Development of A Travel Speed Estimation Model for Effective Snow Removal Operations on Urban Arterial Roads

街路における効率的な除雪作業のための旅行速度推定モデルに関する研究

by

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ABSTRACT

Traffic congestion in winter is affected not only by travel speed, traffic volume and density, but also by external factors such as weather conditions, road works, road surface conditions and snow removal operations. To explain traffic conditions, transportation engineers need to identify and analyze these factors. Previous researchers have addressed the relationship between traffic performance and non-traffic factors, including weather conditions, using data collected by various sensors. And many researchers have developed traffic condition prediction models. However, they have not considered the effects of snow removal operations in microscopic approaches on travel time or traffic conditions for forecasting winter traffic congestion, which means that they did not evaluate traffic performance according to snow removal for each road. Therefore, the purpose of the present study is to develop the methodology for travel speed prediction model that consider weather conditions and snow removal operation factors, toward quantifying the effects of snow removal operations in Sapporo. Cyber-physical system (CPS) is a smart cycle system that collects and analyzes real-world data, and then the real-world can be given feedback from the analysis results. CPSs allow us to collect valuable data, such as traffic data, weather data and snow removal operation factors from advanced sensors. Physical-world data are now easily convertible into computerized data through CPSs.

The location of the present study was a 4.8-km section of Nishi-5-chome Tarukawa Dori, a major arterial in Sapporo, Japan. The duration for analysis was on weekdays for the winter season of 2013-2014 (December, 2013 to March, 2014). The variables of traffic conditions, weather conditions, and snow removal operation factors were considered for the analysis in the present study. Four steps were performed to develop the travel speed prediction model for the effective snow removal operations. The first step was to establish a dataset for analysis by combining traffic conditions, weather conditions and snow removal operation factors. The second step was to develop two regression models, which were multiple linear

regression (MLR) models and panel data models, with all the variables. The third step was to investigate the autocorrelation of the residuals between the actual values and estimated values of the regression models, in order to apply an autoregressive integrated moving average (ARIMA) model to the residuals. If the residuals were autocorrelated with among the others, they would be predicted by ARIMA model. This kind of model, which is combined both a regression model and an ARIMA model, is called a regression with ARIMA (RegARIMA) model. The fourth step was to verify the developed RegARIMA models under different weather conditions: snow conditions and non-snow conditions. In addition, using the developed travel speed prediction model, the travel time saving effects of snow removal operations were quantified.

According to the model validation results, the developed RegARIMA model was more suitable for forecasting travel speed in winter regardless of snow weather conditions than the univariate ARIMA model, which is a prediction model using only the past observations. The developed RegARIMA models showed that temperature had a U-shaped relationship with travel speed and deep snow had a negative correlation with travel speed. Snow removal for road widening and fresh snow removal had a positive correlation with travel speed. In addition, the vehicle turning rate was negatively correlated and the intersection size had a positive relationship with travel speed in the MLR with ARIMA model. Vehicles going straight were obstructed by the vehicles turning left and right at intersection especially on the winter road which were narrowed by fresh snow removal operations. On the other hand, the negative effects of the turning rate would be decreased if the intersection size were big enough space to wait for an opportunity to turn right and left at intersections. From the estimation for the effects of snow removal operations, around 1,076 JPY per vehicle for the road widening operations and 3,420 JPY per vehicle for the fresh snow removal operations could be found as the travel time saving benefits during from February 13 to February 20, 2014. In terms of individual snow removal operation, most of the travel time saving benefits for fresh snow removal operation was less than 100 JPY/veh a day among all sections, and the effects of snow hauling were the greatest of any snow removal operation.

The results suggest a methodology for predicting the travel speed, considering weather conditions and snow removal operations in an urban area. This methodology can be used when forecasting traffic congestion in winter in an urban area, and it can be used for developing winter road maintenance strategies in an urban area. For example, the locations and times of traffic congestion could be predicted by the proposed methodology. Then, snow removal equipment could be deployed more economically in advance to the proper locations. The evaluation of snow removal operations also can be calculated by estimating travel speed or travel time. To develop the present study further, the road networks of the city should be considered, in which case the effectiveness of snow removal in reducing traffic congestion would be clearer.

< This dissertation is the modified and revised from the following original journals and proceeding>

1. Hong, S., T. Hagiwara, S. Takeuchi, and B. Lu (2015). Effect of Weather Conditions and Snow-removal Operations on Travel Speed in an Urban Area. *Transportation Research Records: Journal of Transportation Research Board*, No.2482, pp.90-101.

2. Hong, S., T. Hagiwara, S. Takeuchi, and B. Lu (2015). Travel Speed Estimation considering Weather Conditions and Snow Removal Operations on an Urban Arterial. *Journal of the Eastern Asia Society for Transportation Studies*, Vol.11, pp.1029-1046.

3. Hong, S., T. Hagiwara, B. Lu, M. Kawasaki (2016). A Method for Estimating Urban Travel Speed in Winter Using Panel Data Models. A proceeding of *the 2016 Transportation Research Board 95th Annual Meeting*, Washington, D.C., No.16-1121.

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1 INTRODUCTION

1.1 BACKGROUND

Sapporo, the fifth-most-populous city in Japan, is the world's snowiest city of more than 1 million residents. According to the City of Sapporo, the city has a population of nearly 1.94 million and averages 600 cm of snowfall annually. It is rare to find such a snowy city of this size (see Table 1-1).

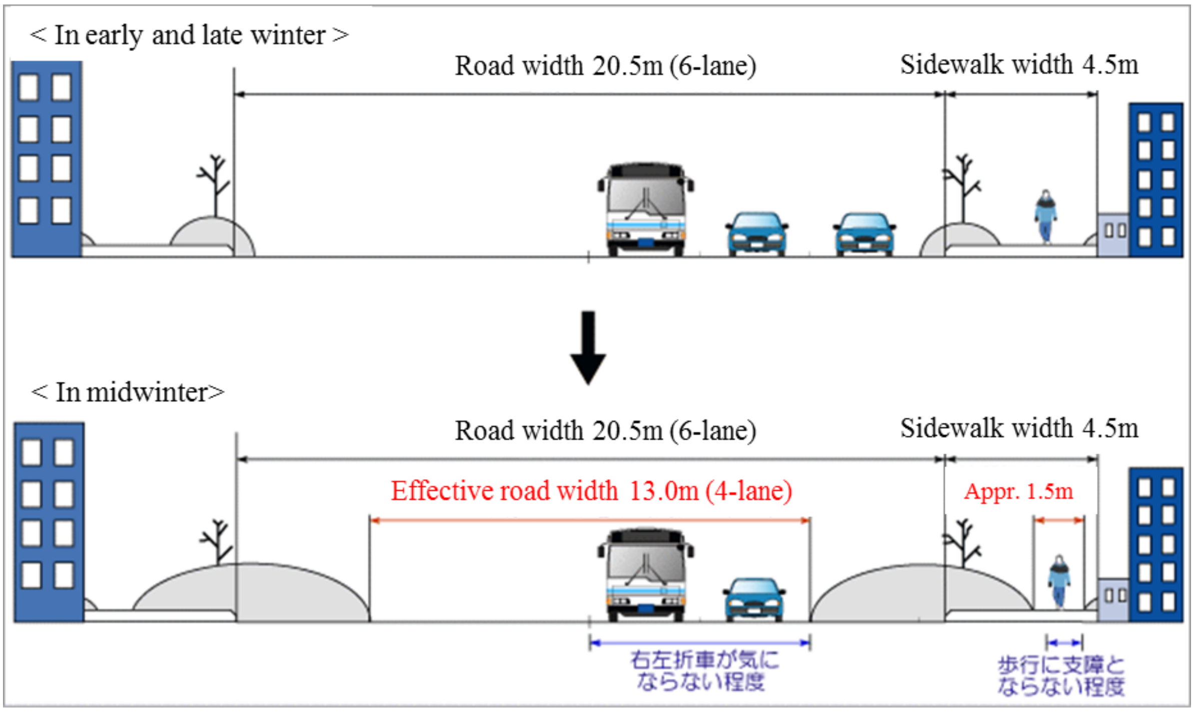
Table 1-1 the major cities of the world in heavy snowfall regions

Countries	Cities	Population (millions)	Snowfall (cm)
Austria	Vienna	1.6	172
Canada	Montreal	1.0	215
China	Shenyang	7.2	49
Germany	Munich	1.2	100
Japan	Sapporo	1.9	630
Russia	St. Petersburg	4.7	297

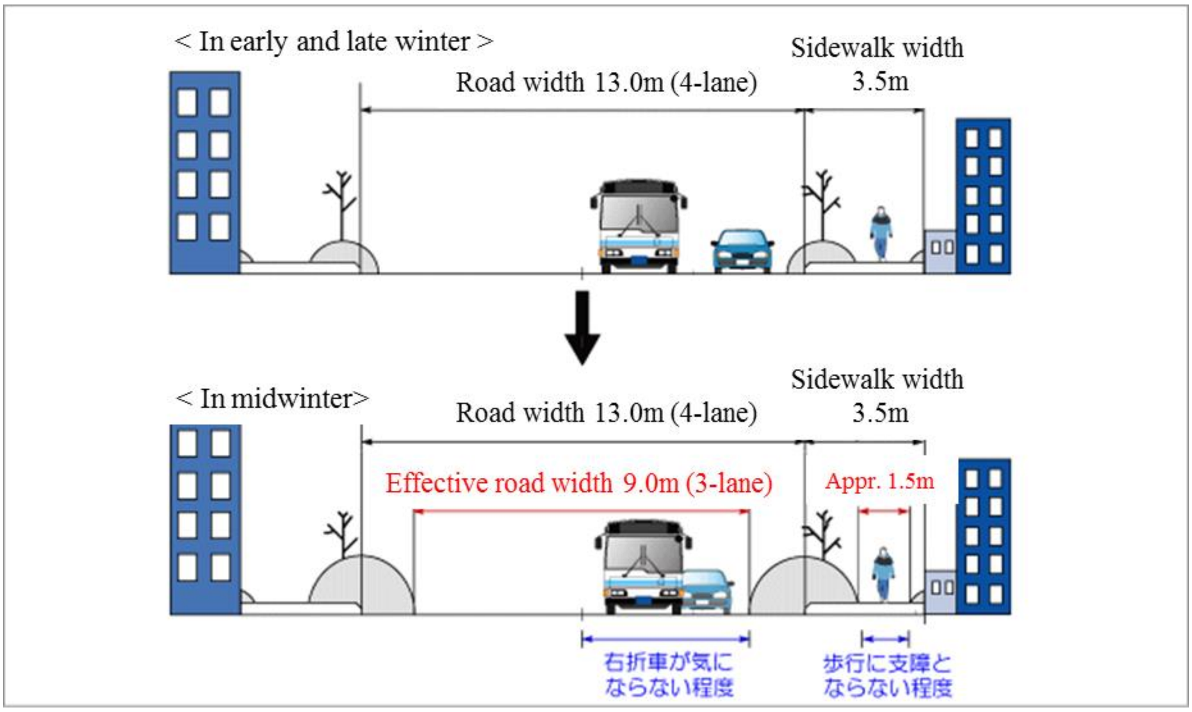
* Population count data was based on population censuses from 1999 to 2004.
* Snowfall data are the average snowfall from 1981 to 2010 in Sapporo, and from 1985 to 1990 in other cities
(Data from the City of Sapporo[1])

This heavy snowfall affects all kinds of transportation in winter, such as road traffic, railway transport and air transport, and it disrupts daily life. For these reasons, snow removal is one of the most important issues in the city. The city appropriates approximately $150 million dollars for snow removal to support socioeconomic activities in winter, and about 76% (about $116 million dollars) of the snow-removal budget is spent on road management annually. In FY2012, more than $175 million dollars was spent on winter road management, because of an unusually heavy cumulative snowfall of 623 cm for that year[2].

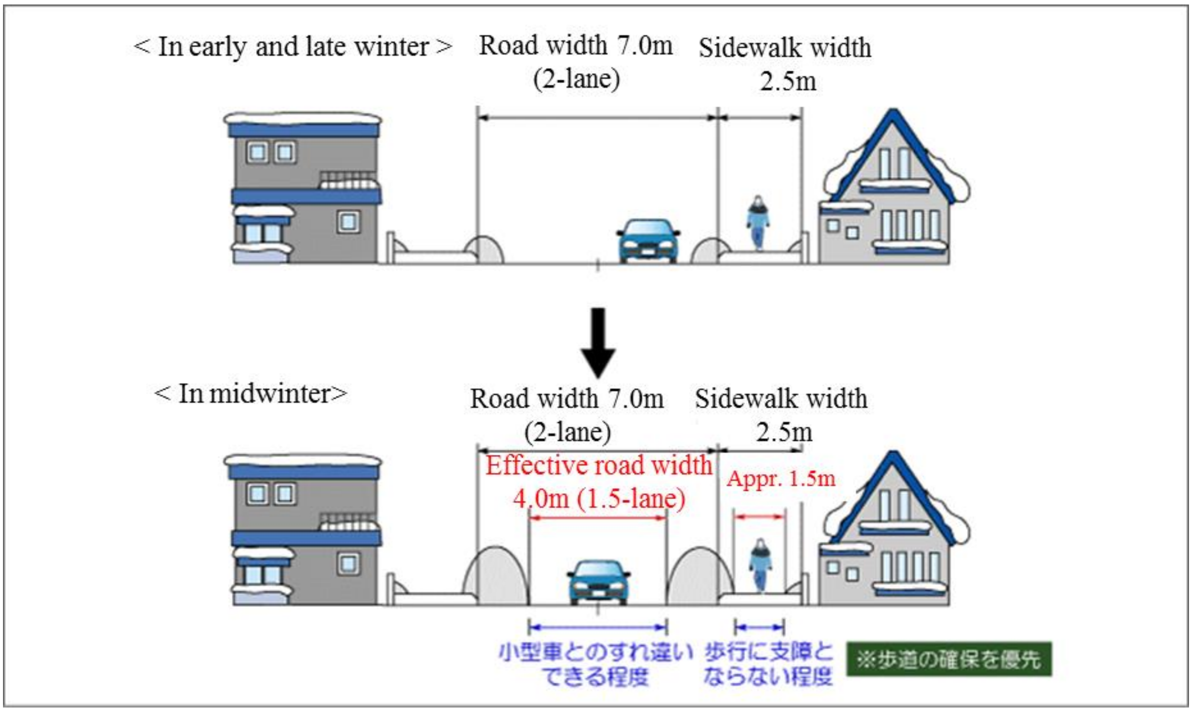
Traffic congestion in winter tend to be affected not only by traffic volume but also by external factors of weather conditions, road design, road works and so on. According to the previous studies, snowfall influences traffic conditions such as travel speed and capacity [3]–[5]. These facts suggest that winter road maintenance is crucial to reduce traffic congestion in Sapporo. The City of Sapporo sets levels of snow removal operations on roads according to the number of lanes the road has. For example, 6-lane arterials are maintained to 4 lanes in winter, and 4-lane arterials are maintained to 3 lanes in winter (see Figure 1-1(a)-(d)). In other words, the number of effective lanes in winter is changed by snow removal operations. The decrease in effective road width leads to road capacity reduction. Besides, vehicles turning left and right at intersections obstruct vehicles going straight during the snow season more than in other seasons because of the reduction in effective number of lanes by snow removal operations. Thus, roads in Sapporo tend to be more congested in winter than in any other season. Figure 1-2 shows the average travel speed for the study area (the arterial Nishi-5-chome St.) in Sapporo, in winter (Feb. 2014) and autumn (Oct. 2014). The travel speed is about 5 to 10 km/h slower in winter than in autumn all day.



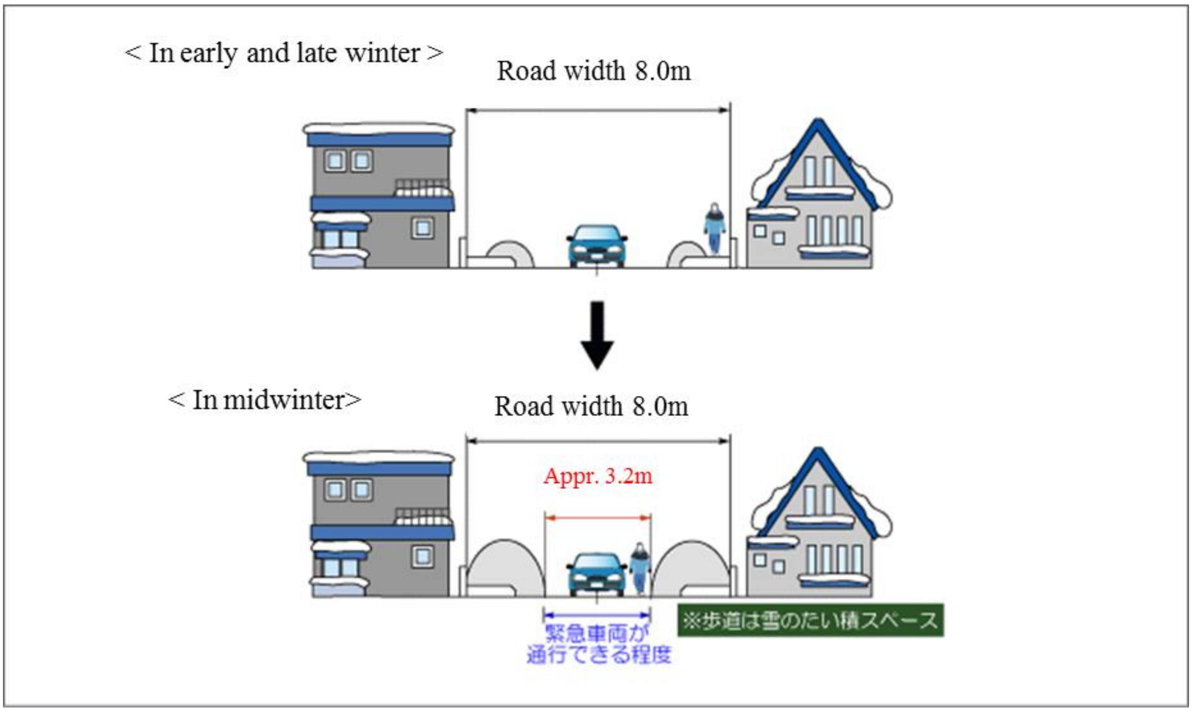
(a) the level of snow removal operation on 6-lane arterials



(b) the level of snow removal operation on 4-lane arterials



(c) the level of snow removal operation on 2-lane arterials



(d) the level of snow removal operation on community roads

Figure 1-1 Levels of snow removal operation on roads in Sapporo

(modified from the city of Sapporo[6])

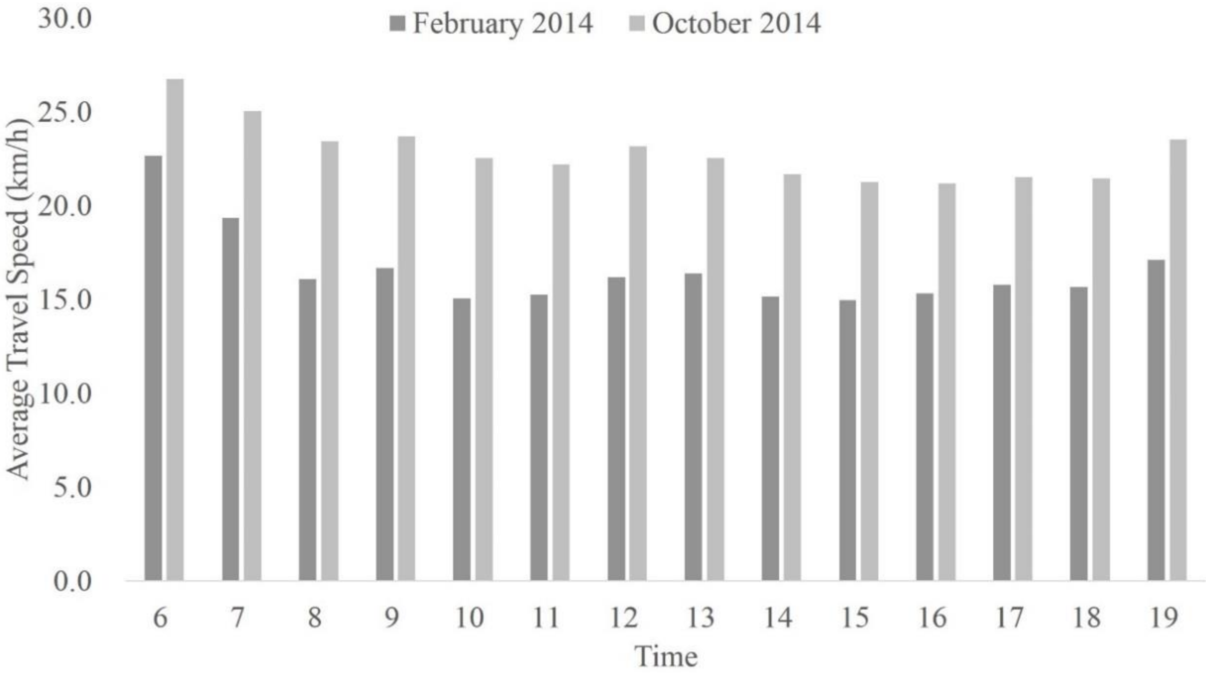


Figure 1-2 Average weekday travel speed in winter and autumn on Tarukawa-dori (Ave.), Sapporo

1.2 RESEARCH OBJECTIVES

Due to snow characteristics, the effect of weather conditions in winter on the travel speed is different from other seasons. For example, when rain falls, the rainwater is drained into the sewer or sinks below ground. On the other hand, snow would remain on the ground until melting or removing it. Moreover, the snow pushed to the shoulders can adversely affect the road capacity by reducing the effective road width. For these reasons, traffic engineers should be more attentive to winter road maintenances.

The objective of this dissertation is to develop a methodology for travel speed prediction considering weather conditions and snow removal operations on an urban arterial in Sapporo, Japan. In addition, a method for quantifying of the effects of snow removal operations is proposed to establish the effective snow removal operation strategy.

1.3 DISSERTATION OUTLINE

This dissertation is composed of 7 chapters. And the contents of these chapters are described as follow.

Chapter 1 is the stage that the importance of recognizing winter road maintenance in urban areas where have a lot of snow. The traffic conditions in Sapporo in winter is explained to emphasize the present study. Cyber physical system (CPS) is also introduced at the end of this chapter. In chapter 2, the literatures related to traffic performance and winter season, and associated with travel behaviors and adverse weather conditions are reviewed. The previous researches on snow removal operations are also reviewed in this chapter. Finally, the literatures on forecasting traffic conditions are reviewed. Chapter 3, data collection, states what kinds of and how processing data used in the present study. In this dissertation, four kinds of data are collected and analyzed: taxi probe data, weather condition data, snow removal operation data and traffic count data. Chapter 4 develops models for forecasting traffic conditions using the processed data in chapter 3. In addition, the developed models are compared each other by some measurement: the R-squared value, the mean absolute error, and the mean absolute percentage error. Chapter 5 forecasts the winter traffic conditions in Sapporo using the suggested model in chapter 4 to validate the model. The validation is conducted whether the suggested model can predict traffic conditions under snowy days or not. Chapter 6 quantifies the effects of snow removal operations by the suggested model. Finally, in chapter 7, the overall conclusions and contributions of this dissertation are discussed and the further researches are presented. The research flow is presented in Figure 1-3.

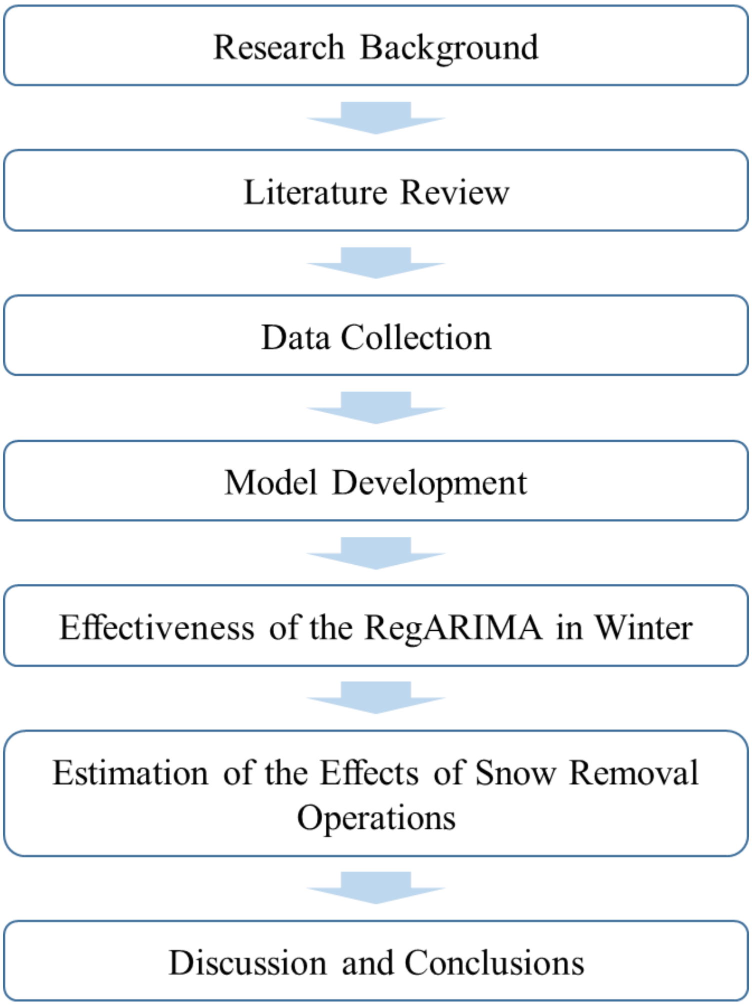


Figure 1-3 Research Flow

1.4 CYBER PHYSICAL SYSTEMS (CPS)

Cyber-physical system (CPS) is a smart cycle system that collects and analyzes real-world data from advanced sensors, and then the feedback on the results is provided to the real-world (see Figure1-4). While information networks have separately developed in each field in an information society, a CPS society creates added value through connecting various fields in our life including transportation, housing, medical fields, and so on. And finally, the results of analyzed data from various fields can led to creative solution for social problems, such as energy, pollution, transportation, and low birthrate problems[7].

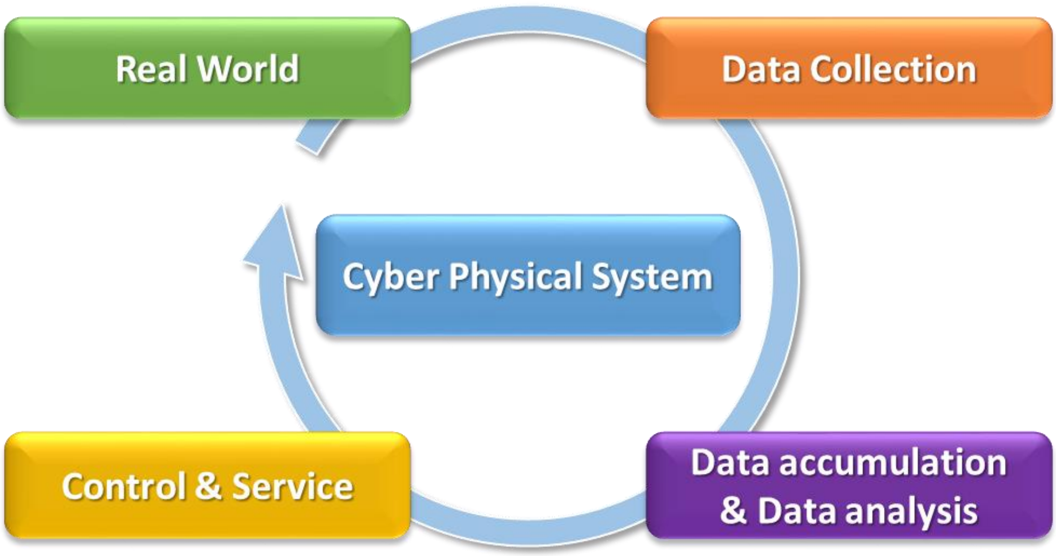


Figure 1-4 CPS cycle

In the future, fully autonomous feedback on the advanced data analysis and decisions can be provided under in a CPS society due to an artificial intelligence (AI) advance depending on fields. According to ministry of economy, trade and industry (METI), Japan[8], there are five levels in an information and communications technology (ICT) as Table 1-2, and today, the ICT lies at the fourth level.

Table 1-2 ICT Levels and changes of each level

Level	Contents	Time
Level I	Separate use by each device (stand-alone)	Until the late 1990's
Level II	Connection with networks in some devices (networked)	Until the early 2000's
Level III	Change the function of collection, accumulation, analysis of data from individual device to a data center on networks (clouded)	Until the late 2000's
Level IV	Data collection from the real-world, analysis the data, and the provision of feedback to the real-world (CPS)	About 2010's (current)
Level V	Value creation and realization of fully autonomous system by AI	In future

(source: Ministry of Economy, Trade and Industry (METI), Japan[8])

In this dissertation, three kinds of real world data are collected and transformed into computerized data: taxi-probe data, weather conditions data and snow removal operations data. These data are used for estimating travel speed by statistical models. And the results of the present study can be used to develop the strategies for winter traffic control and for snow removal operations. If the results of the present study were applied to the strategies for the traffic control and snow removal operations, it would affect the real world, traffic condition and snow removal operations. Therefore, the present study can expect to contribute to realization of a CPS society.

2 LITERATURE REVIEW

This chapter reviews the relationship among traffic condition changes, weather conditions, and snow removal operations. Section 2.1 reviews the previous studies related to weather conditions and traffic performance, such as traffic volume, travel speed, and road capacity. In section 2.2, the previous studies associated with the effects of adverse weather conditions on travel behaviors are reviewed, such as a change in the mode choice and route choice under adverse weather conditions. In section 2.3, the literatures on estimating and forecasting the traffic conditions are reviewed. And section 2.4 investigates researches on snow removal operations. At the end of each section, the summarized results of the reviewed researches are presented (Table 2-1, 2-2, 2-3 and 2-4). Section 2.5 summarizes the literatures and differentiates between the previous studies and the present study.

2.1 RESEARCHES ON THE EFFECTS OF WEATHER CONDITIONS ON TRAFFIC CONDITIONS

Ibrahim and Hall [9] studied the effect of adverse weather conditions on the relationships of flow-occupancy and speed-flow. They collected the data on the Queen Elizabeth Way Mississauga freeway for five months from October 1990 to February 1991. According to their study, the free-flow speed was reduced by 2 km/h under the light rain condition, and reduced by 3 km/h under the light snow condition. In case of heavy precipitation, the decrease in free-flow speed was larger than light precipitation. The free-flow speed was dropped around 5~10 km/h under heavy rain, and round 38~50 km/h under heavy snow. Maximum traffic flow rate was decreased by 10~20% under heavy rain conditions, and by 30~48% under heavy snow conditions.

Agarwal et al.[3] investigated the adverse weather impacts on urban freeway segments. The study area was the freeway road network of the Twin Cities, and the traffic and weather information data were a four-year dataset from Jan. 2000 to Apr. 2004. The authors divided the weather information into several categories to know the traffic condition changes depending on the severity of the adverse weather: rain, snow, wind speed, low visibility, and temperature. The authors indicated that the traffic conditions, which were capacity, and average operating speed, decreased with the severity of the adverse weather conditions. And they compared the results from their study and from Highway Capacity Manual 2000 (HCM 2000). According to their results, the impact of light rain on capacity was greater than the HCM 2000. In contrast, the impacts of light rain, light snow and moderate snow on operating speeds were similar with the HCM 2000. However, the speed reductions caused by heavy rain and snow from the HCM 2000 were significant higher than the results from the study. The impacts of all snow severities on capacity were similar with the HCM 2000.

Maze et al.[4] reviewed the literatures on the impact of adverse weather conditions on traffic demand, traffic safety, and traffic flow relationships: volume, speed and density. The authors found that the traffic volume was reduced by 5% under rain conditions and by 7 to 80% under snow conditions depending on the traffic types (commuter, commercial, long-distance travel) and the severity of adverse weather conditions. In terms of traffic safety, the authors mentioned accident rates increased rapidly under snow conditions. And the authors mentioned that the severity of traffic accidents caused by adverse weather conditions were related to both the location and the weather condition at the time when the accident took place. The authors also mentioned that the capacity and speed on highways were significantly related with the adverse weather conditions. According to their research, the freeway capacity was decreased by an average of 14% under heavy rain conditions, and by an average of 22% under heavy snow conditions.

Datla and Sharma [10] investigated the change of highway traffic with adverse weather conditions: temperature, snowfall, and combined cold and snow. Their study area was a highway in Alberta, Canada, and they collected and used hourly traffic data and weather data in winter months (from November to March) for the study for 11 years between 1995 and 2005. The multiple regression analysis was used, and they considered the effects of time of day, day of week and type of highway separately. According to their study, the effect of low temperature on the weekend traffic was more than the weekday traffics regardless of road types: commuter and recreational roads. Similarly, the commuter road traffic was less affected by cold weather than the recreational road traffic. In other words, depending on the trip necessity, the effects of low temperature on the traffic was different. The authors argued that the commuter roads were less correlated with snowfall. On the other hand, the effects of snowfall on the recreational roads were larger when the temperature was low.

Dehman [11] investigated the effects of weather conditions on two capacities of freeway bottlenecks: free-flow capacity (pre-breakdown flow (PBDF)) and congested-flow capacity (queue discharge flow (QDF)). The study areas were four bottlenecks in Milwaukee freeway, Wisconsin, and the author collected precipitation amount and visibility distance as weather conditions. The author argued that the QDF was more sensitive to weather conditions than the PBDF. According to the study, the PBDF was reduced by 2.1%, 5.4%, and 12.1% due to very light rain, light rain, and moderate rain, respectively. And under the very light snow and light snow conditions, the PBDF was decreased by 3.4% and 13.2%. In addition, the thick fog and shallow fog reduced the PBDF by 5.0% and 1.6%. On the other hand, the QDF was reduced by 7.7%, 11.8%, and 16.8% under very light rain, light rain, and moderate rain conditions. In case of snow, very light snow and light snow reduced the QDF by 8.8% and 22.3%. The QDF in thick fog and shallow fog were decreased by 6.5% and 4.3%. Finally, the author indicated that the principal reason why the effect of fog was the smallest was fog makes poor visibility only, but the snow and rain makes both poor visibility and slippery surfaces.

Zhao et al.[12] studied the effect of adverse weather conditions on the free-flow speed of freeways in the Buffalo metropolitan area from both micro and macro levels. The authors developed linear regression models to predict average speed for the macro-level analysis. According the results, the speed increased by about 0.77 mph as visibility increased by 1 mile. And the travel speed at the below freezing temperature was 0.98-mph slower than at the above freezing temperature. Finally, when the wind speed was increased by 10 mph, the travel speed was decreased by around 0.5 mph. As a micro-level approach, the authors calibrated the TRANSIMS model, which is a cellular-automata (CA) based traffic simulation model, for driving behaviors to be reflected adverse weather conditions.

Kwon et al. [13] identified the factors affecting capacity and free-flow speed on urban freeways under adverse weather conditions. The study area of the study was the Don Valley Parkway (DVP) in Toronto. And they used traffic, weather, and road condition data from 2010 to 2012 in winter seasons. The authors considered temperature, wind speed, and visibility, snowfall, deep snow, and road surface conditions (icy or dry) as weather and road surface condition factors. The authors found the visibility and road surface conditions were statistically related with both capacity and free-flow speed. On the other hand, the authors argued that the snowfall affects capacity and free-flow speed only if the visibility factor was not included in their model. According to their study, the capacity was decreased by 31.97 vphpl for each increase of 1 mm/h snow intensity, and was increased by 226.51 vphpl for each increase of 1 km visibility. On the other hand, the free-flow speed was increased by 5.84 km/h every increase of 1 km visibility, and was decreased by 0.86 km/h every increase of 1 mm/h snow intensity.

Tsapakis et al. [14] investigated the impact of rain, snow, and temperature on macroscopic travel times during morning and evening peak period and non-peak period. The study area and period were London area in UK during from October to December 2009. The authors found that the total travel time were increased by 0.1~2.1%, 1.5~3.8%, and 4.0~6.0% because of the light rain, moderate rain, and heavy rain, respectively. And light snow and heavy snow increased the travel time by 5.5~7.6% and 7.4~11.4%. The temperature effects on the travel time was not significant in their study.

Lin et al. [15] quantified the impact of adverse weather conditions extracted from social media data on freeway traffic speed. They argued that the real world weather information could be inferred from social media service data such as Twitter and Facebook. The study area of their study was two freeways in Buffalo-Niagara metropolitan area, and they collected weather data, Twitter data, and traffic data from the study area. They developed linear regression models to identify the weather effects on freeway speed with and without the Twitter-based weather variables. According to the authors, the model with twitter-based weather data was relatively more accurate than the without twitter-based weather data model especially during daytime with snowfall. Based on the middle lane of the freeway, the freeway speed was increased by 0.23 mph for every 1-mile increase in visibility, and decreased by from 24 to 30 mph for every 1-mm increase in snowfall. In addition, the number of snow events recorded in Twitter led to from 0.5 to 1.0 mph decreases in the freeway speed.

Table 2-1 Literatures on the relationship between weather conditions and traffic conditions

Researchers (year)	Road types/ Regions	Weather	Traffic condition reductions	
Ibrahim and Hall (1994)	Freeway / Ontario, Canada	Rain	Max. traffic flow rate	10~20%
			Free-flow speed	2~10 km/h
		Snow	Max. traffic flow rate	30~48%
			Free-flow speed	3~50 km/h
Agarwal et al. (2005)	Freeway / Minnesota, US	Rain	Capacity	1~17%
			Free-flow Speed	1~7%
		Snow	Capacity	3~28%
			Free-flow Speed	3~15%
		Low Temperature	Capacity	1~10%
			Free-flow Speed	1~3.6%
		Wind speed	Capacity	1~2%
			Free-flow Speed	1~1.5%
		Visibility	Capacity	9~10.5%
			Free-flow Speed	6~11%

Table 2-1(continued) Literatures on the relationship between weather conditions and traffic conditions

Researchers (year)	Road types/ Regions	Weather		Traffic condition reductions	
Maze et al. (2006)	Review paper (average reduction of traffic conditions)	Rain		Capacity	2~14%
				Speed	2~6%
		Snow		Capacity	4~22%
				Speed	4~13%
		Temperature		Capacity	1~8%
				Speed	1~2%
		Wind speed		Capacity	1%
				Speed	1%
		Visibility		Capacity	10~12%
				Speed	7~12%
Datla and Sharma (2010)	Highway / Alberta, Canada	Snow	> 0℃	Commuter Traffic	0.5~1.7%
				Recreational Traffic	
			≤ 0℃	Commuter Traffic	0.7~1.8%
				Recreational Traffic	0.5~3.1%
		Temperature		Commuter Traffic	0~14%
				Recreational Traffic	0~31%
Dehman (2012)	Bottleneck of freeway/ Wisconsin, US	Snow		Free-flow capacity	3.4~13.2%
				Congested-flow capacity	8.8~22.3%
		Rain		Free-flow capacity	2.1~12.1%
				Congested-flow capacity	7.7~16.8%
		Fog		Free-flow capacity	1.6~5.0%
				Congested-flow capacity	4.3~6.5%
Zhao et al. (2012)	Freeway / Buffalo, US	Visibility		Travel speed	10-mph/ 1-mile decrease in visibility
		Wind speed			0.5-mph/ 10-mph increase in wind speed
		Temperature			0.98-mph at above freezing temperature

Table 2-1(continued) Literatures on the relationship between weather conditions and traffic conditions

<table>
<tr><th>Researchers (year)</th><th>Road types/ Regions</th><th colspan="2">Weather</th><th colspan="2">Traffic condition reductions</th></tr>
<tr><td rowspan="4">Kwon et al. (2013)</td><td rowspan="4">Freeway/ Toronto, Cananda</td><td colspan="2" rowspan="2">Snow intensity</td><td>Free-flow speed</td><td>0.86 km/h</td></tr>
<tr><td>Capacity</td><td>31.97 vphpl</td></tr>
<tr><td colspan="2" rowspan="2">Visibility</td><td>Free-flow speed</td><td>5.84 km/h</td></tr>
<tr><td>Capacity</td><td>226.51 vphpl</td></tr>
<tr><td rowspan="3">Tsapakis et al. (2013)</td><td rowspan="3">Urban road network / London, UK</td><td colspan="2">Rain</td><td rowspan="3">Travel time</td><td>0.1~6.0% increased</td></tr>
<tr><td colspan="2">Snow</td><td>5.5~11.4% increased</td></tr>
<tr><td colspan="2">Temperature</td><td>Not significant</td></tr>
<tr><td rowspan="3">Lin et al. (2015)</td><td rowspan="3">Freeway / Buffalo, US</td><td colspan="2">Visibility</td><td rowspan="3">Travel speed</td><td>0.23 mph/ 1-mile decrease in visibility</td></tr>
<tr><td rowspan="2">Snow</td><td>inch</td><td>24~30 mph/ 1-mm decrease in snowfall</td></tr>
<tr><td>number</td><td>0.5~1.0 mph</td></tr>
</table>

2.2 RESEARCHES ON THE RELATIONSHIP BETWEEN WEATHER CONDITIONS AND TRAVEL BEHAVIORS

Khattak et al.[16] investigated factors which influence automobile commuters' enroute decisions to divert from their regular route in response to information about incidents and other factors which influence a subsequent decision to return to the regular route after diversion. The authors obtained data from a survey of automobile commuters in downtown Chicago to develop models of diversion and return behavior. The authors mentioned that drivers would change their route based on their expectations of the change in traffic conditions due to events including incidents and adverse weather conditions.

Mahmassani et al.[17] reviewed various existing researches on the subject of the relationship between traffic and weather events, with an emphasis on two sides: traffic supply side impacts and traffic demand side impacts. They argued that traffic demand for drivers would be reduced under adverse weather conditions because of abandoning or holding off their trips, but for pedestrians and cyclists, the rising traffic demand could be observed when they changed their mode to private vehicles. Furthermore, they mentioned that inclement weather conditions can move the traffic demand for peak-hour when commuters decided to go to work earlier or later than usual.

Khattak and Palma [18] identified the impact of weather conditions on car commuters' behavior. The study was conducted in Brussels, Belgium. The authors found that the weather conditions affected commuters' travel decisions especially on departure time. The weather conditions influenced the travel pattern of around half of the motor vehicle drivers. 60% of automobile commuters changed their departure time, and 35% of respondents used alternate routes due to adverse weather conditions. On the other hand, though around 70% of respondents had an alternative transportation, they did not change their transportation mode according to seasons and weather conditions.

Nankervis [19] presented the relationship between bicycle commuting and the weather (short-term) and seasonal (long-term) variation. The study area was Melbourne, Australia and the author surveyed to students of three universities in Melbourne. The author found that the seasonal weather affected commuting by bike. The cycling commuters were the most in summer and autumn, and less in winter. For short term weather conditions, the author considered wind, rain, and temperature. According to the study, wind, rain, and temperature had a significant relationship with the number of bike riders. And especially, the effect of temperature was larger than other weather conditions. According to the survey in the study, only less than 5 % of respondents would not ride bike under adverse weather conditions.

Cools et al.[20] investigated that the effect of weather conditions on travel behavior, and in the adverse weather condition, whether people change the travel behavior depending on their trip purposes (commuting, shopping, and leisure). The six weather conditions were considered in their study: cold, snow, rain, fog, warm, and storm. And five kinds of travel behavior were considered: mode change, time-of-day change, location change, trip cancellation, and route change. The study was conducted in Flanders, Belgium. According to their research, the commuting trips was less affected by weather conditions than other purposes. However, the impact of snowy weather on travel behavior was the largest of other weather conditions which were cold, rain, fog, warm, and storm. Regardless of their purposes, people tend to change mode, time-of-day, location, or route during snowy weather; even went as far as to cancel the trip. Finally, the authors argued that the results of the study can contribute weather-related policy issues.

Flynn et al. [21] quantified the effects of weather conditions on the commute decisions of bike commuters. They collected data, personal characteristics, distances from home to work, transportation mode, and weather data, for 4 weeks in period between 2009 and 2010 in Vermont, US. Weather conditions data, which were temperature (°F), wind speed (mi/h), rainfall, and deep snow (inches), collected from 18 stations. According the results of their study, the bike commuting under no-rain weather conditions was almost twice as likely to commute by bike under rain weather conditions. A 1-°F increase in temperature increased the bike commuter by about 3%. Similarly, the bike commuting was decreased by around 5% for each increase of 1-mi/h wind speed, and decreased by about 10% for each increase of 1-inch deep snow.

Saneinejad et al.[22] investigated the impact of weather on the five transport modes: auto drive, auto passenger, transit, bike and walk. They used the multinomial logit (MNL) model for identifying the impact. Moreover, the interaction among weather, age, and gender was considered through interaction models. The authors collected three kinds of data in Toronto, Canada: travel survey data, level of service data, and weather data. The data were collected for Sep. 8^{th} to Dec. 16^{th}, 2001 and May 8^{th} to Jun. 12^{th}, 2002. According to their study, walking and cycling younger groups were more negative relationship with cold than older groups. In terms of gender, cycling female group was around 1.5 times more negative relationships with temperature than males. Furthermore, cycling groups were more influenced by weather conditions which were low temperature, wind speed, and precipitation than pedestrian groups. The authors also investigated the effects of weather changes on the mode choice and trip rate. They found an increase of 17% cycling trips and 2% walk and transit trips for each 6℃ increase in temperature. On the other hand, the effects of rain precipitation were less than the effects of temperature.

Sears et al. [23] measured the seasonal change in bicycle commuting trips in the northeastern state of Vermont. According to their study, the temperature and precipitation had strong effects on the commuters' decision whether to commute by bicycle. And the bike commute was similar trend regardless of gender and age under adverse weather conditions. In summer, the bicycle commuters were more than winter or fall in the study. The authors found that the wind speeds had a significant relationship with the bike commuting, while the daylight was not statistically related. And deep snow had a negative relationship with commuting bicycle. The rates of bike commuting were an increase of 3% for each 1°F increase in temperature, and a decrease of 5% for each 1mph increase in wind speed. The bike commuters were decreased by 10% with every 1-in increase in snowfall.

Meng et al. [24] examined the effects of weather conditions and weather forecasts on bike travel behavior. The study area was a tropical country, Singapore, which has a hot temperature, humid, and rainy weather. They investigated the traveler behaviors according to the timings of getting weather information: during trip and before trip. The authors indicated the cyclists preferred to ride bicycle at lower temperature (29.5°C - 31.5°C) and humidity (52.3% - 62.7%), and no rain (in the past hour). According to the results, though the cyclists got the forecasted rain information, the cyclists' behaviors were different depending on the current weather conditions. When the current weather condition was normal, the cyclists were less believed the weather information. 41.3% of cyclists who got the information before the trip would change their mode, while 30.3% of cyclists who got the information during the trip would change their mode. On the other hand, when the current weather conditions were poor or very poor conditions, 67.5% and 92.7% of people who got the information before the trip would change their mode, while half and 70% of people who got the information during the trip would change their mode.

Table 2-2 Literatures on the relationship between weather conditions and travel behaviors

Researchers (year)	Targets / Regions	Weather conditions	Results	
Khattak and Palma (1997)	Automobile commuters / Brussels, Belgium	Adverse weather	Departure time change	60%
			Route change	35%
Nankervis (1999)	Students riding bike / Melbourne, Australia	Wind	Don't ride bike	3.0%
		Rain	Don't ride bike	0.0%
		Temperature	Don't ride bike	3.0%
Cools et al. (2010)	Mode changes / Flanders, Belgium	Cold temperature	Commuting	6.2%
			Shopping	8.5%
			Leisure	10.1%
		Snow	Commuting	24.2%
			Shopping	21.8%
			Leisure	25.6%
		Rain	Commuting	15.2%
			Shopping	14.4%
			Leisure	16.1%
		Fog	Commuting	5.4%
			Shopping	8.1%
			Leisure	12.7%
		Warm temperature	Commuting	18.4%
			Shopping	20.3%
			Leisure	22.7%
		Storm / heavy wind	Commuting	13.2%
			Shopping	13.2%
			Leisure	14.4%

Table 2-2(continued) Literatures on the relationship between weather conditions and travel behaviors

<table>
<tr><th>Researchers (year)</th><th>Targets / Regions</th><th>Weather conditions</th><th colspan="2">Results</th></tr>
<tr><td rowspan="3">Flynn et al. (2012)</td><td rowspan="3">Bicycle commuter trips / Vermont, US</td><td>Temperature</td><td colspan="2">3% increased (1°F)</td></tr>
<tr><td>Wind speed</td><td colspan="2">5% decreased (1 mph)</td></tr>
<tr><td>Snow</td><td colspan="2">10% decreased (1 inch)</td></tr>
<tr><td rowspan="7">Saneinejad et al. (2012)</td><td rowspan="7">Number of trips / Toronto, Canada</td><td rowspan="5">6℃ decrease in temperature</td><td>Walk</td><td>2% decreased</td></tr>
<tr><td>Transit</td><td>2% decreased</td></tr>
<tr><td>Bike</td><td>17% decreased</td></tr>
<tr><td>Drive</td><td>Little increased</td></tr>
<tr><td>Auto passenger</td><td>7% increased</td></tr>
<tr><td>20% decrease in rain frequency</td><td rowspan="2">All mode</td><td>1~1.7% increased</td></tr>
<tr><td>20% increase in rain frequency</td><td>1~1.9% decreased</td></tr>
<tr><td rowspan="3">Sears et al. (2012)</td><td rowspan="3">Bicycle commuter trips / Vermont, US</td><td>Temperature</td><td colspan="2">3% increased (1°F)</td></tr>
<tr><td>Wind speed</td><td colspan="2">5% decreased (1 mph)</td></tr>
<tr><td>Snow</td><td colspan="2">10% decreased (1 inch)</td></tr>
<tr><td rowspan="6">Meng et al. (2016)</td><td rowspan="6">Mode shift rate from cycle to others/ Singapore</td><td rowspan="3">Got the weather forecast information “rain in the day” during trips</td><td>Current normal weather</td><td>30.3%</td></tr>
<tr><td>Current poor weather</td><td>50.3%</td></tr>
<tr><td>Current very poor weather</td><td>70.2%</td></tr>
<tr><td rowspan="3">Got the weather forecast information “rain in the day” before trips</td><td>Current normal weather</td><td>41.3%</td></tr>
<tr><td>Current poor weather</td><td>67.5%</td></tr>
<tr><td>Current very poor weather</td><td>92.7%</td></tr>
</table>

2.3 RESEARCHES ON TRAFFIC CONDITIONS ESTIMATION/PREDICTION

Huang and Ran[25] suggested a neural network (NN) model based on back-propagation algorithm to predict travel speed under adverse weather conditions. The authors used travel time as representing traffic conditions, and temperature, humidity, and visibility were considered as weather conditions. And other weather conditions were included in the model as indicator variables: clear day have 0, otherwise, the value of variables was 1. The authors argued that the predicted speed by the NN model is more reasonable and acceptable than the time-series model.

Williams et al.[26] developed a seasonal Autoregressive Integrated Moving Average (ARIMA) model to predict vehicular traffic flow on two fixed locations: freeways in United States (I-75) and in the United Kingdom (M25). They compared their model with other heuristic approaches: random walk forecast, historical average forecast, and deviation from historical average forecast. The predictive performance of each model were compared by three statistics: root mean square error of prediction (RMSEP), mean absolute deviation (MAD), and mean absolute percentage error (MAPE). In their study, the seasonal ARIMA models had the best predictive performance (8.74% of MAPE for M25 and 8.97% of MAPE for I-75. And the deviation from the historical average heuristic prediction method were the second best method in the forecast performance (9.78% of MAPE for M25 and 9.54% of MAPE for I-75).

Van den Bossche et al. [27] developed models to forecast the frequency and severity of traffic accidents in Belgium. They used the monthly accidents data from 1974 to 1999 to develop the prediction model, and the accidents in 2000 were predicted by a regression model with ARMA errors. They considered monthly percentage of frost days, snow, sunlight, precipitation and thunderstorm as weather conditions. And five laws related traffic safety were included as dummy variables. According to their study, the weather conditions and some regulations were significantly related with traffic safety. The authors argued that the predicted accidents trend by the model were quite accurate.

Billings et al[28]. predicted the arterial travel time for a part of Minnesota State Highway 194. The authors used the Global Positioning System (GPS) probe vehicle data to apply the ARIMA model. And their target to predict was the afternoon peak hour travel time from 3:30pm to 5pm. They argued that the ARIMA model performed well for urban arterials including queuing and signal delays which had a bad predictive accuracy by other prediction methods on freeways.

Zeng et al[29]. proposed the combined ARIMA and Multilayer Artificial Neural Network (MLANN) to predict the complex and random traffic flow. The study area was 45km-length of Guangyuan Highway in Guangzhou. And the data of their study was collected every 8 minutes from 7am to 7pm of weekdays. To check the predictive accuracy, three statistics were applied: Relative Mean Errors (RME), Mean Absolute Relative Error (MARE) and Root Mean Squared Errors (RMSE). The authors found that the hybrid model the forecasting errors were significantly reduced: the predictive accuracy of the hybrid model was higher by 46% than the ARIMA model. They argued that the combined model was better the forecasting accuracy than the models used separately.

Vlahogianni and Karlaftis[30] investigated the effects of precipitation on the temporal evolution of lane by lane speed patterns on freeways in Athens. They used recurrence quantification analysis (RQA) to quantify the effects of precipitation on the travel speed. According to the authors, the travel speed on right side lane have different patterns with the travel speed patterns of left and middle lanes. In terms of rain and snow, irrespective of precipitation intensity, the accuracy for forecasting lane speed patterns were changed. The authors argued that employing a single model for forecasting traffic conditions can lead to fallacious results.

Yang et al.[5] identified traffic deterioration according to weather conditions such as snowfall and temperature. An 8km-length section of Seohaean freeway in Korea was selected as the study area. Traffic volume and speed were obtained from 8 vehicle detection systems (VDS), and weather data (snowfall, deep snow, and temperature) were obtained from the weather center for four months (Oct. 2005 to Feb. 2006) Using the collected data, the ANOVA analysis was conducted to know the characteristics of the traffic volume and travel speed depending on the weather conditions. According to the authors, the average speed was 6.7% in light snow (3cm or less), 9.0% in moderate snow (3cm~10cm), and 12.8% in heavy snow (10cm or above) slower than the speed of normal days. Whereas the standard deviation of the speed was increased by 8.7% in light snow, 33.6% in moderate snow, and 114.7% in heavy snow. And the authors also developed the multiple linear regression (MLR) models. According to the MLR models developed in this research, ravel speed was reduced to 0.4% as snowfall increased by 1cm, while traffic volume was reduced to 13.8%.

Dunne and Ghosh[31] used stationary wavelet transform (SWT) which is the stationary form of discrete wavelet transform (DWT) to develop a neuro-wavelet prediction algorithm to forecast hourly traffic flow considering rainfall effects. The study collected rain precipitation data and real-time traffic flow data from urban arterials in Dublin, Ireland. The authors developed the switchable algorithm between a dry model and a wet model, depending on the rainfall forecast. The results forecasted by the suggested models (neuro-wavelet model) were more accurate than the standard artificial neural network (ANN) model results.

Zhang and Ge [32] employed a Takagi–Sugeno–Kang Fuzzy Neural Network (TSKFNN) approach to predict freeway travel time. TSKFNN is a combination of a Takagi–Sugeno– Kang (TSK) type fuzzy logic system and a neural network (NN). They collected traffic data from freeway in Houston, Texas. The authors compared their model with other prediction models: the back propagation neural network (BPNN) and the time series model (ARIMA). And the authors argued that the TSKFNN model showed the best accuracy of the considered prediction models.

Kim et al.[33] predicted traffic speed on the freeway under different snow intensity level: normal, light snow, and heavy snow. The traffic data was collected by vehicle detecting system (VDS) on a freeway in Korea, and the weather conditions was collected by road weather information system (RWIS) for two years. The k-nearest neighbors (k-NN) algorithm was used to forecast speed for real-time during winter. According to the result of their study, the mean absolute percentage error (MAPE) was less than 6% under normal weather conditions, and less than 8% under light snow conditions across all time steps considered: from 5 minute to 60 minute. On the other hand, the MAPE was more than 6% under heavy snow conditions.

Wang et al. [34] forecasted the short-term traffic speed using the hybrid model of empirical mode decomposition (EMD) and autoregressive integrated moving average (ARIMA). They set three scenarios: mixed flow in freeway work zones, vehicle-type specific in freeway work zones, and on-ramp. The selected areas for the study were the work zone on a freeway in Springfield, MA and the on/off-ramp on a freeway in Atlanta, GA. And the authors argued that the hybrid EMD-ARIMA model offered higher predictive performances in all scenarios than the traditional forecasting models: the traditional ARIMA, the Holt–Winters, the artificial neural network models, and a naive model. According to their results.

Mais et al. [35] investigated the weather effects on traffic accident fatalities, and estimated the unaffected accident fatality series by weather conditions. They estimated the effects of temperature and precipitation on traffic accident fatalities in UK for the period 1991-2014 using the combination model of a regression model and ARIMA model (RegARIMA). The authors argued if the weather-related accidents were excluded from the series, the rest might be due to other factors which can control by policy makers.

Roh et al.[36] investigated the variations of daily traffic volumes related to weather conditions, such as snow and temperature, with an emphasis on class of vehicles (passenger cars and trucks). The authors developed multiple categorical linear regression (MCLR) models to identify the relationship among classified traffic, snowfall and temperature. The authors obtained the traffic data at one Weigh-In-Motion

(WIM) site at Leduc located on highway 2A in Canada. And they collected the weather data from Environment Canada weather information archives. According to their study, the effects of snowfall and cold on daily volumes were totally opposite for passenger cars and trucks. The passenger cars decreased when weather is snow or the temperature dropped below -25℃. Truck traffic, however, increase regardless of snowfall and cold temperature. The authors argued that passenger cars are more susceptible to inclement weather conditions than trucks. Besides, they also argued that this is because truck drivers change their route from frontage roads to highways in adverse weather conditions. Furthermore, truck drivers drive vehicles without regard to weather conditions because most of them follow a strict schedule.

Table 2-3 Literatures on the traffic condition estimation/prediction

Researcher (year)	Regions/Countries	Road types	Targets	Method
Huang and Ran (2003)	Chicago, US	Motorways	Traffic speed	NN
Williams et al. (2003)	Atlanta, US and London, UK	Freeways	Traffic flow	SARIMA
Van den Bossche et al. (2004)	Belgium	Whole country	Accidents	RegARMA
Billings et al. (2006)	Minnesota, US	Urban arterial	Travel time	ARIMA
Zeng et al. (2008)	Guangzhou, China	Highway	Traffic flow	ARIMA +MLANN
Vlahogianni and Karlaftis (2012)	Athens, Greece	Freeway	Travel speed	RQA
Yang et al. (2012)	Jeonbuk, Korea	Freeway	Travel speed Traffic volume	MLR
Dunne and Ghosh (2013)	Dublin, Ireland	Urban arterials	Traffic flow	SWT
Zhang and Ge (2013)	Houston, US	Freeway	Travel time	TSKFNN
Kim et al. (2015)	Gyeonggi, Korea	Freeway	Traffic speed	k-NN
Wang et al. (2015)	Atlanta, US and Springfield, US	Freeway	Traffic speed	EMD–ARIMA
Mais et al. (2016)	UK	Whole country	Traffic accident fatalities	RegARIMA
Roh et al. (2016)	Alberta, Canada	Highway	Traffic volume	MCLR

2.4 RESEARCHES ON SNOW REMOVAL OPERATIONS

Tanabe et al.[37] measured separate effects for each type of snow removal operations. They measured the individual effect of snow removal by choice-based conjoint analysis. The authors considered frequent snow removal operations, road width, sight distance, slippery road surface, and bumpy road surface as independent variables, and the amount of willing to pay for snow removal operation was considered as the dependent variable. They collected the dependent variable data from a questionnaire survey in Sapporo, Japan. The authors argued that the respondents have great interest in the effective road width and deicing materials.

Hayashiyama et al. [38] evaluated the indirect benefits of snow removal operations in Sapporo by the contingent valuation method (CVM). They considered willingness to pay (WTP) and willingness to accept compensation (WTA) for improving or deteriorating the level of snow removal. According to their results, the average WTA was much higher than the average WTP for both the raising and reducing snow removal service level. The WTP for reducing the snow removal operation level was $27 million to $33 million, the WTA was $190million to $300million. In contrast, the WTP for raising the level of snow removal operation was $17 million to $23 million, and the WTA was $180 million to $200 million. The authors argued that the WTP was better to measure the benefits because the WTA tended to overestimate in the study. And the authors also mentioned the present level of snow removal service in Sapporo is high because the values of WTA and WTP were bigger for reducing the level than for raising the level.

Lin [39] estimated the effects of weather conditions and maintenance on road surface conditions and on traffic volume and travel speed. Plowing, sanding, chemical were considered as road maintenance factors, and temperature and wind speed were considered as weather condition factors. The road maintenance factors in the study was included as indicator variables in the study. The author defined two kind of effects on traffic conditions in the road maintenance works and weather conditions: direct effect and indirect effect.

The effect of road maintenance works and weather conditions on traffic conditions is defined as the direct effect. On the other hand, the mixed effect, which is a combination of the effect of road maintenance works and weather conditions on road surface conditions and the effect of road surface condition on traffic conditions, is defined as the indirect effect. And the author argued that when estimating traffic conditions, both direct and indirect effects of maintenance works and weather conditions should be considered.

Koizumi and Naoi [40] verified the dispatch criteria for three kind of snow removal operations: fresh fallen snow removal operation, road surface leveling operation, and snow compacting operation. To verify the criteria, the authors considered two types of cost which are the loss cost due to travel speed reduction by snowfall and the cost for snow removal operations. Travel speed reduction was estimated by linear regression model in their study.

Table 2-4 Literatures on the traffic condition estimation/prediction

Researcher (year)	Regions /Countries	Purpose	Method
Hayashiyama et al. (2001)	Sapporo, Japan	To measure the benefits of snow removal	Contingent valuation method (CVM)
Tanabe et al. (2002)	Sapporo, Japan	To measure the benefits of snow removal	Choice-based conjoint analysis
Lin (2008)	Iowa, US	To investigate the effects of snow removal on the road surface condition	Decision tree (CHAID) and multinomial logistic regressions
Koizumi and Naoi (2012)	Hokuriku, Japan	To verify the current snow removal strategy	Find the snow removal level to minimize cost

2.5 SUMMARY & RESEARCH OPPORTUNITY

As a result of reviews of previous studies, an amount of researches have been conducted on the effects of weather conditions on traffic performances which are traffic volume, travel speed, and road capacity. Most of the previous studies focused on the decreasing rate of free-flow speed, traffic volume, and road capacity by adverse weather conditions. According to their studies, weather conditions, such as rain, snow, fog, and low temperature, affects traffic performances in a negative way. Some researchers developed traffic performance estimation models through statistical methods. They quantified the effects of weather conditions on transportation performances. The relationship between weather conditions in winter and traffic conditions is studied very much by the previous researches. However, most of the studies considered the effects of various weather conditions including rainfall, snowfall, temperature and fog, but did not consider the effects of snow removal operations. Therefore, this dissertation considers the effect of both weather conditions and snow removal operations on traffic conditions.

Many researchers have studied the relationship between weather conditions and travel behaviors. According to the previous studies, not only traffic modes but also departure time of day, destination, and route can be changed under adverse weather conditions. Most of studies mentioned that people on foot or cyclist are more easily affected by cold temperature and both snow and rain precipitation than other modes. Therefore, some researchers[16] mentioned that the increased traffic demand for vehicle trips can be observed when pedestrians and cyclists changed their mode to vehicles. From the previous studies, it was found that adverse weather conditions affect the vehicle demand in two ways: positive and negative effects. In other words, motorists are unwilling to drive in adverse weather conditions, whereas pedestrians and cyclists tend to change their mode to vehicles including passenger cars and public transportation. The target season of the present study is winter in urban area. The weekday modal split in urban area in Japan is as Table 2-4. According to Table 2-5, around 40~45% of people have taken walk, bicycle or motorcycle for their trips. In other word, many portion of these group would change their modes. This is a reason that the winter road maintenance in urban areas is important.

Table 2-5 Weekday modal split in urban area in Japan (%)

City size	Walk	Motorcycle/ Bike	Bus	Rail	Car
More than 1 million	27.4	17.7	4.3	26.9	23.8
0.5 ~ 1 million	23.1	18.4	2.5	25.6	30.4
0.3 ~ 0.5 million	24.0	15.6	2.9	18.9	38.6
Less than 0.3 million	23.1	18.5	2.0	16.7	39.7
Total	24.9	17.6	3.1	21.4	33.1

(source: H. G. Retzko [41])

As a result of the previous researches reviews, many researchers estimated and predicted traffic conditions, such as travel speed, traffic volume, and even including traffic accidents, by diverse methodologies: ARIMA, NN, RegARIMA, MLR and so on. However, the weather-related traffic estimation and prediction studies have been comparatively scarcer than traffic condition prediction studies under incidents and events. Some authors of the previous studies[25], [30], [31], [33] emphasized the importance of developing traffic prediction models under adverse weather conditions because the traffic patterns during adverse weather conditions are significantly affected like other incidents and events. Though they tried to forecast traffic condition considering weather conditions, most researchers considered only one kind of weather conditions: rainfall or snowfall or fog. In this dissertation, not only a weather condition but also three kinds of weather conditions and snow removal operations are considered to forecast the travel speed. To estimate the travel speed, the present study uses a regression model with autoregressive integrated moving average (RegARIMA) model. Because the RegARIMA model have both characteristics of regression models and time series models, it can forecast the travel speed considering weather and snow removal[35].

The studies on the effects of snow removal operations were rare to find. Some previous studies estimated the effects of snow removal operations in the economic aspect based on the answers from the questionnaire survey. These researchers, however, did not consider the relationship between snow removal operations and traffic performances. On the other hand, a researcher[37] considered maintenance works in winter, such as plowing, sanding, and chemical, to estimate the road surface conditions. And the researcher argued the traffic performances are affected not only by maintenance works directly but also by the indirect effects which are the road surface conditions affected by maintenance works. The researcher considered only one kind of snow removal operation as an indicator variable: plow snow removal. However, there are several kinds of snow removal operations in heavy snow areas such as the fresh snow removal, the widening of effective road width, the surface leveling, and the snow hauling. Furthermore, the direct effects of the snow removal operation on traffic performances were not considered. In this dissertation, the direct effects of three kinds of snow removal operations except the surface leveling operations mentioned above on the travel speed are considered.

3 DATA COLLECTION

This chapter describes how and what kinds of data were collected. In section 3.1, the location and regional characteristics of selected arterial are provided. Section 3.2 explains how this dissertation collected and processed travel speed data. Section 3.3 defines each weather condition considered, and describes what kinds of weather condition data were collected. In section 3.4, types of snow removal operations in Sapporo are introduced. Besides, this chapter explains how each snow removal operation is reflected in this dissertation. Finally, in section 3.5, the plans and results of traffic count which conducted in this research are produced.

3.1 STUDY AREA

To identify the relationships among weather conditions, snow removal operations, and travel speed, this dissertation selected a 4.8-km segment of the Nishi 5-chome Tarukawa Dori (an urban arterial) from JR Sapporo Station to Subway Asabu Station as the study area (see Figure 3-1). The study area was divided into 10 sections demarcated by major intersections, and each section was separated by direction: northbound versus southbound. In other words, the study area is composed of 20 links as Figure 3-2. The length of each section is presented in Table 3-1. Nishi-5-chome Tarukawa Dori is a four-lane arterial. This route is a main street that connects the central commercial/business district of Sapporo to residential areas north of that district. The annual average daily traffic (AADT) for the 12 hours from 07:00 to 19:00 was 17,888 vehicles, and the traffic volume was greater southbound (9,739 veh/12h) than northbound (8,149 veh/12h) in 2010 [42].

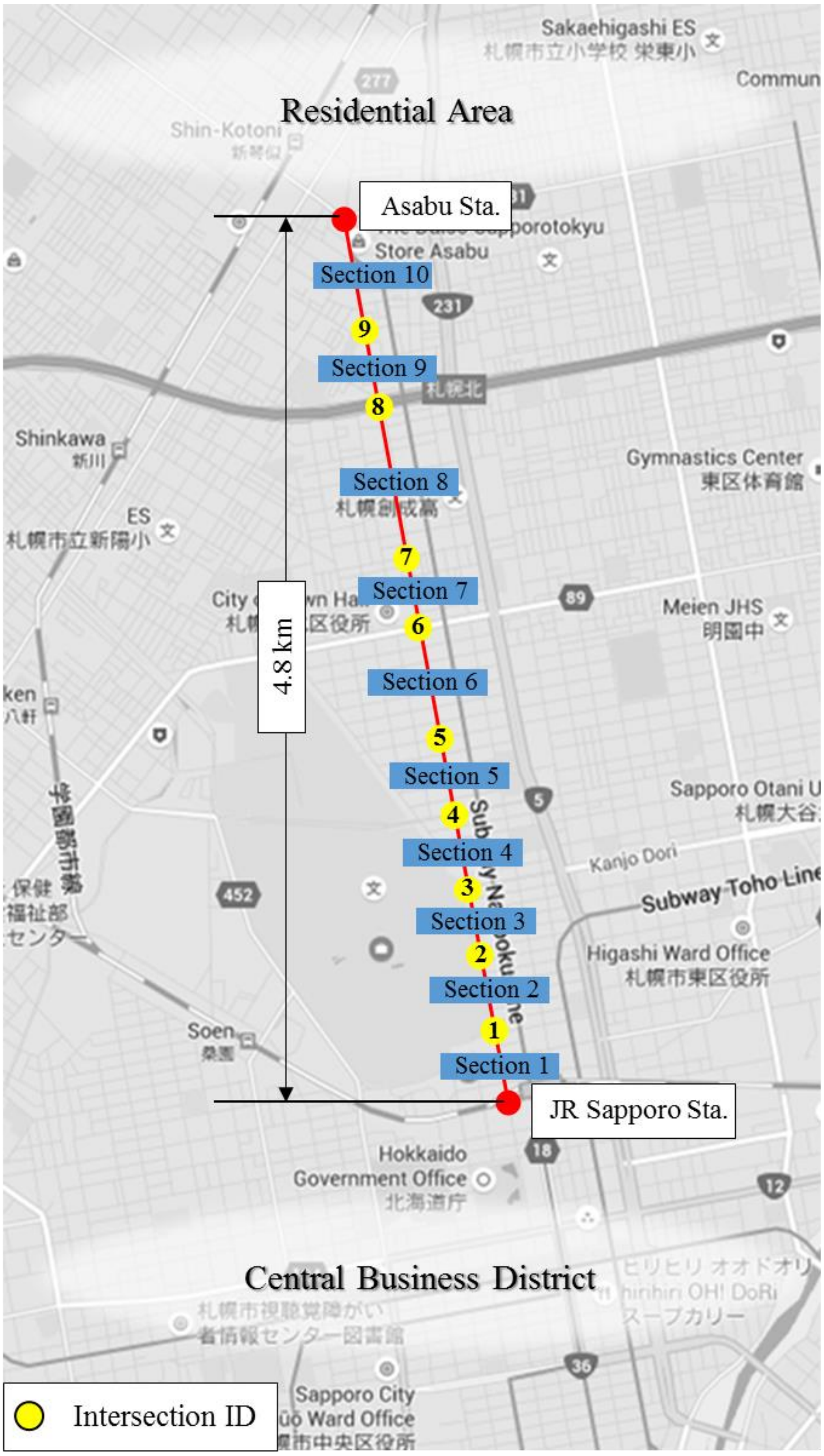
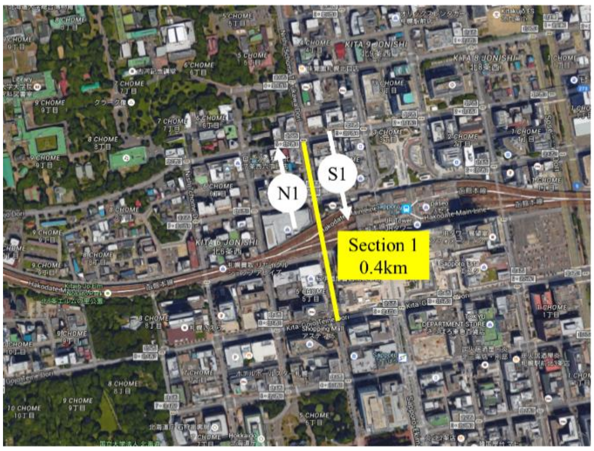


Figure 3-1 The study area: Nishi 5-chome Tarukawa Dori

(modified from Google Maps)



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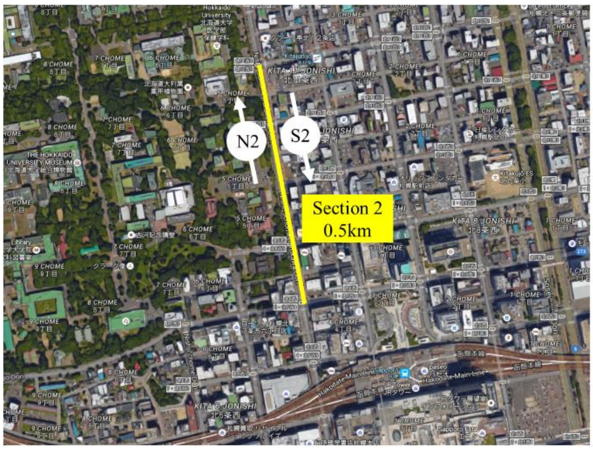

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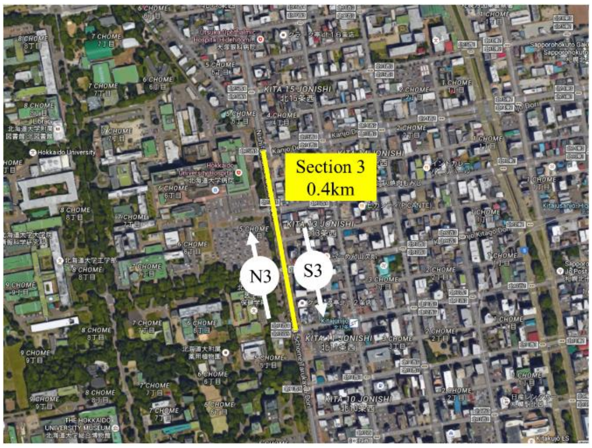
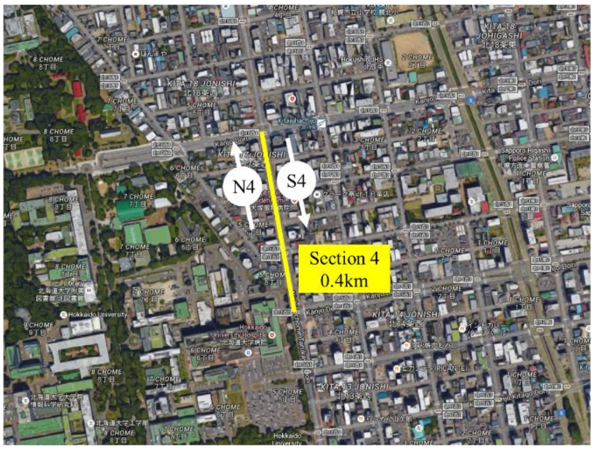


(c) section 3



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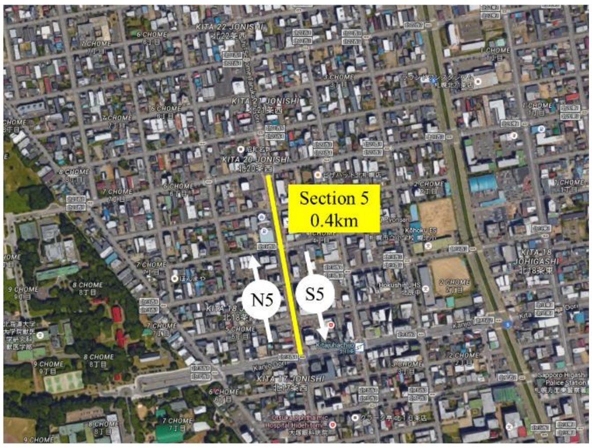

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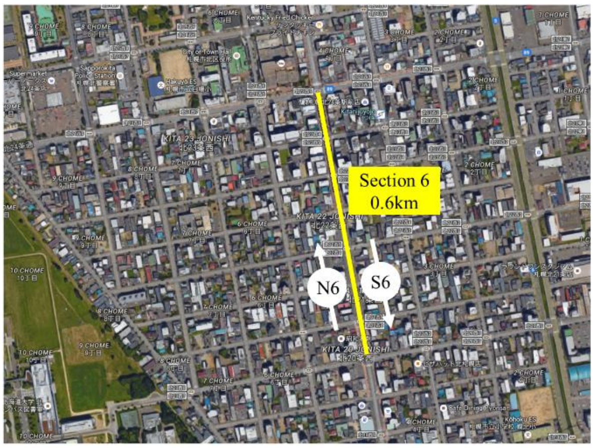
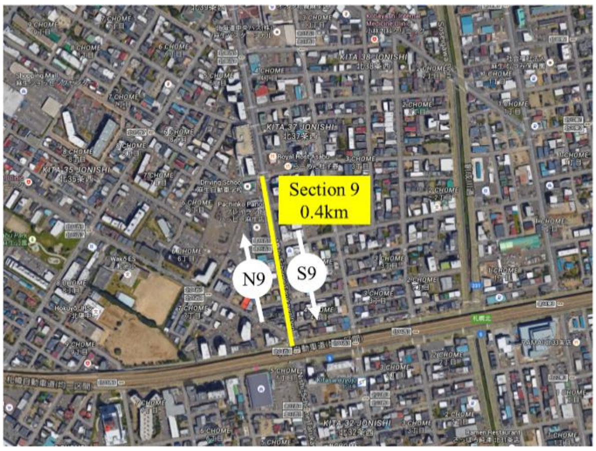


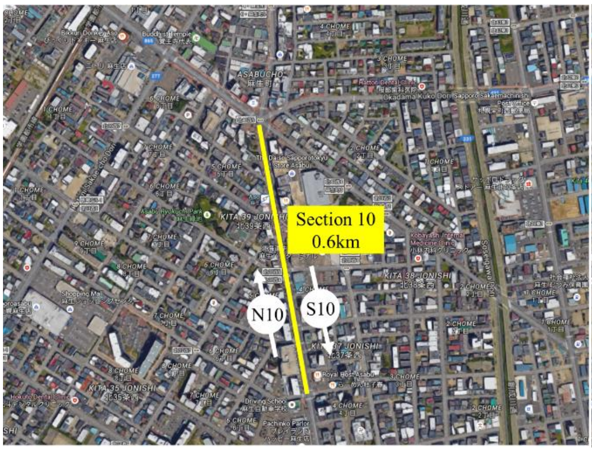
(f) section 6

(g) section 7

(h) section 8



(i) section 9



(j) section 10

Figure 3-2 Sections of the study area

(modified from Google Maps)

Table 3-1 The section lengths

Section ID	Length (km)	Section ID	Length (km)
1	0.4	6	0.6
2	0.5	7	0.35
3	0.4	8	0.8
4	0.4	9	0.35
5	0.4	10	0.6
Whole section (km)		4.8	

3.2 TRAVEL SPEED

Travel speed (km/h) was collected from probe taxis in Sapporo provided by Fujitsu Intelligent Society Solution, SPATIOWL. These data are 5-minute link-based data that include the locational information (geographic coordinates) for the departure and arrival nodes, road types, link lengths, travel time, the number of taxis during the collection interval, and the locational information for the departure and arrival nodes of the next links that the taxis are going to head. The travel direction for probe taxis can be clearly discerned by collecting the information of next links.

The data were aggregated into hourly data to match the interval of the weather condition data. Taxi probe data for the hours of 20:00 to 07:00 were not included in the analysis, because night taxi ridership is rare in Sapporo. The duration for analysis was the winter of 2013-2014, from 10 December 2013 to 31 March 2014. Only weekdays were used for analysis, because the traffic patterns of these periods differ from general traffic patterns. Additionally, taxis slower than preferred walking speed (1.21 mi/h = 4.356 km/h) [43] were excluded to ignore abnormally slow taxis, such as those waiting for passengers, and vehicles broken down on the road. In summary, the analysis period covered 13 hours per day for weekdays in the winter of 2013-2014 (10 December 2013 to 31 March 2014), with other times excluded from analysis. Descriptive statistics of the travel speed for each month and for each link are shown in Table 3-2 and Table 3-3 respectively.

Table 3-2 Descriptive statistics of the travel speed for each month (unit: km/h)

Month	Max.	85%	Mean	15%	Min.	S.D.
December, 2013	40.36	25.82	20.00	13.50	4.42	6.12
February, 2014	42.18	23.36	17.40	10.13	4.36	5.56
January, 2014	39.84	23.00	17.37	11.29	4.36	6.03
March, 2014	59.16	26.44	20.32	13.82	4.43	6.17
Whole period	59.16	24.82	18.69	11.79	4.36	6.13

Table 3-3 Descriptive statistics of the travel speed for each link (unit: km/h)

Link ID	Max.	85%	Mean	15%	Min.	S.D.
N1	25.80	15.15	12.01	8.93	4.43	3.06
N2	39.57	28.87	24.33	19.63	11.97	4.41
N3	59.16	29.72	24.41	18.79	7.06	5.46
N4	35.50	25.47	21.52	17.20	4.37	4.23
N5	39.37	29.45	24.52	19.77	7.68	5.09
N6	29.38	21.45	16.84	11.72	4.69	4.54
N7	32.09	23.13	19.20	15.40	4.64	4.30
N8	32.59	24.93	18.71	9.63	4.59	6.46
N9	40.36	29.20	25.09	21.06	7.56	4.10
N10	34.34	20.98	17.09	13.04	4.63	4.10
Northbound total	59.16	26.64	20.37	13.42	4.37	6.22
S1	22.74	11.50	8.31	5.58	4.36	2.87
S2	27.50	20.15	15.25	8.86	4.42	4.95
S3	37.09	22.06	17.35	12.18	4.42	4.87
S4	30.55	22.22	17.10	11.40	5.15	4.77
S5	30.90	23.97	18.70	12.50	4.62	5.50
S6	34.13	26.25	20.18	15.32	4.53	5.38
S7	28.71	20.85	16.16	11.36	5.29	4.37
S8	27.41	23.06	19.65	16.51	6.58	3.22
S9	37.85	23.66	18.69	12.93	4.79	5.27
S10	30.57	21.33	18.01	14.73	5.48	3.42
Southbound total	37.85	22.37	17.00	10.23	4.36	5.54
Whole section	59.16	24.82	18.69	11.79	4.36	6.13

3.3 WEATHER CONDITIONS

The weather condition data were collected by the Automated Meteorological Data Acquisition System (AMeDAS) of Sapporo. AMeDAS automatically collects various weather data at weather stations, such as weather, wind direction/speed, amount of precipitation, type and height of cloud, visibility, air temperature, humidity and atmospheric pressure. And there are about 1,300 AMeDAS stations in Japan[44]. The AMeDAS station in Sapporo is about 1.8 km from JR Sapporo Station and 5.6 km from the Asabu Subway Station (Figure 3-3). The present study assumes that the weather conditions are same at the AMeDAS station and in the study area. Among the weather data, the air temperature, snowfall, and deep snow, was considered for the analysis.

Figure 3-3 The location of the AMeDAS station in Sapporo

Definitions of each weather term are defined on the website of the Japan Meteorological Agency (JMA)[45]. Deep snow (cm) is defined as the depth of snow and hail cover on the ground, including both fresh and old snow and hail per unit time of observation (1 hour), whereas snowfall (cm) includes only fresh snow and hail. Temperature (℃) is the value measured 1.25~2.0 m above the ground. These are represented by continuous variables. All these weather data were collected every hour. Descriptive statistics of the weather condition for the winter of 2013-2014 are presented in Table 3-4.

Table 3-4 Descriptive statistics of the weather conditions for the winter season of 2013-2014

		Max.	85%	Mean	15%	Min.	S.D.
Dec. 2013	Temperature (℃)	10.6	3.7	0.8	-2.7	-5.3	3.0
	snowfall(cm)	5.0	0.0	0.1	0.0	0.0	0.5
	Deep snow(cm)	52.0	29.0	13.2	0.0	0.0	14.4
Jan. 2014	Temperature (℃)	8.1	-0.2	-4.1	-7.3	-10.7	3.2
	snowfall(cm)	7.0	0.0	0.2	0.0	0.0	0.7
	Deep snow(cm)	75.0	65.0	57.5	49.0	41.0	7.1
Feb. 2014	Temperature (℃)	7.3	-0.3	-3.5	-7.3	-13.7	3.5
	snowfall(cm)	5.0	0.0	0.2	0.0	0.0	0.6
	Deep snow(cm)	113.0	93.0	81.2	70.0	61.0	12.1
Mar. 2014	Temperature (℃)	13.0	4.9	0.5	-3.5	-7.1	4.1
	snowfall(cm)	5.0	0.0	0.1	0.0	0.0	0.5
	Deep snow(cm)	107.0	87.0	74.6	56.5	28.0	16.7
Total	Temperature (℃)	13.0	2.6	-1.5	-5.9	-13.7	4.1
	snowfall(cm)	7.0	0.0	0.2	0.0	0.0	0.6
	Deep snow(cm)	113.0	85.0	56.0	8.0	0.0	29.6

The average travel speeds on Nishi 5-chome Tarukawa Dori during the study period are illustrated in Figure 3-4, which shows that the relationship between travel speed and temperature plots as a “U” shape. In terms of temperature, some researchers have studied the relationship between temperature and traffic accidents, and they have proposed that the relationship is J- or U-shaped. Lee et al.[46] found a J-shaped relationship between temperature and the number of injuries from traffic accidents. They mentioned that the injuries accidents decreased as the temperature decreased under condition of above 0℃. On the other hand, the accidents increased as the temperature decreased under condition of below zero degree Celsius. Takahashi et al.[47] noted that accidents in winter in Hokkaido tend to be most frequent at the temperature range between -6 and 0℃. Asano and Hirasawa[48] also found that the average number of skid accidents peaks when the daily average temperature is around -4℃. A U-shaped relationship of the average travel speed and temperature in Figure 3-4 is partly relevant to the previous studies mentioned above. The relationship between temperature and traffic accidents in the previous studies also represents as U and J shapes. These results might be because the road surface at the certain range of temperatures has mixed freezing conditions, such as ice, slush, and water. For this reason, drivers feel more difficultly driving at the temperature of the minimum point on the J-curve or U-curve than at other temperature ranges because the mixed freezing condition is more slippery than homogeneous freezing conditions. Thus, the squared temperature variable ($℃^2$) is also included in the speed prediction model of the present study.

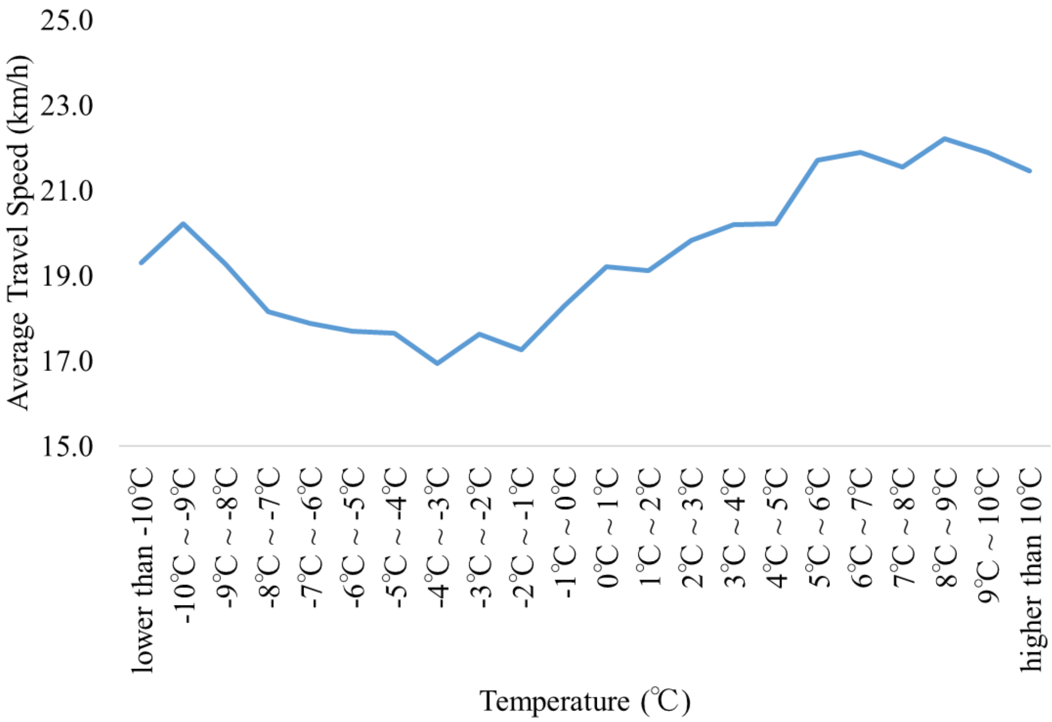


Figure 3-4 Average travel speed sections versus air temperature

3.4 SNOW REMOVAL OPERATIONS

Four kinds of snow removal operations are performed on roads in Sapporo: fresh snow removal, road surface leveling, widening of the effective road width, and snow hauling. Snow removal operations are performed based on the threshold level of effective road width as Figure 1-1. Road snow removal in Sapporo is done by machines such as snow graders, snow bulldozers, rotary snow blowers and backhoes (see Figure 3-5). About 1,400 snow removal machines and 6,000 dump trucks are deployed[49] to complete such removal in the 7 hours from midnight to 7 a.m.[50].

(a) snow grader

(b) snow bulldozer

(c) rotary snow blower

(d) backhoe

Figure 3-5 Snow removal equipment

(source: the City of Takikawa[51])

Snow removal operations for urban areas are shown in Figure 3-6. In fresh snow removal operations, newly fallen snow is pushed to the shoulders. The operations are executed by snow graders and snow bulldozers. The fresh snow removal affects traffic in two opposite ways. This operation can maintain the roads in good condition by removing newly fallen snow on the road surface. However, the effective road width is narrowed when the snow is pushed to the shoulders. In leveling operations, snow graders and snow bulldozers flatten rough roads. In road widening operations, the effective width of roads that have been narrowed by fresh snow removal is increased. The widening operations are performed by rotary snow blowers. In snow hauling, piled snow is hauled to disposal sites by rotary snow blowers, backhoes, and dump trucks. Fresh snow removal operations are performed when the deep snow on the road is more than 10 cm, while other operations are performed when the city deems it necessary.

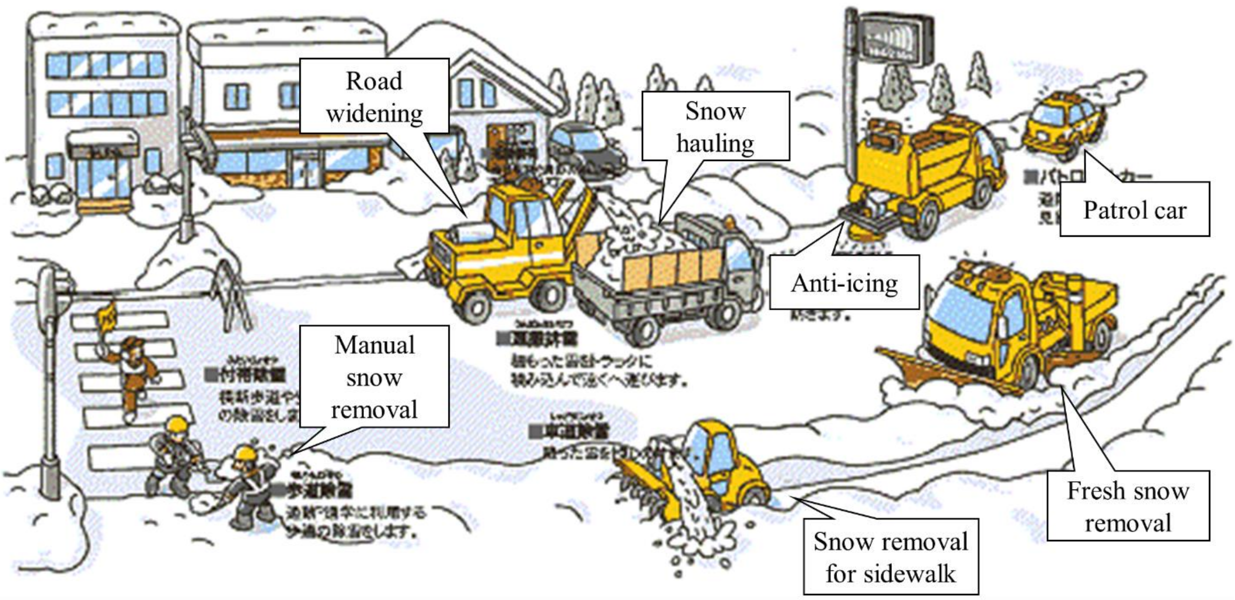


Figure 3-6 Snow removal operations for urban areas

(source: Wakkanai Development and Construction Department, MLIT[52])

This dissertation addresses the three snow removal operations other than road surface leveling. To develop the speed estimation model, the road widening snow removal operations are expressed as the indicator variable. The road widening operation indicator was defined as “1” for links on which the effective road width was increased by road widening operation, and “0” for links on which the effective road width was decreased by fresh snow removal operation. So long as the fresh snow removal pushes snow to the shoulders, the road surface is clearer but the effective road width is narrower. Therefore, fresh removal operations are represented as both an indicator variable and a discrete variable to reflect the effects on traffic in two opposite ways. The fresh snow removal operation indicator is defined as “1” when the road surface was cleaned by fresh snow removal operation, and “0” when the road was covered with snow. And the number of fresh snow removal operations between two road widening operations was represented as a discrete variable. Lastly, snow hauling operations were not employed as an independent variable, but the effects were reflected by changes in the deep snow variable. After performing the hauling operation on a section, the deep snow variable on that section was changed to 0 cm. The conditions of deep snow and snow removal on link N5 for the winter of 2013-2014 are shown as an example in Figure 3-7.

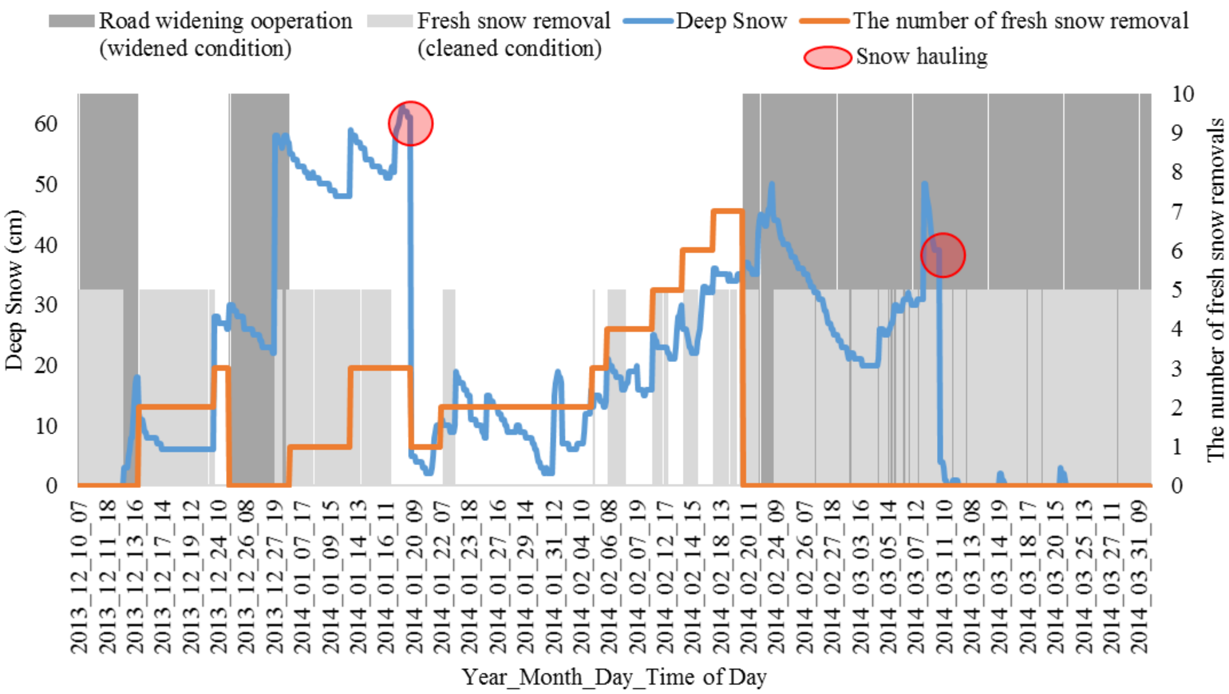


Figure 3-7 Deep snow and snow removal conditions for the winter of 2013-2014 (Link N5)

3.5 TRAFFIC COUNT SURVEYS

This dissertation assumes that vehicles turning left and right at intersections obstruct vehicles going straight during the snow season more than in other seasons because of the reduction in effective number of lanes by snow removal operations. The traffic count survey was conducted to know how the turning rates at intersections would affect travel speed. The vehicles were counted by directions and classified by the vehicle classes, and the traffic counts were done on Wednesday and Thursday for two weeks in winter, and the recorded results for a week made one set. Two sets of traffic count survey were conducted. The date of the 1st set was 17th and 18th February, 2016 and the 2nd set was 24th and 25th February, 2016. Table 3-5 shows the dates which the traffic counts were conducted by intersections. The counted vehicles were recorded three times a day: morning peak hours (7am~9am), non-peak hours (2pm~4pm), and evening peak hours (6pm~8pm). Before starting the traffic count survey, all surveyors were given the guideline for the survey and conducted the survey using the traffic count recording sheets.

Table 3-5 The traffic count survey dates and times by intersections

Intersection ID	1st set		2nd set	
	Northbound	Southbound	Northbound	Southbound
1	17 Feb.	17 Feb.	24 Feb.	25 Feb.
2	17 Feb.	17 Feb.	24 Feb.	24 Feb.
3	18 Feb.	17 Feb.	25 Feb.	24 Feb.
4	18 Feb.	17 Feb.	24 Feb.	25 Feb.
5	18 Feb.	17 Feb.	24 Feb.	24 Feb.
6	17 Feb.	17 Feb.	25 Feb.	24 Feb.
7	17 Feb.	18 Feb.	25 Feb.	25 Feb.
8	18 Feb.	17 Feb.	25 Feb.	24 Feb.
9	17 Feb.	18 Feb.	24 Feb.	25 Feb.

* 17th and 24th February are Wednesday, 18th and 25th February are Thursday.

Vehicles on roads are mixed with various classes, this dissertation were classified into two vehicle classes as Table 3-6: heavy vehicle class and passenger car class. They were converted to the passenger car unit (PCU) based on the passenger car equivalent (PCE) (see Table 3-7). PCE is defined by Highway Capacity Manual (HCM) 2010[53] as "the number of passenger cars displaced by a single heavy vehicle of a particular type under specified roadway, traffic, and control conditions". Using the PCE and the percentage of each vehicle type, the counted number of vehicles can be converted into PCU by Equation 3-1:

$$Q_{PC\_i} = Q_{V\_i}(P_{PC\_i} + E_{HV\_i} \cdot P_{HV\_i}) \tag{3-1}$$

Where,

Q_{PC_i} is the number of passenger cars (pcu) on link i.

Q_{V_i} is the number of unclassified vehicles (veh) on link i.

P_{PC_i} and P_{HV_i} are the percentage of passenger car and heavy vehicle respectively (%)on link i.

E_{HV_i} is the PCE on link i.

Table 3-6 Vehicle classification under the road traffic act and the present study

Classification		Description
Dissertation	Road Traffic Act	
Heavy vehicle class	Special-Purpose Motor Vehicles	Motor vehicles with caterpillar treads such as bulldozers, steamrollers, graders, snowplows, tractors, etc. are classified into two categories: large and small. Small special-purpose motor vehicles are those of up to 15km per hour in maximum speed, up to 4.7m in length, up to 2m in height, and up to 1.7m in width
	Large Motor Vehicles	- Gross vehicle weight: ≥11 tons - Payload: ≥6.5 tons or Occupancy: ≥30 persons
	Middle-Category Motor Vehicles	- Gross vehicle weight: 5≤tons<11 - Payload: 3≤tons<6.5 or Occupancy: 11≤persons<30
Passenger car class	Ordinary Motor Vehicles	- Gross vehicle weight: <5 tons - Payload: <3 tons or Occupancy: <11 persons

(source: Japan Automobile Manufacturers Association, *the Motor Industry of Japan 2010*, 2010[54])

Table 3-7 Passenger car equivalent (PCE) by the terrain types in Japan

	urban & level	mountainous	at intersections
1-lane & 2-lane roads	2.0	3.5	1.7
More than 3-lane roads	2.0	3.0	

(source: Japan Road Association, *Road Traffic Capacity*, 1984[55])

In this dissertation, the rates of turning vehicles at intersections and the sizes of intersections were considered to explain the characteristics of each intersection. The rate of turning vehicles at the intersection is defined as the rate of vehicles turning left and right of outflow vehicles at the intersection. It is expected to identify the effects of the rate of turning vehicles at intersection on the travel speed. The size of intersection is defined as the number of lanes of the approach from the right at the intersection. The larger size of intersection indicates that the waiting space for vehicles turning left and right would be increased. The sizes of each intersection on the study area are shown in Table 3-8, and the rates of turning vehicles are presented in Table 3-9 for northbound traffic and Table 3-10 for southbound traffic. The dissertation employed the average turning vehicle rate of the two traffic count survey sets mentioned above as an independent variable to develop the travel speed estimation model.

Table 3-8 The sizes of each intersection on the study area

Intersection ID	Intersection size	Intersection ID	Intersection size	Intersection ID	Intersection size
1	4	4	6	7	4
2	4	5	4	8	9
3	7	6	4	9	2

Table 3-9 The rates of turning vehicles at the intersections (northbound traffic)

Time	Set*	Intersections (Northbound)								
		1	2	3	4	5	6	7	8	9
Morning-peak	1st set	8.0%	11.6%	18.1%	28.9%	5.9%	17.6%	9.4%	52.4%	11.3%
	2nd set	2.8%	12.8%	15.3%	38.6%	9.9%	16.6%	9.4%	56.3%	9.2%
	average	5.5%	12.2%	16.6%	33.3%	8.2%	17.1%	9.4%	54.4%	10.2%
Non-peak	1st set	6.2%	6.9%	15.6%	20.1%	5.4%	18.4%	6.4%	33.8%	8.9%
	2nd set	4.9%	7.5%	16.9%	30.5%	8.6%	22.2%	7.6%	42.4%	10.0%
	average	5.6%	7.2%	16.2%	25.2%	6.9%	20.3%	7.0%	38.0%	9.4%
Evening-peak	1st set	3.5%	4.3%	9.7%	23.7%	6.5%	19.3%	7.8%	36.5%	14.4%
	2nd set	2.7%	5.3%	12.3%	27.3%	5.1%	16.5%	8.0%	36.0%	13.0%
	average	3.1%	4.8%	11.0%	25.5%	5.8%	17.9%	7.9%	36.3%	13.7%

* 1st set: 17th and 18th Feb., 2016.

Table 3-10 The rates of turning vehicles at the intersections (southbound traffic)

Time	Set*	Intersections (Southbound)								
		1	2	3	4	5	6	7	8	9
Morning-peak	1st set	30.5%	12.6%	30.5%	23.6%	4.2%	21.9%	3.0%	29.3%	2.3%
	2nd set	31.2%	15.4%	31.1%	18.0%	4.4%	21.5%	3.8%	32.9%	2.9%
	average	30.9%	14.1%	30.8%	20.2%	4.3%	21.7%	3.5%	31.0%	2.6%
Non-peak	1st set	32.6%	9.2%	27.7%	20.8%	3.7%	26.0%	9.2%	31.0%	4.5%
	2nd set	26.4%	10.3%	37.6%	21.7%	5.2%	31.2%	5.3%	32.6%	8.2%
	average	29.6%	9.7%	32.5%	21.2%	4.4%	28.5%	7.2%	31.7%	6.3%
Evening-peak	1st set	33.3%	11.3%	29.3%	26.6%	5.7%	27.7%	6.0%	38.4%	5.5%
	2nd set	21.8%	8.5%	27.6%	20.6%	5.0%	32.8%	5.2%	34.7%	7.7%
	average	27.0%	10.1%	28.5%	24.0%	5.4%	30.1%	5.6%	36.7%	6.6%

* See Table 3-4.

4 MODEL DEVELOPMENT

This chapter develops a travel speed prediction model considering weather conditions and snow removal operations, and an appropriate model for speed estimation in winter is suggested. As a travel speed prediction model, the present study employed regression with the autoregressive integrated moving average error (RegARIMA) model. Figure 4-1 shows the analysis flow for developing the travel speed estimation model. The first step is to set up a dataset for analysis by combining traffic, weather, and snow removal operation data. The second step is to develop a multiple linear regression (MLR) and a fixed effects (FE) models, which is a linear regression model for panel data, with all the variables to identify the effects of external variables in winter on the travel speed (section 4.1 and section 4.2). The third step is to investigate the autocorrelation of the residuals between observed values and estimated values of the MLR model and FE model, in order to apply autoregressive integrated moving average (ARIMA) models. Then, ARIMA models are developed with the residuals, and two regression models and ARIMA model are combined (section 4.3). The last step is to compare the predictive accuracies of developed models to select the appropriate model for travel speed estimation in winter (section 4.4).

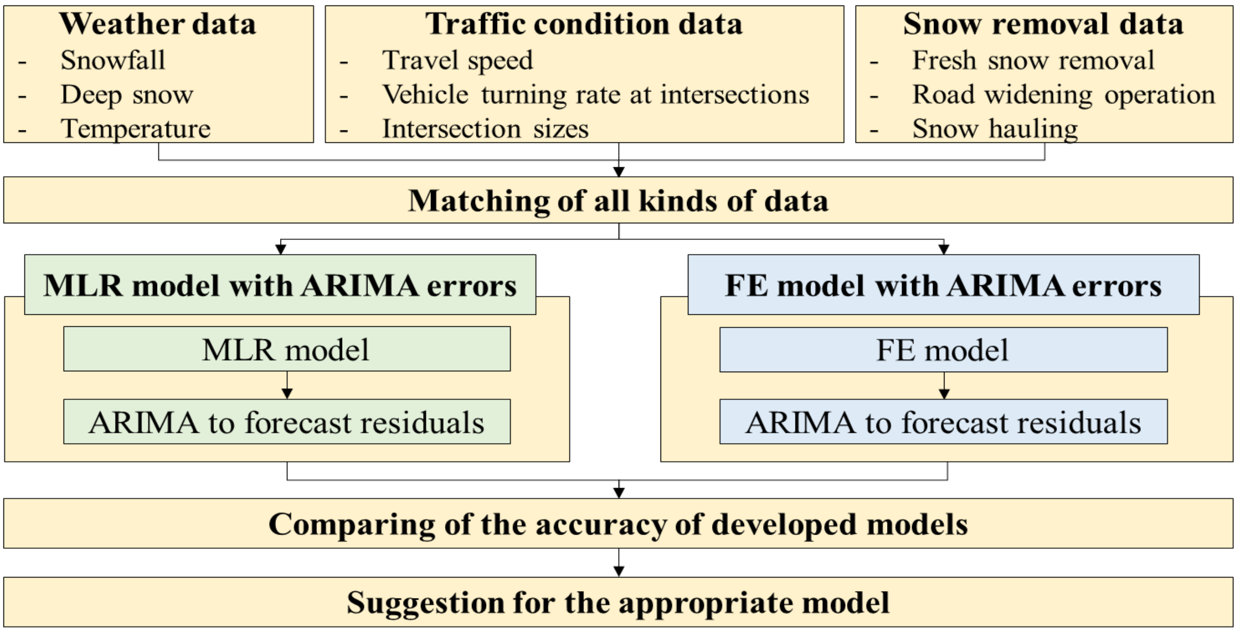


Figure 4-1 Analysis flow

4.1 MULTIPLE LINEAR REGRESSION MODEL

A linear regression model is a modeling technique to explain the relationship among the factors by a line. The slope of the line and the intercept can be used to estimate the influence of the factor. The model is commonly used for analysis of the cross-sectional data, which is obtained at the same point in time or regardless of difference in time from the survey of many subjects such as individuals, groups, countries, or companies. A linear regression model is also used to forecast change in the dependent variable by changing the independent variable. If one independent variable is related with the dependent variable, the linear regression is called simple linear regression. And if the linear regression has two or more independent variables, it is called multiple linear regression (MLR).

The MLR is based on fallowing five assumptions[56].

1. Linearity – the dependent variable and independent variables need to be linearly related.
2. Normality – all variables in MLR are normally distributed.
3. Lack of collinearity – it is also called multicollinearity. MLR is required to have little or no multicollinearity. Multicollinearity means that some independent variables have relationships with other independent variables.
4. Homoscedasticity – it means that the variance of all residuals are equal.
5. Independence of errors – It is called autocorrelation (also known as serial correlation). The errors should not be correlated with each other.

Several tests can be used in determining whether assumptions are violated or not. The F-test is used to check the linearity assumption. In this test, the null hypothesis (H_0) is that all regression coefficients (β) is zero which means the regression line is not statistically significant ($\beta_i = 0$). On the other hand, the alternative hypothesis (H_1) is that at least one regression coefficient is not zero which means the regression line is statistically significant ($\beta_i \neq 0$). The variance inflation factor (VIF) shows how much independent variables correlated each other in the MLR. When the VIF of 1 means independent variables are not correlated. And generally, the rule of thumb is that if VIF value not exceed 10, it is regarded as little or no multicollinearity. Durbin-Watson test is usually considered to test the autocorrelation in the residuals. When Durbin-Watson statistic (*d*) of 2 indicates no correlation. The range of the *d* is between 0 and 4, and if the *d* is much less than 2, the residuals are positively correlated, while much larger than 2, the residuals have a negative correlation with other residuals. As a roughly, the acceptable range of *d* is between 1.5 and 2.5[57], [58]. Coefficient of determination (also known as R-squared) can be used to examine the goodness of fit of MLR models. The range of R-squared is between 0 and 1, and the larger R-squared means better explanation performance of the model. It can be calculated by Equation 4-1.

$$\frac{SSR}{SST} = \frac{\sum(\hat{y}_i - \overline{y})^2}{\sum(y_i - \overline{y})^2} = \frac{SSR}{SSE + SSR} = \frac{\sum(\hat{y}_i - \overline{y})^2}{\sum(y_i - \hat{y}_i)^2 + \sum(\hat{y}_i - \overline{y})^2} = R^2, \qquad 0 \leq R^2 \leq 1 \tag{4-1}$$

where,

SST, SSR and SSE are total, regression (explained), and error (unexplained) sum of squares respectively.

y_i is the observed value of the dependent variable.

$\overline{y}$ is the mean of the observed values.

$\hat{y}_i$ is the predicted value.

In this dissertation, travel speed is considered as the dependent variable and the other variables are independent variables: vehicle turning rates at intersections, the intersection size, weather conditions and snow removal variables. To identify the relationships between travel speed and the other variables, the MLR models could be developed and expressed as following Equation 4-2:

$$
\begin{aligned}
&(Travel\ \ Speed) \\
&= (constant) + (Temperature^2)\beta_1 + (Temperature)\beta_2 \\
&+ (Snowfall)\beta_3 + (Deep\ \ snow)\beta_4 + (\#\ \ of\ \ fresh\ \ snow\ \ removal)\beta_5 \\
&+ (Road\ \ widening)\beta_6 + (Fresh\ \ snow\ \ removal)\beta_7 \\
&+ (Turning\ \ rate)\beta_8 + (Intersection\ \ size)\beta_9 + \varepsilon
\end{aligned} \tag{4-2}
$$

where,

ε is error term.

β_i is regression coefficients (also called effects).

The links (S1 and N10) at both ends of the study route were not included in the analysis because the traffic data were collected at intersections from 1 to 9 in Figure 3-1 and 3-2. These links did not include the two information of turning rates and intersection sizes. The other links of the study area were analyzed by the MLR model using the stepwise method to select the statistically significant variables in the model, and the analysis results are shown in Table 4-1. The results of the MLR models, deep snow has a negative relationship with travel speed, whereas snowfall variable were not statistically significant at the 95% confidence level. The reason can be easily found in the definition of these. As a mentioned above, deep snow is defined as the depth of snow including both fresh and old snow, whereas snowfall includes only fresh snow. It means the snowfall is a subset of the deep snow. Therefore, at the step of selecting variables, the snowfall is excluded from the model by the stepwise method. According to the result, travel speed is analyzed to be reduced by 0.14 km/h as the deep snow increase by 1 cm. In case of temperature, the temperature squared value correlated positively with the travel time. This means that the relationship between the temperature and the travel speed are U-shaped in the present study. This result is related with previous studies[46]–[48]. The researchers found the relationship between temperature and traffic accidents represents as U or J shapes. The number of fresh snow removals had a negative correlation with travel speed, while the operation itself was positively correlated. The result has shown that fresh snow removal operations affected traffic in two opposite ways. Firstly, these operations can keep the roads in good condition by the removal of snow from the carriageway. Secondly, the effective road width is narrowed when the snow is pushed to the shoulders. According to the result of MLR analysis, the coefficient of the number of fresh snow removal operations was -0.36, and the operation was 0.67. It indicates that if the fresh snow removal operations were performed more than 3 times without the road widening operation, despite removing the snow from the road by the operation, the travel speed would be slow. However, road widening operation was negatively correlated with travel speed. This result is counterintuitive, because an increase in the effective road width should leads to a decrease in the traffic density. More research is required regarding these variables. In case of the vehicle turning rate at intersections and the intersection size, the turning rate was negative correlated and the intersection size had a positive relationship with travel speed. Vehicles going straight are affected by the vehicles turning left and right at intersection especially on the winter road which are narrowed by fresh snow removal operations. However, the negative effects of the turning rate decrease if the intersection has enough space to wait for turning at intersection. The developed model by the MLR can be expressed as Equation 4-3.

$$\begin{aligned}(Travel\ \ Speed) \\ &= 22.72 + 0.01(Temperature^2) - 0.03(Temperature) \\ &- 0.14(Deep\ \ snow) - 0.36(\#\ \ of\ \ fresh\ \ snow\ \ removal) \\ &- 0.34(Road\ \ widening) + 0.67(Fresh\ \ snow\ \ removal) \\ &- 16.48(Turning\ \ rate) + 0.60(Intersection\ \ size) + \varepsilon\end{aligned} \tag{4-3}$$

Table 4-1 Result of the MLR model

Variables	Estimate	t-value	VIF
Constant	22.72	147.59	
Temperature^2 (℃^{2})	0.01	6.02	1.05
Temperature (℃)	-0.03	-2.95	1.47
Snowfall (cm)			
Deep snow (cm)	-0.14	-70.39	1.31
The number of fresh snow removal	-0.36	-12.19	2.00
Road widening snow removal*	-0.34	-3.23	1.89
Fresh Snow removal*	0.67	7.80	1.19
Turning rate	-16.48	-34.73	2.13
Intersection size	0.60	21.77	2.11
F-value (p-value)	1,007.712 (0.00)		
R-squared	0.38		
Durbin-Watson	0.79		

* indicator variables

All independent variables included in the MLR models were statistically significant at the 95% confidence level. And the sample sizes are 16,614. According to the result of the developed MLR model, the model explains around 40% of the dependent variable. In addition, the F-value from the F-test for verifying the linearity assumption was 1,007.712: thus, the regression was statistically significant at the 0.05 significance level ($p<0.05$). All the VIF values of the selected independent variables were less than 10, therefore the model was regarded as no multicollinearity. However, the Durbin-Watson statistic (0.79) was lower than 1.5. This indicates that the residuals of the model serially correlate with each other. This assumption violation often occurs when analyzing time series data[59]. It is necessary to correct residuals by transforming from the autocorrelated errors to the uncorrelated errors (white noise).

4.2 FIXED EFFECTS MODEL

A fixed effects (FE) model is a linear regression for panel data. In econometrics, data types are divided into cross-sectional data, time-series data, and panel data as Figure 4-2, according to the data collection methods. Panel data, also known as longitudinal data, represents a fusion of cross-sectional data and time series data. Frees[60] explained panel data that “unlike regression data, with longitudinal data we observe subjects over time. Unlike time-series data, with longitudinal data we observe many subjects”. Because panel data has not only cross-sectional information, but also time-series information, a panel data analysis model has some important advantages over other data models[60]. First, the panel data model is able to analyze dynamic relationships. For example, in case of traffic accidents, the accident rates can be estimated if cross-sectional data is only considered. And the change in accident rates over time can be estimated when time-series data is used only. In contrast, other useful information, such as the driving experience of drivers, can be drawn by tracking individual drivers (panel data). Secondly, the panel data model can model individual heterogeneity among the subjects. In other words, the panel data model can control for unobserved and unmeasured variables, such as the cultural background and driving habits of drivers. Furthermore, the panel data model has less multicollinearity among independent variables than other data models have: cross-sectional data models and time-series data models. On the other hand, there are some drawbacks in the panel data model. The often referred drawback is hard to collect and design data for analysis because the dataset for panel data is composed of time-series and cross-sectional data[61]. And a drawback of the FE model is that it is unable to estimate the coefficient for time-invariant effects, but these effects are included in the intercept of the model.

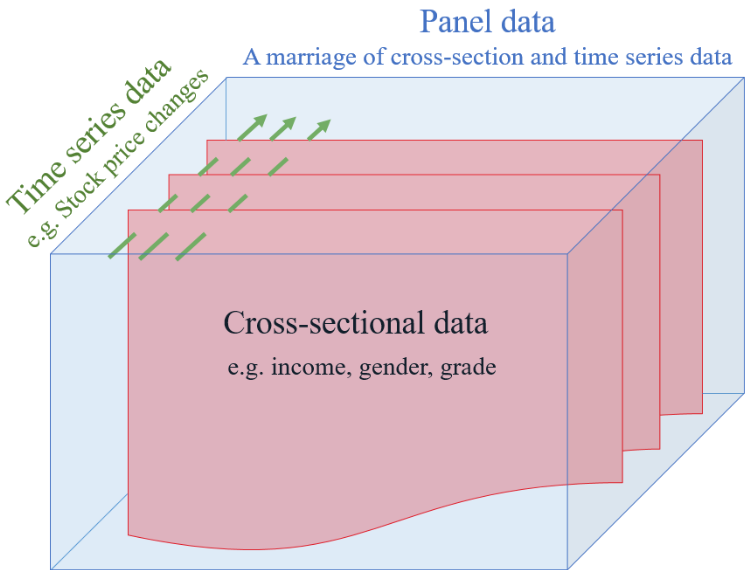


Figure 4-2 Types of econometric data

Two major models for panel data are the fixed effects (FE) model and the random effects (RE) model. The FE model assumes that the unobserved time-invariant individual (subject) effects can be explained as the individual specific effects through fixed intercepts, whereas the RE model assumes that the unobserved individual effects are stochastic[61]. In the FE model, the individual specific effects are considered as a parameter, in the RE model, on the other hand, the individual specific effects are included as an error[62]. In other words, the main difference between the two models is whether the individual specific effects are related with other independent variables or not[63]. However, Rendon [62] mentioned that to treat the effects as parameters or as an error term is not important for econometricians, but whether they decide to use it or not is. Therefore, this dissertation decided to use the FE model, and each link ID of the present study is regarded as individuals in the model. Because, the travel speed on each link is expected to be different due to unobserved variables on links and at intersections.

As that in Equation 4-2, the observed travel speed is considered as the dependent variable, and the other variables are included as independent variables for the FE model. Besides, the dataset has 18 links (individuals) and 923 hours (duration) information. The MLR model without a constant can be expressed by Equation 4-4. The independent variables of the turning rate and the intersection size were not included in the fallowing model. The reason is that the two variables are not time-variant variables, but time-invariant variables: the data was collected by traffic counts survey.

$$
\begin{aligned}
(Travel\ \ Speed)_{it} \quad & \qquad\qquad\qquad \textit{(4-4)}\\
&= (Temperature^2)_t\beta_1 + (Temperature)_t\beta_2 + (Snowfall)_t\beta_3\\
&+ (Deep\ \ snow)_{it}\beta_4 + (\#\ \ of\ \ fresh\ \ snow\ \ removal)_{it}\beta_5\\
&+ (Road\ \ widening)_{it}\beta_6 + (Fresh\ \ snow\ \ removal)_{it}\beta_7 + \mu_{it}\\
for\ \ i(link) &= N1, N2, \dots, S9, S10,\\
t(time) &= \textit{2013-D10-07, 2013-D10-08, 2013-D10-09, ..., 2014-F13-07,}\\
&\quad \textit{2014-F13-08, ..., 2014-M31-18, 2014-M31-19}
\end{aligned}
$$

where,

β_i is regression coefficients as the MLR model.

$(variable\ \ name)_{it}$ is the observed variables for the i link at the t time period.

μ_{it} is the error term for the i link at the t time period.

The FE model considers the section (individual) specific effects. Thus, the FE model can be provided as the extension of Equation 4-4 by Equation 4-5.

$$
\begin{aligned}
(Travel\ \ Speed)_{it} \quad & \qquad\qquad\qquad \textit{(4-5)}\\
&= (Temperature^2)_t\beta_1 + (Temperature)_t\beta_2 + (Snowfall)_t\beta_3\\
&+ (Deep\ \ snow)_{it}\beta_4 + (\#\ \ of\ \ fresh\ \ snow\ \ removal)_{it}\beta_5\\
&+ (Road\ \ widening)_{it}\beta_6 + (Fresh\ \ snow\ \ removal)_{it}\beta_7 + v_i + \varepsilon_{it}
\end{aligned}
$$

where, $\mu_{it} = v_i + \varepsilon_{it}$.

The error term (μ_{it}) of Equation 4-4 was disassembled into the unobserved time-invariant effects, which is replaced with the section specific effects (v_i), and the residuals (ε_{it}).

The independent variables in FE models explain part of the dependent variable. And the leftover variation of the dependent variable, which means the dependent variable (travel speed) cannot be explained by the independent variables on each link, is the section-specific effect estimate. In other words, the structure of the FE model is the same as the MLR model with individual dummy variables as intercept shifters. So, it is also called the least squares dummy-variable model (LDV).

As the MLR models, all links except the link N10 and S1 were analyzed by the FE model. The analysis results are shown in Table 4-2 and the section-specific effects are presented in Figure 4-3 and Table 4-3. The basic assumption of the FE model is the same as the MLR model, excluding multicollinearity: the panel model has less multicollinearity as mentioned above. All independent variables selected for the FE models were statistically significant at the 95% confidence level. The R-squared value of FE model was 0.51 and it means that it explains more than 50% of the dependent variable. The R-squared value of the FE model increased by 0.13 from the value of the MLR, though the FE model has less independent variables than the MLR model. This result is the FE model has captured the unobserved individual specific effects by intercept shifters. An example of the estimated travel speed on link N9 by the FE model and the MLR model were shown with the observed travel speed in Figure 4-4. In addition, the F-value from the F-test for verifying the linearity assumption was 1,422.8: thus, the developed FE model was statistically significant at the 0.05 significance level ($p<0.05$). In case of the Durbin-Watson statistic, it was larger than the MLR but the statistic (1.13) was still lower than 1.5. It indicates the residuals of the model were serially correlated each other. This indicates that the residuals of the model serially correlate with each other. In other words, the correlated residuals should be corrected to uncorrelated errors (white noise) as the residuals of the MLR. The method will be discussed in the next section.

The employed variables in the FE model were similar with the MLR result. However, all employed variables in the FE were intuitive unlike the MLR result. Though the number of fresh snow removal deployments variable was not selected in the model, the fresh snow removal and the road widening operations had positive relationships with the travel speed. Both the temperature and the temperature squared value correlated positively with the travel time. This means that the relationship between the temperature and the travel speed are U-shaped in the present study. According to the estimated section-specific effects, the southbound travel speeds were more explained by the independent variables of the FE model than the northbound travel speeds. In other word, there were more of unobserved variables on the northbound links than on the southbound links such as the time-of-day traffic patterns by directions.

Table 4-2 Result of the FE model

Variables	Estimate	t-value	p-value
Temperature^2 (°C^2)	0.01	6.02	0.00
Temperature (°C)	0.02	-2.95	0.03
Snowfall (cm)			
Deep snow (cm)	-0.13	-70.39	0.00
The number of fresh snow removal			
Road widening snow removal*	0.70	-3.23	0.00
Fresh Snow removal*	0.63	7.80	0.00
F-value (p-value)	1,422.8 (0.00)		
R-squared	0.51		
Durbin-Watson	1.13		

* indicator variables

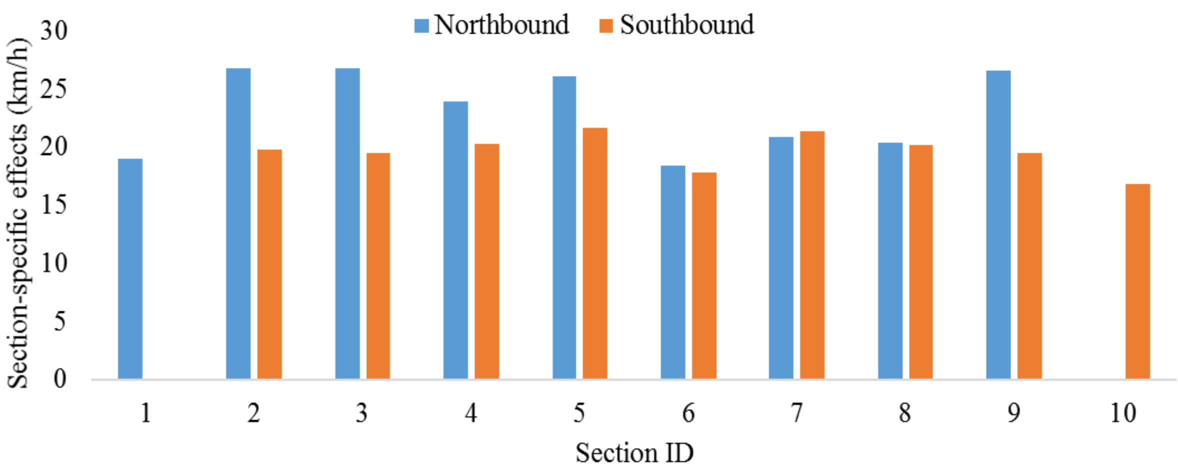


Figure 4-3 Section-specific effect estimates

Table 4-3 Section-specific effect estimates

Link ID (Northbound)	Estimate	Std. Error	t-value	Link ID (Southbound)	Estimate	Std. Error	t-value
N1	19.02	0.18	106.87	S1		-	
N2	26.73	0.15	179.75	S2	19.74	0.15	132.28
N3	26.81	0.15	180.21	S3	19.52	0.15	130.99
N4	23.92	0.15	160.77	S4	20.25	0.15	134.71
N5	26.05	0.15	173.42	S5	21.69	0.15	144.20
N6	18.38	0.15	122.39	S6	17.82	0.15	118.15
N7	20.86	0.15	138.47	S7	21.32	0.15	141.52
N8	20.38	0.15	135.22	S8	20.21	0.15	134.09
N9	26.61	0.15	176.50	S9	19.53	0.15	129.57
N10		-		S10	16.86	0.15	17.65

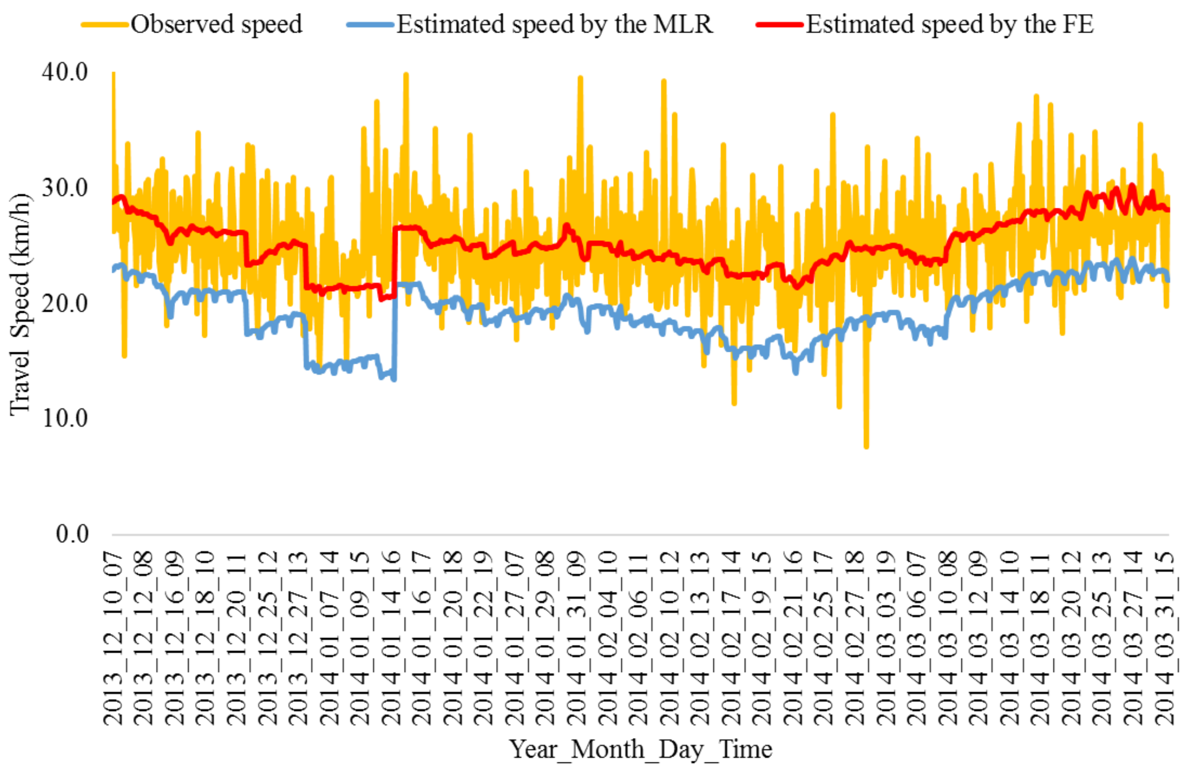


Figure 4-4 Comparison of the estimated travels speed by the FE and the MLR (Link N9)

4.3 REGRESSIONS WITH ARIMA ERRORS (RegARIMA)

According to the results the MLR model and the FE model, the residuals of the models are serially correlated each other. However, it violated the no autocorrelation assumption of regressions: the residuals of the regression model should be uncorrelated with other residuals. The autocorrelated residuals will probably include more information which could be not explained by the regression models[27]. Hence, the autocorrelated residuals should be extracted to transform them into the white noise with mean zero and variance, σ^2. Though there are several methods to correct the correlated residuals, this dissertation used the autoregressive integrated moving average (ARIMA) model to correct correlated errors. Some researchers have used this method which called the linear regression model with ARIMA (RegARIMA) model [27], [35], [64], [65]. The RegARIMA consists of two parts: the regression part and the ARIMA part. The basic steps are shown in Figure 4-5.

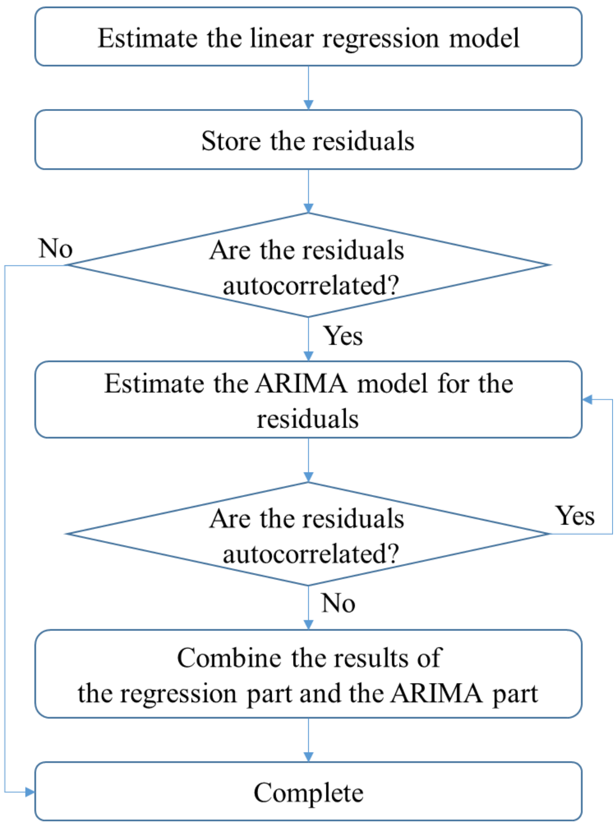


Figure 4-5 The steps for the RegARIMA

4.3.1 Autoregressive Integrated Moving Average (ARIMA)

The ARIMA model is a general model for forecasting a time series, and it assumes that future values can be explained through the values of several past observations and random errors. It gives higher weight to the recent past than to the distant past, so the model is suitable for predicting short-term values in the time-series[66]. The ARIMA model is employed in various fields for forecasting time series, but the general ARIMA model is hard to apply some time series that are periodic or seasonal. The seasonal ARIMA model could be applied instead of the general ARIMA model to overcome the periodic limitation. The seasonal ARIMA model can describe future values not only concerning recent past trend but also concerning periodic trend. For example, the road tends to be crowded with commuters at morning and evening peak times on weekdays, and this occurs periodically.

Section 4.1 and 4.2 revealed that the developed models of MLR and FE have an autocorrelation problem. It can be presented as Equation 4-6. The developed two regression models, the MLR and the FE allow the estimated travel speed to differ from link to link, so the residuals can be different across links. ARIMA models account for the residuals on each link. An ARIMA model is a general model for forecasting a time series, and a seasonal ARIMA model that is an expanded ARIMA model can be applied for periodic or seasonal time series.

$$(Travel\ \ speed)_{it} = \ \ \alpha + \beta(Independent\ \ variables)_{it} + \mu_{it} \tag{4-6}$$
$$\mu_{it} = (ARIMA\ \ model) + \varepsilon_{it}$$

where,

μ_{it} is the autocorrelated residuals of the regression models: the MLR and the FE models

(hereinafter referred to as “unexplained travel speed” at the section 4.3.1)

ε_{it} is a serially independent error which cannot be estimated by the ARIMA model.

Now, the new error term is a white noise. In other words, the "unexplained travel speed" (μ_t) can be predicted by the ARIMA model. The equation of the ARIMA (p, d, q) model for the "unexplained travel speed" (μ_t) can be written as follow:

$$\emptyset_p(B)(1-B)^d \mu_t = \theta_q(B)\varepsilon_t \tag{4-7}$$

where,

d is the number of non-seasonal differences.

$\emptyset_p(\mathrm{B})$ represents a stationary autoregressive (AR) operator of order p.

It can be expressed by $\emptyset_p(\mathrm{B}) = 1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p$,

$\theta_q(B)$ is a moving average (MA) operator of order q.

It can be expressed by $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$.

μ_t is the "unexplained travel speed" of Equation 4-7.

ε_t is a new error term which is independent each other.

B is a backshift operator.

It is a useful notation for time series lags: for example, $B^k \mathrm{y}_t = y_{t-k}$.

As mentioned above, the traffic patterns are periodic. Thus the seasonal ARIMA should be considered and the seasonal ARIMA model (ARIMA$(p, d, q)(P, D, Q)_s$) can be expressed by Equation 4-8.

$$\phi_p(B)(1-B)^d \Phi_P(B^s)(1-B^s)^D \mu_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \tag{4-8}$$

where,

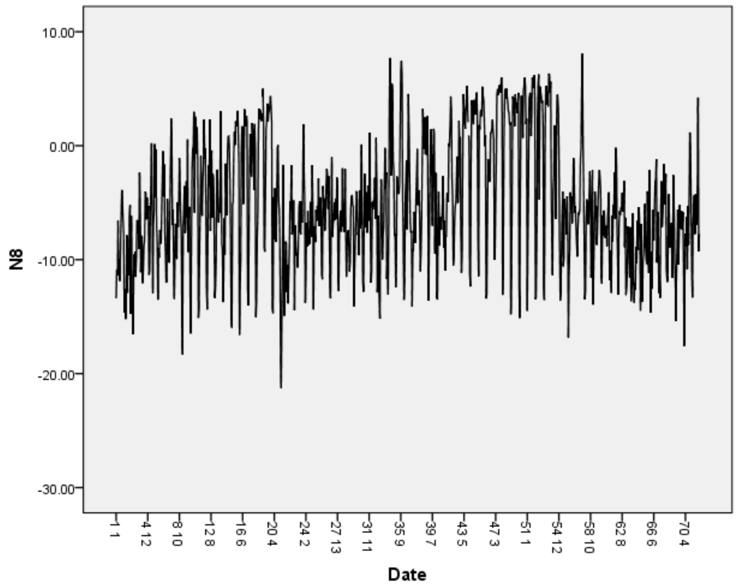
D is the number of seasonal differences.

$\Phi_P(B^s)$ and $\Theta_Q(B^s)$ express seasonal AR operator of order P and seasonal MA operator of order Q respectively.

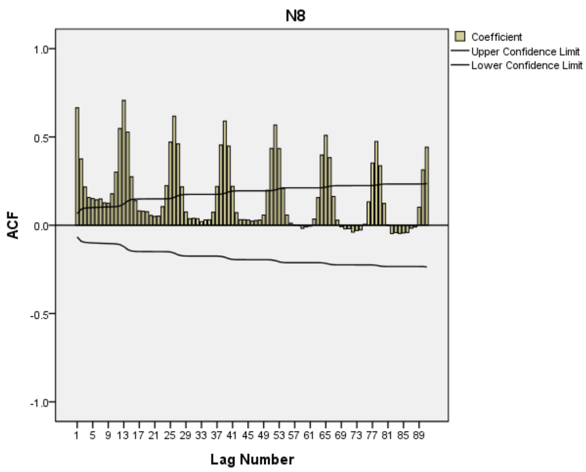
S is the length of a cycle.

A periodic cycle defined as 13 hours in the present study (from 7 am to 8 pm).

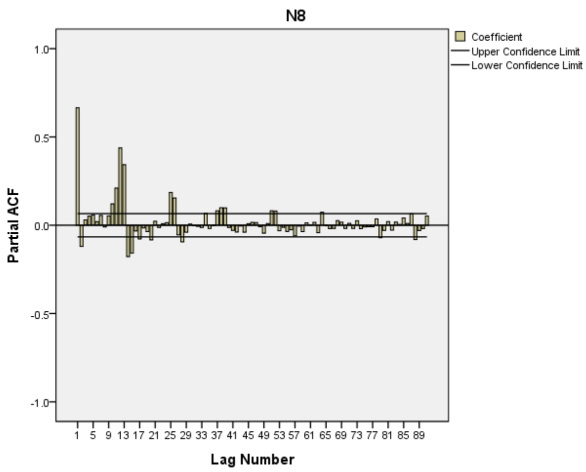
This dissertation illustrates the ARIMA model estimation process using the unexplained travel speed by the MLR of link N8. To analysis the seasonal ARIMA models, the data to be predicted should be stationary time series which has constant mean, variance, and autocorrelation over time. It can be checked by time series plot in Figure 4-6(a). The mean of time series plot fluctuated over time: nonstationary. Figure 4-6(b) and (d) represents the plot of the autocorrelation function (ACF) the seasonal ACF respectively, and Figure 4-6(c) and (e) are the partial autocorrelation function (PACF) and the seasonal PACF. Both the ACF and the PACF explains the correlation between current value and past value, and they show which past value should be considered in estimating the ARIMA model. As shown the ACF and the PACF in Figure 4-6, spikes can be found at the seasonal lags: 13^{th}, 26^{th}, 39^{th}, …$13n^{th}$. Hence, a seasonal difference was taken, and the results are presented in Figure 4-7 (ARIMA$(0,0,0)(0,1,0)_{13}$). In Figure 4-7(a), the time series plot looks still non-stationary thus an additional first difference was taken. After first and seasonal differencing, the time series plot was turned into stationary as Figure 4-8 (ARIMA$(0,1,0)(0,1,0)_{13}$). At lag 1 of Figure 4-8(b) and season lag 1, the spikes were protruding above the line of 95% confidence level. Consequently, the ARIMA$(0,1,1)(0,1,1)_{13}$ was considered.



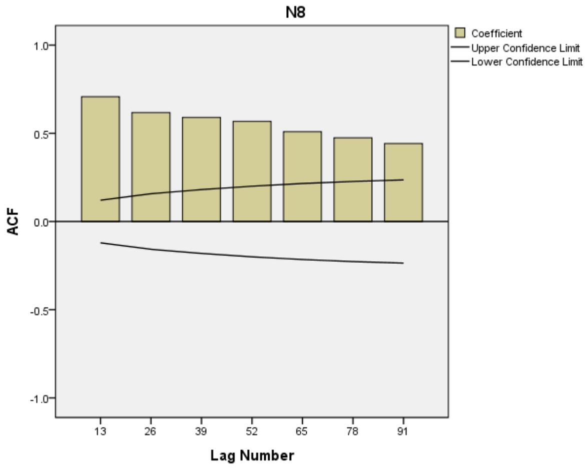
(a) time series plot for residuals



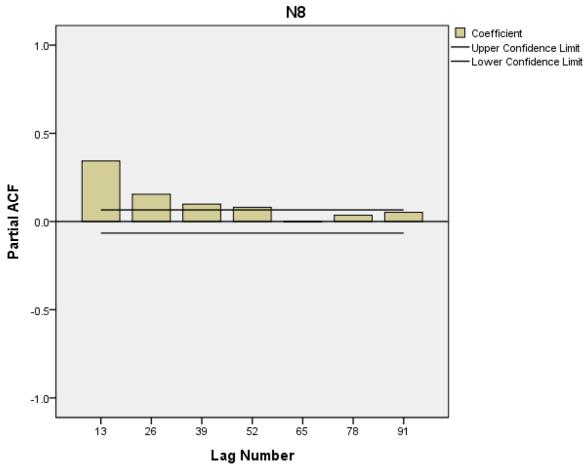
(b) ACF



(c) PACF

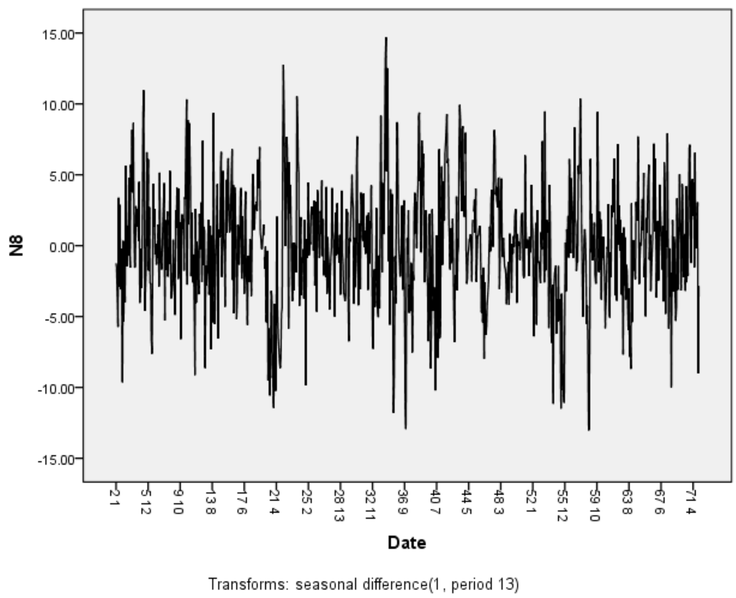


(d) seasonal ACF

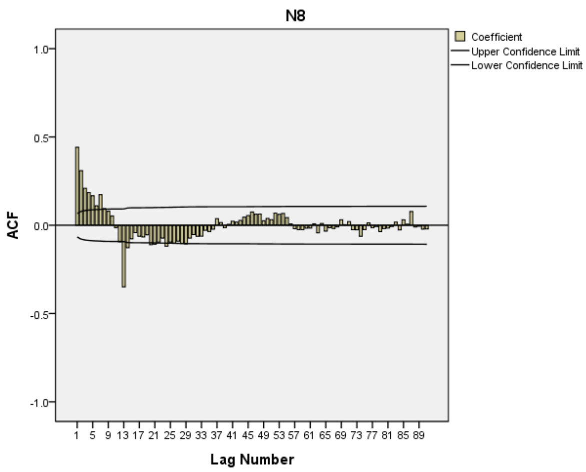


(e) seasonal PACF

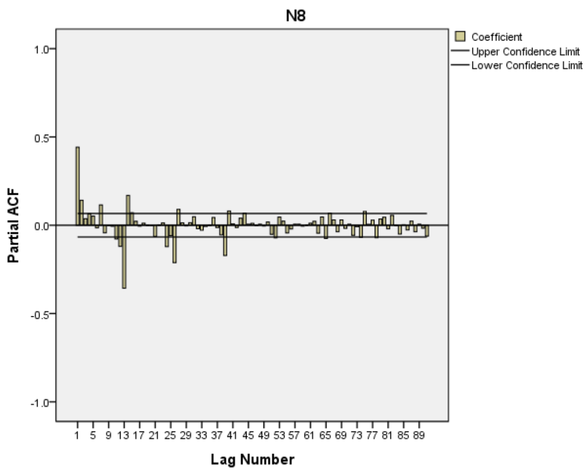
Figure 4-6 The residuals between observed and estimated by MLR on Link N8 (ARIMA(0,0,0)(0,0,0)$_{13}$)



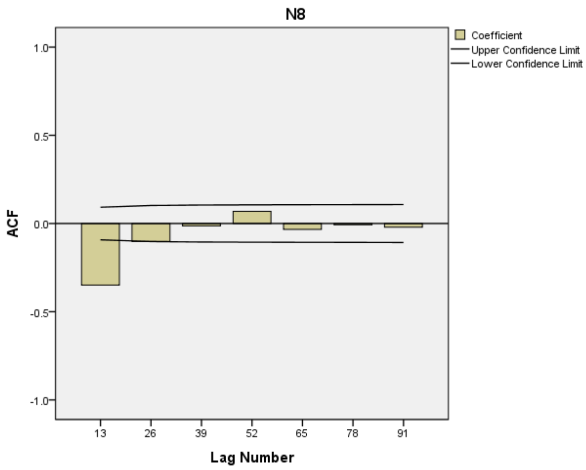
(a) time series plot for residuals



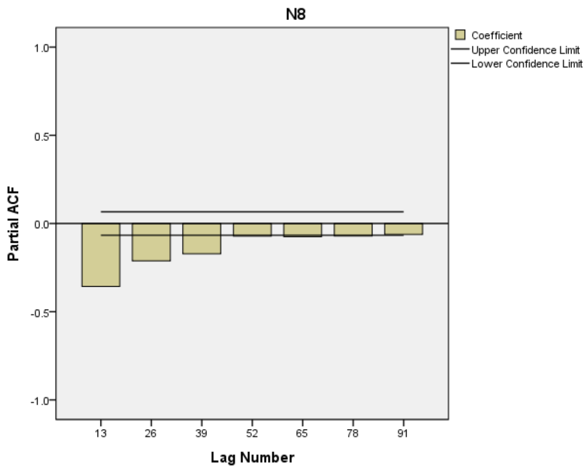
(b) ACF



(c) PACF

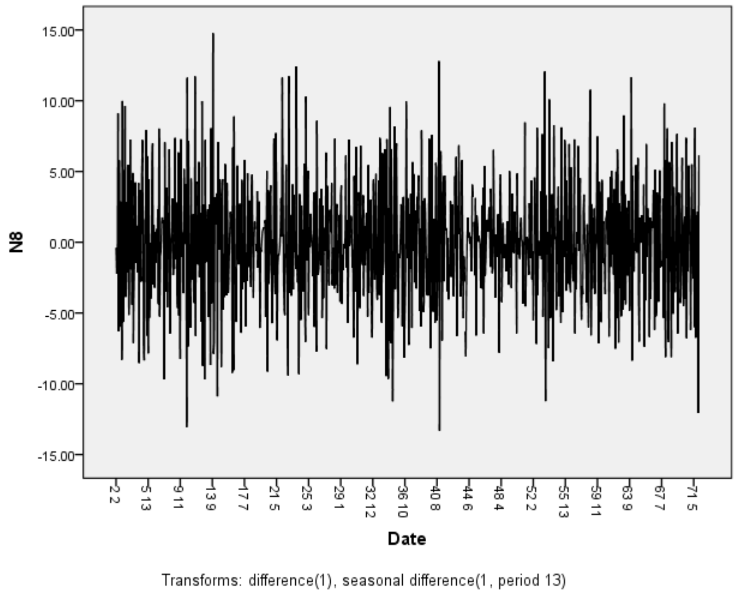


(d) seasonal ACF

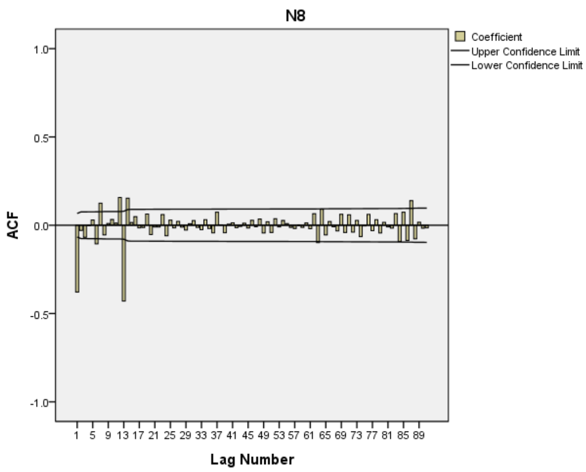


(e) seasonal PACF

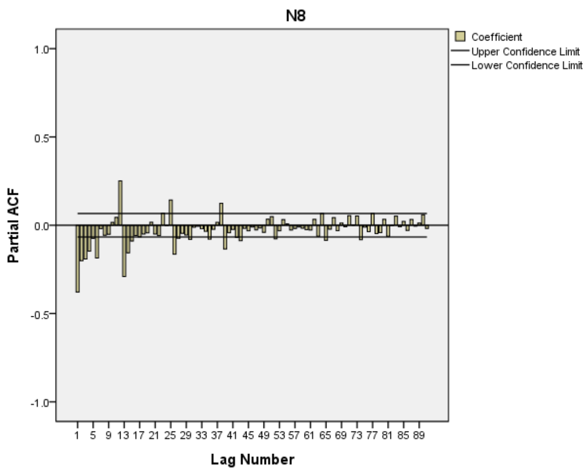
Figure 4-7 The seasonal difference on Link N8 (ARIMA(0,0,0)(0,1,0)$_{13}$)



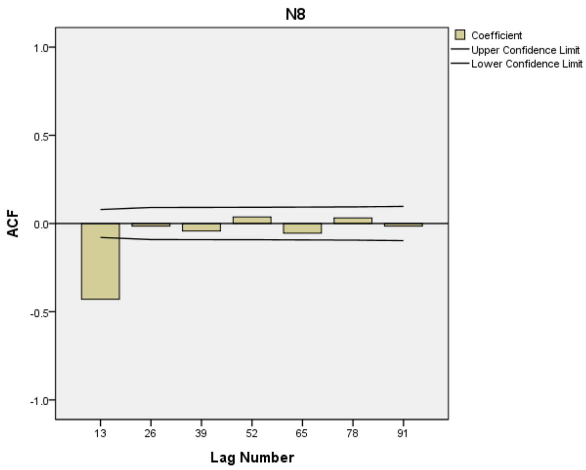
(a) time series plot for residuals



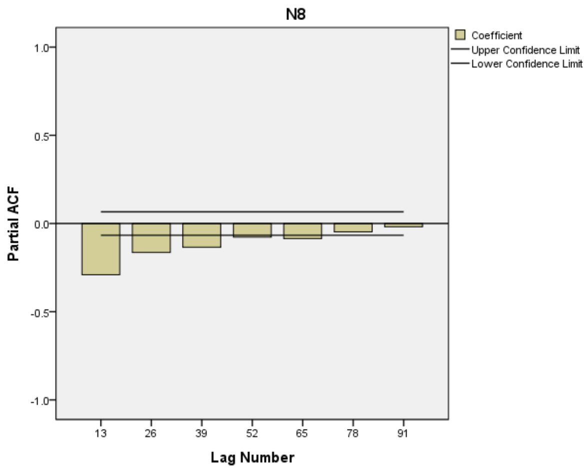
(b)



(c)



(d)



(e)

Figure 4-8 The first difference of seasonal difference on Link N8 (ARIMA(0,1,0)(0,1,0)$_{13}$)

The residuals in ARIMA models should be not correlated each other: white noise, independent identically distributed. However, the residuals of the ARIMA$(0,1,1)(0,1,1)_{13}$ analysis were correlated with the past errors especially at lag 1 according to the residual ACF and residual PACF in Figure 4-9. The spike at lag 1 in the residual PACF suggests AR(1) component, so the ARIMA$(1,1,1)(0,1,1)_{13}$ was analyzed. In Figure 4-10, no more spikes were found in both the residual ACF and residuals PACF. Therefore, ARIMA$(1,1,1)(0,1,1)_{13}$ was selected to predicted the future values. The statistics for the significant test of the considered ARIMA models, ARIMA$(0,1,1)(0,1,1)_{13}$ and ARIMA$(1,1,1)(0,1,1)_{13}$, are presented in Table 4-4.

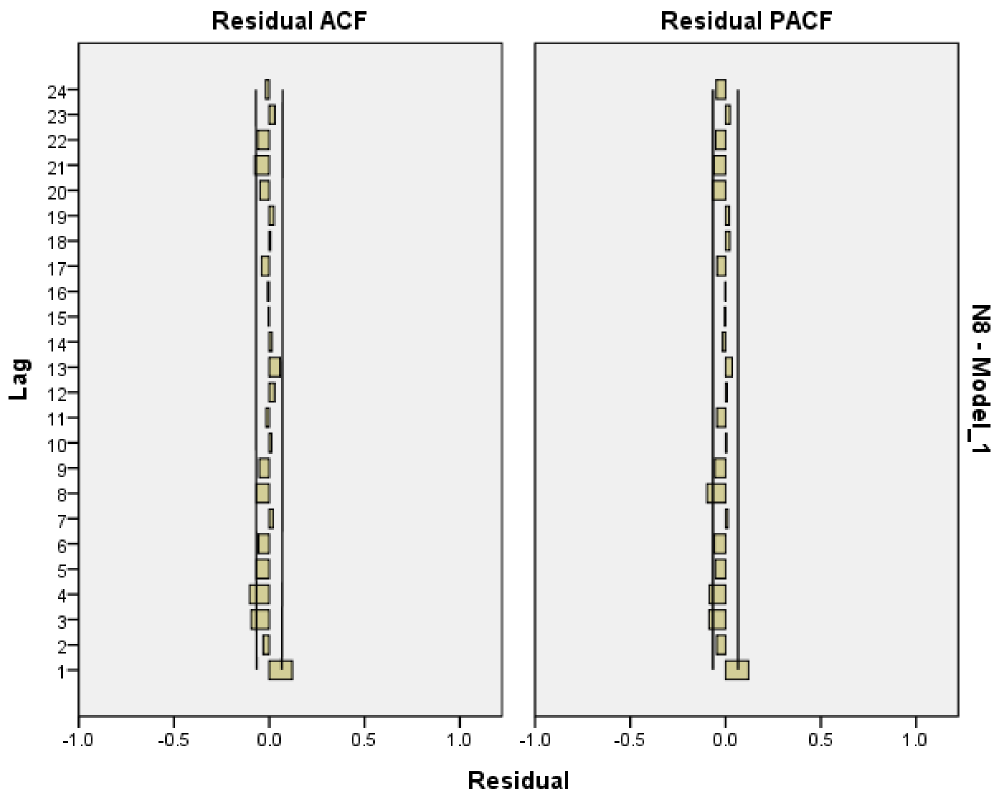


Figure 4-9 Residual ACF and PACF of ARIMA$(0,1,1)(0,1,1)_{13}$

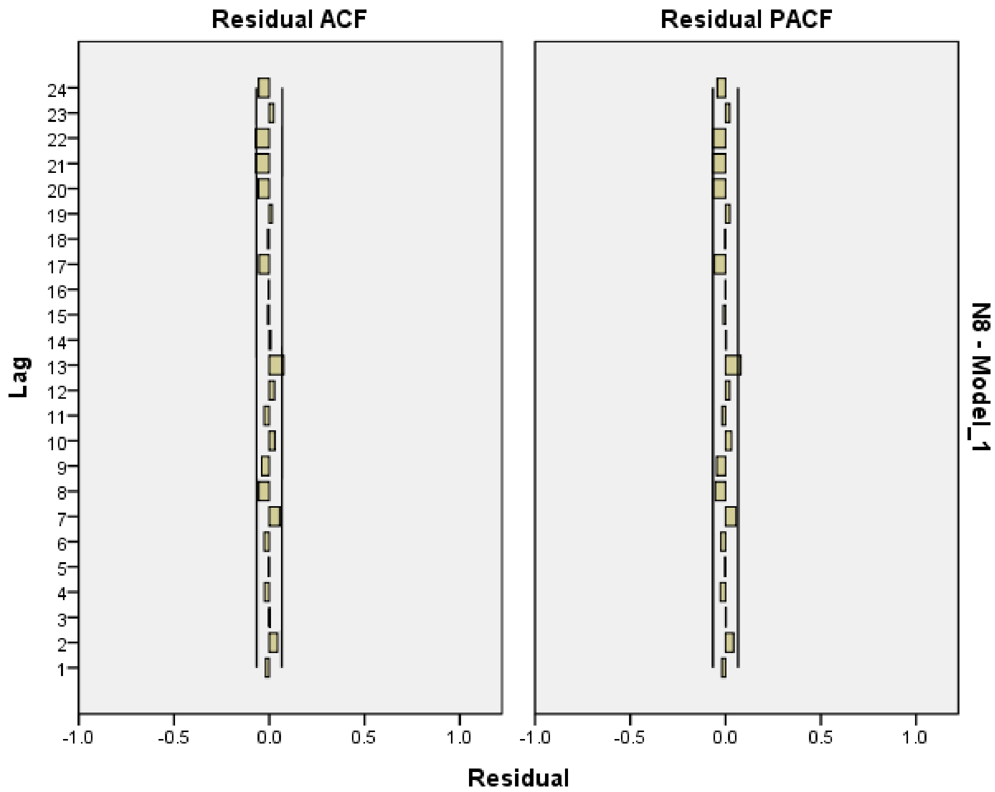


Figure 4-10 Residual ACF and PACF of ARIMA(1,1,1)(0,1,1)$_{13}$

Table 4-4 The results of the seasonal ARIMA model for the residuals from the MLR (Link N8)

Model	Model Fit Statistics	Ljung-Box Q		
	Stationary R^2	Statistics	DF	Sig.
ARIMA(0,1,1)(0,1,1)$_{13}$	0.471	52.180	16	0.000
ARIMA(1,1,1)(0,1,1)$_{13}$	0.493	20.644	15	0.149

In Table 4-4, the R-squared value and the results of Ljung-Box test were shown. The R-squared value means the same as other statistical models, it describes how well the data are explained by the model. The Ljung-Box statistics is a statistical test whether the correlation coefficient among the errors are different from zero or not. The null hypothesis (H_0) of this test is that the errors are independently distributed. According to the results of Ljung-Box test in Table 4-3, the model of ARIMA(0,1,1)(0,1,1)$_{13}$ was rejected the alternative hypothesis and accepted null hypothesis, it means the residuals of the model are autocorrelated. In case of ARIMA(1,1,1)(0,1,1)$_{13}$ model, the residuals were independent and the R-squared value was higher than ARIMA(0,1,1)(0,1,1)$_{13}$ model. Ultimately, the ARIMA(1,1,1)(0,1,1)$_{13}$ model was selected to estimate the unexplained travel speed by the MLR models on link N8. The predicted unexplained travel speed is shown in Figure 4-11.

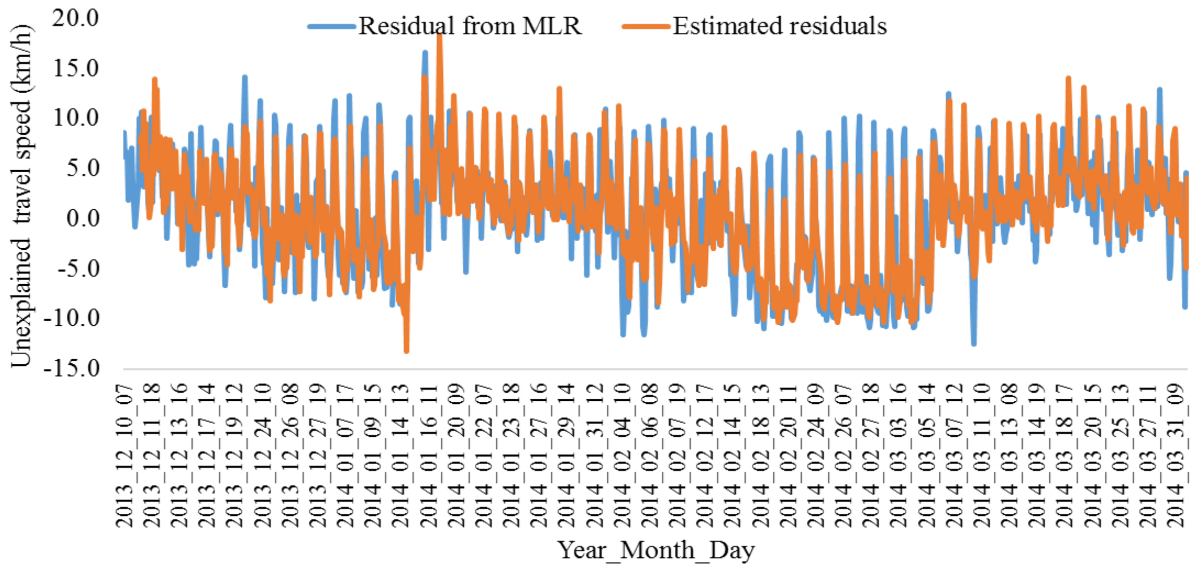


Figure 4-11 Actual and estimated “unexplained travel speed” by ARIMA(1,1,1)(1,1,1)$_{13}$ (Link: N8)

Using the same method as above, the unexplained travel speeds of other links were analyzed and the results were presented in Table 4-5. The R-squared values of the ARIMA models for the unexplained travel speeds by FE models were slightly higher than the ARIMA models for the unexplained travel speeds by MLR models on most of links.

Table 4-5 The results of the ARIMA model for the residuals from the regressions

Link ID	ARIMA	Stationary R^2		Sig. of Ljung-Box Q	
		MLR error	FE error	MLR error	FE error
N1	ARIMA $(0,1,2)(0,1,1)_{13}$	0.653	0.659	0.227	0.255
N2	ARIMA $(2,1,1)(0,1,1)_{13}$	0.656	-	0.578	-
	ARIMA $(1,1,2)(0,1,1)_{13}$	-	0.658	-	0.389
N3	ARIMA $(0,1,2)(0,1,1)_{13}$	0.664	0.664	0.169	0.155
N4	ARIMA $(2,1,1)(0,1,1)_{13}$	0.649	0.650	0.615	0.555
N5	ARIMA $(0,1,2)(0,1,1)_{13}$	0.644	0.644	0.648	0.666
N6	ARIMA $(5,1,4)(0,1,1)_{13}$	0.622	0.623	0.352	0.371
N7	ARIMA $(4,1,2)(0,1,1)_{13}$	0.613	0.612	0.108	0.109
N8	ARIMA $(1,1,1)(0,1,1)_{13}$	0.493	0.493	0.149	0.187
N9	ARIMA $(1,1,1)(0,1,1)_{13}$	0.684	0.687	0.789	0.793
S2	ARIMA $(1,1,2)(0,1,1)_{13}$	0.581	0.583	0.075	0.069
S3	ARIMA $(14,1,2)(0,1,1)_{13}$	0.624	0.627	0.371	0.335
S4	ARIMA $(12,1,1)(1,1,1)_{13}$	0.614	0.616	0.480	0.498
S5	ARIMA $(2,1,1)(1,1,1)_{13}$	0.534	0.534	0.824	0.810
S6	ARIMA $(12,0,7)(0,1,1)_{13}$	0.420	0.428	0.073	0.086
S7	ARIMA $(5,1,1)(0,1,1)_{13}$	0.632	0.631	0.506	0.534
S8	ARIMA $(1,1,2)(0,1,1)_{13}$	0.608	0.611	0.220	0.300
S9	ARIMA $(5,1,6)(0,1,1)_{13}$	0.698	0.459	0.575	0.679
S10	ARIMA $(0,1,1)(0,1,1)_{13}$	0.716	0.720	0.379	0.388

4.3.2 Combining Two Models: Regression Model and ARIMA Model

In section 4.1 and 4.2, the travel speed was estimated by MLR and FE models. And in section 4.3, the residuals (unexplained travel speed) of MLR and FE models was estimated by ARIMA models. In this section, the results of the estimated travel speed and residuals were combined to get more accurate estimate travel speed (RegARIMA model). The predictive abilities of two RegARIMA models (MLR+ARIMA and FE+ARIMA) were also compared to find which combined model is more accurate. The predictive accuracies of the two models were compared in terms of the R-squared value, the mean absolute error (MAE), and the mean absolute percentage error (MAPE). The smaller the MAE and the MAPE, the better the predictive ability, while the larger the R-squared value, the better the predictive ability. The equation of the R-squared is the same as Equation 4-1, and the others are as follows (Equation 4-9 and 4-10):

$$MAE = \frac{1}{n}\sum_{i}^{n}\left|Y_i - \widehat{Y_i}\right| \ , \tag{4-9}$$

$$MAPE(\%) = \frac{1}{n}\sum_{i}^{n}\left|\frac{Y_i - \widehat{Y_i}}{Y_i}\right| \ \times 100 \tag{4-10}$$

Where,

n is the number of observations.

Y_i is the observed value at i.

$\hat{Y}_i$ is the predicted value at i.

The measures of the RegARIMA models were presented in Table 4-6. According to the results, the R-squared value of the FE+ARIMA model was increased from the FE model (Table 4-2) by estimating the residuals. On the other hand, the R-squared value of the MLR+ARIMA model was slightly decreased from the MLR model (Table 4-1). In addition, the MAE and the MAPE of the FE+ARIMA model had higher values than the MLR+ARIMA. It might be because that the MLR model expressed a line for 18 links in the present study, while the FE model had multiple lines for each links by the individual specific effects. In other words, the residuals of the FE model were relatively stable regardless of links, and the residuals of the MLR model were disorderly. Furthermore, even though the number of independent variables of the FE+ARIMA were less than the MLR with ARIMA, the accuracies of the FE+ARIMA model were larger: the turning rates at intersections and the intersection size were not included in the FE model. According to the MAPE of the model, the model has around 80% accuracy, and the model has around 3.3 km/h error on average on the study area. Finally, the MLR showed the counterintuitive result in Table 4-1, and the FE result was intuitive. Therefore, the FE+ARIMA model was selected appropriate model in this dissertation. The R-squared value was 0.725, it represents that the model can explain 72.5% of the dependent variable. An example of the estimated travel speed plots on link N9 were presented in Figure 4-12. As shown in Figure 4-12, the accuracy of estimated speed by the RegARIMA model, which was combined of the FE model and the ARIMA, was much higher than the FE model.

Table 4-6 Comparison of the MLR with ARIMA model and the FE with ARIMA model

Link ID	MAE		MAPE		R-squared	
	MLR with ARIMA	FE with ARIMA	MLR with ARIMA	FE with ARIMA	MLR with ARIMA	FE with ARIMA
N1	7.126	3.521	64.39%	30.92%	0.525	0.911
N2	11.749	2.950	47.22%	12.57%	0.276	0.779
N3	14.434	3.831	58.15%	17.03%	0.302	0.609
N4	12.394	2.868	56.92%	14.56%	0.405	0.570
N5	10.655	3.256	41.96%	15.18%	0.228	0.744
N6	4.337	2.687	32.19%	19.65%	0.327	0.804
N7	3.849	2.739	24.42%	17.83%	0.343	0.502
N8	12.159	4.214	64.05%	32.42%	0.417	0.800
N9	12.686	3.121	49.86%	12.97%	0.259	0.720
S2	6.018	3.749	49.29%	36.14%	0.445	0.813
S3	5.423	3.255	40.21%	23.67%	0.324	0.611
S4	6.169	2.880	34.77%	21.18%	0.552	0.708
S5	6.552	3.010	41.06%	25.61%	0.359	0.751
S6	4.497	4.457	26.04%	21.85%	0.180	0.793
S7	3.599	3.871	24.89%	30.61%	0.533	0.794
S8	2.903	1.971	15.84%	10.46%	0.453	0.690
S9	7.860	3.233	41.11%	20.79%	0.455	0.589
S10	4.475	3.052	28.41%	17.64%	0.389	0.354
total	7.607	3.259	41.15%	21.16%	0.367	0.725

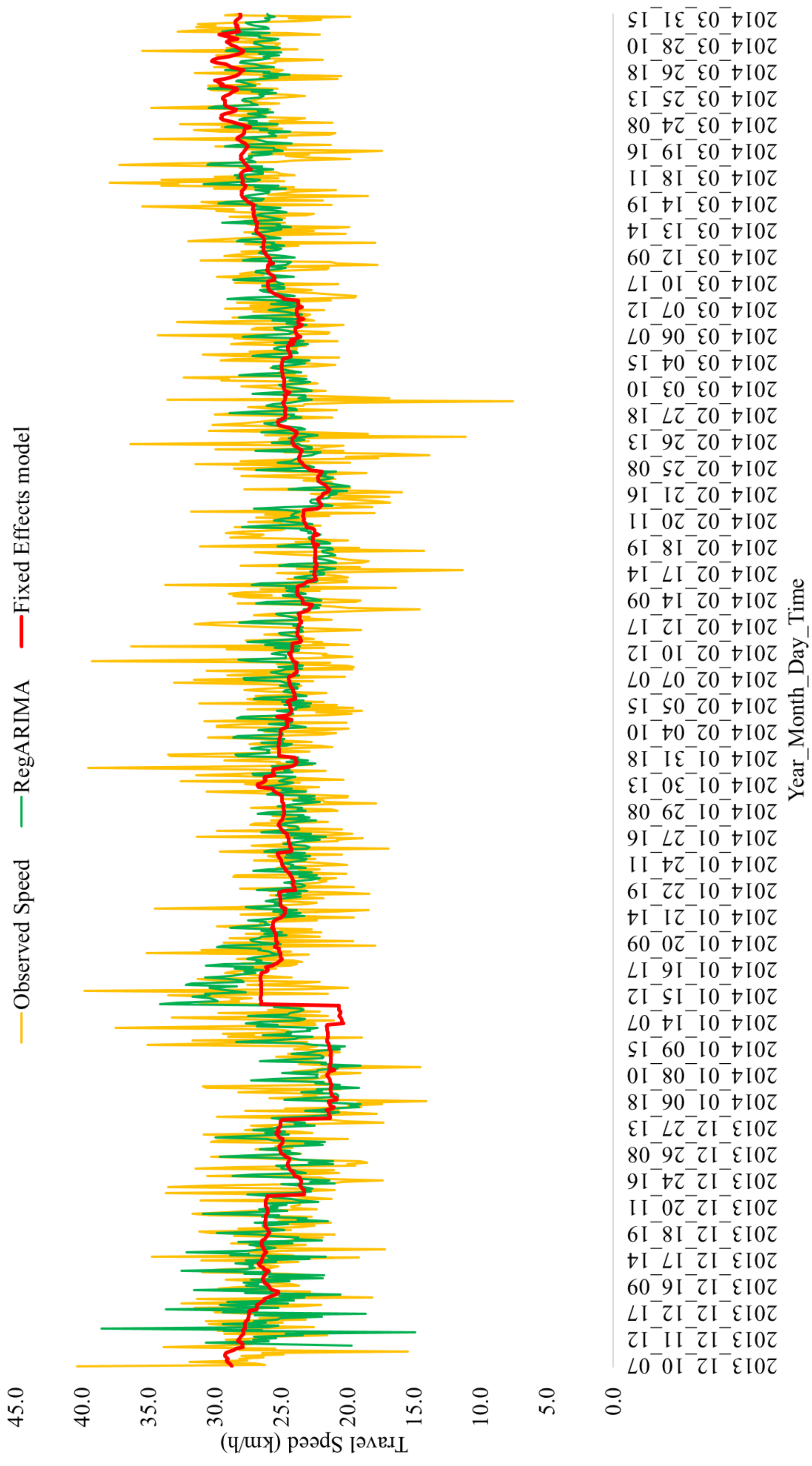


Figure 4-12 Estimated speeds by the FE model and the RegARIMA model (FE with ARIMA) (link: N9)

5 EFFECTIVENESS OF THE REGARIMA IN WINTER

The present study developed the RegARIMA models to predict the travel speed in winter on urban arterials. The developed model showed around 80 percent predictive accuracy of the observed travel speed using in-sample of data. Then, the model validation process is necessary using out-of-sample of data in order to see how the model can forecast well in winter. And it should to be checked whether the predicted results using out-of-sample of data have similar predictive accuracy with the results using in-sample of data or not. Since the present study is related to snow in winter, the two periods were used for the model validation according to the weather conditions: non-snow day (section 5.1) and snow day (section 5.2). The FE with ARIMA model was used as a RegARIMA model for model validation in this chapter. Furthermore, the travel speed predicted by the RegARIMA under two different weather conditions was compared with the univariate ARIMA results, which has only the observed travel speed data as a variable, to investigate the effectiveness of the model in winter.

5.1 NON-SNOW CONDITIONS

The travel speed for the three weekdays which are March 25, 26, and 27 of 2014 was predicted by both the univariate ARIMA model and the RegARIMA model in order to compare the performance of the models under non-snow conditions. The weather of this period had no precipitation, and the travel speed of these days were predicted by the data until the day before, and the MAE and the MAPE are shown in Table 5-1.

According to Table 5-1, the predictive accuracy of the RegARIMA was around 88.7% and of the univariate ARIMA was around 88.4% on non-snow days. Although the accuracy of the RegARIMA model was not so different with the univariate ARIMA model. In other words, the two models are acceptable for forecasting the travel speed in non-snow conditions. The error rates were relatively high in the southern sections on both directions of the study area: the section 1, 2, and 3 (link N1, N2, N3, S2, and S3 in Table 5-1). This is because that the traffic pattern in this area was quite different with other area due to the traffic control system and the geometric designs. For example, the turning right is prohibited at the intersection 1 (see Figure 3-1 and 3-2), and Hokkaido University adjoins the west side of the intersection 2 and 3. It means that the vehicles turning left for northbound and the vehicles turning right for southbound are limited at these intersections, so the turning rates for the university are very low.

Table 5-1 The MAE and the MAPE of forecasted travel speeds on non-snow days

Link ID	MAE		MAPE	
	ARIMA	RegARIMA	ARIMA	RegARIMA
N1	2.554	2.438	18.1%	20.1%
N2	2.375	2.481	8.9%	9.6%
N3	4.435	4.791	17.6%	19.8%
N4	2.129	2.283	9.4%	10.5%
N5	2.983	2.967	10.5%	10.5%
N6	1.498	1.651	6.7%	7.4%
N7	1.887	1.951	8.4%	8.7%
N8	2.075	2.189	8.3%	8.7%
N9	2.187	2.268	8.3%	8.6%
S2	3.756	1.817	22.5%	12.0%
S3	3.558	2.743	21.9%	18.9%
S4	2.153	1.947	9.3%	8.8%
S5	1.596	1.600	6.6%	6.7%
S6	2.799	2.721	10.9%	10.0%
S7	2.346	2.351	10.8%	11.2%
S8	1.283	1.227	5.5%	5.3%
S9	1.977	2.017	8.6%	8.9%
S10	2.705	2.772	16.7%	17.5%
Total	2.461	2.345	11.6%	11.3%

5.2 SNOW WEATHER CONDITIONS

The travel speed for another three weekdays which are February 13, 14, and 17 of 2014 was predicted by both the univariate ARIMA model and the RegARIMA model in order to compare the performance of the models under snow conditions. During the snow period, around 20 cm of snow fell in Sapporo. The amount of hourly falling snow during the period is shown as Figure 5-1. The predictive accuracies of the two models were compared in terms of the MAPEs and the MAEs using the out-of-sample data, and the results are presented in Table 5-2.

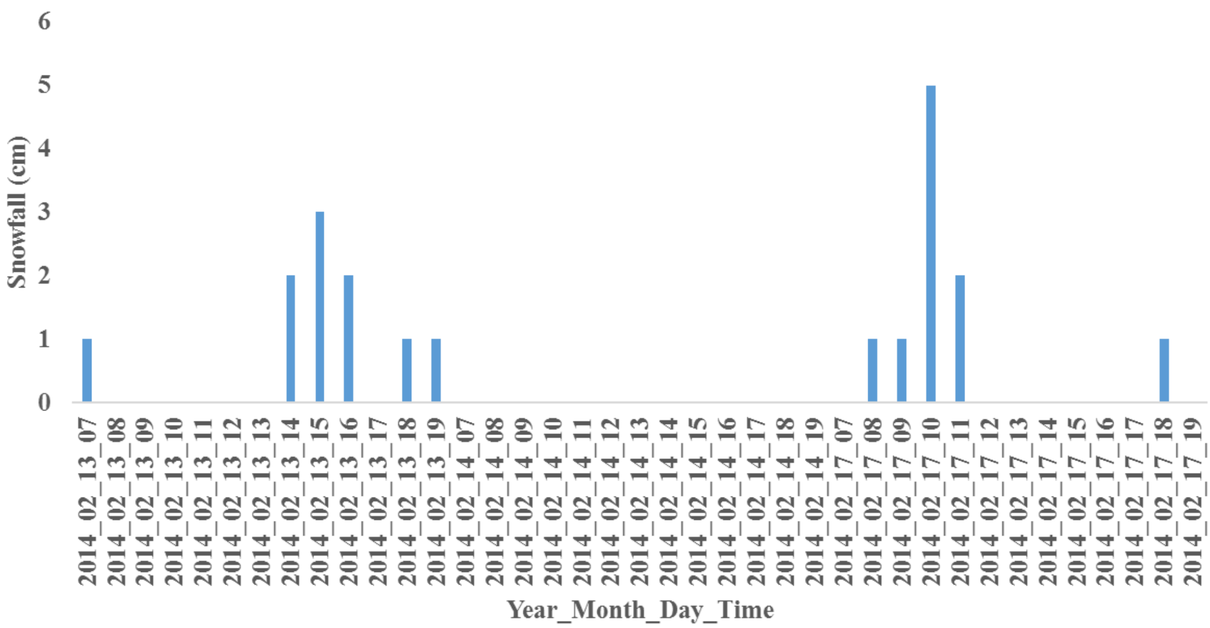


Figure 5-1 Snowfall from Feb. 13th to 17th, 2014 in Sapporo

According to Table 5-2, the predictive accuracy of the univariate ARIMA was about 82.1% and of the RegARIMA was about 84.1% under snow conditions. Although the predictive accuracy of the RegARIMA model under snow weather conditions was reduced by 4.6% compared to non-snow weather conditions, the difference in accuracy between the univariate ARIMA and the RegARIMA was increased. In other words, the RegARIMA model is more appropriate than the univariate ARIMA model regardless of snow weather conditions. The reason is that the univariate ARIMA model only considered its own previous data, but the RegARIMA included other external information of weather conditions and snow removal operations.

Table 5-2 The MAE and the MAPE for the forecasted travel speeds by links on snow days

Link ID	MAE		MAPE	
	ARIMA	RegARIMA	ARIMA	RegARIMA
N1	1.89	1.97	19.7%	20.0%
N2	2.39	2.06	10.9%	9.2%
N3	4.04	3.45	20.4%	17.0%
N4	2.89	2.43	14.6%	11.4%
N5	3.82	3.66	20.2%	18.3%
N6	3.22	2.31	21.3%	15.2%
N7	2.70	1.99	18.3%	13.0%
N8	2.80	3.26	20.9%	21.5%
N9	3.53	3.12	18.5%	16.2%
S2	2.45	2.83	20.6%	22.5%
S3	2.26	1.97	14.0%	11.9%
S4	3.20	2.51	23.6%	18.0%
S5	3.12	2.63	20.4%	17.0%
S6	2.61	2.22	16.2%	13.5%
S7	2.08	1.97	18.5%	17.6%
S8	1.54	1.31	9.2%	7.7%
S9	3.39	3.79	21.8%	22.4%
S10	2.23	2.47	13.0%	14.0%
Total	2.79	2.55	17.9%	15.9%

Table 5-3 shows how the predictive accuracy of the two models changes over time under different weather conditions. The results show that the predictive accuracy regardless of weather conditions was changed over time in both models: the univariate ARIMA and the RegARIMA. When focusing on the predictive accuracy over time, the difference in the accuracy between the two models increased substantially under snowy condition. In other words, the predictive accuracy of ARIMA decreased over time under snow conditions, while the RegARIMA was relatively stable over time regardless of weather. As mentioned above, it is because of the difference in the employed variables in the models. In other words, the travel speed estimation model in winter should consider not only the past observations but also other external factors to obtain more accurate results. A sample speed profile from February 10 to February 20 of 2014 on link S7 was shown in Figure 5-2. As shown in Figure 5-2, the gap between the ARIMA and the RegARIMA is getting wider after snowing over time.

Table 5-3 Changes in the MAE and the MAPE of forecasted travel speeds over time

Weather	Predicted day	MAE			MAPE		
		ARIMA	RegARIMA	Difference	ARIMA	RegARIMA	Difference
Non-Snow	1st day	2.34	2.37	-0.03	11.8%	12.2%	-0.4%
	2nd day	2.51	2.40	0.11	11.9%	11.5%	0.4%
	3rd day	2.53	2.27	0.26	11.2%	10.2%	1.0%
Snow	1st day	2.62	2.81	-0.19	14.3%	14.9%	-0.6%
	2nd day	2.59	2.42	0.17	17.5%	16.5%	1.0%
	3rd day	3.15	2.43	0.72	21.8%	16.4%	5.4%

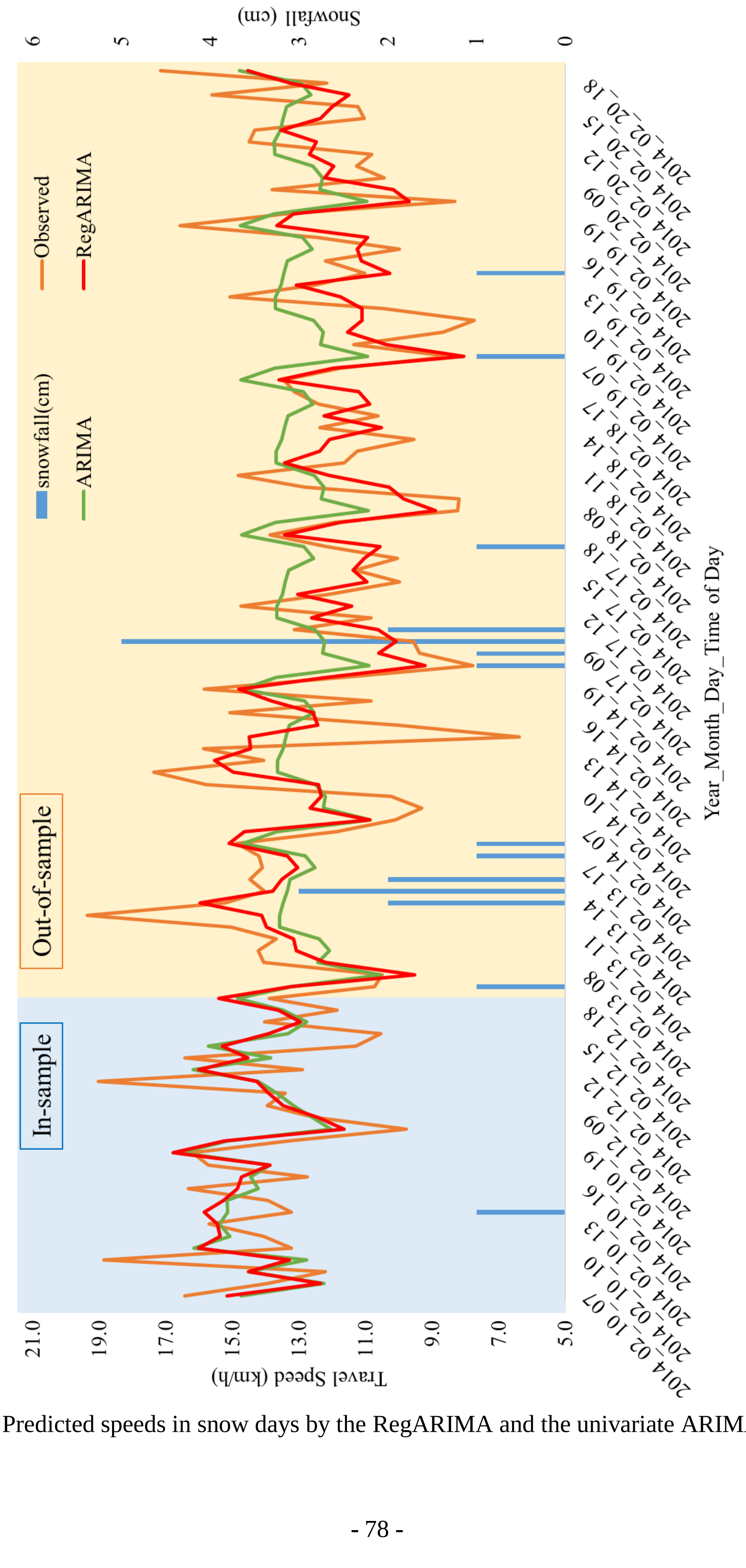


Figure 5-2 Predicted speeds in snow days by the RegARIMA and the univariate ARIMA (link: S7)

6 ESTIMATION OF THE EFFECTS OF SNOW REMOVAL OPERATIONS

This chapter presents a methodology for quantifying the effects of the snow removal operations. The effects of snow removal operations were represented as the travel time reduction afforded by such operations. The predicted travel time can be derived from the predicted travel speed and the link length on each link. Chapter 5 confirmed that the developed RegARIMA model in the present study can predict the travel speed in winter. Section 6.1 quantify the effect of a snow removal operation conducted independently in winter season of 2013-2014 in Sapporo. In section 6.2, the effect of several snow removal operations conducted in combination during a certain period in winter were quantified.

6.1 EFFECTS OF A SINGLE SNOW REMOVAL OPERATION

Figure 6-1 shows the flow of estimation for the travel time saving effects by three types of snow removal operation. First of all, the travel speed prediction model should be developed as chapters 4. The second step is to forecast the future travel speed by the travel speed prediction model with the observed travel speed data, weather forecasts information, and snow removal operations as chapter 5. To identify the effects of individual snow removal operations, the recorded independent variables until each snow removal operation performed are used. In other words, the effect of a single snow removal operation is defined as the saved travel time for the day after the operation is performed. For example, when a fresh snow removal operation on link S5 was performed on the night of Jan. 6, the difference in travel time between with and without the operation on Jan. 7 is defined as the fresh snow removal effect on link S5. And the travel time can be forecasted by the prediction travel speed and the link lengths (see Table 3-1) by Equation 6-1. At last, the travel time reduction is the difference in predicted travel time between the case with snow removal and that without snow removal, and the travel time saved by a snow removal operation is transformed into the travel time-saving benefit (Equation 6-2). In Japan, the unit costs for travel time by types of vehicle is classified into three by the Ministry of Land, Infrastructure, Transport and Tourism (MLIT)[67] as Table 6-1. The present study considers only the value of only passenger car class (45.78 JPY/min./veh) which includes both passenger cars and buses [68].

Table 6-1 Units of the time value cost by types of vehicle

Vehicle Type	Unit cost (JPY/min/veh)
Passenger car class	45.78
Light goods vehicle	47.91
Heavy goods vehicle	64.18

(Source: MLIT [67])

$$(Predicted\ \ Travel\ \ Time)_{it} = \frac{(Link\ \ length)_i}{(Predicted\ \ travel\ \ speed)_{it}} \times 60\ \ (minute) \tag{6-1}$$

$$for\ \ i(Link) = link\ \ ID\ \ (N1, N2, \dots, S9, S10)$$

$$t(time) = the\ \ time\ \ of\ \ day\ \ from\ \ 7{:}00\ \ to\ \ 20{:}00$$

$$on\ \ the\ \ day\ \ after\ \ snow\ \ removal\ \ operations$$

$$\begin{aligned}(Travel\ \ time\ \ saving\ \ benefit)_i &\\ = \Bigg(\sum_{t=7}^{20} (Predicted\ \ Travel\ \ Time)_{it\_with} &\\ - \sum_{t=7}^{20} (Predicted\ \ Travel\ \ Time)_{it\_without}\Bigg) \times U_T &\end{aligned} \tag{6-2}$$

for with: with snow removal operations

without: without snow removal operations

U_T *is the unit cost of travel time for the passenger car class (45.78 JPY/min/veh)*

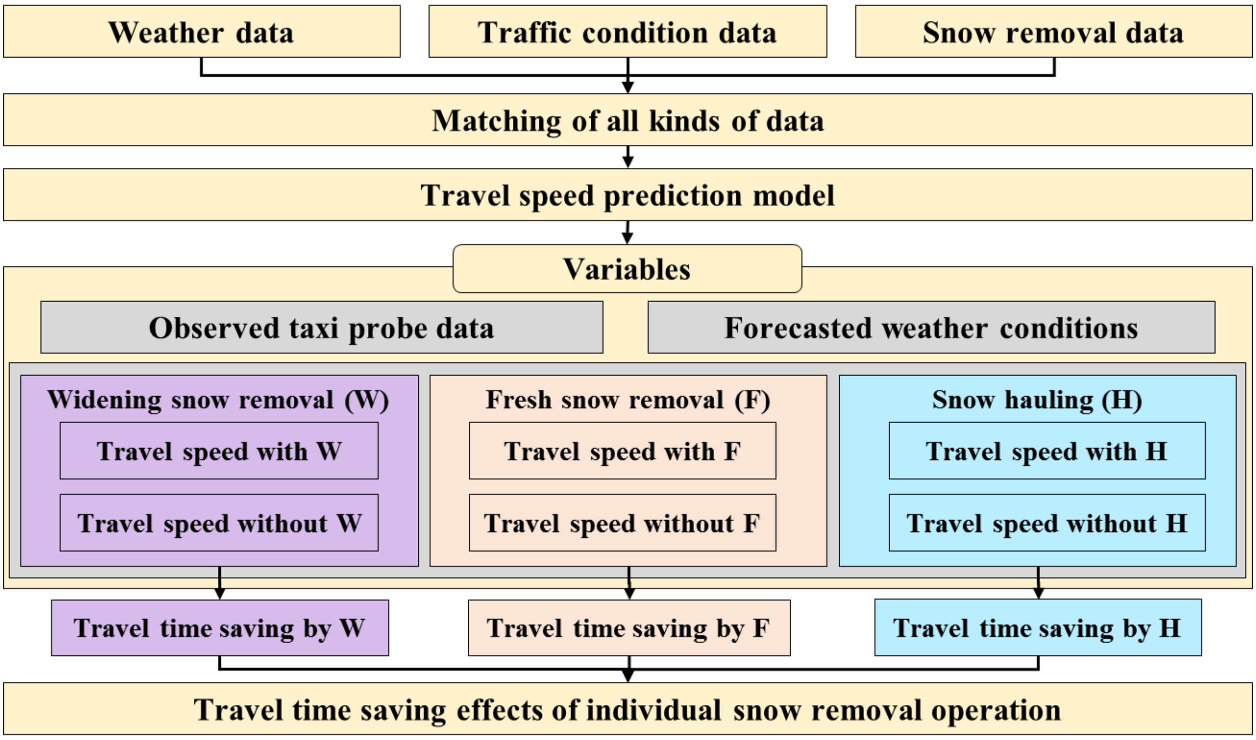


Figure 6-1 Flow of estimating the travel time saving effects of individual snow removal operation

In the winter of 2013-2014, ten fresh snow removal deployments, two road widening deployments and two snow hauling deployments were conducted, and these operations were selected to estimate the snow removal effects of each operation taken independently. The dates on which snow removal operations were performed are shown in Table 6-2. The RegARIMA model in the present study considered only the weekdays and the travel speed on weekends and holidays were not included. Because F3 was Friday, the next study day to estimate the effect of the snow removal operation is Monday (Jan. 20). However, the snow fell in Sapporo on Sunday (Jan. 19), and it eliminated the effects of snow removal operation in the suggested RegARIMA model. The reason is that the fresh snow removal variable in the RegARIMA model was reflected as whether snow on the road surface or not. Therefore, the fresh snow removal operation of F3 was excluded from the analysis.

Table 6-2 The dates the snow removal operations were performed

Fresh snow removal			Road widening			Snow hauling		
ID	Date	Section	ID	Date	Section	ID	Date	Section
F1	Jan. 6	All	W1	Feb. 19	All	H1	Jan. 14~ Jan. 23	2~10
F2	Jan. 12 & Jan. 13	All	W2	Feb. 23 ~ Feb. 24	5 ~ 10	H2	Mar. 8 ~ Mar. 10	5 ~ 10
F3	Jan. 17	All						
F4	Jan. 21	All						
F5	Feb. 4	All						
F6	Feb. 5	All						
F7	Feb. 11	All						
F8	Feb. 13	All						
F9	Feb. 17	All						
F10	Feb. 21	All						

(Source: the City of Sapporo[69])

The travel speed with and without snow removal operations on days after each snow removal operation performed were predicted to estimate the effects of the operations by the travel speed prediction model. For instance, to estimate the effects of F1 which performed on Jan. 6, both of the travel speeds with and without F1 on Jan. 7 were forecasted. The predicted travel speeds with and without fresh snow removal operations were presented in Table 6-3 and road widening operations and snow hauling operations were presented in Table 6-4. The travel speeds in both of the two tables is the daily average travel speed.

Table 6-3 The predicted travel speed with and without fresh snow removal operations by link (km/h)

Link ID	F1		F2		F4		F5		F6	
	With*	Without*	With	Without	With	Without	With	Without	With	Without
N1	9.20	8.56	9.96	9.33	9.79	9.25	13.34	13.24	12.83	12.19
N2	21.08	20.45	23.91	23.28	18.10	17.56	22.45	22.35	23.26	22.62
N3	20.37	19.73	24.28	23.65	18.11	17.57	23.74	23.64	25.52	24.89
N4	18.19	17.56	18.93	18.30	17.56	17.02	21.83	21.73	20.15	19.52
N5	20.66	20.02	24.63	23.99	26.43	25.89	25.82	25.72	23.15	22.51
N6	13.48	12.85	11.53	10.90	19.65	19.12	16.25	16.15	16.28	15.64
N7	16.20	15.57	13.97	13.34	21.56	21.02	18.30	18.21	19.14	18.51
N8	13.64	13.00	6.94	6.31	23.52	22.98	17.11	17.02	15.51	14.87
N9	21.04	20.41	24.63	24.00	23.81	23.27	25.75	25.66	24.41	23.77
S2	14.88	14.25	6.10	5.46	7.42	6.88	18.49	18.39	17.77	17.13
S3	17.72	17.09	11.53	10.90	11.62	11.08	19.39	19.29	19.70	19.07
S4	13.51	12.88	10.66	10.03	9.80	9.26	18.48	18.38	18.02	17.38
S5	16.13	15.50	10.48	9.85	12.55	12.01	21.53	21.44	20.25	19.62
S6	14.39	13.75	14.29	13.65	20.25	19.71	20.48	20.38	18.56	17.93
S7	11.02	10.38	10.66	10.03	19.49	18.95	16.35	16.25	17.39	16.76
S8	15.60	14.97	15.56	14.92	21.17	20.63	18.96	18.86	17.86	17.23
S9	13.48	12.85	10.34	9.70	20.80	20.27	19.80	19.70	19.21	18.58
S10	14.94	14.31	15.30	14.66	18.29	17.75	17.75	17.65	18.42	17.78

Link ID	F7		F8		F9		F10	
	With	Without	With	Without	With	Without	With	Without
N1	13.12	12.49	13.02	12.39	11.97	11.34	10.67	10.03
N2	23.78	23.14	26.78	26.15	20.90	20.26	20.14	19.51
N3	27.47	26.84	24.78	24.15	21.28	20.64	21.41	20.78
N4	23.61	22.97	23.35	22.72	20.20	19.56	17.80	17.16
N5	27.40	26.77	25.66	25.02	16.99	16.35	17.45	16.81
N6	15.87	15.24	15.14	14.51	11.12	10.49	10.51	9.88
N7	17.81	17.17	18.03	17.40	15.66	15.03	16.97	16.34
N8	14.09	13.45	18.55	17.92	13.73	13.09	12.04	11.40
N9	24.79	24.15	23.98	23.34	21.93	21.29	21.40	20.77
S2	17.69	17.06	18.02	17.39	15.80	15.16	13.58	12.94
S3	17.19	16.55	18.92	18.29	16.30	15.66	15.79	15.16
S4	17.89	17.25	19.80	19.17	14.23	13.60	12.94	12.31
S5	19.56	18.93	20.33	19.70	15.69	15.05	12.24	11.61
S6	18.85	18.21	18.73	18.10	15.47	14.83	14.67	14.04
S7	14.72	14.09	14.54	13.91	11.63	10.99	11.35	10.72
S8	18.42	17.79	19.55	18.92	16.05	15.42	16.14	15.50
S9	16.51	15.87	17.89	17.26	16.90	16.27	12.95	12.32
S10	16.66	16.03	18.67	18.04	16.83	16.19	15.93	15.30

(*With and Without: with and without snow removal operations)

Table 6-4 The predicted travel speed with and without road widening operations and snow hauling operations by link (km/h)

Link ID	W1		W2		H1		H2	
	With	Without	With	Without	With	Without	With	Without
N1	12.37	11.73						
N2	19.19	18.56			33.80	25.56		
N3	19.91	19.28			33.50	25.27		
N4	21.62	20.98			33.21	24.98		
N5	17.80	17.16	17.45	16.81	29.74	22.75	25.13	20.17
N6	10.79	10.16	10.51	9.88	19.63	12.65	18.68	13.73
N7	9.49	8.85	12.14	11.50	28.53	21.92	21.14	17.08
N8	4.52	3.89	9.37	8.74	32.12	25.52	22.54	18.48
N9	24.96	24.33	23.55	22.92	33.71	26.92	27.22	23.03
S2	15.31	14.68			30.90	22.67		
S3	17.74	17.10			28.71	20.47		
S4	14.07	13.43			28.38	20.15		
S5	14.52	13.88	12.24	11.61	17.59	10.60	17.64	12.68
S6	16.66	16.02	14.67	14.04	19.83	12.84	20.99	16.04
S7	12.37	11.74	12.36	11.73	20.79	14.19	15.42	11.35
S8	17.16	16.53	18.61	17.97	27.15	20.54	19.99	15.93
S9	13.02	12.38	13.02	12.38	18.29	11.50	18.94	14.74
S10	16.63	16.00	16.91	16.28	23.51	16.72	18.54	14.35

According to the travel speed in Table 6-3 and 6-4, the travel speed can be seen to increase when the snow removal operations were performed. The predicted travel time with and without snow removal operations are shown as Table 6-5 and 6-6. The travel time in the tables were calculated by Equation 6-1. Both of the two tables represent the sum of the average hourly travel time on the predicted day.

Table 6-5 The predicted travel time with and without fresh snow removal operations by link (minute/veh)

Link ID	F1		F2		F4		F5		F6	
	With	Without	With	Without	With	Without	With	Without	With	Without
N1	35.5	38.3	32.3	34.7	32.7	34.8	23.8	23.9	24.5	25.9
N2	18.7	19.2	16.4	16.8	21.7	22.4	17.5	17.6	16.8	17.3
N3	15.5	16.0	12.9	13.2	17.3	17.9	13.3	13.3	12.3	12.6
N4	17.3	17.9	16.6	17.2	17.9	18.4	14.4	14.4	15.5	16.1
N5	15.2	15.7	12.7	13.0	11.8	12.1	12.1	12.2	13.5	13.9
N6	36.0	37.9	42.2	44.8	24.1	24.9	29.3	29.4	29.0	30.2
N7	16.9	17.6	19.7	20.7	12.7	13.0	15.0	15.0	14.3	14.8
N8	48.1	50.7	130.7	164.9	26.7	27.4	37.5	37.7	41.7	43.6
N9	13.1	13.5	11.1	11.4	11.5	11.8	10.6	10.7	11.2	11.5
S2	28.1	29.5	85.7	103.8	60.8	68.1	21.3	21.4	22.1	22.9
S3	18.2	18.9	29.0	31.0	28.5	30.3	16.4	16.5	16.0	16.6
S4	23.7	25.0	30.4	32.5	32.5	34.7	17.0	17.1	17.5	18.1
S5	19.6	20.5	31.3	33.6	27.9	29.8	14.5	14.6	15.5	16.0
S6	33.0	34.6	35.9	38.1	23.4	24.1	22.9	23.0	25.4	26.3
S7	25.0	26.6	26.0	27.7	14.1	14.5	16.8	16.9	15.8	16.4
S8	40.1	41.8	40.5	42.2	29.6	30.4	33.0	33.2	35.0	36.3
S9	20.5	21.6	28.5	30.7	13.2	13.6	13.8	13.9	14.3	14.8
S10	31.5	32.9	30.9	32.3	25.7	26.5	26.5	26.6	25.5	26.4

Link ID	F7		F8		F9		F10	
	With	Without	With	Without	With	Without	With	Without
N1	24.0	25.3	24.2	25.4	26.4	27.9	29.7	31.6
N2	16.5	16.9	14.6	15.0	18.8	19.4	19.5	20.1
N3	11.4	11.7	12.7	13.0	14.8	15.2	14.7	15.1
N4	13.3	13.6	13.4	13.8	15.5	16.1	17.6	18.3
N5	11.4	11.7	12.2	12.5	18.5	19.2	18.0	18.7
N6	29.8	31.0	31.3	32.8	43.3	46.1	46.0	49.1
N7	15.4	16.0	15.2	15.7	17.5	18.2	16.1	16.8
N8	46.0	48.4	34.1	35.4	47.0	49.5	54.3	57.6
N9	11.0	11.3	11.4	11.7	12.5	12.9	12.8	13.2
S2	22.2	23.0	21.8	22.6	25.0	26.0	29.2	30.7
S3	18.4	19.1	16.7	17.2	19.3	20.1	19.9	20.8
S4	17.6	18.2	15.9	16.4	22.1	23.1	24.4	25.7
S5	16.1	16.6	15.4	15.9	20.1	21.0	26.0	27.5
S6	25.0	25.8	25.1	26.0	30.5	31.8	32.6	34.2
S7	18.6	19.5	18.9	19.8	23.7	25.1	24.3	25.8
S8	33.9	35.2	32.0	33.1	39.0	40.6	39.1	40.8
S9	16.7	17.4	15.4	16.0	16.3	17.0	21.6	22.8
S10	28.2	29.3	25.2	26.1	27.9	29.0	29.5	30.8

Table 6-6 The predicted travel time with and without road widening operations and snow hauling operations by link (minute/veh)

Link ID	W1		W2		H1		H2	
	With	Without	With	Without	With	Without	With	Without
N1	25.5	27.0						
N2	20.4	21.2			11.6	15.3		
N3	15.8	16.3			9.3	12.4		
N4	14.5	14.9			9.4	12.5		
N5	17.6	18.3	18.0	18.7	10.5	13.8	12.5	15.6
N6	44.6	47.6	46.0	49.1	24.1	38.0	25.4	34.9
N7	29.2	31.4	22.6	23.8	9.6	12.5	12.9	16.0
N8	188.4	253.9	72.1	78.3	19.7	25.0	28.2	34.8
N9	11.0	11.3	11.6	11.9	8.1	10.2	10.0	11.9
S2	25.8	26.9			12.7	17.5		
S3	17.7	18.4			11.0	15.5		
S4	22.4	23.4			11.1	15.7		
S5	21.8	22.9	26.0	27.5	18.1	31.0	17.9	25.2
S6	28.4	29.5	32.6	34.2	24.1	38.3	22.5	29.7
S7	22.3	23.5	22.3	23.6	13.2	19.5	18.0	24.7
S8	36.5	37.9	33.8	35.1	23.1	30.6	31.5	39.7
S9	21.4	22.5	21.6	22.8	15.2	25.0	14.7	19.1
S10	28.3	29.4	27.8	28.9	20.0	28.3	25.5	33.3

According to the travel speed in Table 6-5 and 6-6, the travel time was decreased when the snow removal operations were performed as the results of the predicted travel speed. The saved travel time by the snow removal operations can be calculated by Equation 6-2, and it was presented in Table 6-7.

Table 6-7 Saved travel time by snow removal operations by link (minute/veh)

Link ID	F1	F2	F4	F5	F6	F7	F8
N1	2.87	2.34	2.13	0.11	1.30	1.25	1.26
N2	0.59	0.45	0.70	0.06	0.48	0.46	0.36
N3	0.51	0.35	0.55	0.05	0.32	0.27	0.34
N4	0.63	0.59	0.59	0.05	0.51	0.37	0.38
N5	0.49	0.34	0.25	0.04	0.38	0.27	0.31
N6	1.91	2.66	0.73	0.11	1.19	1.26	1.41
N7	0.70	0.96	0.33	0.07	0.49	0.57	0.56
N8	2.62	34.15	0.65	0.12	1.91	2.35	1.25
N9	0.41	0.30	0.26	0.03	0.30	0.29	0.31
S2	1.45	18.17	7.30	0.08	0.83	0.84	0.81
S3	0.73	2.00	1.77	0.05	0.54	0.72	0.59
S4	1.23	2.08	2.14	0.09	0.65	0.65	0.53
S5	0.83	2.26	1.95	0.07	0.51	0.55	0.50
S6	1.57	2.21	0.68	0.11	0.91	0.88	0.89
S7	1.56	1.71	0.41	0.11	0.60	0.85	0.87
S8	1.71	1.76	0.77	0.19	1.30	1.22	1.08
S9	1.05	2.22	0.35	0.08	0.50	0.68	0.58
S10	1.41	1.36	0.78	0.15	0.92	1.12	0.89

Link ID	F9	F10	W1	W2	H1	H2
N1	1.52	1.93	1.42			
N2	0.59	0.64	0.71		3.76	
N3	0.46	0.45	0.53		3.07	
N4	0.51	0.66	0.44		3.12	
N5	0.73	0.69	0.66	0.69	3.26	3.10
N6	2.79	3.16	2.97	3.16	13.92	9.53
N7	0.74	0.63	2.18	1.25	2.92	3.10
N8	2.45	3.31	65.50	6.13	5.31	6.52
N9	0.37	0.39	0.29	0.32	2.05	1.83
S2	1.07	1.48	1.14		4.78	
S3	0.80	0.85	0.67		4.53	
S4	1.05	1.29	1.08		4.61	
S5	0.87	1.49	1.03	1.49	12.89	7.27
S6	1.33	1.56	1.15	1.56	14.24	7.16
S7	1.40	1.48	1.23	1.24	6.29	6.78
S8	1.62	1.64	1.42	1.22	7.50	8.23
S9	0.65	1.18	1.15	1.18	9.83	4.43
S10	1.10	1.24	1.13	1.10	8.28	7.72

The saved travel time by a snow removal operation was changed into the economic value by the travel time unit cost, and the results show in Table 6-8. Most of the fresh snow removal benefit is found to be less than 100 JPY per vehicle, and the benefit of road widening is greater than that of fresh snow removal in the study area. The benefit of snow hauling was the largest of snow removal in the present study. According to the results, some benefits of link N8 were much larger than of the other links. This is because the travel speed on link N8 was relatively slower than other links on that dates. For example, the average speed of N8 on Jan. 14 (for F2) was 7.78 km/h, while the average speed of the whole study area on that date was 13.73 km/h. In other words, snow removal operations were more effective on congested roads.

Table 6-8 Value for the saved travel time by snow removal operations by link (JPY/veh)

Link ID	F1	F2	F4	F5	F6	F7	F8
N1	131.5	107.3	97.5	4.9	59.6	57.2	57.7
N2	26.9	20.7	32.2	2.6	21.8	20.9	16.3
N3	23.2	15.9	25.3	2.2	14.5	12.5	15.4
N4	29.0	26.9	27.0	2.2	23.3	16.9	17.2
N5	22.2	15.4	11.5	1.6	17.5	12.4	14.2
N6	87.6	121.9	33.3	5.0	54.7	57.8	64.6
N7	31.8	43.8	15.2	3.1	22.6	26.2	25.4
N8	119.8	1,563.6	30.0	5.6	87.4	107.6	57.1
N9	19.0	13.5	12.0	1.5	13.7	13.4	14.3
S2	66.5	832.0	334.1	3.8	37.8	38.2	36.9
S3	33.3	91.4	81.1	2.5	24.9	33.1	27.0
S4	56.5	95.4	98.1	4.0	29.7	29.9	24.4
S5	38.0	103.5	89.4	3.1	23.4	25.0	23.1
S6	71.9	101.1	31.2	4.9	41.8	40.2	40.6
S7	71.6	78.4	18.7	5.0	27.7	38.8	39.9
S8	78.1	80.4	35.2	8.7	59.4	55.6	49.4
S9	47.9	101.5	16.0	3.7	22.8	31.2	26.6
S10	64.7	62.4	35.6	6.7	42.0	51.4	40.8
Average	56.6	193.1	56.8	3.9	34.7	37.1	32.8

Table 6-8 (continued) Value for the saved travel time by each snow removal operation (JPY/veh)

Link ID	F9	F10	W1	W2	H1	H2
N1	69.4	88.3	64.8	na	na	na
N2	27.2	29.3	32.4	na	172.3	na
N3	21.1	20.8	24.2	na	140.7	na
N4	23.4	30.0	20.2	na	142.9	na
N5	33.3	31.6	30.2	31.6	149.4	142.0
N6	127.6	144.7	135.8	144.7	637.4	436.2
N7	33.9	28.9	99.8	57.4	133.5	141.9
N8	111.9	151.6	2,998.5	280.8	243.0	298.6
N9	17.1	18.0	13.2	14.8	93.9	84.0
S2	48.9	67.8	52.2	na	219.0	na
S3	36.6	39.0	30.7	na	207.3	na
S4	48.0	58.9	49.2	na	211.1	na
S5	39.8	68.3	47.3	68.3	590.1	332.8
S6	60.7	71.4	52.8	71.4	651.9	327.7
S7	64.0	67.7	56.1	56.7	287.9	310.4
S8	74.0	75.3	64.8	55.8	343.1	377.0
S9	30.0	54.2	52.4	54.1	449.9	202.9
S10	50.4	56.8	51.8	50.2	379.1	353.6
Average	51.0	61.3	215.4	80.5	297.2	273.4

6.2 THE EFFECTS OF SNOW REMOVAL OPERATIONS FOR A PERIOD

It is similar with the estimation of individual snow removal effects to estimate for the travel time saving effects by snow removal operations for a period. However, several snow removal operations are performed in winter. Therefore, in the present study, some snow removal operation scenarios are designed to estimate the effects of snow removal operations for a period.

The period from Feb. 13 to 20 of 2014 was selected for estimation of the effects of snow removal operations. During this period, 22 cm of snow fell in Sapporo, and two fresh snow removals and one road widening were performed. The fresh snow removal operations were performed on Feb. 13 and 17, and the road widening operation was performed on Feb. 19th. The snow removal equipment dispatching criteria were not changed in the present study. Four scenarios were designed for estimating the effects of snow removal operations for the period, and the analysis flow is presented in Figure 6-2.

- Scenario 1: both fresh snow removal and road widening operations
- Scenario 2: road widening operation only
- Scenario 3: fresh snow removal operation only
- Scenario 4: no snow removal operations

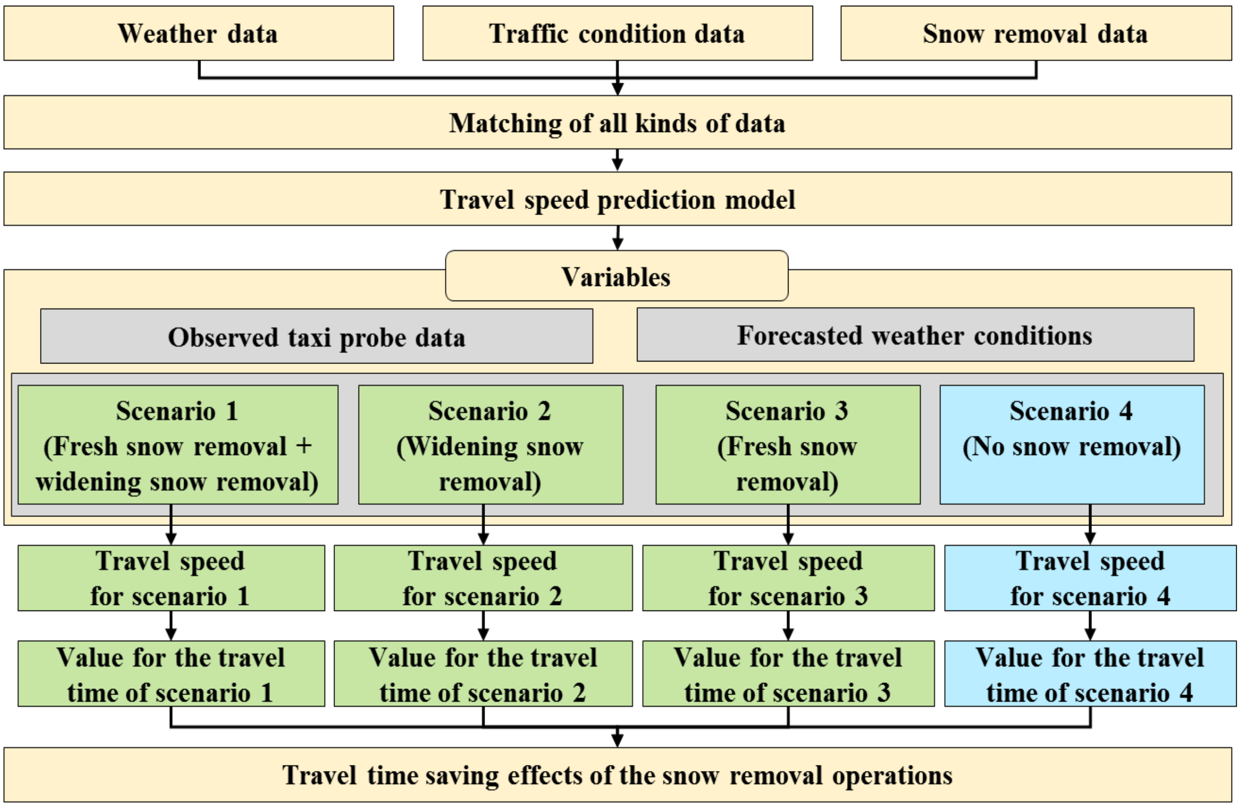


Figure 6-2 Process for calculating the benefit of snow removal operations

The difference in the predicted travel time between Scenario 4 and each other scenario is defined as the effect of snow removal for each of those scenarios. For example, the difference in the travel time between scenario 4 and scenario 3 is the saved travel time by the fresh snow removal operation for a period. As section 6.1, the travel time saving benefits can be estimated by the unit costs for travel time.

First of all, the travel speed of the study period was predicted by the RegARIMA model depending on the snow removal scenarios designed above in order to calculate the travel time on each link. The predicted travel time by the scenario can be expressed similar to section 6.1 by Equation 6-3.

$$(Predicted\ \ Travel\ \ Time)_{idt} = \frac{(Link\ Length)_i}{(Predicted\ Travel\ speed)_{idt}} \times 60\ \ (minute) \tag{6-3}$$

$$for\ \ i(Link) = link\ \ ID\ \ (N1, N2, \dots, S9, S10)$$
$$d(date) = each\ \ date\ \ from\ \ Feb.13\ \ to\ \ Feb.20.$$
$$t(time) = the\ \ time\ \ of\ \ day\ \ from\ \ 7:00\ \ to\ \ 20:00.$$

The travel time saving benefits are estimated by Equation 6-4.

$$(Travel\ \ time\ \ saving\ \ benefit)_i = \left(\sum_{d=13}^{20} \sum_{t=7}^{20} \frac{(Link\ \ length)_i}{(Predicted\ \ travel\ \ speed)_{idt\_4}} - \sum_{d=13}^{20} \sum_{t=7}^{20} \frac{(Link\ \ length)_i}{(Predicted\ \ travel\ \ speed)_{idt\_S}} \right) \times 60 \times U_T \tag{6-4}$$

$$for\ \ S(scenario) = the\ \ scenario\ \ (1, 2, or\ \ 3)$$

Table 6-9 represents the average predicted travel speed during the study period on each link by the scenarios. The travel speed of scenario 1 had the fastest (average 17.36 km/h) of the scenarios, flowed by scenario 3 (17.25km/h), 2 (16.96km/h), and 4 (16.84km/h). According to the results, the predicted travel speed of scenario 3 exceed those of scenario 2 during the period. This is because each operation has a different duration of effectiveness. Road widening was performed on the night of Feb. 19, whereas fresh snow removal was performed on the nights of Feb. 13 and 17. Although the predicted speed of scenario 3 exceed those of scenario 2 during the period, Figure 6-3 shows that the difference in the predicted speeds between Scenario 4 and Scenario 2 exceed the difference between Scenario 4 and Scenario 3 on Feb. 20. In other words, the effects of snow removal in the present study were not absolute; rather, they differ according to the selected period.

Table 6-9 The average predicted travel speed by snow removal scenario from Feb. 13 to Feb. 20

Link ID	Average predicted travel speed (km/h)			
	(Scenario 1) Both snow removal operations	(Scenario 2) Only road widening operation	(Scenario 3) Only fresh snow removal operation	(Scenario 4) No snow removal operation
N1	12.08	11.68	11.97	11.56
N2	23.25	22.85	23.14	22.73
N3	23.41	23.01	23.30	22.89
N4	20.97	20.56	20.85	20.45
N5	19.55	19.14	19.43	19.02
N6	10.91	10.51	10.80	10.39
N7	16.37	15.96	16.25	15.84
N8	12.83	12.43	12.72	12.31
N9	24.19	23.79	24.08	23.67
S2	16.08	15.67	15.97	15.56
S3	17.07	16.66	16.95	16.55
S4	18.12	17.71	18.00	17.60
S5	19.66	19.25	19.55	19.14
S6	17.11	16.70	16.99	16.59
S7	12.52	12.11	12.40	11.99
S8	17.46	17.05	17.34	16.94
S9	15.23	14.82	15.11	14.71
S10	15.70	15.30	15.59	15.18
Average	17.36	16.96	17.25	16.84

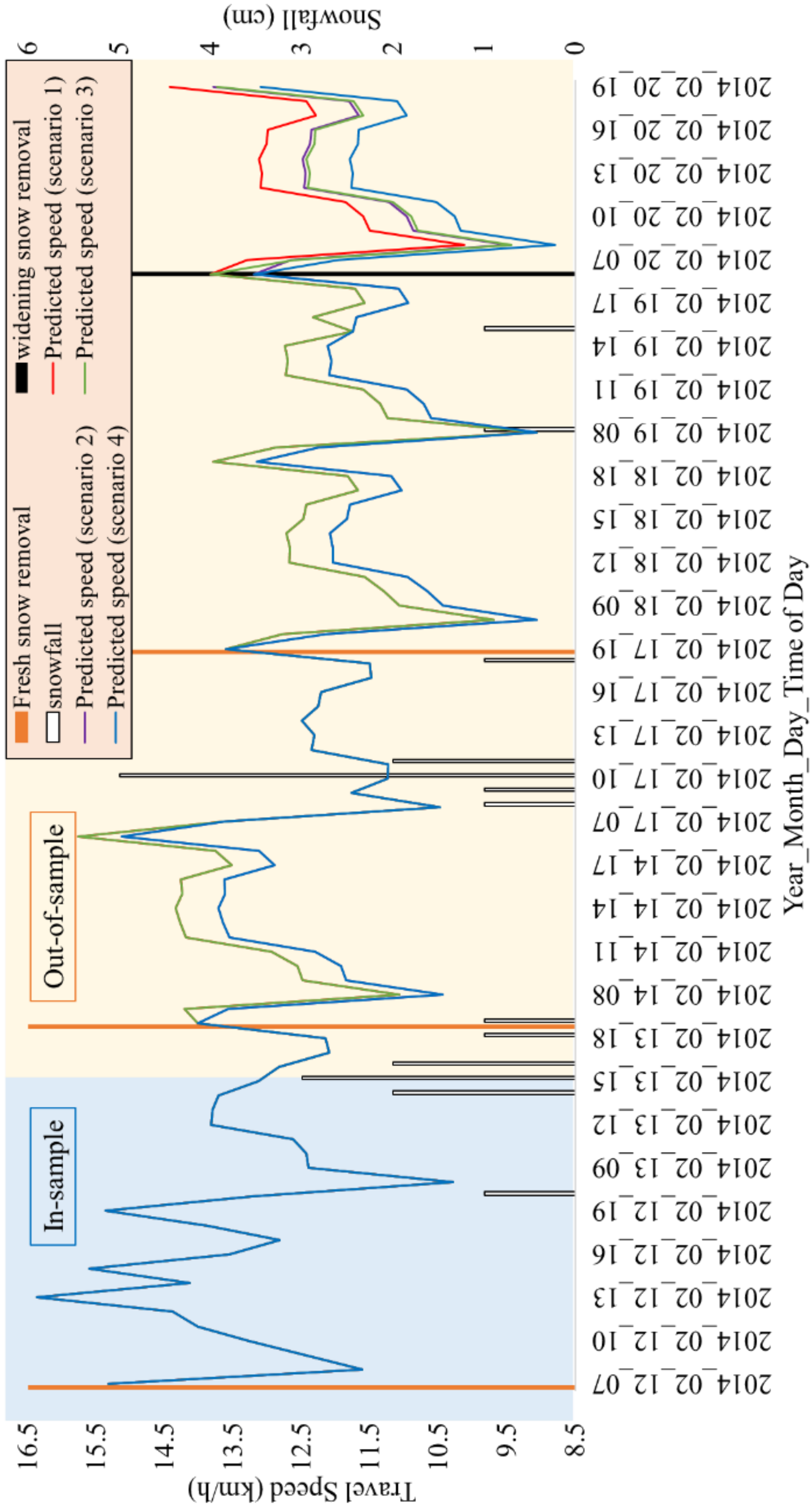


Figure 6-3 The travel speed profiles by snow removal scenario (link: S7)

The estimated travel time per vehicle on each link by snow removal scenario was presented in Table 6-10, and the value of travel time per vehicle was calculated as Table 6-11. Finally, the travel time saving effects of each snow removal operation scenario were estimated in Table 6-12.

Table 6-10 The travel time by snow removal scenario from Feb. 13 to Feb. 20

Link ID	Travel Time (minute/veh)			
	(Scenario 1) Both snow removal operations	(Scenario 2) Only road widening operation	(Scenario 3) Only fresh snow removal operation	(Scenario 4) No snow removal operation
N1	157.50	163.00	158.96	164.62
N2	101.21	103.03	101.72	103.58
N3	80.62	82.08	81.04	82.52
N4	89.81	91.59	90.31	92.12
N5	96.38	98.49	97.00	99.16
N6	266.14	277.81	269.78	282.03
N7	100.62	103.25	101.38	104.07
N8	307.84	319.47	311.55	323.70
N9	67.92	69.09	68.25	69.44
S2	146.89	150.80	148.02	152.03
S3	111.19	113.98	111.98	114.83
S4	104.04	106.43	104.71	107.15
S5	95.91	97.89	96.43	98.45
S6	165.18	169.16	166.29	170.36
S7	132.10	136.61	133.41	138.08
S8	215.15	220.31	216.62	221.90
S9	108.97	112.07	109.87	113.06
S10	179.70	184.54	181.07	186.03
Total	2,527.19	2,599.61	2,548.41	2,623.12

Table 6-11 The value of travel time by snow removal scenario from Feb. 13 to Feb. 20

Link ID	Travel Time Value (JPY/veh)			
	(Scenario 1) Both snow removal operations	(Scenario 2) Only road widening operation	(Scenario 3) Only fresh snow removal operation	(Scenario 4) No snow removal operation
N1	7,211	7,462	7,277	7,536
N2	4,633	4,717	4,657	4,742
N3	3,691	3,758	3,710	3,778
N4	4,112	4,193	4,134	4,217
N5	4,412	4,509	4,441	4,539
N6	12,184	12,718	12,351	12,911
N7	4,606	4,727	4,641	4,764
N8	14,093	14,626	14,263	14,819
N9	3,109	3,163	3,125	3,179
S2	6,725	6,903	6,776	6,960
S3	5,090	5,218	5,126	5,257
S4	4,763	4,873	4,794	4,905
S5	4,391	4,482	4,415	4,507
S6	7,562	7,744	7,613	7,799
S7	6,048	6,254	6,108	6,321
S8	9,849	10,086	9,917	10,159
S9	4,989	5,131	5,030	5,176
S10	8,227	8,448	8,290	8,517
Total	115,695	119,010	116,666	120,086

Table 6-12 The travel time saving effects of each snow removal operation

Link ID	Travel Time Saving Effects (Benefits) (JPY/veh)		
	(Scenario 1) Both snow removal operations	(Scenario 2) Only road widening operation	(Scenario 3) Only fresh snow removal operation
N1	325.91	74.45	259.12
N2	108.68	25.14	84.92
N3	86.65	20.06	67.70
N4	105.65	24.11	82.99
N5	127.12	30.50	98.67
N6	727.47	193.07	560.61
N7	157.93	37.66	123.24
N8	726.18	193.68	556.30
N9	69.28	15.84	54.26
S2	235.07	56.29	183.35
S3	166.60	39.12	130.47
S4	142.11	32.72	111.66
S5	116.21	25.54	92.26
S6	237.31	54.98	186.37
S7	273.55	66.98	213.54
S8	309.12	72.60	241.80
S9	186.84	45.04	145.73
S10	289.94	68.45	227.05
Total	4,391.64	1,076.23	3,420.06

Scenario 1 is found to save 4,392 JPY per vehicle from Scenario 4 (no snow removal) during the period. The benefits of Scenarios 2 and 3 were 1,076 and 3,420 JPY per vehicle during the period. As mentioned above, the benefits of snow removal in the present study were not absolute. However, the traffic administrators can estimate the effects of snow removal operations by the suggested methodology on their selected period to perform more cost-effective snow removal operations.

7 CONCLUSIONS AND FURTHER RESEARCH

This chapter describes the conclusions and further researches of the present study. Section 7.1 provides the summary of the overall results of the present study. And the contribution and the further research of the present study are discussed.

7.1 CONCLUSIONS

Many previous researchers identified the relationship between traffic performances and weather conditions such as rainfall, snowfall, fog, and so on. Also lots of studies investigated about the impact of weather conditions on travel behaviors including mode choice and route choice. Some researchers have studied about the snow removal operation for various purposes. However, the effects of snow removal operations on traffic performance were rarely considered in previous studies. Therefore, this dissertation developed a methodology for quantifying snow removal effects by the RegARIMA model considering weather and snow removals on an urban arterial in Sapporo, Japan.

The study area of the present study was a 4.8-km section of Nishi-5-chome Tarukawa Dori, a major arterial connecting the CBD to residential areas of Sapporo. The data of traffic conditions, weather conditions, and snow removal operation were collected from 07:00 to 20:00 on weekdays in winter season of 2013-2014 (December, 2013 to March, 2014) by CPSs. CPSs allow us to collect valuable data, such as traffic data, weather data and snow removal operation factors from advanced sensors. Physical-world data are now easily convertible into computerized data through CPSs. In the weather condition data, snowfall, deep snow, and temperature were included. Three kinds of snow removal operations were considered in the present study: the fresh snow removal operation, the widening operation of effective road width, and the snow hauling operation. The travel speed was collected by probe taxis, and the turning rate at intersections was collected by the traffic count survey.

Four steps were performed to develop the travel speed prediction model for the effective snow removal operations. The first step was to establish a dataset for analysis by combining traffic conditions, weather conditions and snow removal operation factors. The second step was to develop two regression models, which were multiple linear regression (MLR) models and panel data models, with all the variables. The third step was to investigate the autocorrelation of the residuals between the actual values and estimated values of the regression models, in order to apply an autoregressive integrated moving average (ARIMA) model to the residuals. If the residuals were autocorrelated with among the others, the residuals were estimated by ARIMA model. This kind of model, which is combined both a regression model and an ARIMA model, is called a regression with ARIMA (RegARIMA) model. The fourth step was to confirm the effectiveness of the developed RegARIMA models in winter under different weather conditions: snow conditions and non-snow conditions. In addition, using the developed travel speed prediction model, the travel time saving effects of snow removal operations were quantified.

According to the models results, the temperature was found to have a U-shaped relationship with travel speed. Deep snow had a negative correlation with travel speed. Meanwhile, both snow removal operations (i.e., road widening and fresh snow removal) had a positive correlation with travel speed. In addition, the vehicle turning rate was negatively correlated and the intersection size had a positive relationship with travel speed in the MLR with ARIMA model. Vehicles going straight were obstructed by the vehicles turning left and right at intersection especially on the winter road which were narrowed by fresh snow removal operations. On the other hand, the negative effects of the turning rate would be decreased if the intersection size were big enough space to wait for an opportunity to turn right and left at intersections.

The model validation was done using out-of-sample of data in order to see how the model can forecast well under different weather conditions: snow day and non-snow day. The predictive accuracies of travel speed for the univariate ARIMA and the RegARIMA under different weather conditions were compared. The predictive accuracy of the developed RegARIMA model was around 88.7% and 84.1% under non-snow and snow days respectively. It was found that under snow weather conditions, the RegARIMA was found to be more stable over time, regardless weather. Besides, the difference in the RegARIMA and the ARIMA models was increased over time.

The travel time reduction afforded by snow removal was defined as the effect of snow removal, and the travel time reduction was converted into travel time saving benefit. The effect of a single snow removal operation and the effect of several snow removal operations in combination during a week were considered. The fresh snow removal benefit was found to be less than 100 JPY per vehicle, and the effects of snow hauling were the greatest of any snow removal operation. In terms of effect of snow removal operations for the study period, the current snow removal strategy (scenario 1) is found to save 4,392 JPY per vehicle from Scenario 4 (no snow removal) during the period from February 13 to February 20, 2014. The benefits of Scenarios 2 (the widening operation) and 3(the fresh snow removal operation) were 1,076 and 3,420 JPY per vehicle during the period.

7.2 CONTRIBUTION AND FURTHER RESEARCH

The results suggested a methodology for predicting the travel speed, considering weather conditions and snow removal operations in an urban area. The suggested methodology can be used for developing winter road maintenance strategies that aim to reduce traffic congestion in winter. For example, the locations and times of traffic congestion could be predicted by the proposed methodology. Then, road traffic administrators could deploy snow removal equipment more economically in advance to the proper locations. In addition, although the current snow removal strategy in Sapporo is based on snowfall accumulation, it could be changed based on the travel speed reduction rate to improve the strategy.

The quantifying methodology for the effects of snow removal operations was also suggested in the present study. The methodology can contribute to develop the cost-efficient snow removal strategy. Road traffic administrators could apply the changed snow removal strategy to the real road networks. In other words, the present study can expect to contribute to realization of a CPS society. Cyber-physical system (CPS) is a smart cycle system that collects and analyzes real-world data, and then it gives feedback from the analysis to the real-world.

Based on the results of this study, further research is needed to obtain more reliable results. First, only five independent variables were used in this study, so if additional independent variables, such as road surface conditions, traffic volume, and measured effective road width, were considered in the models, it would help toward the development of more reliable travel speed estimation models. Second, urban roads have many intersections. Therefore, not only should the impacts of winter weather and snow removal operations on a single arterial be considered, but so should those impacts on the overall road network be considered. Finally, more accurate weather data would be helpful. The weather data of the present study were collected from a weather station that is a few kilometers from the study area. However, if the road weather information system (RWIS) data were used, the results would be improved.

REFERENCES

[1] The City of Sapporo. *How much snow falls in Sapporo?* [Online] Available: http://www.city.sapporo.jp/kensetsu/yuki/kids/kids_seikatsu2.html. [Accessed: 12-Jun-2016]（札幌にはどのくらいの雪がふるの？）(in Japanese)

[2] The City of Sapporo. *Expenses on Prevention of Snow Disasters*. [Online] Available: http://www.city.sapporo.jp/kensetsu/yuki/jigyou/budget.html. [Accessed: 12-Jun-2016] (雪対策費実績) (in Japanese)

[3] M. Agarwal, T. Maze, and R. Souleyrette. *Impact of Weather on Urban Freeway Traffic Flow Characteristics and Facility Capacity*. Center for Transportation Research and Education, Iowa State University, Integration of Road Weather Information with Traffic Data—Aurora Project, 2005.

[4] T. Maze, M. Agarwal, and G. Burchett. Whether weather Matters to Traffic Demand, Traffic Safety, and Traffic Operations and Flow. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1948, 170-176, 2006.

[5] C. Yang, S. Hong, C. Oh, and W. Jeon. Estimation of Traffic Deterioration by Snowfall on a Korean Freeway for Winter Operations. A Proceedings at *the 91st Annual Meeting of the Transportation Research Board*, Washington, D.C., 2012.

[6] The City of Sapporo. *Snow Removal Levels by Road Types*. [Online] Available: http://www.city.sapporo.jp/kensetsu/yuki/plan/contents/plan99-3.html. [Accessed: 12-Jun-2016] (道路種別毎の除雪水準) (in Japanese)

[7] Japan Electronics and Information Technology Industries Association (JEITA). *What is CPS?* [Online] Available: http://www.jeita.or.jp/cps/about/. [Accessed: 12-Jun-2016] (CPS とは?) (in Japanese)

[8] Industrial Structure Council Commerce, Distribution and Information Committee and Information Economy Subcommittee. *Changes in response to the arrival of a data-driven society using CPS*, Interim report. Ministry of Economy, Trade and Industry. 2015.

[9] A. T. Ibrahim and F. L. Hall. Effect of Adverse Weather Conditions on Speed-Flow-Occupancy Relationships. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1457, 184-191, 1994.

[10] S. Datla and S. Sharma. Variation of Impact of Cold Temperature and Snowfall and Their Interaction on Traffic Volume. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2169, 107-115, 2010.

[11] A. Dehman. Effect of Inclement Weather on Two Capacity Flows at Recurring Freeway Bottlenecks. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2286, 84-93, 2012.

[12] Y. Zhao, A. W. Sadek, and D. Fuglewicz. Modeling the Impact of Inclement Weather on Freeway Traffic Speed at Macroscopic and Microscopic Levels. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2272, 173-180, 2012.

[13] T. J. Kwon, L. Fu, and C. Jiang. Effect of Winter Weather and Road Surface Conditions on Macroscopic Traffic Parameters. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2329, 54-62, 2013.

[14] I. Tsapakis, T. Cheng, and A. Bolbol. Impact of weather conditions on macroscopic urban travel times. *Journal of Transport Geography*, Vol. 28, 204-211, 2013.

[15] L. Lin, M. Ni, Q. He, J. Gao, and A. W. Sadek. Modeling the Impacts of Inclement Weather on Freeway Traffic Speed: Exploratory Study with Social Media Data. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2482, 82-89, 2015.

[16] A. J. Khattak, J. L. Schofer, and F. S. Koppelman. Commuters' Enroute Diversion and Return Decisions: Analysis and Implications for Advanced Traveler Information Systems. *Transportation Research Part A: Policy and Practice*, Vol. 27, Issue 2, 101-111, 1993.

[17] H. S. Mahmassani, J. Dong, J. Kim, R. B. Chen and B. Park. *Incorporating Weather Impacts in Traffic Estimation and Prediction Systems*. U. S. Department of Transportation, FHWA-JPA-09-065, EDL 14497, Final Report, 2009.

[18] A. J. Khattak and A. De Palma. The impact of adverse weather conditions on the propensity to change travel decisions: A survey of Brussels commuters. *Transportation Research Part A: Policy and Practice*, Vol. 31, No. 3, 181-203, 1997.

[19] M. Nankervis. The effect of weather and climate on bicycle commuting. *Transportation Research Part A: Policy and Practice*, vol. 33, no. 6, 417-431, 1999.

[20] M. Cools, E. Moons, L. Creemers, and Geert Wets. Changes in Travel Behavior in Response to Weather Conditions: Do Type of Weather and Trip Purpose Matter? *Transportation Research Record: Journal of the Transportation Research Board*, No. 2157, 22-28, 2010.

[21] B. S. Flynn, G. S. Dana, J. Sears, and L. Aultman-Hall. Weather factor impacts on commuting to work by bicycle. *Preventive Medicine,* Vol. 54, No. 2, 122-124, 2012.

[22] S. Saneinejad, M. J. Roorda, and C. Kennedy. Modelling the Impact of Weather Conditions on Active Transportation Travel Behaviour. *Transportation Research Part D: Transport and Environment*, Vol. 17, Issue. 2, 129-137, 2012.

[23] J. Sears, B. S. Flynn, L. Aultman-Hall, and G. S. Dana. To Bike or Not to Bike: Seasonal Factors for Bicycle Commuting. *Transportation Research Record: Journal of the Transportation Research Board,* No. 2314, 105-111, 2012.

[24] M. Meng, J. Zhang, Y. D. Wong, and P. H. Au. Effect of Weather Conditions and Weather Forecast on Cycling Travel Behavior in Singapore. *International Journal of Sustainable Transportation*, DOI: 10.1080/15568318.2016.1149646, 2016.

[25] S. H. Huang and B. Ran. An Application of Neural Network on Traffic Speed Prediction Under Adverse Weather Condition. A Proceedings at *the 82nd Annual Meeting of the Transportation Research Board*, Washington, D.C., 2003.

[26] B. M. Williams and L. A. Hoel. Modeling and Forecasting Vehicular Traffic Flow as a Seasonal ARIMA Process: Theoretical Basis and Empirical Results. *Journal of Transportation Engineering*, vol. 129, Issue. 6, 664-672, 2003.

[27] F. Van den Bossche, G. Wets, and T. Brijs. A regression model with ARIMA errors to investigate the frequency and severity of road traffic accidents. A proceeding at *the 83th Annual Meeting of the Transportation Research Board*, Washington, D.C., 2004.

[28] D. Billings and J. S. Yang. Application of the ARIMA Models to Urban Roadway Travel Time Prediction - A Case Study. A Proceedings at *2006 IEEE International Conference on Systems, Man and Cybernetics*, Taipei, Vol. 3, 2529-2534, 2006.

[29] D. Zeng, J. Xu, J. Gu, L. Liu, and G. Xu. Short Term Traffic Flow Prediction Using Hybrid ARIMA and ANN Models. A Proceedings at *Power Electronics and Intelligent Transportation System (PEITS) 2008*, 621-625, 2008.

[30] E. I. Vlahogianni and M. G. Karlaftis. Comparing Traffic Flow Time-Series under Fine and Adverse Weather Conditions using Recurrence-Based Complexity Measures. Nonlinear Dynamics: *An International Journal of Nonlinear Dynamics and Chaos in Engineering Systems*, Vol. 69, Issue 4, 1949-1963, 2012.

[31] S. Dunne and B. Ghosh. Weather Adaptive Traffic Prediction Using Neurowavelet Models. *IEEE Transactions on Intelligent Transportation Systems*, Vol. 14, No. 1, 370-379, 2013.

[32] Y. Zhang and H. Ge. Freeway Travel Time Prediction Using Takagi–Sugeno–Kang Fuzzy Neural Network. *Computer-Aided Civil and Infrastructure Engineering*, Vol. 28, No. 8, 594-603, 2013.

[33] S. Kim, H. Rim, C. Oh, E. Jeong, and Y. Kim. Multiple-Step Traffic Speed Forecasting Strategy for Winter Freeway Operations. *Transportation Research Record: Journal of the Transportation Research Board*, No. 2482, 133-140, 2015.

[34] H. Wang, L. Liu, S. Dong, Z. Qian, and H. Wei. A novel work zone short-term vehicle-type specific traffic speed prediction model through the hybrid EMD–ARIMA framework. *Transportmetrica B: Transport Dynamics*, http://dx.doi.org/10.1080/21680566.2015.1060582, 2015.

[35] D. Mais, D. Lloyd, and J. Davies. Modelling weather effects on road casualty statistics. *Significance*, Vol. 13, Issue. 1, 28-31, 2016.

[36] H. J. Roh, S. Sharma, and P. K. Sahu. Modeling Snow and Cold Effects for Classified Highway Traffic Volumes. *KSCE Journal of Civil Engineering*, Vol. 20, Issue 4, 1514-1525, 2016.

[37] S. Tanabe, Y. Hayashiyama, K. Mori, and H. Tamaki. Monetary Evaluation of Various Snow Removal Attributes by Conjoint Analysis. A Proceedings at *New Challenges for Winter Road Service. XIth International Winter Road Congress*, CD-ROM, 2002.

[38] Y. Hayashiyama, S. Tanabe, and F. Hara. Economic Evaluation of Snow-Removal Level by Contingent Valuation Method. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1741, 183-190, 2001.

[39] Q. Lin. *Performance Measurement for Highway Winter Maintenance Operations*. PhD thesis, the University of Iowa, 2008.

[40] M. Koizumi and S. Naoi. Verification of Dispatch Criteria for Snow Removal Operation. A Proceedings at *2012 Hokuriku Regional Development Bureau conference*, Hokuriku Regional Development Bureau, Ministry of Land, Infrastructure, Transport and Tourism, No.22, 2012. (除雪作業出動基準の検証) (in Japanese)

[41] H.-G. Retzko. A Comparison of Modal Split of Passenger Transport between German and Japanese Cities. *Transport Policy Studies*, Vol. 1, No. 2, 43-48, 1998. (ドイツと日本の都市における旅客輸送に関する交通機関選択の比較) (in Japanese)

[42] Japan Society of Traffic Engineers. *FY 2010 Road Traffic Census*, DVD-ROM edition. Maruzen Publishing Co., Ltd., Tokyo, Japan, 2012. (平成 22 年度道路交通センサス) (In Japanese)

[43] B. J. Mohler, W. B. Thompson, S. H. Creem-Regehr, H. L. Pick Jr., and W. H. Warren Jr.. Visual Flow Influences Gait Transition Speed and Preferred Walking Speed. *Experimental Brain Research*, Vol. 181, Issue 2, 221-228, 2007.

[44] Japan Meteorological Agency. *Weather Observation*.
[Online] Available: http://www.jma.go.jp/jma/en/Activities/weather_obs/weather_obs.html.
[Accessed: 12-Jun-2016].

[45] Japan Meteorological Agency. *Weather Terms and Definitions*.
[Online] Available: http://www.jma.go.jp/jma/kishou/know/yougo_hp/kousui.html. [Accessed: 12-Jun-2016] (予報用語) (in Japanese)

[46] W. K. Lee, H. A. Lee, S. S. Hwang, H. Kim, Y. H. Lim, Y. C. Hong, E. H. Ha, and Hyesook Park. A Time Series Study on the Effects of Cold Temperature on Road Traffic Injuries in Seoul, Korea. *Environmental Research*, Vol. 132, 290-296, 2014.

[47] N. Takahashi, R. A. Tokunaga, M. Asano, and N. Ishikawa. Developing a method to predict road surface temperatures: Applying heat balance model considering traffic volume. Proceedings of *the 13th Standing International Road Weather Commission (SIRWEC) conference*, Torino, Italy, 58-66, 2006.

[48] M. Asano and M. Hirasawa. Characteristics of Traffic Accidents in Cold, Snowy Hokkaido, Japan. Proceeding of *the 5th International Conference of Eastern Asia Society for Transportation Studies*, Fukuoka, Japan, No. 4, 1426-1434, 2003.

[49] Snow Management Office. *The City of Sapporo Snow Response Plan* (the press briefing material). the City of Sapporo. December, 2015. (札幌市の雪対策事業について(記者説明会資料)) (in Japanese)

[50] N. Kanemura. Road Snow Removal and the Snowfall Information System in the City of Sapporo. *Transportation Research Record: Journal of the Transportation Research Board*, No. 1627, 34-40, 1998.

[51] The City of Takikawa. *About the Snow Removal Equipment*.
[Online] Available:
http://www.city.takikawa.hokkaido.jp/240kensetsu/01doboku/07zyosetu/haisetu_4.html. [Accessed: 12-Jun-2016] (除雪機械について) (in Japanese)

[52] Wakkanai Development and Construction Department. *The Types of Snow Removal Operations*. [Online] Available: http://www.wk.hkd.mlit.go.jp/road/ijikanri/page.html. [Accessed: 12-Jun-2016]

[53] Transportation Research Board. *Highway Capacity Manual 2010.* Transportation Research Board, National Research Council., Washington, D.C., 2010.

[54] Japan Automobile Manufacturers Association. *the Motor Industry of Japan 2010*, 2010.

[55] Japan Road Association. *Road Traffic Capacity*. 1984. (道路の交通容量) (in Japanese)

[56] J. W. Osborne and E. Waters. Four Assumptions of Multiple Regression that Researchers Should Always Test. *Practical Assessment, Research, and Evaluation*, Vol. 8, No. 2, 1-5, 2002.

[57] M. Aga, O. V. Safakli. An Empirical Investigation of Service Quality and Customer Satisfaction in Professional Accounting Firms: Evidence from North Cyprus. *Problems and Perspectives in Management*, Vol. 5, Issue 3, 84-98, 2007

[58] S. A. Zakerian and I. D. Subramaniam. The Relationship Between Psychosocial Work Factors, Work Stress and Computer-Related Musculoskeletal Discomforts Among Computer Users in Malaysia. *International Journal of Occupational Safety and Ergonomics*, Vol. 15, No. 4, 425-434, 2009.

[59] L. Keele, N. J. Kelly. Dynamic Models for Dynamic Theories: The Ins and Outs of Lagged Dependent Variables. *Political Analysis*, Vol. 14, Issue 2, 186-205, 2006.

[60] E. W. Frees. *Longitudinal and Panel Data: Analysis and Applications in the Social Sciences*. Cambridge University Press., New York, 2004.

[61] C. Choi. Panel Data Model: Time-series Analysis and Cross-sectional Analysis all at Once. *Planning and Policy: Korea Research Institute for Human Settlements*, No. 320, 120-127, 2008. (패널모형: 시계열 분석과 횡단면 분석을 한번에) (in Korean)

[62] S. R. Rendon. Fixed and Random Effects in Classical and Bayesian Regression. *Oxford Bulletin of Economics and Statistics*, Vol. 75, Issue 3, 460-476, 2013.

[63] J. Johnston and J. Dinardo. *Econometric Methods*. McGraw-Hill, 4th Edition, 1996.

[64] R. Wu and Q. Wang. Shrinkage estimation for linear regression with ARMA errors. *Journal of Statistical Planning and Inference*, Vol. 142, Issue. 7, 2136-2148, 2012.

[65] E. Smeral. World tourism forecasting – keep it quick, simple and dirty. *Tourism Economics*, Vol. 13, No. 2, 309-317, 2007.

[66] G. E. P. Box, G. M. Jenkins, and G. C. Reinsel. *Time Series Analysis. Fourth Edition*. Hoboken, NJ. John Wiley & Sons, Inc., 2008.

[67] Regional Development Bureau, The Minister of Land, Infrastructure, Transport and Tourism. *Cost-Benefit Manual*. 2008. (費用便益分析マニュアル) (in Japanese)

[68] Regional Development Bureau, The Minister of Land, Infrastructure, Transport and Tourism. *Cost-Benefit Manual <for IC>*. 2008. (費用便益分析マニュアル＜連続立体交差事業編＞) (in Japanese)

[69] The City of Sapporo. *Unpublished raw data*.