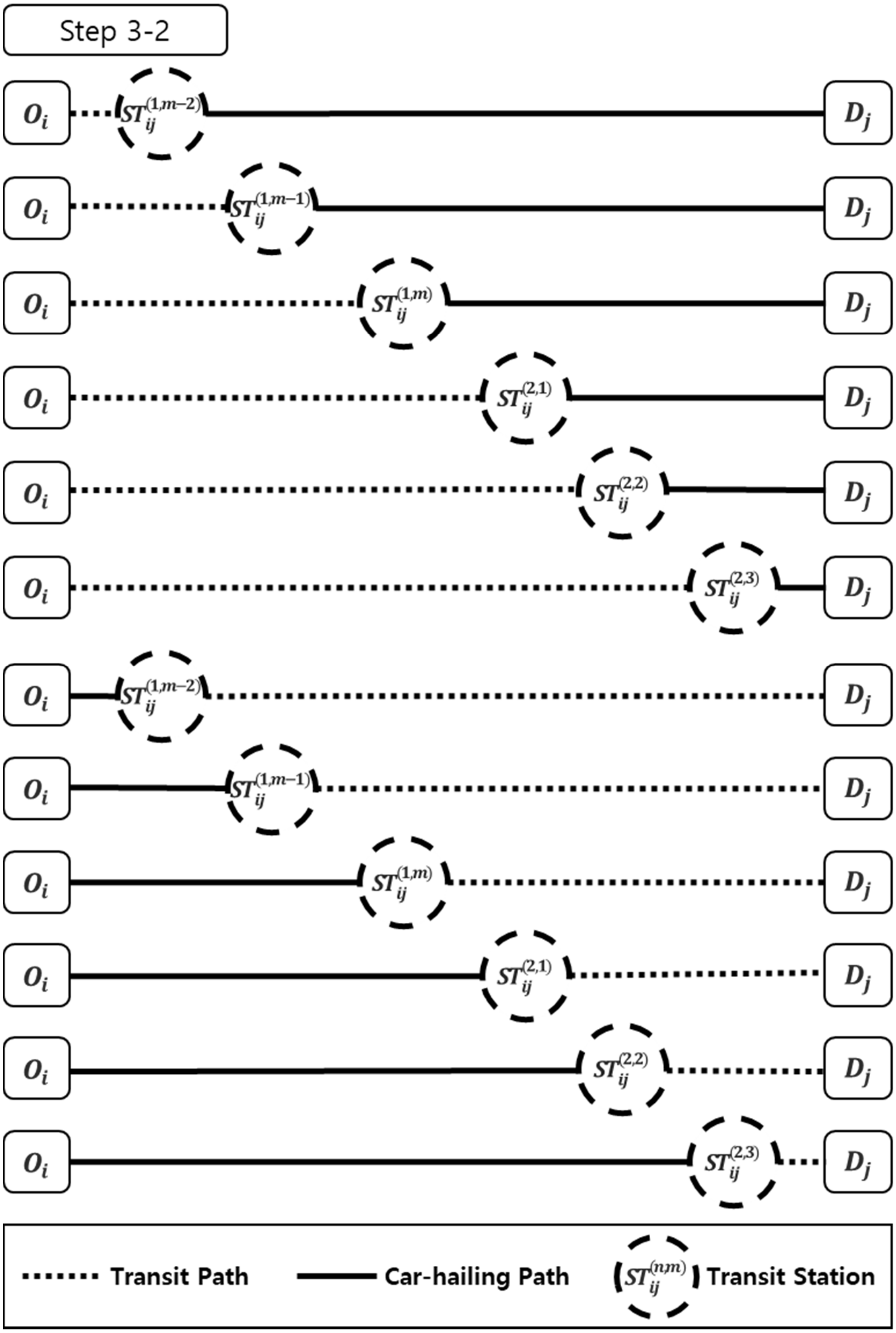


Figure 4.7 Multimodal paths of Step 3-2 in the second algorithm
(If the type of first mode is the same as the type of the second mode)

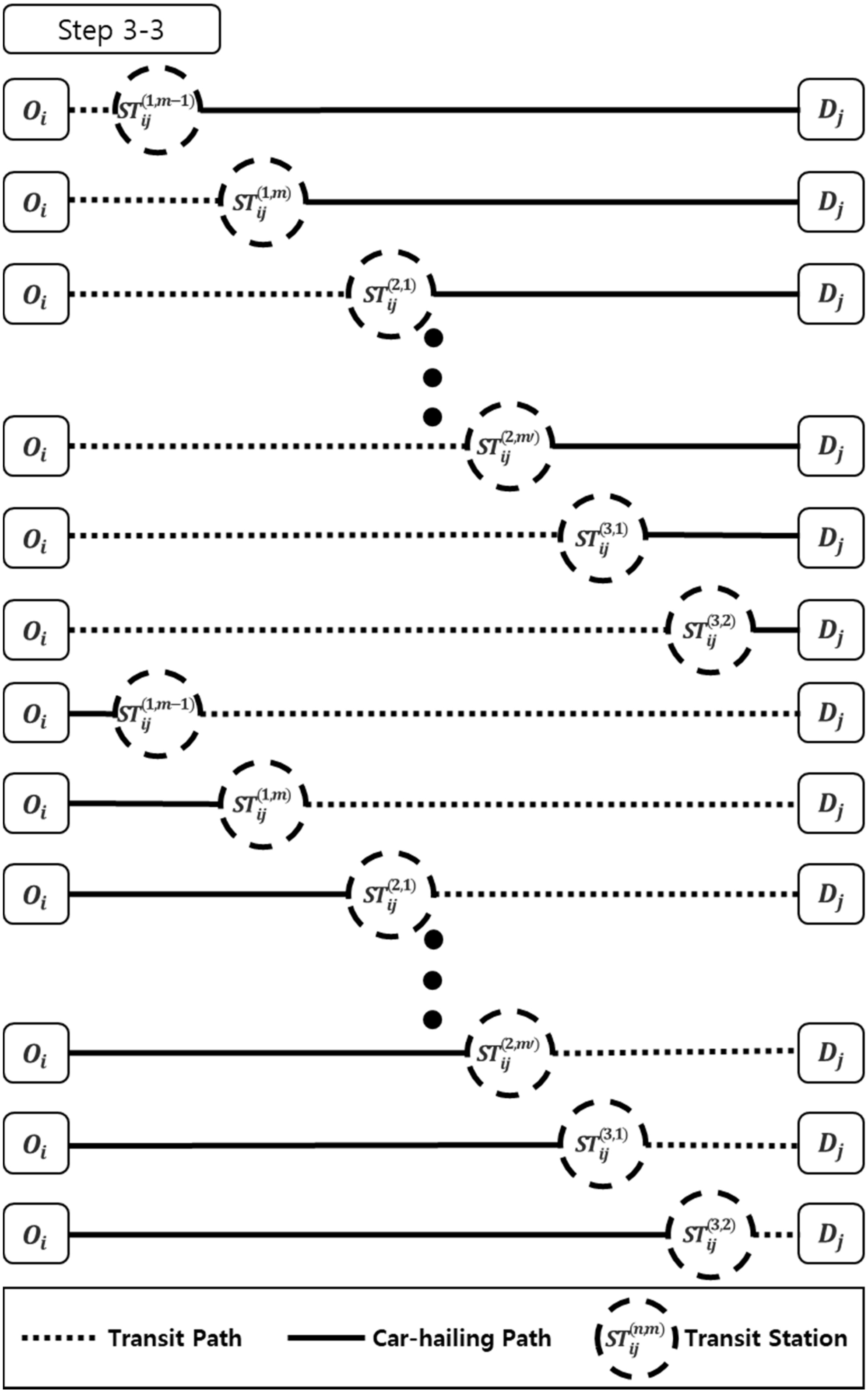


Figure 4.8 Multimodal paths of Step 3-3 in the second algorithm
(If the number of stations of the second mode is less than five)

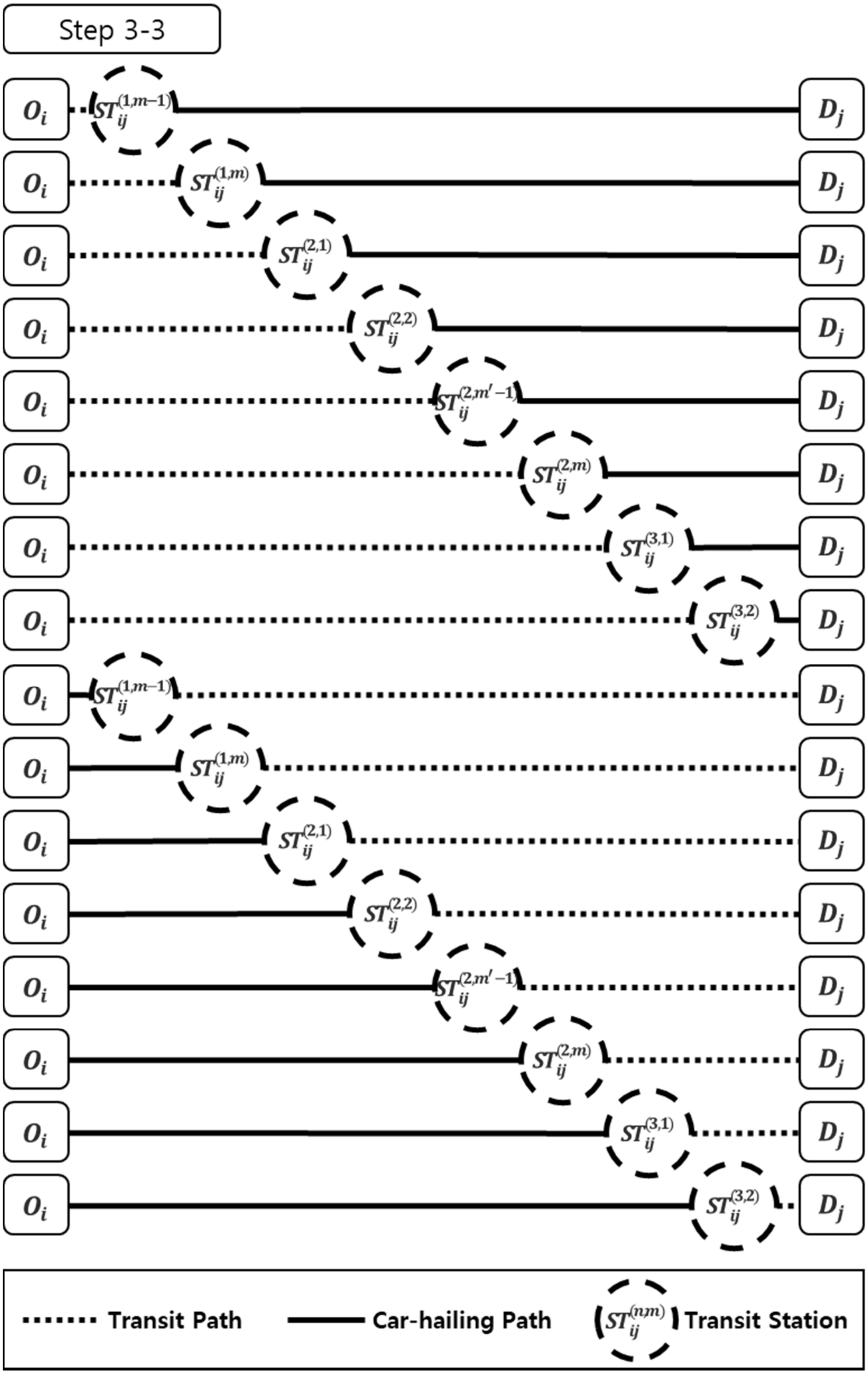


Figure 4.9 Multimodal paths of Step 3-3 in the second algorithm
(If the number of stations of the second mode is more than four)

The third algorithm used the method of finding the station with the worst directness in the transit path and replacing the inefficient path of transit with car-hailing. Usually, directness is defined as the ratio of the travel distance of transit between two points to the shortest network distance between two points. However, since the subway network is different from the road network, this study defined directness as the ratio of the travel distance of transit between two points to the Euclidean distance between two points. The third algorithm calculates the directness of the transit path from the origin to every station, selects the station with the worst directness as the transfer point, and replaces the transit path from the origin to the corresponding station with car-hailing. On the other hand, since the directness of the transit path from the station to the destination may be poor, the directness of the transit path from every station to the destination is calculated, and also selects the station with the worst directness as the transfer point, and replaces the transit path from corresponding station to destination with car-hailing.

```
Step 1. Obtain each path of transit and car-hailing from origin i to destination j, ($Path^{Ch}(O_i, D_j)$, $Path^{PT}(O_i, D_j)$).
Step 2. List all stations' coordinates of transit path, ($ST_{ij}^{(1,1)}, \cdots, ST_{ij}^{(n,m)}$).
Step 3-1. For every station $(a,b) = [(1,1), \cdots, (n,m)]$,
do the following:
        Calculate the Euclidean distance from the origin to station, ($d_{i(1,1)}^{Eud}, \cdots, d_{i(n,m)}^{Eud}$).
        Calculate the Euclidean distance from the station to destination, ($d_{(1,1)j}^{Eud}, \cdots, d_{(n,m)j}^{Eud}$).
        Calculate the travel distance of transit from the origin to station, ($d_{i(1,1)}^{PT}, \cdots, d_{i(n,m)}^{PT}$).
        Calculate the travel distance of transit from the station to destination, ($d_{(1,1)j}^{PT}, \cdots, d_{(n,m)j}^{PT}$).
```

Calculate the $D_O^{(a,b)} = \frac{d_{i(a,b)}^{PT}}{d_{i(a,b)}^{Eud}}$ and $D_D^{(a,b)} = \frac{d_{(a,b)j}^{PT}}{d_{(a,b)j}^{Eud}}$.

Step 3−2. Do the following:

$[Path^{PT}(O_i, ST_{ij}^{(a,b)^*}),\ Path^{Ch}(ST_{ij}^{(a,b)^*}, D_j)]$

$[Path^{Ch}(O_i, ST_{ij}^{(a,b)^*}),\ Path^{PT}(ST_{ij}^{(a,b)^*}, D_j)]$

$where\ \ (a,b)^* = \underset{(a,b)}{\operatorname{argmax}} D_O^{(a,b)}$

Step 3−3. Do the following:

$[Path^{PT}(O_i, ST_{ij}^{(a,b)^*}),\ Path^{Ch}(ST_{ij}^{(a,b)^*}, D_j)]$

$[Path^{Ch}(O_i, ST_{ij}^{(a,b)^*}),\ Path^{PT}(ST_{ij}^{(a,b)^*}, D_j)]$

$where\ \ (a,b)^* = \underset{(a,b)}{\operatorname{argmax}} D_D^{(a,b)}$

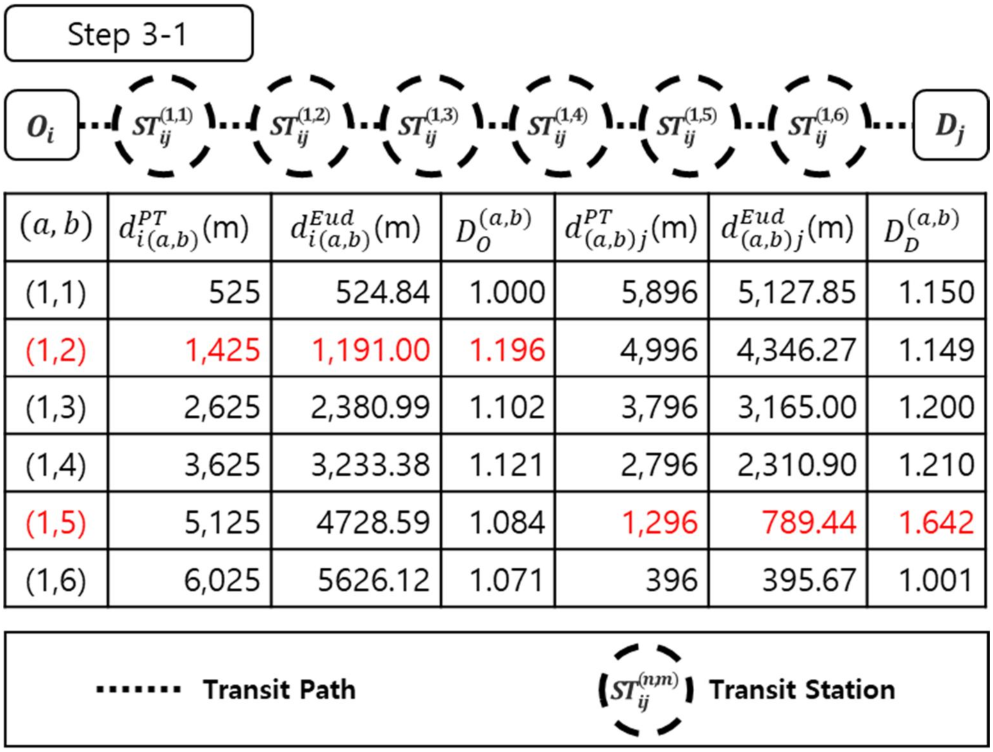
Step 4. For every path, do the following:

Compute the generalized cost.

Step 5. Select the path with lowest generalized cost as optimum multimodal path.

where,

$d_{i(n,m)}^{Eud}$	Euclidean distance from i to mth station of nth mode
$d_{(n,m)j}^{Eud}$	Euclidean distance from mth station of nth mode to j
$D_O^{(n,m)}$	Directness index from the origin to mth station of nth mode
$D_D^{(a,b)}$	Directness index from mth station of nth mode to the destination



(a, b)	$d_{i(a,b)}^{PT}$(m)	$d_{i(a,b)}^{Eud}$(m)	$D_O^{(a,b)}$	$d_{(a,b)j}^{PT}$(m)	$d_{(a,b)j}^{Eud}$(m)	$D_D^{(a,b)}$
(1,1)	525	524.84	1.000	5,896	5,127.85	1.150
(1,2)	1,425	1,191.00	1.196	4,996	4,346.27	1.149
(1,3)	2,625	2,380.99	1.102	3,796	3,165.00	1.200
(1,4)	3,625	3,233.38	1.121	2,796	2,310.90	1.210
(1,5)	5,125	4728.59	1.084	1,296	789.44	1.642
(1,6)	6,025	5626.12	1.071	396	395.67	1.001

Figure 4.10 Multimodal paths of Step 3-1 in the third algorithm

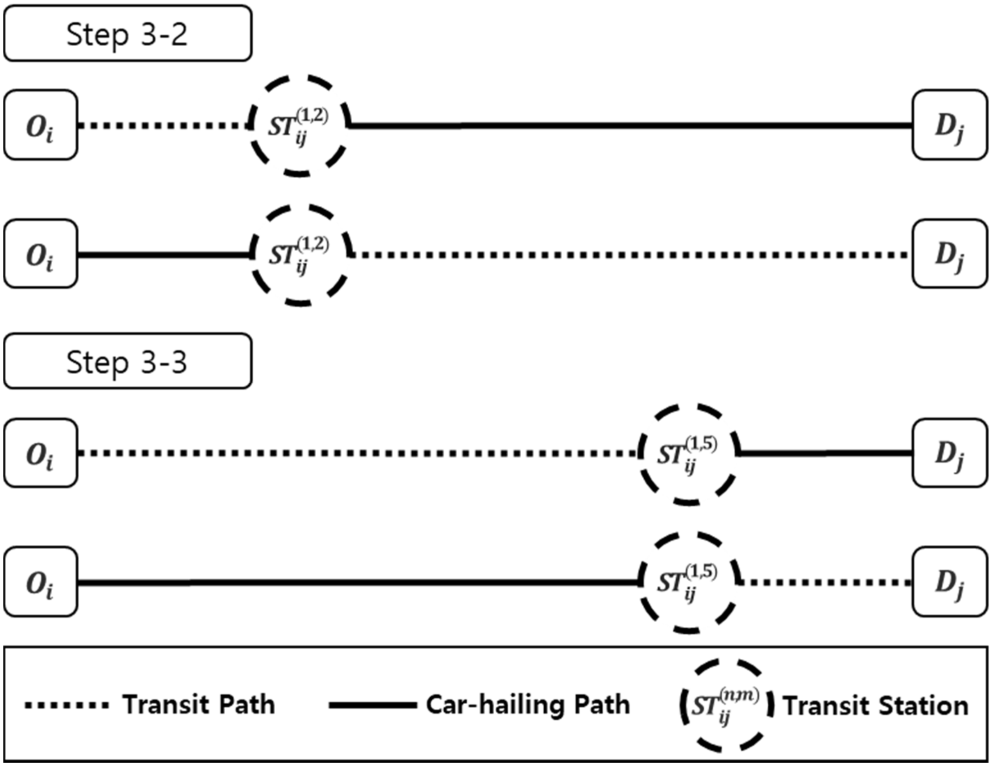


Figure 4.11 Multimodal paths of Step 3-2 and 3-3 in the third algorithm

Finally, the fourth algorithm generates paths using subway and car–hailing. First, search for subway stations within 1.5km of the origin and destination, and select three stations that are closest to the origin and destination each. Next, generate paths that use car–hailing from the origin to stations that are close to the origin and take the subway for the rest section of whole travel, and paths that take the subway from the origin to the stations that are close to the destination and use car–hailing from the stations that are close to the destination to the destination.

Step 1. Search for subway stations within 1.5km of the origin and destination and select three stations that are closest to the origin and destination, $(ST_O^1,\cdots,ST_O^3, ST_D^1,\cdots,ST_D^3)$.

Step 2. List all stations' coordinates, $(ST_O^1,\cdots,ST_O^3, ST_D^1,\cdots,ST_D^3)$.

Step 3. **For** every station $c = 1,2,3$, **do the following**:

$[Path^{Subway}(O_i,ST_O^c),\ Path^{Ch}(ST_O^c,D_j)]$
$[Path^{Ch}(O_i,ST_O^c),\ Path^{Subway}(ST_O^c,D_j)]$
$[Path^{Subway}(O_i,ST_D^c),\ Path^{Ch}(ST_D^c,D_j)]$
$[Path^{Ch}(O_i,ST_D^c),\ Path^{Subway}(ST_D^c,D_j)]$

Step 4. **For** every path, **do the following**:

Compute the generalized cost.

Step 5. Select the path with lowest generalized cost as optimum multimodal path.

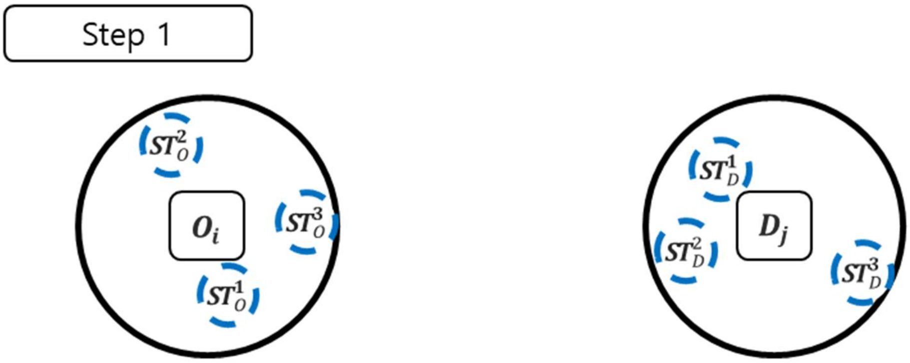


Figure 4.12 Multimodal paths of Step 1 in the fourth algorithm

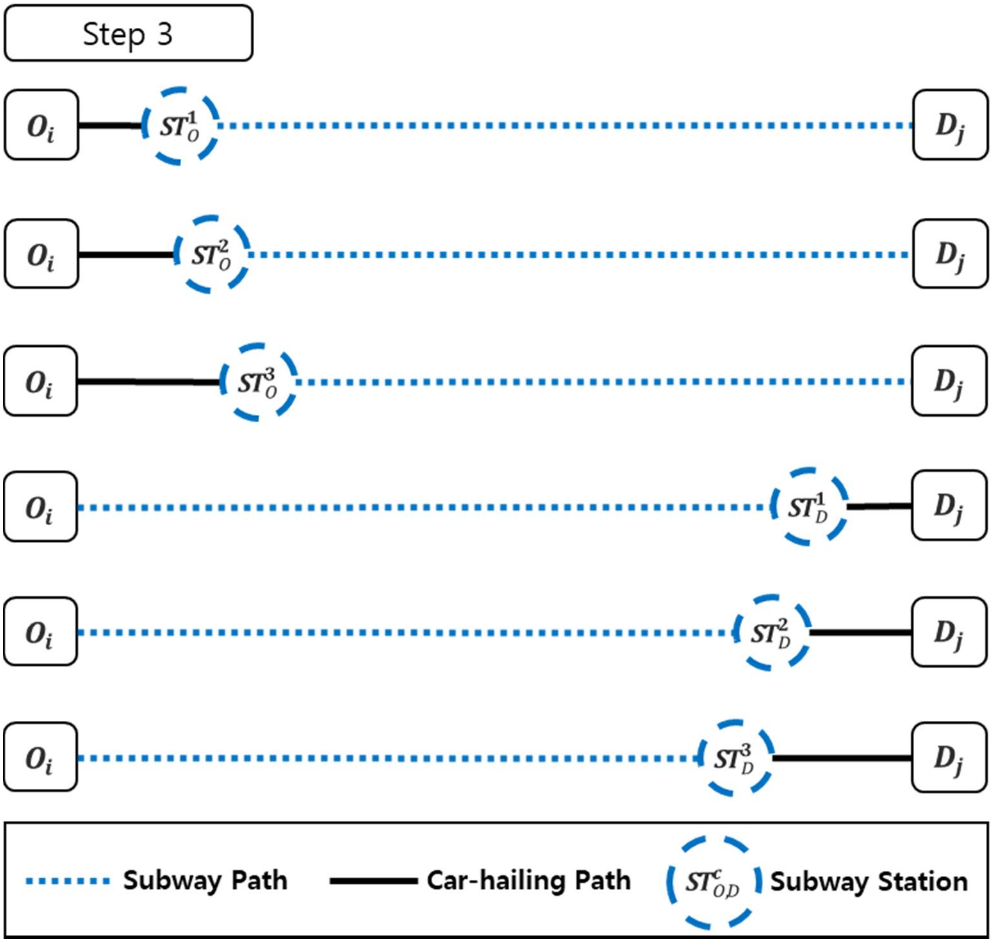


Figure 4.13 Multimodal paths of Step 3 in the fourth algorithm

As mentioned above, the route of car–hailing service is the same as that of private auto or taxi, and the fare is different from that of taxi service. In the case of Kakao Carpool, which was discontinued but the largest carpool service in Korea, the service charge was set at 80% level of the taxi. Therefore, in this study, the fare of car–hailing service was set at 80% level of the taxi fare.

Chapter 5. Results

5.1 Transit Vulnerable ODs

299 transit vulnerable ODs at morning peak hour among 56,451 ODs were selected by applying the rule described in Chapter 4. Transit vulnerable ODs are indicated by arrows on the map. In Figure 5.1, the transit passengers move in the direction of the arrows, and the greater the number of passengers, the thicker the arrow tail. Also, the darker the red color, the greater the difference in travel time between transit and auto. According to the map, it was found that ODs headed to the southwestern part of Seoul were selected a lot, and they were aggregated to origin zone and destination zone in Table 5.1 and Table 5.2.

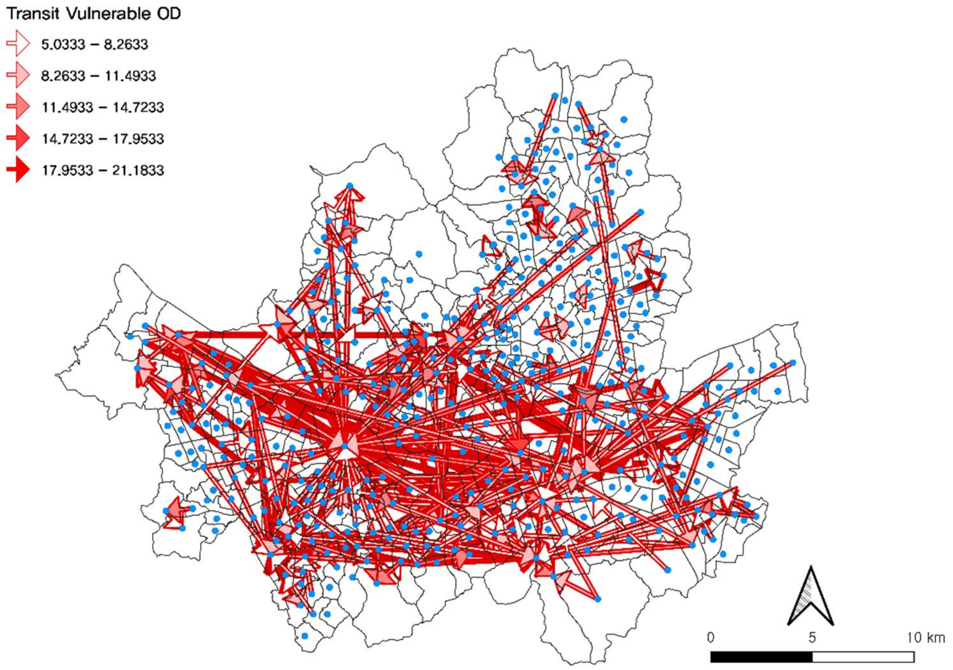


Figure 5.1 Transit vulnerable ODs at morning peak hour in Seoul

Table 5.1 shows that the origins are distributed in several zones, but the destinations shown in Table 5.2 are mainly concentrated in some zones. In particular, 52 ODs which headed to Yeoui-dong were selected as transit vulnerable ODs. It means that at the morning peak hour, people commute from several residential areas to a certain number of work areas, and among them, some ODs are less competitive with transit.

Table 5.1 Top 10 transit vulnerable origin zones in Seoul

Origin	ODs	Transit Passengers
Yeomchang-dong, Gangseo-gu	10	9,823
Sadang 2-dong, Dongjak-gu	10	8,120
Daebang-dong, Dongjak-gu	8	6,382
Seowon-dong, Gwanak-gu	7	6,996
Inheon-dong, Gwanak-gu	7	5,637
Jungang-dong, Gwanak-gu	6	4,645
Seongnae 2-dong, Gangdong-gu	6	4,447
Seongsan 2-dong, Mapo-gu	6	4,846
Sangdo 1-dong, Dongjak-gu	6	4,404
Jamsil 2-dong, Songpa-gu	5	5,419

Table 5.2 Top 10 transit vulnerable destination zones in Seoul

Destination	ODs	Transit Passengers
Yeoui-dong, Yeongdeungpo-gu	52	50,523
Gasan-dong, Geumcheon-gu	22	20,046
Yeoksam 1-dong, Gangnam-gu	17	13,478
Samseong 1-dong, Gangnam-gu	15	13,354
Yangjae 1-dong, Seocho-gu	14	8,783
Guro 3-dong, Guro-gu	8	6,728
Sajik-dong, Jongno-gu	8	5,525
Seocho 3-dong, Seocho-gu	7	5,269
Sangam-dong, Mapo-gu	6	4,184
Samseong 2-dong, Gangnam-gu	6	4,035

Information on the top 10 ODs with the highest number of transit passengers is shown in Table 5.3. As shown in Table 5.2, the top five ODs were all going to Yeoui–dong. Normally, travel times of auto were about 10 minutes shorter than transit.

Table 5.3 Top 10 transit vulnerable ODs at the morning peak hours

Origin	Destination	TT_{ij}^{T} (min)	TT_{ij}^{A} (min)	ΔTT_{ij} (min)	Transit Passengers
Yeomchang–dong	Yeouidong	30	17.95	12.05	3,891
Gayang 1–dong	Yeouidong	48	34.02	13.98	2,571
Ahyeon 1–dong	Yeouidong	22	14.03	7.96	2,437
Gayang 2–dong	Yeouidong	36	21.18	14.82	2,358
Dangsan 2–dong	Yeouidong	21	13.37	7.63	2,073
Jamsil 2–dong	Sogong–dong	48	33.78	14.22	2,019
Seowon–dong	Guro 3–dong	26	18.97	7.03	1,952
Jayang 2–dong	Samseong 1–dong	27	20.68	6.32	1,857
Daebang dong	Yeouidong	20	14.57	5.43	1,780
Doksan 1–dong	Gasan–dong	14	5.77	8.23	1,752

5.2 Optimum Multimodal Paths

The multimodal paths combining transit and car−hailing were generated using MIPG algorithms explained in Chapter 4 for the 299 transit vulnerable ODs. Table 5.4 shows the number of multimodal paths generated by each algorithm, the average number of multimodal paths generated per OD, and so on. The first algorithm generated multimodal paths for all 299 ODs, but the second and third algorithms generated multimodal paths only for 205 ODs, and the fourth algorithms generated only for 201 ODs. The reason for the difference is that the multimodal paths generated by the first algorithm were significantly less competitive than the existing transit and car−hailing paths when the car−hailing fare was close to the initial charge due to the relatively short travel distance. Because the multimodal paths use both car−hailing and transit, the minimum fare is more expensive than the unimodal path. Therefore, from the second algorithm, the multimodal path was not generated when the fare of car−hailing service is less than 4,800 won. The fourth algorithm generated multimodal paths for fewer ODs than the second and third algorithms, because the fourth algorithm takes only the subway, not the bus, so multimodal paths could not be generated for ODs that cannot be moved using the subway. The ODSAY API used to obtain transit travel information does not give any travel information if there are no stations of transit within 700m radius of the origin or the destination.

Table 5.4 Comparison of multimodal path generation results by algorithm

Algorithm	OD	Multimodal paths	Average multimodal paths	Ratio to the first algorithm
1	299	88,535	440	100.0%
2	205	12,484	61	14.1%
3	205	5,813	28	6.6%
4	201	1,951	10	2.2%

Among the multimodal paths generated by OD, the paths with the lowest generalized cost were selected and compared by the algorithm. Table 5.5 shows that the number of ODs whose multimodal path generated by the first algorithm had the lowest generalized cost compared to the other paths generated by the other algorithms was 43 and that of the second algorithm was 15 and so on. The number of ODs whose multimodal paths generated by the first and second algorithm had the lowest generalized cost compared to the other paths generated by the other algorithms was 49. The results aggregated by the algorithm are shown in Table 5.6. As a result, the first algorithm generated multimodal paths with the lowest generalized cost at the most ODs, and the fourth algorithm generated the optimum paths at the least of ODs.

Table 5.5 The number of ODs with the lowest generalized cost by combination of algorithms

Algorithm	1	2	3	4	ODs
Combination	O				43
		O			15
			O		39
				O	27
	O	O			49
	O		O		5
	O			O	0
		O	O		0
		O		O	0
			O	O	0
	O	O	O		12
	O	O		O	8
	O		O	O	1
		O	O	O	2
	O	O	O	O	4

Table 5.6 Aggregated result of Table 5.5 by algorithm

Algorithm	1	2	3	4
ODs	122	90	62	42

Next, the number of ODs with minimum generalized cost by modes was compared by algorithms. As shown in Table 5.7, there was only one OD whose multimodal path had the lowest generalized cost compared to car−hailing and transit paths, and there were three ODs that are within 110% of the generalized cost of the transit path. It has been found that the generalized costs of multimodal paths in more than half the ODs were between that of auto and transit paths. Moreover, the result of the first algorithm and that of the second and the third algorithms did not show much difference, but the fourth algorithm showed did not produce good results compared to other algorithms.

Table 5.7 The number of ODs with minimum generalized cost by modes

Algorithm	$\boldsymbol{GC_{ij}^{Multimodal} < GC_{ij}^{Ch}, GC_{ij}^{PT}}$	$\boldsymbol{GC_{ij}^{PT} \cong GC_{ij}^{Multimodal} < GC_{ij}^{Ch}}$	$\boldsymbol{GC_{ij}^{PT} < GC_{ij}^{Multimodal} < GC_{ij}^{Ch}}$	$\boldsymbol{GC_{ij}^{Ch}, GC_{ij}^{PT} < GC_{ij}^{Multimodal}}$
1	1 (0.3%)	3 (1.0%)	160 (53.5%)	135 (45.2%)
2	0	1 (0.5%)	157 (76.6%)	47 (22.9%)
3	0	1 (0.5%)	150 (73.2%)	54 (26.3%)
4	0	1 (0.5%)	120 (59.7%)	84 (41.8%)

As shown in Table 5.8, comparing the modes by only considering the travel time, the number of OD in which multimodal path had the minimum travel time compared to other modes, was more than expected. Including ODs in which the travel time of multimodal path was within 110% of the car−hailing path, the multimodal path appears to be able to compete with car−hailing at about 40% of the ODs, confirming the competitiveness of the path combining transit and car−hailing.

Table 5.8 Minimum travel time comparison by modes

Algorithm	$TT_{ij}^{Multimodal} < TT_{ij}^{Ch}, TT_{ij}^{PT}$	$TT_{ij}^{Ch} \cong TT_{ij}^{Multimodal} < TT_{ij}^{PT}$	$TT_{ij}^{Ch} < TT_{ij}^{Multimodal} < TT_{ij}^{PT}$	$TT_{ij}^{Ch}, TT_{ij}^{PT} < TT_{ij}^{Multimodal}$
1	51 (17.1%)	66 (22.1%)	182 (60.9%)	0
2	45 (22.0%)	47 (22.9%)	110 (53.7%)	3 (1.5%)
3	35 (17.1%)	44 (21.5%)	124 (60.5%)	2 (1.0%)
4	24 (11.9%)	36 (17.9%)	78 (38.8%)	63 (31.3%)

In the case of comparing the travel times of the paths with the minimum generalized cost by modes, the number of ODs whose travel time of the multimodal path was similar to that of the car-hailing path was slightly decreased, but it is still competitive. Table 5.8 and 5.9 show that the results of the fourth algorithm are worse than those of the other algorithms and are inadequate to find the optimum path of multimodal.

Table 5.9 Travel time comparison of the path with minimum generalized cost by modes

Algorithm	$TT_{ij}^{Multimodal} < TT_{ij}^{Ch}, TT_{ij}^{PT}$	$TT_{ij}^{Ch} \cong TT_{ij}^{Multimodal} < TT_{ij}^{PT}$	$TT_{ij}^{Ch} < TT_{ij}^{Multimodal} < TT_{ij}^{PT}$	$TT_{ij}^{Ch}, TT_{ij}^{PT} < TT_{ij}^{Multimodal}$
1	37 (12.4%)	53 (17.7%)	207 (69.2%)	2 (0.7%)
2	40 (19.6%)	41 (19.6%)	120 (58.8%)	4 (2.0%)
3	22 (10.7%)	43 (21.0%)	134 (65.4%)	6 (2.9%)
4	23 (11.2%)	37 (18.0%)	80 (39.0%)	61 (31.7%)

The following Figure 5.2 shows the ratio of the generalized cost of the multimodal paths to those of transit according to the travel time of transit. The longer the travel time of the transit, the closer to the generalized cost of the multimodal paths to that of transit paths.

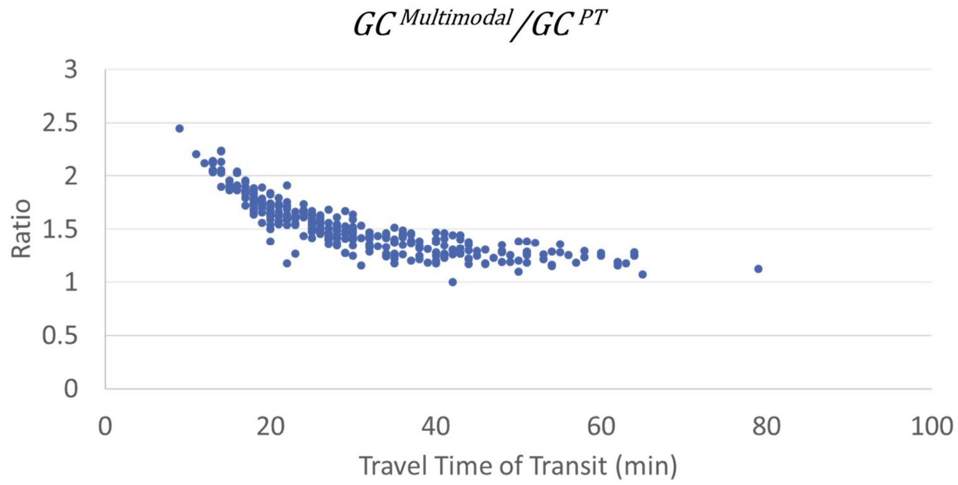


Figure 5.2 The ratio of the generalized cost of the multimodal path to the transit path according to the transit travel time

Figure 5.3 shows the ratio of the generalized cost of the multimodal paths to that of transit according to the ratio of transit travel distance to that of car–hailing service. It was thought that the worse the directness of the transit path was than that of the car–hailing path, the better the effect of introducing multimodal, but it was not particularly correlated. Also, it was thought that the number of ODs whose transit distance is longer than that of car–hailing would be larger, but 173 ODs among 299 transit vulnerable ODs had shorter transit distance than that of car–hailing.

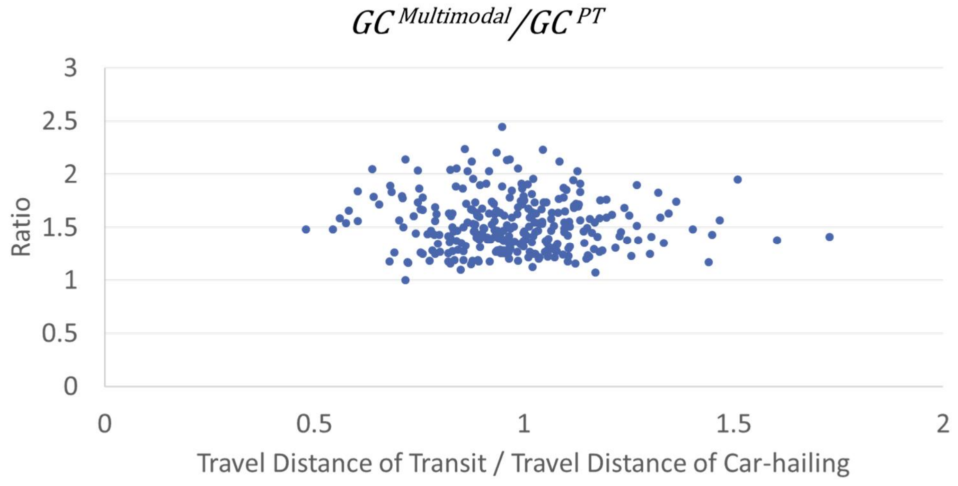


Figure 5.3 The ratio of the generalized cost of the multimodal path to the transit path according to the transit travel time

Figures 5.4 through 5.7 showed the generalized costs of the modes generated by each algorithm. It appeared that the average generalized cost of multimodal paths generated by the first algorithm was 67.7% between transit and car-hailing on average. The paths of multimodal generated by the second algorithm had a generalized cost of 71.9% between transit and car-hailing on average, which is larger than the value of the first algorithm. The third algorithm showed 76.2%, and the fourth algorithm had 94.1% generalized cost.

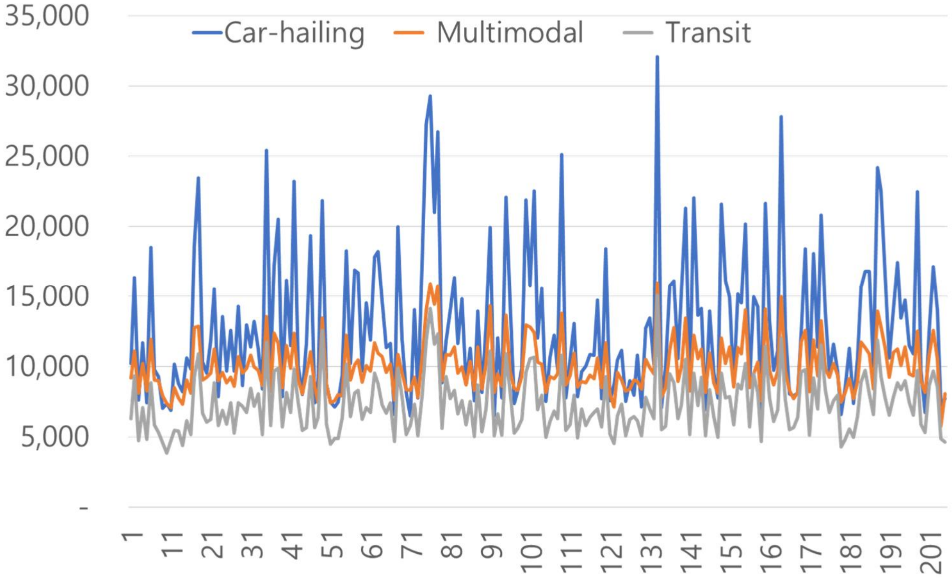


Figure 5.4 Generalized cost of modes calculated by the first algorithm

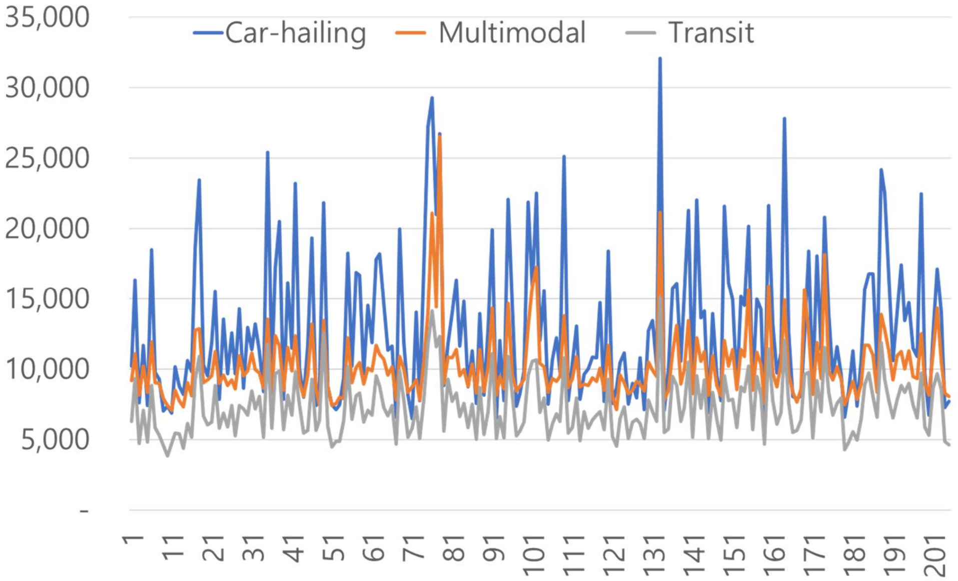


Figure 5.5 Generalized cost of modes calculated by the second algorithm

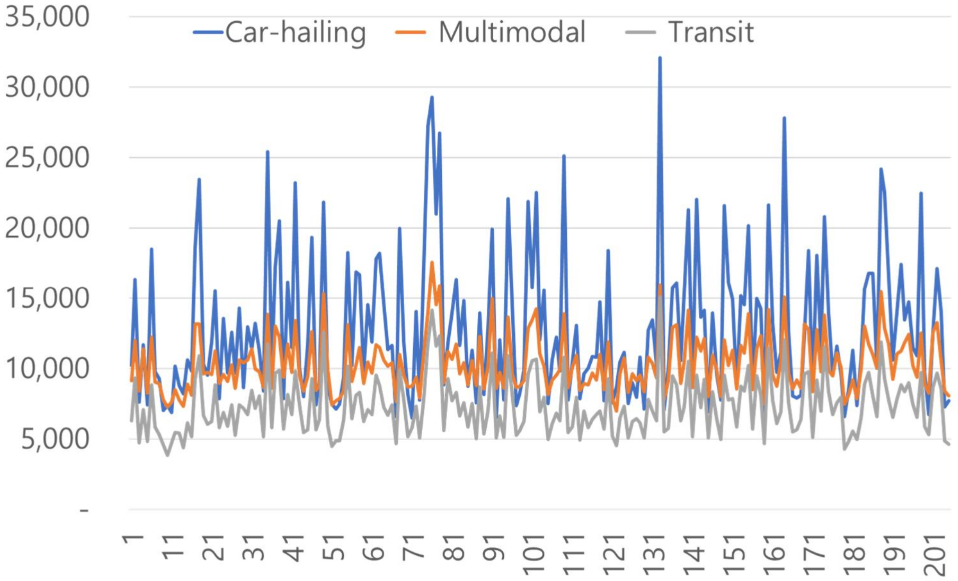


Figure 5.6 Generalized cost of modes calculated by the third algorithm

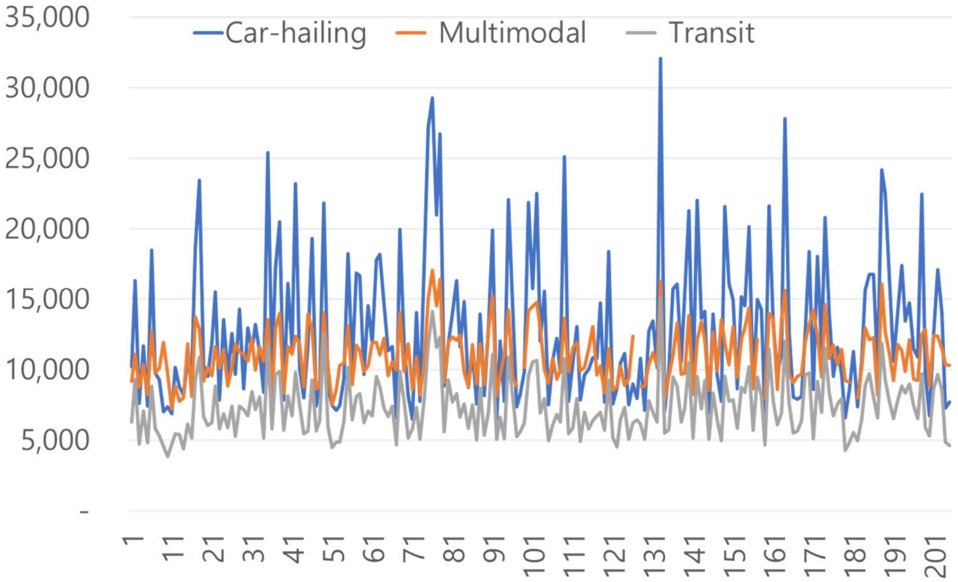


Figure 5.7 Generalized cost of modes calculated by the fourth algorithm

Figures 5.8 through 5.11 showed the travel time of the modes generated by each algorithm. It appeared that the average travel time of multimodal paths generated by the first algorithm was 30.7% between car−hailing and transit on average. The paths of multimodal generated by the second algorithm had a travel time of 34.7% between car−hailing and transit on average, which is larger than the value of the first algorithm. The third algorithm showed 55.6%, and the fourth algorithm had 83.7% travel time.

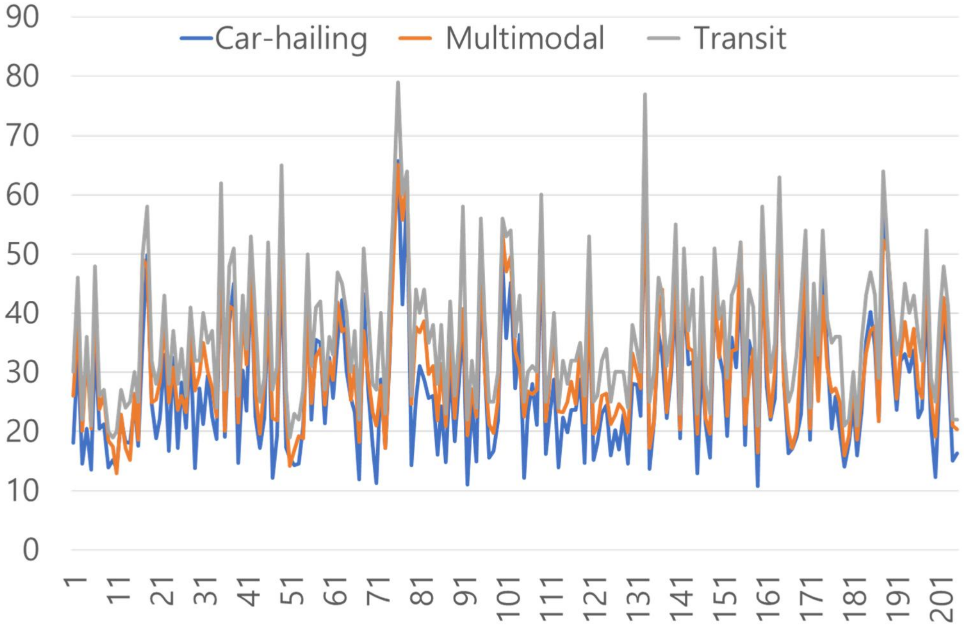


Figure 5.8 Travel time of modes calculated by the first algorithm

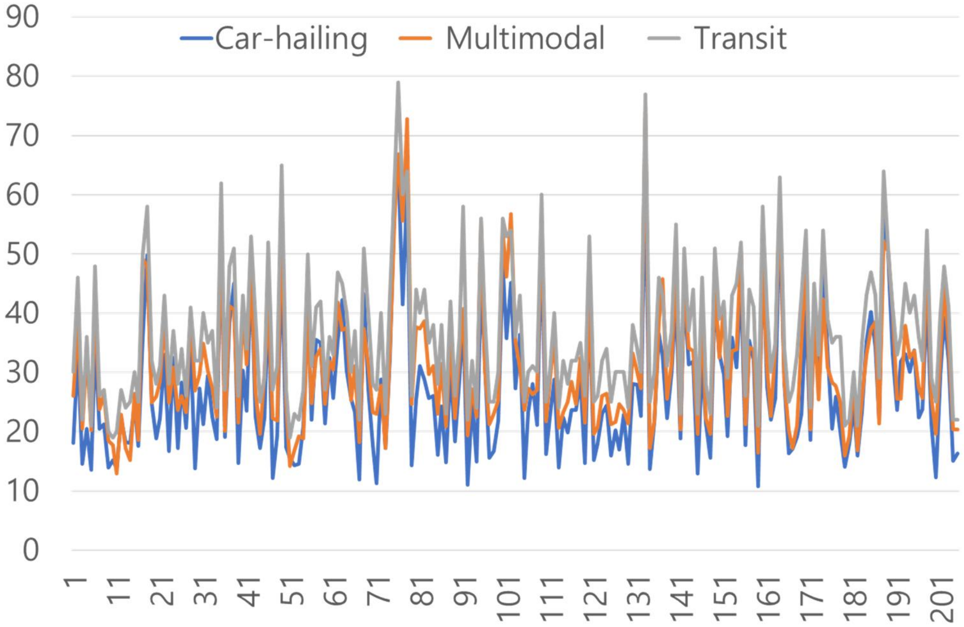


Figure 5.9 Travel time of modes calculated by the second algorithm

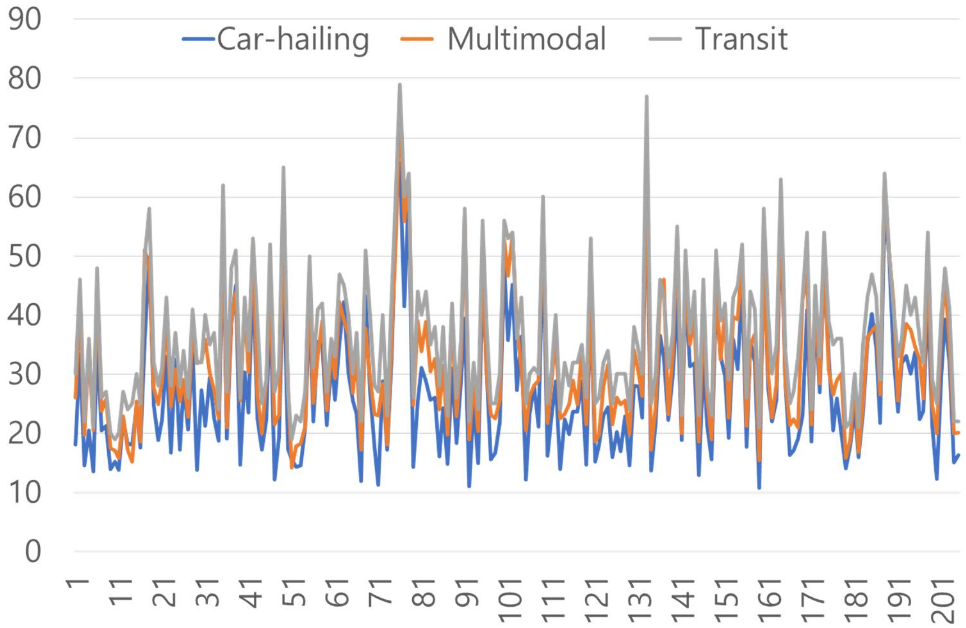


Figure 5.10 Travel time of modes calculated by the third algorithm

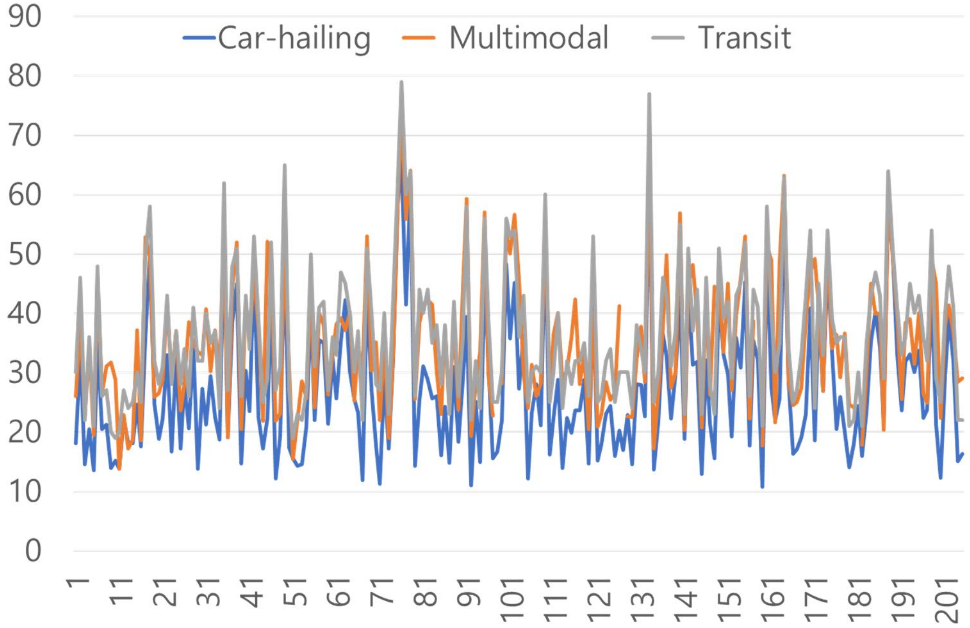


Figure 5.11 Travel time of modes calculated by the fourth algorithm

Figures 5.12 through 5.15 showed the travel fare of the modes generated by each algorithm. It appeared that the average travel fare of multimodal paths generated by the first algorithm was 46.7% between transit and car−hailing on average. The paths of multimodal generated by the second algorithm had a travel fare of 48.9% between transit and car-hailing on average, which is larger than the value of the first algorithm. The third algorithm showed 47.7%, and the fourth algorithm had 48.4% travel fare.

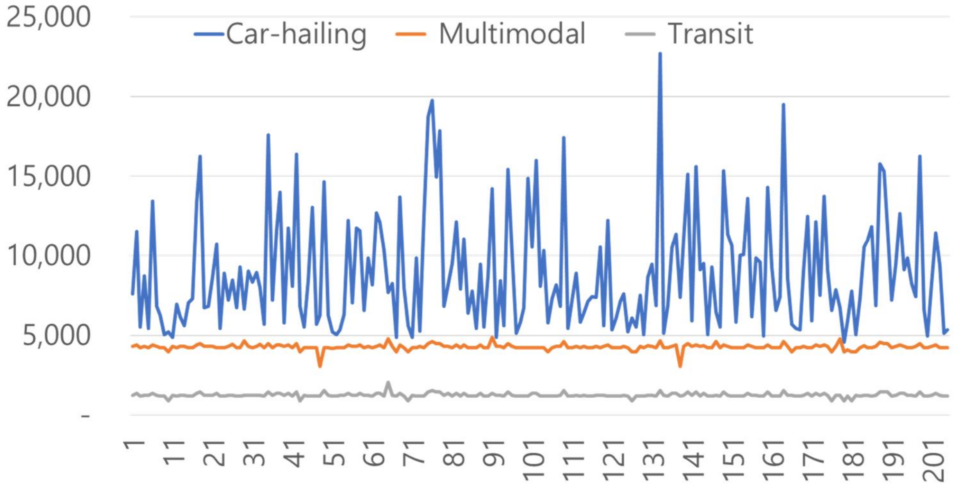


Figure 5.12 Travel fare of modes calculated by the first algorithm

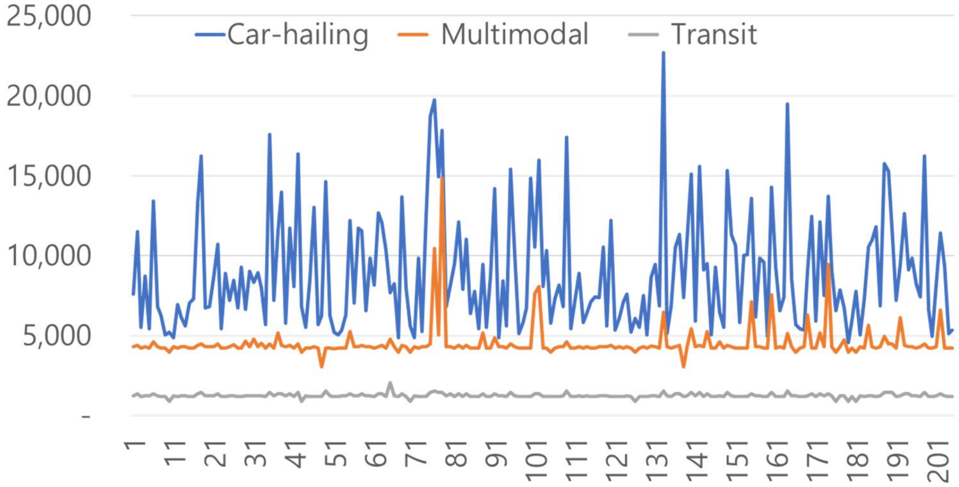


Figure 5.13 Travel fare of modes calculated by the second algorithm

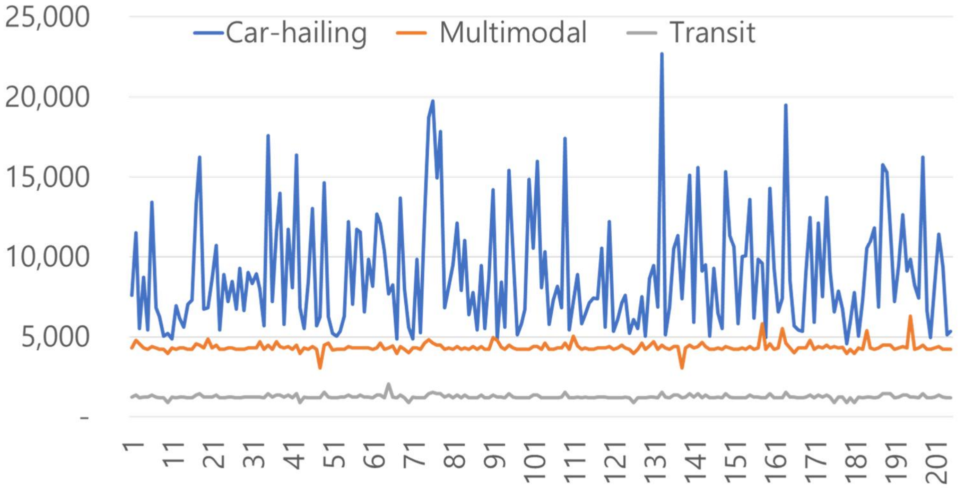


Figure 5.14 Travel fare of modes calculated by the third algorithm

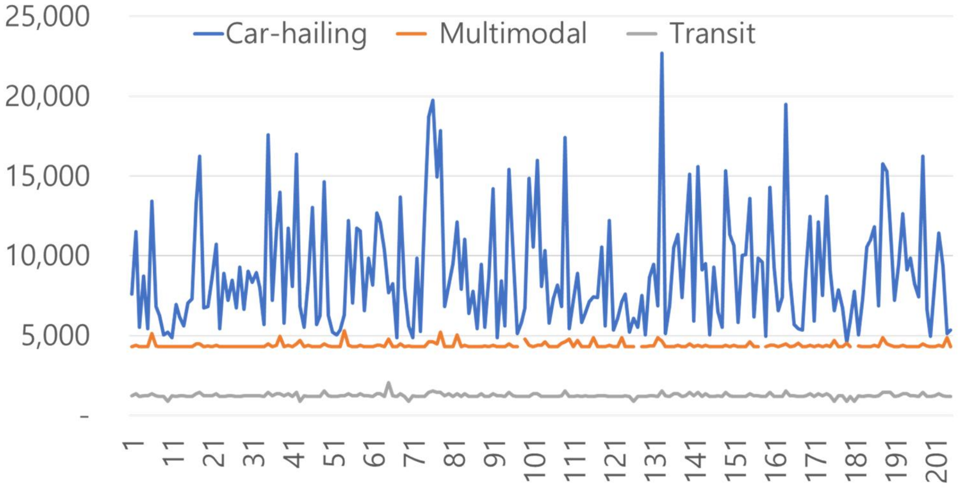


Figure 5.15 Travel fare of modes calculated by the fourth algorithm

In Table 5.10, the average values of travel information of multimodal path by algorithms are shown. It showed that as the number of algorithms increases, the generalized cost and travel time of multimodal path increase, and the multimodal path generated by the second algorithm was the most expensive. The average travel fare had a value close to the sum of 1,250 won, the basic fare for transit, and 3,040($3,800 \times 0.8$) won, the initial charge for car-hailing service. In other words, the most competitive path is to use car-hailing service only for the initial charge and use the remaining segments for transit.

Table 5.10 Average values of multimodal path generated by algorithms

Algorithm	$GC^{Multimodal}$ (won)	$TT^{Multimodal}$ (min)	$TF^{Multimodal}$ (won)
1	9,989	30.69	4,277
2	10,263	30.98	4,534
3	10,352	31.87	4,349
4	11,020	35.01	4,382

The detailed analysis was performed on the top three ODs of the transit vulnerable ODs. In Table 5.11, detailed travel information of the first transit vulnerable OD by modes generated by all algorithms was summarized. The paths that use only transit had a long walking distance, and the paths that use only car-hailing shortened the travel time because there is no walking distance. It showed that the generalized cost of the multimodal path had a larger value than that of transit and smaller value than that of car-hailing service. Except for the third algorithm, the optimum multimodal paths from the first, second and fourth algorithm were the same.

Table 5.11 Travel information by modes from Yeomchang-dong to Yeouidong at the morning peak hours

Algorithm	# of Multimodal Paths	Mode	TF (won)	TD (km)	WKD (m)	TT (min)	TR	GC (won)
-	-	Subway	1,250	6.42	921	30	0	6,274
-	-	Bus	1,250	7.94	827	32	0	6,494
-	-	Subway+Bus	1,250	6.92	734	34	1	7,568
-	-	Subway+Bus	1,250	6.85	746	34	1	7,577
-	-	Car-hailing	7,600	8.25	0	18.13	0	10,225
1	377	Car-hailing +Subway	4,290	6.45	396	26.03	1	9,205
2	49	Car-hailing +Subway	4,290	6.45	396	26.03	1	9,205
3	25	Bus+ Car-hailing	4,290	8.45	144	26.77	1	9,125
4	8	Car-hailing +Subway	4,290	6.45	396	26.03	1	9,205

Figure 5.16 shows the optimum paths by modes. The optimum multimodal path shows the path with the lowest generalized cost among the paths generated through the four algorithms, the green points are the car−hailing path, and the orange points are the subway stations.

In Figure 5.16, it was found that car−hailing was used to the second station of transit path and then subway was used in the multimodal path.

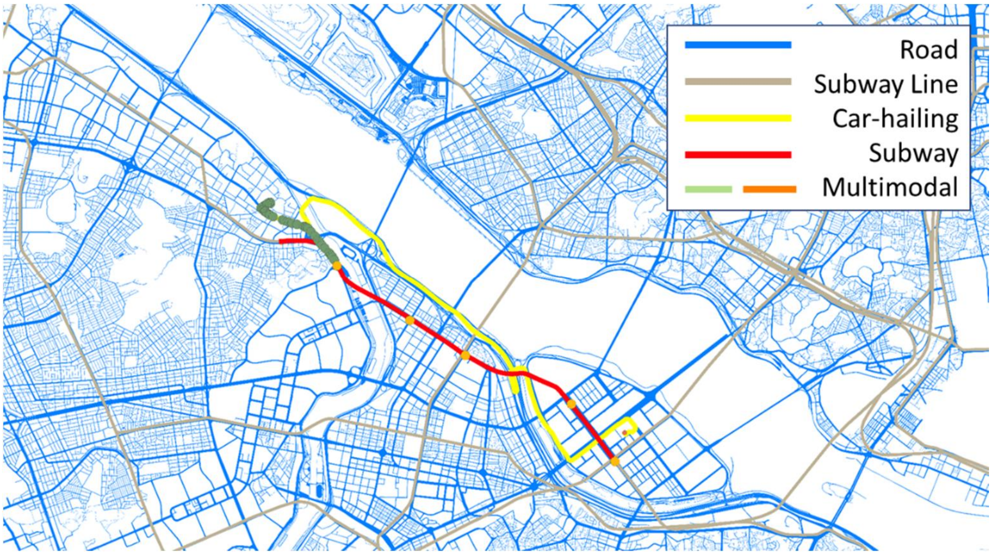


Figure 5.16 Path of each mode

In Table 5.12, detailed travel information of the second transit vulnerable OD by modes generated by all algorithms was summarized. It showed that the generalized cost of integrated mode had the similar value with that of transit and smaller value than that of car−hailing service like the first transit vulnerable OD. Except for the fourth algorithm, the other algorithms generated the same optimum multimodal path, which had the minimum generalized cost. The multimodal path generated by the third algorithm had longer travel time and higher cost. The first algorithm generated 512 multimodal paths, the second algorithm generated 48 paths, and the fourth generated only 9 paths, but they had the same optimum path. It shows that the first algorithm is very inefficient. As mentioned above, the travel fare of the optimum multimodal path was $1{,}350 + 3{,}040 = 4{,}390$ won, and car−hailing was used first, and the subway was used for the rest of the path in all optimum multimodal paths.

Table 5.12 Travel information by modes from Gayang 1−dong to Yeouidong at the morning peak hours

Algorithm	# of Multimodal Paths	Mode	TF (won)	TD (km)	WKD (m)	TT (min)	TR	GC (won)
−	−	Bus+Subway	1,350	11.4	807	48	1	9,749
−	−	Bus+Subway	1,350	12.3	637	46	1	9,334
−	−	Bus+Subway	1,350	14.7	755	47	1	9,566
−	−	Bus+Subway	1,350	11.1	947	49	1	9,997
−	−	Car−hailing	11,520	13.7	0	33.3	0	16,341
1	512	Car−hailing +Subway	4,390	12.4	396	38.5	1	11,110
2	48	Car−hailing +Subway	4,390	12.4	396	38.5	1	11,110
3	25	Car−hailing +Subway	5,110	14.5	367	41.5	1	12,243
4	9	Car−hailing +Subway	4,390	12.4	396	38.5	1	11,110

In Table 5.13, detailed travel information of the third transit vulnerable OD by modes generated by all algorithms was summarized. In this case, the travel distance was very short compared to other ODs. Therefore, the travel times of multimodal paths were similar to that of transit paths and travel fare was much higher. There was no effect of introducing multimodal in this short OD. Of course, it is possible to increase the convenience of the user by shortening the walking time of the path using only transit, but the generalized cost was twice as expensive because the travel fare was more than three times higher.

Table 5.13 Travel information by modes from Ahyeon 1−dong to Yeouidong at the morning peak hours

Algorithm	# of Multimodal Paths	Mode	TF (won)	TD (km)	WKD (m)	TT (min)	TR	GC (won)
−	−	Bus	1,200	4.56	744	22	0	4.737
−	−	Bus	1,200	4.50	506	22	0	4,759
−	−	Subway	1,250	5.50	780	23	0	5,156
−	−	Car−hailing	5,520	4.73	0	14.55	0	7,626
1	257	Car−hailing +Bus	4,240	4.85	180	20.07	1	8,132
2	68	Car−hailing +Bus	4,240	5.19	164	20.43	1	8,173
3	29	Car−hailing +Bus	4,560	4.82	164	19.67	1	8,383
4	8	Subway+ Car−hailing	4,290	5.72	414	22.63	1	8,726

In Table 5.14, detailed travel information of the sixth transit vulnerable OD by modes generated by all algorithms was summarized. Unlike other ODs, the travel information of the second optimum multimodal path generated by the first and second algorithms is also added to the last row. In this OD, the travel distance of the path using only transit was much longer than that of the car−hailing path. Figure 5.17 shows how inefficient the transit path is. If the transit path is more inefficient than the car−hailing path, it was judged that it is best to select the station with the worst value as the transfer point by measuring the directness like the third algorithm, and the directness of every transit stations is shown in Figure 5.18. As in Figure 5.19, Although it is expected that the path using the car−hailing from origin to the station with the largest directness and using the subway for the rest of the path will be the most competitive, as the travel distance of car−hailing is longer and the generalized cost becomes more expensive. As a result, in Table 5.14, the most competitive multimodal path was the path generated by the first and second algorithms, whose travel distance of car−hailing was short in Figure 5.17.

Table 5.14 Travel information by modes from Jamsil 2−dong to Sogongdong at the morning peak hours

Algorithm	# of Multimodal Paths	Mode	TF (won)	TD (km)	WKD (m)	TT (min)	TR	GC (won)
−	−	Subway	1,350	18.2	709	48	0	8,823
−	−	Bus+ Subway	1,450	18.7	519	51	1	10,071
−	−	Bus +Subway	1,450	18.9	487	52	1	10,192
−	−	Car−hailing	13,440	13.6	0	35.02	0	18,510
1	580	Car−hailing +Subway	4,870	17.5	74	42.58	1	11,943
2	29	Car−hailing +Subway	4,870	17.5	74	42.58	1	11,943
3	14	Car−hailing +Subway	5,130	18.6	74	45.23	1	12,245
4	8	Subway+ Car−hailing	5,130	18.6	75	46.23	1	12,732
1&2	−	Car−hailing +Subway	6,450	15.0	74	38.43	1	12,922

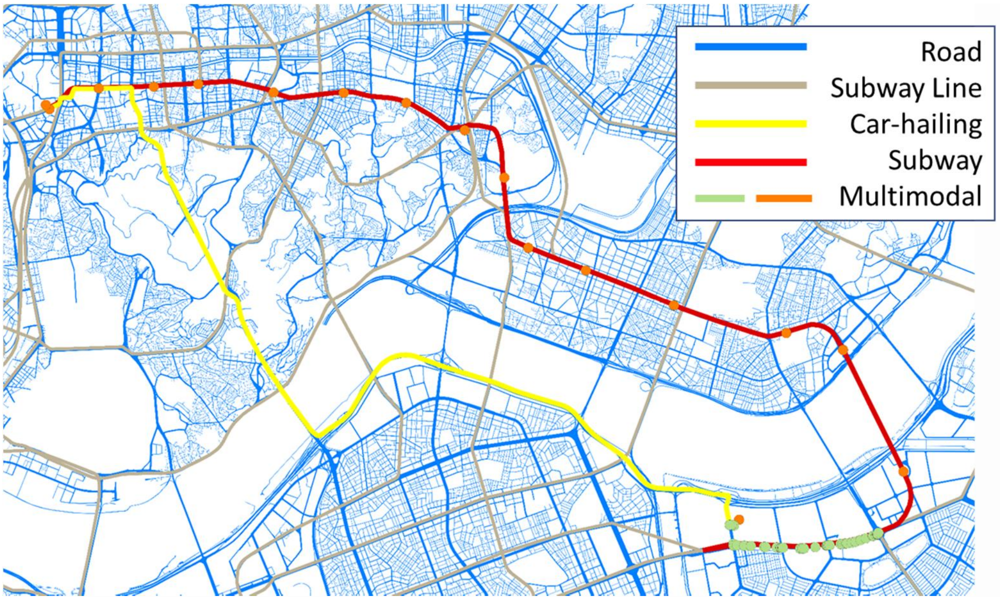


Figure 5.17 Path of each mode

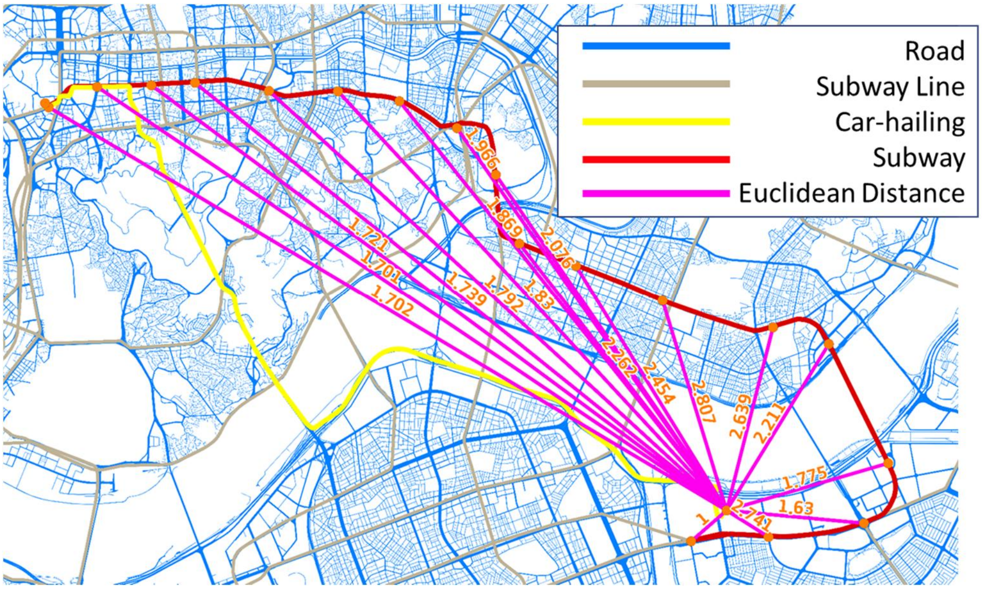


Figure 5.18 Directness of every transit station

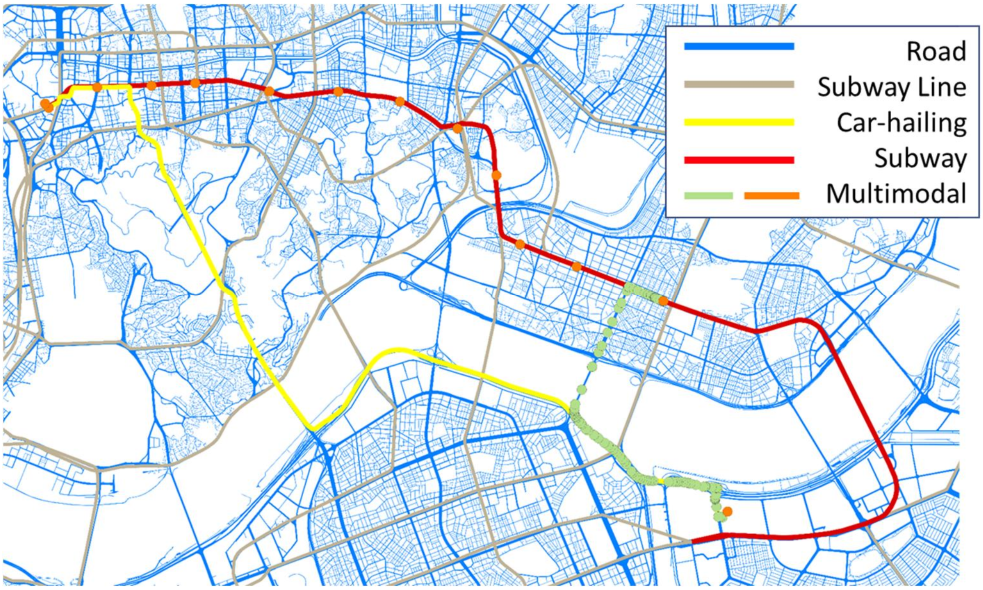


Figure 5.19 The second optimum multimodal path generated by the first and second algorithms

In Table 5.15, detailed travel information of the tenth transit vulnerable OD by modes generated by the first algorithm was summarized. As mentioned above, the travel fare of car-hailing service was less than 4,800won. Therefore, except the first algorithm, the rest did not generate the multimodal path. The table showed that the generalized cost of the multimodal path had much larger value than that of transit and car–hailing service. Because the travel distance was short, there was no benefit to taking transit and car–hailing combined mode.

Table 5.15 Travel information by modes from Doksan 1–dong to Gasan–dong at the morning peak hours

Algorithm	# of Multimodal Paths	Mode	TF (won)	TD (km)	WKD (m)	TT (min)	TR	GC (won)
–	–	Bus	900	1.62	1,237	14	0	3,841
–	–	Bus	1,200	1.44	1,098	14	0	4,038
–	–	Bus	1,200	2.09	1,497	17	0	4,767
–	–	Car–hailing	3,040	1.67	0	5.67	0	3,861
1	33	Car–hailing +Bus	3,940	1.46	734	11.53	1	7,005

In the order from Table 5.16 to 5.18, travel information of each 19th, 45th, 225th transit vulnerable OD was shown. The competitiveness of multimodal path was higher in ODs with relatively long travel distance, and travel time was shorter than car–hailing.

Table 5.16 Travel information by modes from Yeomchang–dong to Yeoksam 1–dong at the morning peak hours

Algorithm	# of Multimodal Paths	Mode	TF (won)	TD (km)	WKD (m)	TT (min)	TR	GC (won)
–	–	Subway+Bus	1,450	17.8	708	57	1	11,079
–	–	Bus+Subway	1,450	23.6	265	58	1	10,897
–	–	Subway+Bus	1,450	17.8	981	59	1	11,570
–	–	Subway+Bus	1,450	18.2	817	60	1	11,594
–	–	Car–hailing	16,240	19.0	0	49.83	0	23,454
1	1,002	Subway+ Car–hailing	4,490	17.7	525	49.4	1	12,884
2	55	Subway+ Car–hailing	4,490	17.7	525	49.4	1	12,884
3	39	Subway+ Car–hailing	4,490	17.7	525	51.3	1	13,159
4	33	Subway+ Car–hailing	4,490	17.7	525	49.4	1	12,884

Table 5.17 Travel information by modes from Daebang−dong to Samseong 2−dong at the morning peak hours

Algorithm	# of Multimodal Paths	Mode	TF (won)	TD (km)	WKD (m)	TT (min)	TR	GC (won)
−	−	Subway	1,350	14.4	1,515	51	0	9,853
−	−	Bus+Subway	1,350	12.9	786	52	1	10,313
−	−	Subway+Bus	1,350	14.8	1,093	52	1	10,540
−	−	Subway+Bus	1,350	14.7	991	53	1	10,609
−	−	Bus+Subway	1,350	13.4	1,009	53	1	10,622
−	−	Car−hailing	14,000	16.4	0	45.03	0	20,519
1	928	Car−hailing +Subway	4,630	12.9	380	40.7	1	11,657
2	87	Car−hailing +Subway	4,630	12.9	380	40.7	1	11,657
3	41	Subway+ Car−hailing	4,390	14.8	845	43.87	1	12,219
4	12	Car−hailing +Subway	4,950	16.8	871	52.03	1	13,980

Table 5.18 Travel information by modes from Yongdap−dong to Samseong 1−dong at the morning peak hours

Algorithm	# of Multimodal Paths	Mode	TF (won)	TD (km)	WKD (m)	TT (min)	TR	GC (won)
−	−	Subway+ Subway+Bus	1,250	8.27	891	43	2	9,841
−	−	Subway+ Subway	1,250	7.79	1,387	44	1	9,499
−	−	Subway Subway+Bus	1,250	8.11	1,008	44	2	10,072
−	−	Car−hailing	9,840	7.16	0	35.33	0	14,955
1	928	Car−hailing +Bus	4,240	7.08	366	28.5	1	9,490
2	87	Car−hailing +Subway	4,770	7.96	820	34.27	1	11,191
3	41	Bus+Subway +Car−hailing	4,290	8.27	465	34.97	2	11,404
4	12	Car−hailing +Subway +Subway	4,290	8.03	777	38.6	2	12,160

Chapter 6. Conclusions

This study selected the transit vulnerable ODs and developed four multimodal integrated path generation algorithms. The travel time was calculated by using API data, which estimates travel information, and the number of transit passengers was obtained from smart card data containing actual transit travel information. Using the difference of travel time between modes and the number of transit passengers, the transit vulnerable ODs at the AM peak hours were selected. For the selected OD, the multimodal integrated paths were generated by using four algorithms.

As a result, the travel information such as travel time and fare of paths that combine car–hailing service and transit was found to have an intermediate level of travel information that only uses car–hailing service and transit. For certain ODs at certain times, the multimodal path had the shortest travel time. In general, the path that combines car–hailing service with transit has a great advantage in reducing walking time. If car–hailing service is used instead of transit, walking time from origin to the first boarding station will be zero, and if car–hailing service is used instead of transit as the last mode, walking time from the last alighting station to the destination will be zero. Among the four algorithms, the second algorithm was found to the most efficient algorithm. In other words, the most competitive path was to replace a bus with car–hailing, which was relatively slower than other modes.

The third algorithm, which measures the directness of every station in the transit route and selects the station with the largest value as the transfer point, also finds the optimum multimodal path efficiently, but overall the result of the second algorithm is slightly better. However, the result of the second algorithm in some ODs was poor because the algorithm did not find the optimum path to use the car–hailing until near the origin. Therefore, the algorithm that complements that part will find the optimum path more stable.

As a result of analyzing the multimodal path generated based on transit vulnerable ODs, by combining car−hailing service and existing transit, the demand of passengers who are forced to use car−hailing service or taxi due to short travel time and walking time would be moved to this new mode. Therefore, transit will be revitalized, and the problems caused by the excessive use of private autos will be alleviated to some extent.

Many studies and researches are working to enhance the competitiveness of the existing transit system. However, in certain cities like Seoul, where transit is already well−equipped, there is a limit to improving the current system. Therefore, it is necessary to boost the use of transit by integrating new modes such as car−hailing and car−sharing.

Currently, the car−hailing service in Seoul is operating a little bit. Although the service is interrupted due to the conflict with the taxi industry, the car−hailing service will be actively operated in the near future according to the global trend, and it is important to create a sustainable transportation system by activating integrating with the existing transit system in the early stages of the new system's introduction.

To improve this study, it is important to reflect the actual demand by all modes. OD, which has a high demand for auto and taxi, and low demand for transit, may be a genuine transit vulnerable OD. Therefore, by increasing the competitiveness of transit to and increasing the connection with new modes, it will be possible to enhance the modal split of transit more effectively. Besides, if there is no daily limit in API service, travel information of auto and car−hailing service can be acquired at the station level, and higher resolution analysis can be performed. Furthermore, the accuracy of the analysis can be improved if the actual travel demand by each OD is known.

In the case of car−hailing service currently in operation in Korea, the travel fare system is operated flexibly according to the time. Therefore, the generalized cost of car−hailing will change, and sensitivity analysis can be performed to produce meaningful results.

In this study, travel information on three modes was compared. However, the choice of modes is solely based on the value and utility of individual passengers, and it is not known which modes will be chosen the most. Generally, the components of utility include travel time, distance and transfer count, etc. and may include additional seating availability and weather condition. Especially on high dust days, which is a recent issue, the utility of car–hailing service and private auto will be higher than that of transit due to the high probability of exposure to fine dust during the waiting time for transit. Thus, by analyzing all the effects on passenger utility, integrated modes may be more activated. In other words, assuming the situation of passengers using taxis due to the high concentration of fine dust and the high level of congestion in transit, they will be forced to use taxi at a high fare, and if multimodal paths are recommended, the inconvenience of transit will be reduced, and the fare will also be reduced compared to taxi or car–hailing service, so possibilities are high that they will choose multimodal paths. Thus, combining the data would contribute more to enhancing the modal split of transit. Also, combinations with other modes, such as shared bicycles, as well as car–hailing service, can sufficiently increase the modal split of transit.

References

Jittrapirom P., Caiati V., Feneri A−M. Ebrahimigharehbaghi S., Alonso M. J., Narayan J. (2017). Mobility as a Service: A Critical Review of Definitions, Assessments of Schemes, and Key Challanges, Urban Planning, 2(2), 139−158.

Jo, J. S., Shin, S. I., Moon, B. S., Lim, G. W. (2006). A K Least Time Paths Searching Algorithm for Time Dependent Intermodal Transportation Networks with Departure Time Schedule Constraints, Journal of Korean Soceity of Transportation, 24(3), 167−176.

Karner, A. (2018). Assessing public transit service equity using route−level accessibility measures and public data. Journal of Transport Geography, 67, 24–32.

Khani, A., Lee, S., Hickman, M., Noh, H., Nassir, N. (2012). Intermodal Path Algorithm for Time−Dependent Auto Network and Scheduled Transit Service. Transportation Research Record: Journal of the Transportation Reseach Board, No. 2284, 40–46. https://doi.org/10.3141/2284−05

Kim, K., Lee, I. (2017). Public Transportation Alighting Estimation Method Using Smart Card Data. Journal of the Korean Society for Railway, 20(5), 692−702.

Litman, T. (2003). Measuring Transportation: Traffic, Mobility and Accessibility. ITE Journal, 73(10), 28–32.

Litman, T. (2018). Evaluating Transportation Equity: Guidance for Incorporating Distributional Impacts in Transportation Planning. Victoria Transportation Policy Institute, Victoria, Br. … 8, 50–65.

Lee, E.H., Lee, H., Kho, S.Y., Kim, D.K. (2019). Evaluation of Transfer Efficiency between Bus and Subway based on Data Envelopment Analysis using Smart Card Data. KSCE Jouranl of Civil Engineering, 23(2), 788–799.

Lo H. K., Yip C. W., Mak B. (2005), Passenger Route Guidance System for Multi−modal Transit Networks, Journal of Advanced Transportation, 39(3), 271−288.

Mamun, M. A., Lownes, N. (2015). A Composite Index of Public Transit Accessibility. Journal of Public Transportation, 14(2), 69–87.

Saghapour, T., Moridpour, S., Thompson, R.G. (2016). Public transport accessibility in metropolitan areas: A new approach incorporating population density. Journal of Transportation Geography, 54, 273–285.

Schoon J. G., Michael M., Lee. A. (1999). Accessibility Indices Pilot Study and Potential Use in Strategic Planning, Transportation Research Record, 1685, 29−38.

Shin S. I., Noh H. S. (2004). An Algorithm for Finding the First K Link Loopless Optimum Paths and Its Application to Multimodal Public Transit Networks, Journal of Transport Research, 11(1), 83−103.

Shin S. I., Park J. J., Lee J. C., Ha T. J. (2008). Development of User Customized Path Finding Algorithm for Public Transportation Information, Journal of Korean Society Civil Engineering, 28(3D), 317−323.

Wang, D., Cao, W., Li, J., Ye, J. (2017). DeepSD: Supply−demand prediction for online car−hailing services using deep neural networks. Proc. – Int. Conf. Data Eng, 243−254. https://doi.org/10.1109/ICDE.2017.83

Wang, F., Xu, Y. (2011). Estimating O−D travel time matrix by Google Maps API: Implementation, advantages, and implications. Annals of GIS, 17(4), 199–209. https://doi.org/10.1080/19475683.2011.625977.

Wu, H. (2017). Accessibility Disparity between Transit and Automobile : a Study of Atlanta and Seattle, Master Degree Dissertation, Georgia Institute of Technology, Atlanta.

Yang H. J. (2018). A Fine−Scale Accessibility Analysis using Public Transport Network and Smart Card Data, Master Degree Dissertation, University of Seoul, Seoul.

Ziliaskopoulos, A., Wardell, W. (2000). Intermodal optimum path algorithm for multimodal networks with dynamic arc travel times and switching delays. Eur. J. Oper. Res. 125, 486–502. https://doi.org/10.1016/S0377-2217(99)00388-4

국문초록

대중교통의 이용을 활성화하는 것은 교통혼잡, 주차문제, 대기오염 등 과도한 승용차의 이용으로 인해 발생하는 여러 문제들을 완화하는데 도움을 준다. 서울의 경우 최근 5년동안 대중교통의 수단분담률이 감소하고 승용차의 수단분담률이 증가하고 있다. 이는 승용차 대비 대중교통의 경쟁력이 낮다는 것을 의미하고, 경쟁력을 제고하기 위해서는 먼저 대중교통의 경쟁력을 평가해야 한다. 대중교통을 평가한 대다수의 논문들은 대중교통의 접근성에 초점을 두었고, 대중교통 접근성은 통행시간, 거리, 요금 등의 요소들을 이용하여 측정할 수 있다. 본 연구는 서울시 평일 5일치 교통카드 데이터를 이용하여 대중교통의 탑승객 수를 구하고, API 서비스를 이용하여, 승용차와 대중교통의 통행시간을 구득하여, 대중교통과 승용차의 통행시간을 비교하고자 한다. 단순히 통행시간만을 비교한 것이 아니라, 해당하는 출발지와 도착지를 통행했던 대중교통 탑승객 수도 같이 고려하여 서울시의 대중교통 취약 OD를 선정한다. 통행이 집중되는 오전 첨두시에 발생한 통행을 분석하고, 대중교통과 승용차의 통행시간 차이가 5분 이상 나고, 대중교통 탑승객 수가 5일동안 500명 이상인 OD를 취약 OD로 선정한다. 선정된 취약 OD에 대하여 총 네가지의 통합 수단 경로 생성 알고리즘을 이용해 car-hailing 서비스와 대중교통이 결합된 경로를 생성하여, 기존의 단일 수단 경로와 비교하고, 대중교통 경쟁력이 얼마나 개선되는지 파악한다. 알고리즘을 이용해 생성된 통합 수단 경로들 중에서 최적 경로는 일반화 비용을 계산하여 선정하고, 알고리즘 별로 선정된 최적 경로를 비교한다. 그 결과 버스를 Car-hailing 서비스로 대체하고, 환승지점 앞, 뒤 정류장들을 Car-hailing의 출발지와 도착지로 선정하는 두번째 알고리즘이 가장 효율적으로 최적의 수단 통합 경로를 찾는 것으로 나타난다. 통합 수단 경로는 특정 시간대에 특정 OD에서는 가장 짧은 통행시간을 갖기도 하지만, 대다수의 OD에서 수단이 통합된 경로는 car-hailing만 이용한 통행과 대중교통만 이용하는 통행사이의 30% 정도 수준의 통행 시간을 갖는 것

으로 나타난다. 또한 통행거리가 짧은 OD에 대해서는 통합수단의 경쟁력이 낮았고, 통행거리가 긴 OD에서 통합수단의 경쟁력이 높았다. 이를 통해 통행거리가 긴 OD 중 접근 시간이 긴 곳에 Car-hailing 서비스를 대중교통 연계수단으로 도입하는 것이 가장 효과적이라 할 수 있다.

주요어: 대중교통, Car-hailing 서비스, 교통카드 데이터, API 서비스, 통합수단경로 생성
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