Ph.D. Dissertation of Engineering

Assessment of Freeway Link Performance Reduction due to Traffic Crashes Using Resilience Indices

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Abstract

This study develops a framework to quantitatively assess traffic resilience on freeway link caused by traffic accident. The term freeway traffic resilience is defined by reviewing literatures on transport system resilience. Indices for freeway traffic resilience are designed based on traffic flow characteristics and adaptive capabilities of transport systems. To identify the accident impact region, traffic state classification technique by utilizing multivariate Gaussian Mixture Model (GMM) is applied. Experimental analysis is conducted on Kyungbu Expressway, Seohaean Expressway, Yeongdong Expressway, and Joongang Expressway. Accident reports and 5-minute aggregated loop detector data are collected between 2010 and 2014. Influential factor analysis reveals the uncharted characteristics of the freeway traffic resilience properties during accident. Potential applications of this study lie in assessment of existing infrastructures during disruptive events, effective analysis of traffic management facilities, and guidelines for roadway design. Traffic resilience assessment framework in this study would be also applicable to other type of roadways, other transport systems (e.g. subway, airline, and maritime), and even different systems (e.g. electric grid, water supply, etc.).

Keyword: Resilience index, performance assessment, freeway crash, traffic state classification

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Table of Contents

List of Tables

List of Figures

Chapter 1. Introduction

1.1 Background

The word resilience generally implies the ability of a system to return to normal condition after occurring disturbances that change its state (Hosseini et al., 2016). Holling (1973) conceptualized a resilience in the context of ecological systems and since then the concept of resilience has been spread to other disciplines such as social science, economics, organization, and engineering. Sustainable Development Goals (SDGs), adopted by the United Nations in 2015, also emphasize the importance of resilience to address global challenges including those related to climate change, urbanization, and environment.

With the increasing threats of natural phenomena and unexpected incidents, resilience becomes an emerging research topic in transport systems (e.g. road, rail, freight, maritime, and air). Current studies focus on natural disaster issues that rarely occurs but causes severe damages on the system performance. It seems that recurrent fluctuations in traffic demand (e.g. temporal increase in traffic flow during peak-time) are not primary concerns in resilience studies due to its predictable and respondable natures.

Nonrecurrent fluctuations in traffic supply (e.g. accident, service failure, or strike) can be another type of disturbances that also affect transport system performance. For example, traffic accident is one of the most frequent and dominant factors of occurring road traffic congestion results in enormous economic and environmental losses (Korea Expressway Corporation 2014; Schrank et al., 2012; Ball et al., 2010; Highways Agency, 2009; Small et al., 2007).

Nonetheless, property of the nonrecurrent congestion has not been fully explored yet due to its stochastic nature of spatiotemporal scales. This is why existing policies in traffic management concentrate on alleviating recurrent congestion rather than nonrecurrent congestion.

Table 1. Types and features of transport system disturbances

Type of disturbances		Intensity*	Frequency
Natural disaster	Earthquake, flooding, tsunami, landslide, volcanic eruptions	High	Rare
Nonrecurrent fluctuation	Accident, service failure, strike, protest	Medium	Occasional
Recurrent fluctuation	Temporal increase in traffic flow (e.g. peak time)	Low	Frequent

* *Intensity: magnitude and duration of disturbances*

Based on the issues discussed above, this study attempts to investigate the accident induced congestion properties utilizing the concept of transport system resilience. Freeway system is selected for this study with sufficient data sources related to disrupted events (e.g. traffic accident, roadwork, and special events) and other influential factors (e.g. geometry, weather, and traffic flow). In comparison with the previously utilized concepts (e.g. robustness, reliability, and vulnerability), resilience can be more comprehensive approach to assess freeway system performances under random disturbances (e.g. traffic accident).

Table 2. Causes of congestion on Kyungbu expressway in 2013

Cause of congestion	Number of occurrences	Total length (km)	Total duration (hr)
Traffic increase	5,895	15,196	8,491
Accident	1,576	3,219	519
Roadwork	488	1,419	1,485
Vehicle breakdown	294	650	126
Road obstruction	53	111	25
Total	8,306	20,595	10,648

1.2 Goal & Objectives

Ultimate goal of this study is development of a framework to quantitatively assess the freeway traffic resilience under random disturbances (e.g. traffic accident). To achieve this goal, several objectives are established as follows:

- Resilience index design to diagnosis and assess the freeway traffic resilience caused by accident
- Traffic state classification to determine spatiotemporal ranges of freeway accident impact region
- Influential factor analysis on freeway traffic resilience to enlarge understanding of accident induced congestion property
- Suggest policy implications and practical applications of freeway traffic resilience assessment methodology

1.3 Research Procedure

This study is structured as follows. Section 2 reviews the existing literatures related to transport system resilience and accident impact analysis. Section 3 constructs a definition of freeway traffic resilience and designs freeway traffic resilience indices. Traffic state classification method is also suggested in this section to figure out

spatiotemporal accident impact region. Section 4 conducts an experimental analysis including site selection, dataset preparation, data analysis, and results. Section 5 discusses the implications of the analysis results and suggest possible applications in the real world. Section 6 summarizes the contents of this study and presents limitations and further research opportunities.

Figure 1 below depicts the simplified procedure of this study.

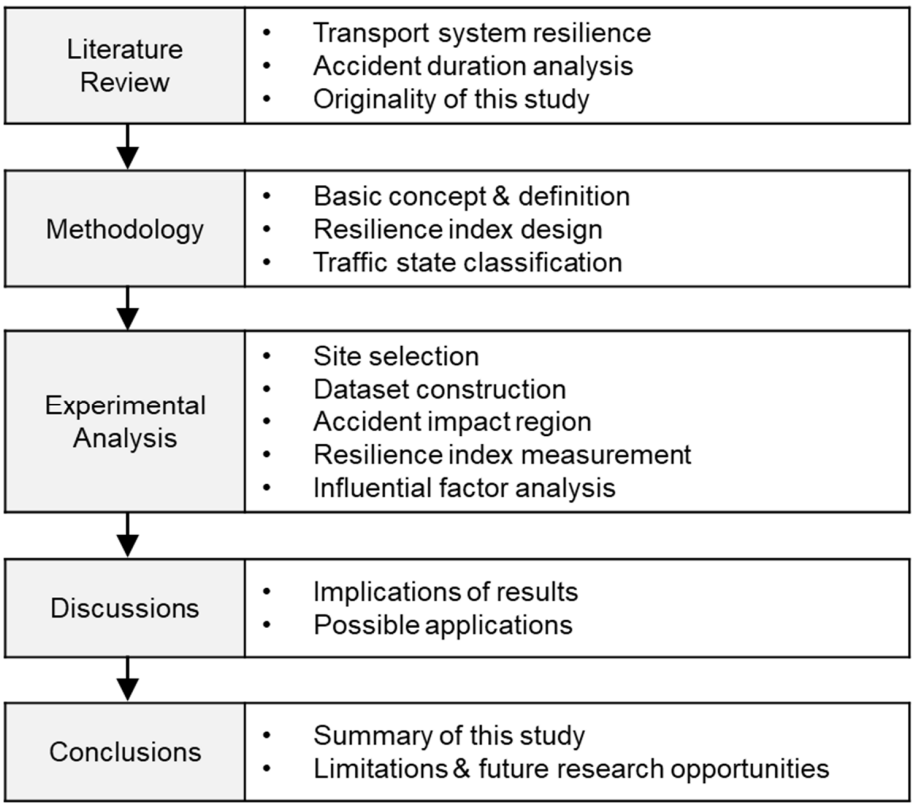


Figure 1. Research procedure

Chapter 2. Literature Review

2.1 Transport System Resilience

2.1.1 Basic concept & definitions

Transport system resilience has been defined in road, rail, freight, maritime, and air transport systems. From the definitions in Table 3, core perspectives of the transport system resilience are ability to maintain the system functionality and to effectively recover from disruptive events.

Table 3. Definitions of transport system resilience

System	Definition	Reference
Road	• Internal strength of the system to recover from unwanted consequences	Ahmed et al. (2019)
	• Ability to retain the same level of travel production after occurrence of a disruption	Amini et al. (2018)
	• System ability to cope with disturbances and recover its original function after a loss of function	Calvert & Snelder (2018)
	• Maximum agitation a system can take in before getting displaced from one state to another	Bhavathrathan & Patil (2015)
Rail	• Ability to experience a damaging event and return to a healthy state of operations in a reasonable amount of time after that event	Chan & Schofer (2016)
	• Speed with which a system recovers from disruptive events or shocks	D' Lima & Medda (2015)

Freight	• System ability to absorb consequences of disruptions to reduce disruptions impacts and maintain freight mobility	Serulle et al. (2011)
	• Post-disaster expected fraction of demand that can be satisfied within specified recovery costs	Nair et al. (2010)
Maritime	• A function of system's vulnerability against potential disruption & adaptive capacity in recovering to an acceptable level of service within a reasonable timeframe	Omer et al. (2012)
	• A time-dependent proportional measure of how the system is performing relative to an as-planned performance level	Baroud et al. (2014)
Air	• Ability to withstand and stay operational at the required level of safety during the impact of a given disruptive event	Janic (2015)

Typical concepts of transport system performance evaluation are robustness, reliability, vulnerability, and risk as described in Table 4. Robustness and reliability assess the remaining performance in a positive manner, whilst vulnerability and risk measure the damage of system in a negative manner.

To compare with those existing concepts, resilience facilitates more comprehensive approach to evaluate the system ability to resist and to efficiently recover from disturbances. Figure 2 visually illustrates the concept of resilience loss that can be measured as the area of a triangle: $(\text{vulnerability} \times \text{recovery time}) \div 2$.

Table 4. Evaluation concepts of transport system performance

Concept	Descriptions	Reference
Robustness	• Remaining level of functionality under disruptions	Snelder et al. (2012)
Reliability	• Probability of meeting a required level of service	Wakabayashi & Lida (1992)
Vulnerability	• Susceptibility of system to incidents or disasters	Berdica (2002)
Risk	• Probability of event occurrence multiplied by	Zhou et al. (2019)
Resilience	• Ability of system to maintain and recover serviceability	Calvert & Snelder (2018)

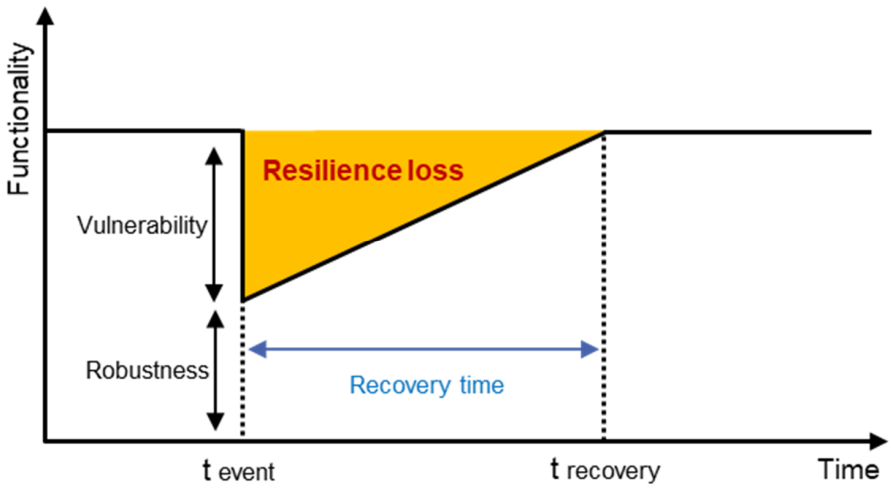


Figure 2. Conceptual illustration of resilience

2.1.2 Performance indicators

Performance indicators to evaluate transport system performance in the previous literatures are summarized in Table 5. Changes in travel time and recovery speed to normal state are popularly utilized in road transport system. Public transport (e.g. railways) system resilience can be assessed by reductions in passenger counts or fraction of satisfied demand during disruptive events. In freight system, vehicle counts and vehicle speed variations are applied as the indicators.

Table 5. Performance indicators for transport system resilience

System	Performance indicators	Reference
Road	• Changes in delay	Ganin et al. (2017), Beiler et al. (2013)
	• Recovery speed to normal state	Calvert & Snelder (2018), Wang et al. (2015)
	• Travel distance & travel time	Donovan & Work (2017)
Rail	• Travel time	Omer et al. (2011)
	• Number of passenger journeys	Cox et al. (2011)
	• Passenger counts	D'Lima & Medda (2015)
	• Satisfied demand	Jin et al. (2014)
Freight	• Vehicle counts & vehicle speed variations	Adams et al. (2012)
Maritime	• Dwell time & transit counts	Farhadi et al. (2016)
Air	• Planned & executed trajectories	Belkoura et al. (2016)

2.1.3 Quantification metrics

Twumasi-Boakye and Sobanjo (2018) proposed a resilience metric considering system failure probabilities, failure consequences, and recovery time as shown in Equation (1). This approach quantifies the degradation of system quality over time, where Q(t) reveals the quality of the system, t_0 is the occurrence time of disruption, and $t_0 + \tau$ is the completed time point of recovery.

$$\mathrm{R} = \int_{t_0}^{t_0+\tau} [100 - Q(t)]dt \qquad (1)$$

From the equation above, system performance under disruptive event is compared to the performance level during normal state. Resilience can be measured by all the performance loss from the occurrence of disaster to the full recovery of system performance (see Figure 1). Larger value indicates lower resilience, and vice versa. This metric can be widely employed in transport resilience studies due to its simple equation and general applicability.

Other studies (e.g. Bocchine and Frangopol 2014; Adjetey-Bahun et al., 2016) suggested concept of average performance loss. In Equation (2), resilience loss is divided by time horizon.

$$\int_{t_0}^{t_1} \frac{[100 - Q(t)]}{t_1 - t_0} dt \qquad (2)$$

Zobel (2011) proposed a resilience metric that calculates the "percentage of the total possible loss over some suitably long-time interval T^*". In Equation (3), $X \in [0,1]$ indicates the percentage of functionality lost after a disruption, $T \in [0, T^*]$ indicates the time required for full recovery, and T^* indicates a suitably long-time interval over which lost functionality is determined.

The author found tradeoffs between lost functionality and recovery time for the same level of resilience. For example, Equation (1) and (2) are insensitive for duration of disturbances. In Figure 3 (cited from Hosseini et al., 2016), total resilience loss can be calculated as triangular area $(XT/2)$ for a single disruptive event.

$$R(X,T) = \frac{T^* - \frac{XT}{2}}{T^*} = 1 - \frac{XT}{2T^*} \tag{3}$$

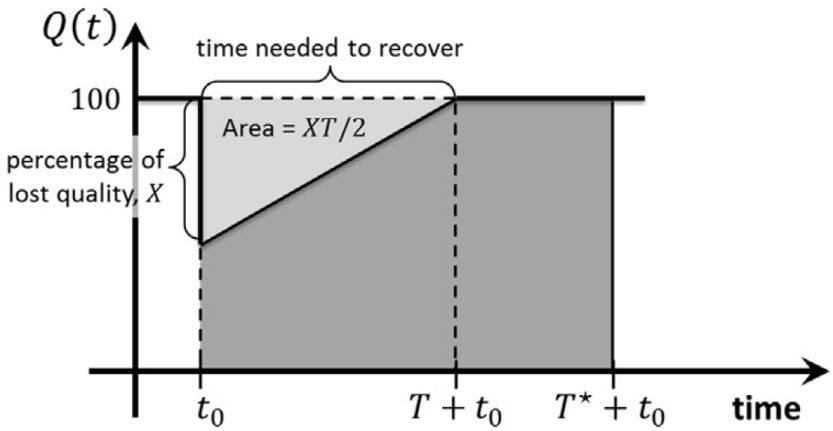


Figure 3. Resilience as a proportion of T^*

Liao et al. (2018) proposed a time-dependent resilience metric as the ratio of time t to function loss at previous time point based on the lifecycle of disasters defined by Henry and Ramirez-Marquez (2012). In Figure 4, disaster lifecycle includes stable original state, system disruption, disrupted state, system recovery, and stable recovered state.

Equation (4) shows the system resilience at time t_r under disruptive event e_j, where $F(t_r|e_j)$ is the function of system at time t_r resulting from disruption e_j, $F(t_d|e_j)$ is the minimum function, and $F(t_0)$ is the function of the system at pre-disruption state.

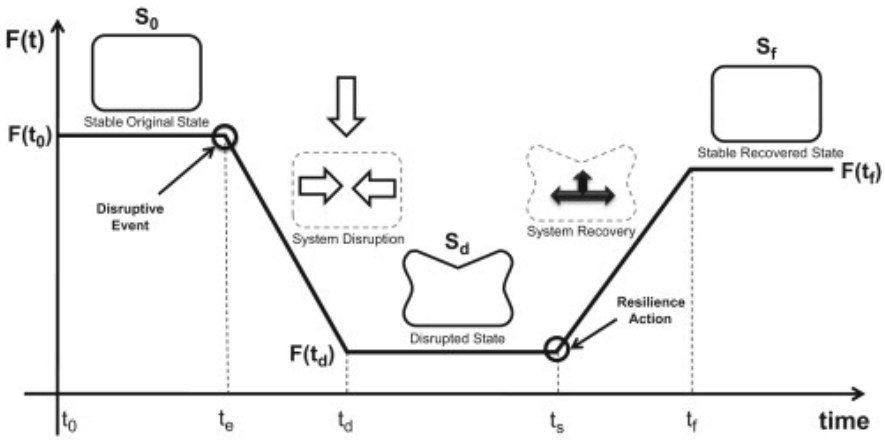


Figure 4. Lifecycle of disasters in resilience

$$R_F(t_r|e_j) = \frac{F(t_r|e_j) - F(t_d|e_j)}{F(t_0) - F(t_d|e_j)} \quad (4)$$

Another resilience metric, proposed by Nair et al. (2010), defines resilience as the expected fraction of demand satisfied by the post-disaster network using specific recovery costs. In Equation (5), d_ω represents the maximum demand satisfied for origin-destination pair ω by the post-disaster network, and D_ω represents the demand satisfied for origin-destination pair ω by the pre-disaster network.

$$\mathrm{R} = \mathrm{E}\left(\frac{\sum_{\omega \in W} d_\omega}{\sum_{\omega \in W} D_\omega}\right) = \frac{1}{\sum_{\omega \in W} D_\omega} E(\sum_{\omega \in W} d_\omega) \tag{5}$$

2.1.4 Research trends

Transport resilience studies usually assess the system performance utilizing the resilience metrics. Optimization approaches focus on critical component analysis to determine the link recovery priority (e.g. Faturechi and Miler-Hooks, 2014; Jin et al., 2014; Khaled et al., 2015; Vugrin et al., 2014; Carvalho et al., 2012; Adjetey-Bahun et al., 2014). Those studies identify the critical components for optimal allocation of limited resources, evaluate increased costs after removing a node or link from the network, and suggest proactive strategies due to sea level rise, floods, or storms.

As a probability theory model, several studies applied Bayesian network model to quantify the transport system resilience (Hosseini

and Barker, 2016) or rank the influential factors in transport system (John et al., 2016). Other studies applied simulation approaches based on discrete or dynamic event simulations.

Current studies in transport system resilience usually overlook the recovery sate, limited in specific scenario analysis, and based on virtual dataset. Therefore, further research opportunities could lie in applying broader concept of resilience incorporating recovery state, various scenario-based analysis, and conducting practical analysis based on real-world data.

2.2 Accident Duration & Impact Analysis

2.2.1 Duration analysis

Traffic incident duration analysis attempts to investigate influential factors on duration and severity of the incidents. Their ultimate goal is to provide policy implications for traffic incident management.

Highway Capacity Manual (Transportation Research Board, 2010) provides four intervals of incident duration: detection, response, clearance, and recovery. Most studies focus on the last three phases and the recovery state is usually overlooked due to limited data availability.

Only few studies (Hojati et al., 2014; Smith and Smith, 2002; Wang et al., 2005) consider the recovery time, from traffic flow characteristics data, to define the incident duration time.

Figure 5, adapted from Haule et al. (2019), depicts the timeline of traffic incident elements from incident occurs to normal flow returns. Due to different data sources utilized in previous studies, range of an incident duration time is differently applied. Therefore, it should be cautious to compare the results between the previous studies. A deeper investigation of traffic incident duration time would be plausible with much detailed data sources.

To estimate the expected duration of future incidents, previous studies construct models to fit a known probabilistic distribution. They show that the incident duration from different datasets have different distribution characteristics (e.g. Log-logistic distribution or Weibull distribution). Zou et al. (2016) proposed a mixture model to fit the traffic incident duration time distribution.

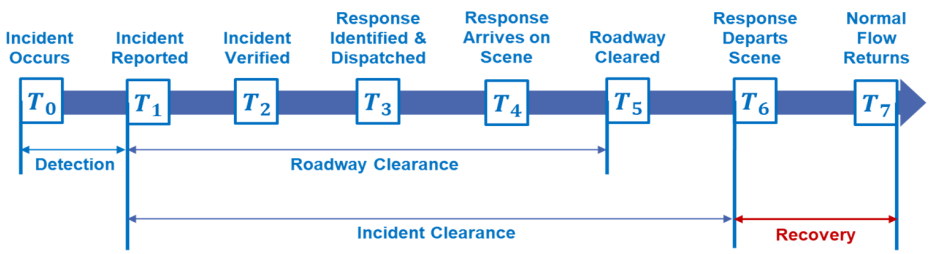


Figure 5. Traffic incident timeline

Various influential factors are also investigated in incident duration studies. Table 6, cited from Li et al. (2018), synthesizes the influence factors of incident duration explored from previous studies.

Table 6. Influence factors of traffic incident duration

Type	Influence factors
Incident characteristics	Incident severity, incident type, towing requirements, type of involved vehicles, number of casualties, number of lanes blocked, incident location
Environmental conditions	Rain, snow, dry, or wet
Temporal factors	Time of day, day of week, season, month of year
Roadway geometry	Street, intersection, road layout, horizontal/vertical alignment, bottlenecks, roadway type
Traffic flow conditions	Flow, speed, occupancy, queue length
Operational factors	Lane closures, freeway courtesy service characteristics
Vehicle characteristics	Large trucks, trucks with trailers, taxis, special vehicles, compact trucks, number of vehicles involved
Others	Driver, special events, time that a police officer reaches the site, police response time, etc.

Hundreds to thousands of incident records were utilized for better results of the analysis. Traffic incident is influenced by various factors and some of them are very complex and subtle, hence, cannot be observed. Larger datasets are required to produce more plausible and more comprehensive results reflecting the characteristics of the traffic incident duration phenomenon.

However, despite the exertions, the conclusions from different datasets from different study sites are not always correspond to others. To exemplify this, weather effects on the incident duration is still controversial between several studies (Hojati et al., 2013; Nam & Mannering, 2000; Alkaabi et al., 2011; Ding et al., 2015). Table 7 summarizes the methodology and data sources utilized in previous studies.

Table 7. Incident duration analysis studies

Methodology	Duration phase	Sample size	Reference
Hazard-based duration model	Response time, clearance time	2,156	Jones et al. (1991)
	Detection/reporting, response time, clearance time	681	Nam & Mannering (2000)
	Clearance time	583	Alkaabi et al. (2011)
	Response time	504	Alkkabi et al. (2012)
Log-linear model	Incident duration	525	Golob et al. (1987)
Statistical tests	Response time, clearance time	512	Giuliano (1989)
Structural equation model	Clearance time	3,147	Lee et al. (2009)
Mechanism-based approach	Response time	828	Hou et al. (2013)
Association rule learning algorithm	Clearance time	999	Lin et al. (2014)
Binary probit and regression models	Response time, clearance time	1,056	Ding et al. (2015)

2.2.2 Duration prediction

Traffic incident duration prediction modelling has been conducted by utilizing different datasets. Various models were applied to predict the traffic incident duration as summarized in Table 8. Classification tree method, artificial neural networks, Bayesian networks, support vector machine are popular methods in incident duration prediction analysis.

Table 8. Incident duration prediction studies

Methodology	Duration phase	Accuracy	Reference
Classification tree method	Incident duration	MAPE (49.1%)	HE et al. (2011)
	Lane clearance time	MAPE (42.7%)	Zhan et al. (2011)
Artificial neural network	Incident duration	RMSE (20%)	Wang et al. (2005)
	Accident duration	MAPE (20−30%)	Wei & Lee (2005)
	Incident duration	MAPE (≤40%)	Wei & Lee (2007)
Support vector machine	Accident duration	MAPE (22%)	Zong et al. (2013)
Combined /hybrid	Accident duration	MAPE (36.2%)	Lin et al. (2016)

Mean absolute percentage error (MAPE), root mean squared error (RMSE), and mean percentage error (MPE) were utilized to evaluate the prediction accuracy. The values of MAPE and RMSE are inversely proportional to the accuracy of the prediction model, whilst the MPE shows prediction bias.

From the literatures, prediction accuracies of the models are still inapplicable due to randomness of the traffic incident duration. To overcome the limitations of the current prediction methods, machine learning approaches have been newly attempted in current studies.

2.2.3 Impact analysis

Several studies seek to investigate the spatiotemporal impact caused by traffic incidents (Haule et al., 2019; Chen et al., 2016; Chung and Recker 2012; Zeng and Songchitruksa, 2010). Impact duration was defined from incident occurrence to return to normal traffic condition. In Figure 6 (cited from Haule et al., 2019), impact duration was estimated by using travel time for normal flow and during incidents. Metrics for the impact analysis were normally speed change, total delay, or backlog length.

From the incident impact studies, definition of 'normal state' can be a critical issue. Previous studies (e.g. Chen et al., 2016; Chung and Recker, 2012) applied subjective assumptions, such as certain

changes of speed or occupancy, to figure out normal and congested states. This is somewhat reasonable but still insufficient to clarify the baseline conditions. Another issue of those studies is that the inherent characteristics (e.g. magnitude, deterioration speed, and recovery speed) of the impact were overlooked.

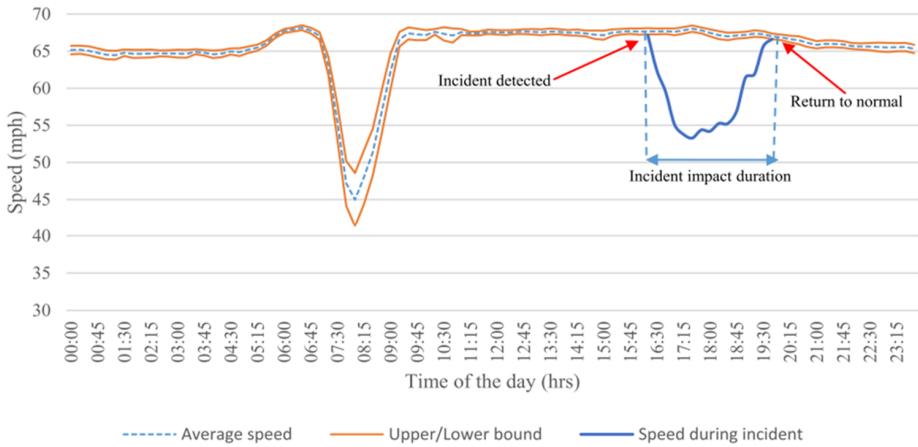


Figure 6. Incident impact duration from speed profiles

2.3 Originality of This Study

Based on the issues discussed in section 2.1 and 2.2, noteworthy contributions of this study are as follows:

- Provides a definition of freeway traffic resilience considering adaptive capability of a transport system. Most resilience studies assumed that system performance during normal state remains at a certain level. However, in the real world, transport system

capability (e.g. maximum throughput during a certain time) varies according to traffic demand.

- Develops comprehensive resilience indices to assess the performance reduction of freeway system caused by traffic accident. Previous studies usually utilize only a single indicator (e.g. duration or total delay) that cannot reveal the inherent features affecting accident-induced congestion. It can be also expected that suggested multiple indices facilitates much detailed interpretations and policy implications.
- Applies a probabilistic approach to determine the traffic states and accident impact region. Previous studies used excessive or suspicious assumptions to define maximum crash impact region (Chung and Recker, 2012) or traffic shockwave front (Chen et al., 2016). In this study, statistical classification method was applied to conduct traffic state classification.
- Conducts a practical analysis based on real data. Common issues of existing resilience studies are lack of data and limited practicality as they cover natural disasters rather than the issues possibly facing in our daily life.

Chapter 3. Methodology

3.1 Concept & Definition

3.1.1 Basic concept

Disturbances on traffic flow affects transport system functionalities such as maximum throughput related to the system capability (Amini et al., 2018; Kim and Yeo, 2016) and travel time (or speed) related to user satisfaction (Daganzo, 2005).

As a distinguishable feature of transport systems, capability of a system depends on traffic demand at certain time period. In Figure 7 (adapted from Kim and Yeo, 2016), a disruptive event, such as traffic accident, is expected to affect the system capability (e.g. maximum throughput) on freeway section.

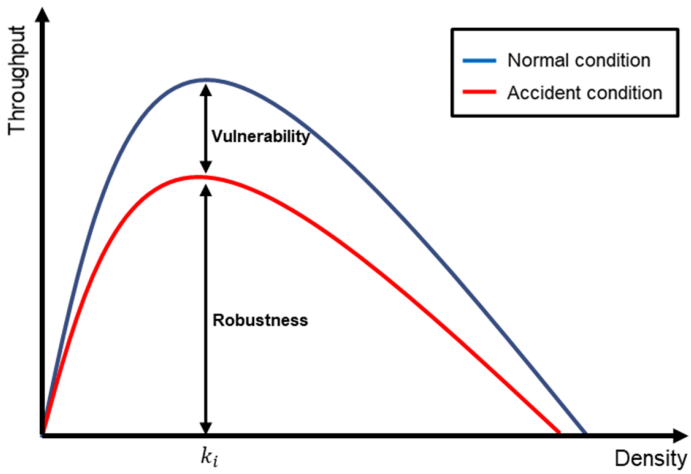


Figure 7. Transport system capability due to demand variation

In Figure 7, robustness can be represented by a maximum throughput at k_i during accident. Vulnerability can be measured as the difference of the maximum throughput at k_i between normal and accident condition (correspond to the definitions in Section 2.2).

Although traffic accident reduces the freeway section capability, traffic demand is expected to remain at the same level until drivers recognize the accident and change their route. To support this assumption, Figure 8 depicts the traffic flow characteristics during normal and accident conditions that represented as blue solid line and red dotted line, respectively. In Figure 8, travel speed decreases while traffic density increases due to traffic accident.

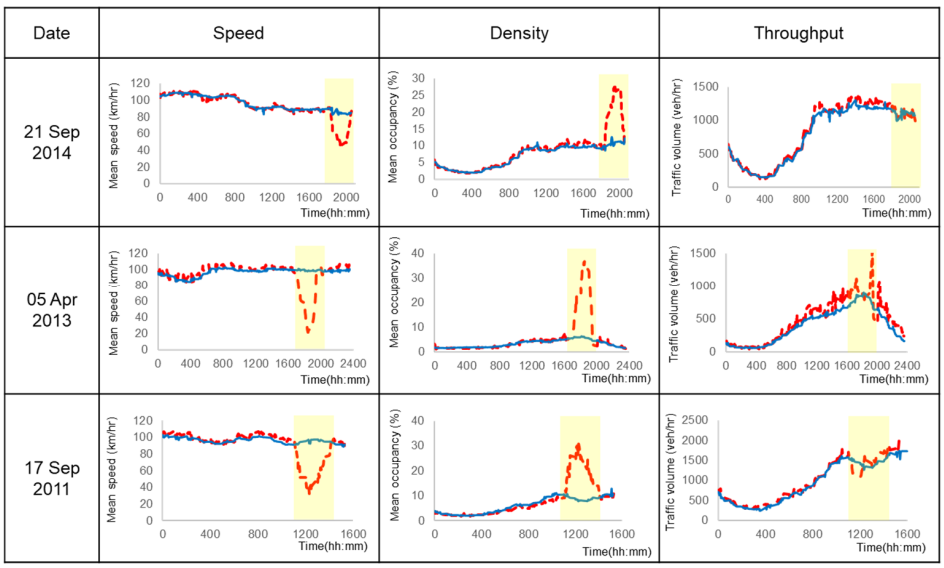


Figure 8. Traffic flow characteristics during accident

Therefore, freeway user satisfactions during accident could be assessed by calculating the speed reduction or density increment. More comprehensively, total travel time (or total delay) induced by traffic accident can be utilized considering total system loss, closer to the resilience concept.

Figure 9 additionally shows the travel speed reductions caused by traffic accident. It can be found that characteristics of the accident impact properties (e.g. magnitude and dispersion) vary possibly due to external factors (e.g. roadway physical characteristics).

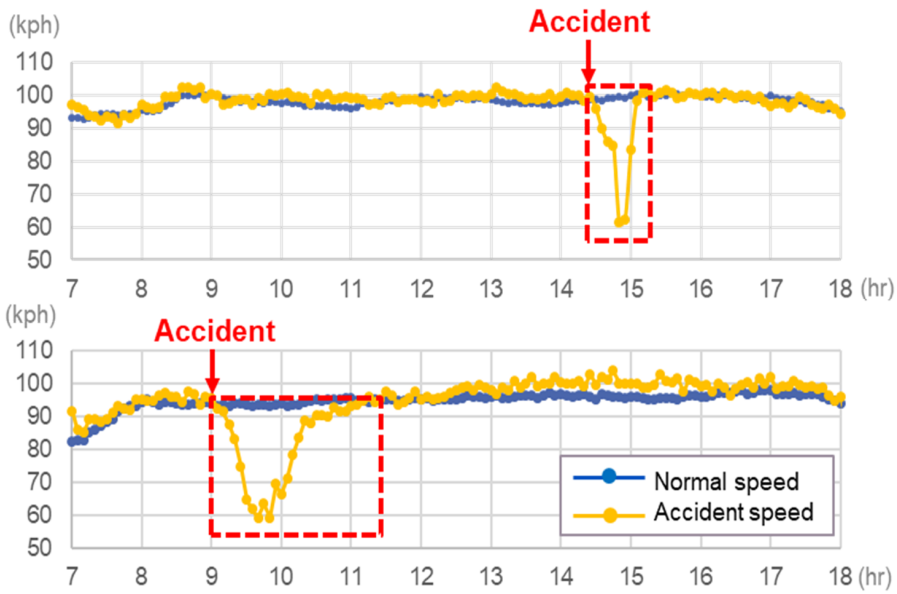


Figure 9. Travel speed reductions during accident

Figure 10 further illustrates the speed reductions on freeway sections caused by accident in a spatiotemporal concept. Interesting point is that the fundamental shapes in Figure 9 and Figure 10 are very similar to the resilience triangle concept (Figure 11, cited from Zhou et al., 2019).

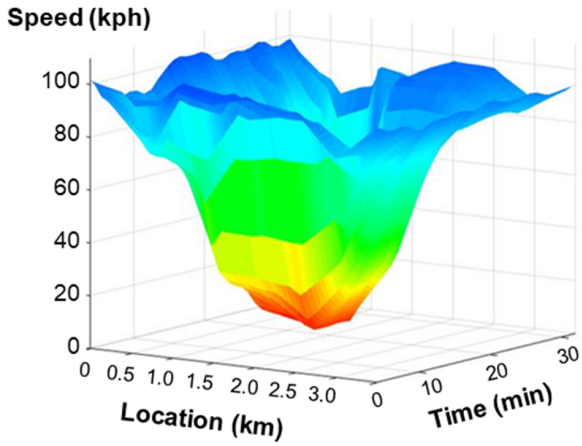


Figure 10. Spatiotemporal speed reductions during accident

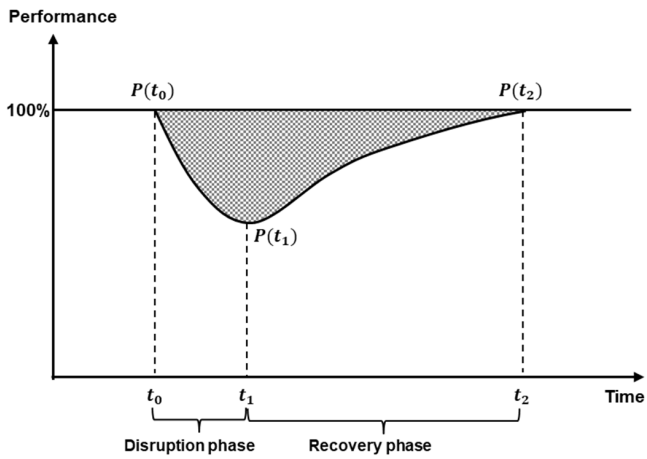


Figure 11. Conceptual illustration of transport system resilience

3.1.2 Definition

Based on the basic concepts discussed above, this study defines the freeway traffic resilience as “the ability of a freeway system to resist and to effectively recover from unexpected perturbations in traffic flow”. Perturbations include accident, roadwork, natural disasters, and other unexpected events that affect traffic flow.

Core elements of the resilience are resistance and performance loss. Resistance refers the ratio of robustness and system capability during normal state, as illustrated in Figure 7. Performance loss can be represented as a total delay caused by disruptive events. Total delay incorporates both deterioration and recovery states of traffic flow caused by accident.

One consideration for this definition is that spatiotemporal impact range varies due to type or severity of disturbances. Therefore, identification of the accident impact region would be an important issue to conduct resilience assessment. In case the spatial impact range does not exceed to other links or lines, freeway link can be considered as the spatial unit to conduct resilience analysis. This will be further discussed in Section 4.3.

3.2 Resilience Index

3.2.1 Resistance

Resistance indicates ability of a system to resist from perturbations. It can be calculated as the minimum ratio of robustness and system capability at density k_i, as shown in Equation (6).

$$R = \min\left(\frac{Robustness}{Robustness + Vulnerability}\right) = \min\left(\frac{q_n(k_i)}{q_a(k_i)}\right) \quad (6)$$

$(where\ , i = 1, \dots n)$

- q_n: maximum throughput at k_i during normal condition
- q_a: throughput flow at k_i during accident condition
- k_i: traffic density at time i,
- i: five-minute segmented time slot
- n: five-minute interval time period for accident impact duration

Figure 12 illustrates the daily traffic flow diagrams and the occupancy values increased when accident occurs (red triangles). It can be seen that the accident impact draws a counterclockwise trajectory on flow-occupancy diagram.

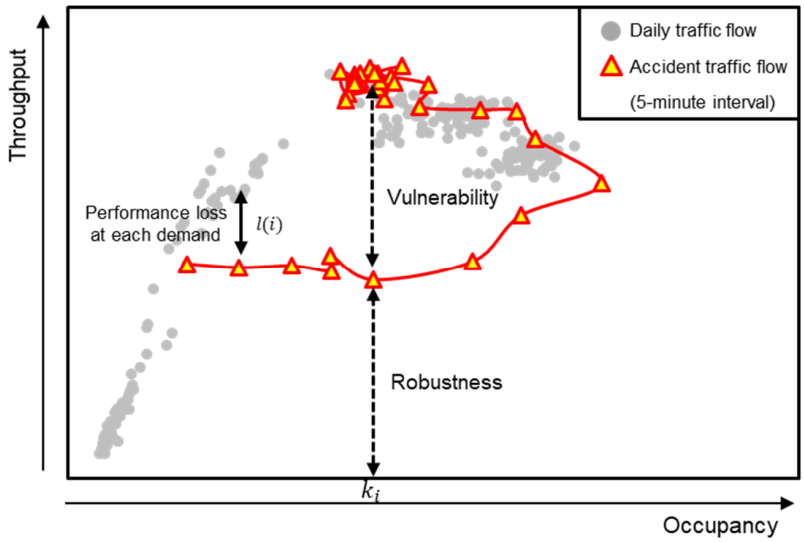


Figure 12. Flow−occupancy diagram during accident

3.2.2 Total delay

Total delay indicates system's performance loss, in perspective of user dissatisfaction, induced by traffic accident. Equation (7) formulates the measurement of total delay.

$$TD = \sum L\left[\frac{1}{V_a(i)} - \frac{1}{V_n(i)}\right] q_i \qquad (7)$$

- L: length of segment
- q_i: traffic volume during time i
- $V_a(i)$: average speed during time i on accident condition
- $V_n(i)$: average speed during time i on normal condition

Total delay could sub-divided as the delay during deterioration state and recovery state that remains as a further research topic. Figure 13 shows the daily traffic flow diagrams and the speed values decreased when accident occurs. There is also a counterclockwise trajectory on speed-occupancy diagram induced by traffic accident.

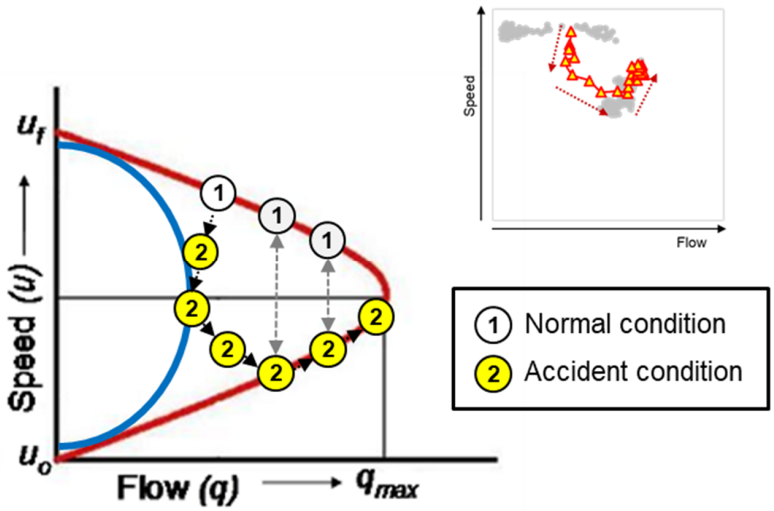


Figure 13. Speed-flow diagrams during accident

3.3 Traffic State Classification

3.3.1 Initial idea

This study conducts a traffic state classification to determine the spatiotemporal ranges of accident impact. A fundamental idea of this section is that the values of a traffic flow characteristic (e.g. speed, flow, or density) will be clustered on certain points if the data is

collected at the same time period i and same location j. The only exception possibly occurs due to unexpected disturbances in traffic flow (e.g. traffic accident) that change the traffic state from 'normal' to 'abnormal'.

Figure 14 depicts the traffic flow characteristics during accident. Red circles indicate the non-accident state and blue stars show the accident state. It can be seen that most of the red circles are bunched together at certain area that represents the normal state. Blue stars are located far from the red circles as the abnormal state.

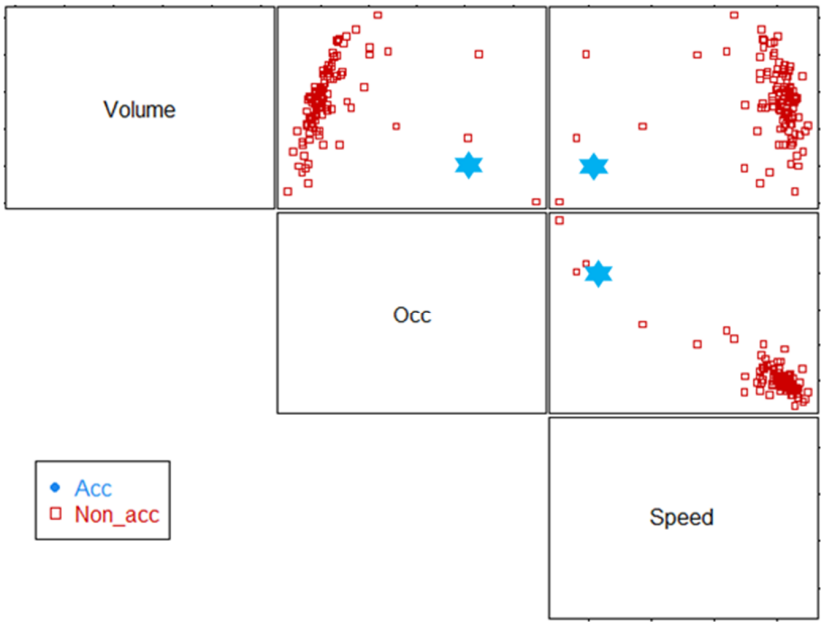


Figure 14. Traffic flow characteristics during accident

To support this idea, Figure 15 depicts the mixed distributions of probability density functions on travel speed that collected during same time of day and day of week i and same location j. Plausible assumption is that normal state speeds are faster than abnormal state speeds and their probability density functions can be clearly distinguished by different distributions.

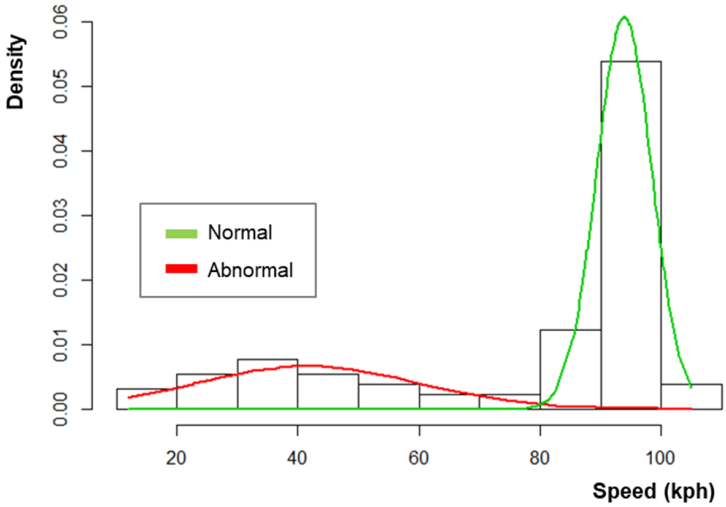


Figure 15. Probability density function of speed data

Figure 16 expands the concept above to multiple spatiotemporal segments. When a disruptive event occurs $(i = 0,\ j = 0)$, its impact would be propagated throughout the time stamps $(i = 1, 2, 3, \ldots)$ and the upstream locations $(j = 1, 2, 3, \ldots)$. If the data collected at time i and location j during accident (V_{ji}^{a}) is located at abnormal state distribution, we may decide that the accident significantly affects the

traffic state at V_{ji}^{a}. $\hat{V}_{ji}^{n}$ indicates the mean value of the normal state distribution that will be utilized to measure total delay.

Overall, traffic state classification method can be utilized in this section to determine whether accident changes traffic state or not. Not only the accident impact duration but also a spatial unit of freeway traffic resilience (e.g. link or network) can be identified as well. Normal state speed, required for total delay calculation, can be easily acquired from the normal state distribution.

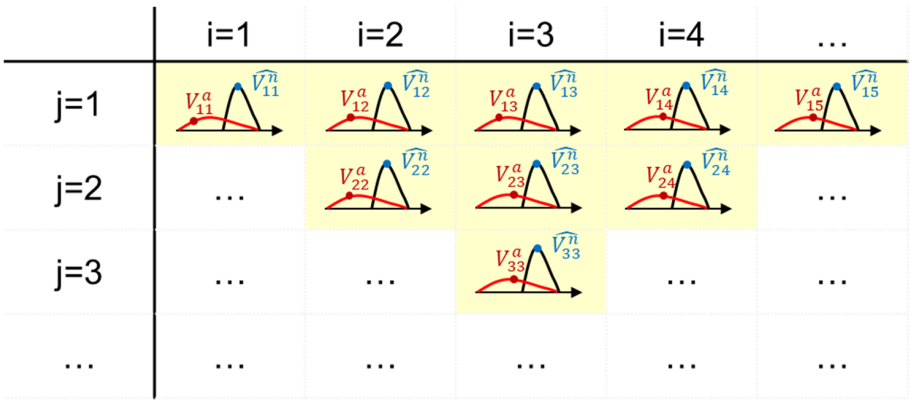


Figure 16. Conceptual illustration of accident impact region

3.3.2 Methodologies

K-means clustering, density-based spatial clustering of applications with noise (DBSCAN), and Gaussian Mixture Model (GMM) can be applied to classify the traffic state.

The K-means algorithm clusters data by trying to separate samples in n groups of equal variances, minimizing a criterion known as the inertia or within-cluster sum-of-squares. It scales well to large number of samples and has been used across a large range of application areas in many different fields.

The DBSCAN algorithm views clusters as areas of high density separated by areas of low density. Due to this rather generic view, clusters found by DBSCAN can be any shape, as opposed to k-means which assumes that clusters are convex shaped. The central component to the DBSCAN is the concept of core samples, which are samples that are in areas of high density.

A Gaussian mixture model (GMM) is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. One can think of mixture models as generalizing k-means clustering to incorporate information about the covariance structure of the data as well as the centers of the latent Gaussians.

Table 9 synthesizes the methods investigated above. GMM is selected to conduct traffic state classifications as it probabilistically catches the accident impact seedpoint. Speed, occupancy, and traffic volume data can be utilized for the state classification.

Table 9. Comparison in existing methods

	Hyper parameter	Pros	Cons
K-means	• Number of groups • End condition	• Easy and intuitive algorithm • Applicable for large data processing • Easy, efficient, and performant	• Sensitive to Outliers • Bad results if dispersion of each data type group is similar and not distributed in a spherical shape
DBSCAN	• Minimum number of groups • Minimum range of density measurem ent	• Outliers can be excluded • Cluster analysis on various distribution data • Does not need a pre-set number of clusters	• Poor results if difference in density between clusters is unclear • Difficult to identify features of each type
GMM	• Number of groups • End condition	• Provide statistically accurate results than the k-means algorithm. • A lot more flexible in terms of cluster covariance than K-Means	• Difficult to use for large amounts of data due to large amount of calculation • Poor results if the distribution of types differs from the normal distribution

3.2.3 Gaussian Mixture Model

The mixture model can be represented by any type of probability density distribution, but in general, the Gaussian mixture model is the most popular method due to the simplicity of the estimation process

(Hastie et al., 2009; Hsu and Lian, 2007; Ueda et al., 2000) and is intensively used for density estimation through computational, mathematical, and optimization operations.

Previous literatures (e.g. Ko and Guensler, 2005; Jun, 2010; Liu et al., 2016) also utilized the GMM for conducting traffic state classification. Several studies classify the traffic state as normal and congested. Other studies further divide the state as free flow, quasi-free flow, slight crowd flow, crowd flow, and traffic jam. Existing studies use GMM to classify daily traffic flow states at certain location, however, none of them attempt to classify the traffic state at both certain location and certain time segment.

GMM can be formed as Equation (8) (Hastie et al., 2009), where $\pi_i(\pi_i > 0)$ is a mixing proportion, and each Gaussian density has a mean u_i, and covariance matrix $\sum i = \sigma_i I$. In case of the two—component mixture (a bimodal) model, P is equal to 2.

$$\mathrm{f(x)} = \sum_{i}^{p} \pi_i \, \theta_i = \sum_{i}^{p} \pi_i \, \theta_i(x; u_i, \sum i) \qquad (8)$$

Due to the apparent bimodality of speed distributions having heavy congestion conditions, a single distribution would not be appropriate, so it needs to be considered two separate underlying regimes as a mixture of two different Gaussian (or normal) density

distributions (Hastie et al., 2009). The first mixture component representing the low speed regime can be depicted as $\theta_1(x) \sim N(u_1, \sigma_1^2)$ and the second mixture component indicating the high−speed regime can be represented by $\theta_2(x) \sim N(u_2, \sigma_2^2)$, where $\mathrm{f(x)}$ indicates the probability that a specific speed (x) can occur. Thus, the mixture model of two different speed distributions can be modeled as follows:

$$\mathrm{f(x)} = (1 - \pi)\theta_1(x) + \pi\theta_2(x) \tag{9}$$

The density parameters of each Gaussian mixture (a low−speed or a high—speed distribution) can be estimated from maximum likelihood by using the Expectation—Maximization (EM) algorithm, one of the optimization methods (Hastie et al., 2009; Ueda et al., 2000; Zhu et a1., 2007). Six parameters need to be estimated for the mixture of two Gaussian distributions, which is $\theta = (\pi, \theta_1, \theta_2) = (\pi_1, u_1, \sigma_1^2, \pi_2, u_2, \sigma_2^2)$, and the log—likelihood is formed like $\lambda(\theta; \mathrm{Z}) = \sum_{i=1}^{N} \log[\pi_1\theta_1(x_i) + \pi_2\theta_2(x_i)]$.

3.2.4 Traffic state classification utilizing GMM

Based on the model descriptions discussed above, Figure 18 shows the sample results of GMM utilizing traffic speed, volume, and occupancy data. Optimal number of distributions are determined by comparing the Akaike's Information Criterion (AIC).

Free flow state, normal state, transition state, and disrupted state are considered as the possible candidates for this analysis, therefore, maximum number of the distributions set as four. It can be also expected that normal state has a major proportion, whilst abnormal state would have relatively a minor proportion.

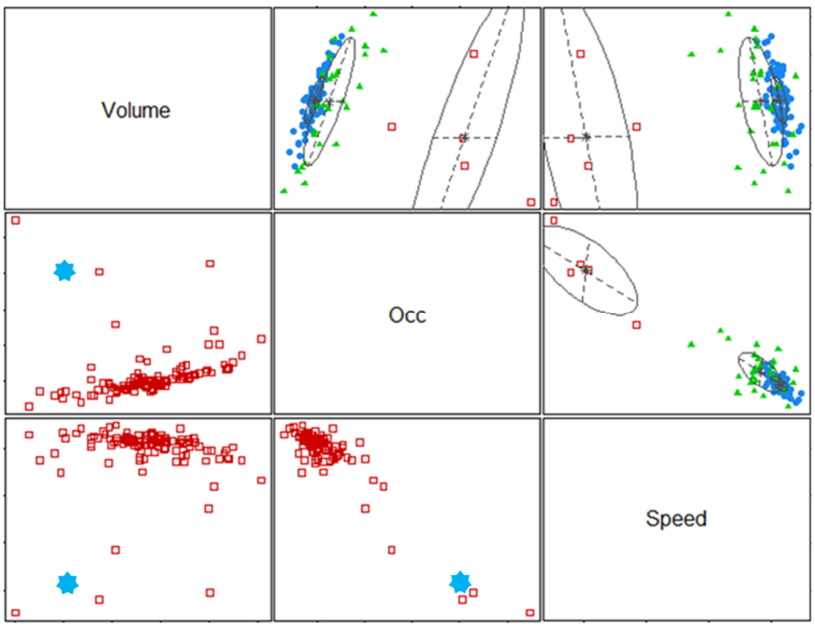


Figure 17. Traffic state classification utilizing GMM

Chapter 4. Experimental Analysis

4.1 Site Selection

Four major Expressways in Korea were selected for this study:

- Kyungbu expressway (Seoul – Busan)
- Seohaean expressway (Seoul – Mokpo)
- Yeongdong expressway (Incheon – Gangreung)
- Joongang expressway (Busan – Choonchun)

Figure 18. Selected study sites

Kyungbu Expressway has 425.5 km of total length that covers 9% of entire Expressways in Korea. 8,890 accidents occurred between 2010 and 2014 and VDS installed in every 1.08 km on average (total 784 VDS stations, bidirectionally). Table 10 shows the annual number of accidents occurred in Kyungbu Expressway. Figure 20 illustrates the VDS installation in Kyungbu Expressway. It can be seen that VDS is uninstalled between Unyang to Yungchun section.

Table 10. Annual number of accidents in Kyungbu Expressway

Year	# of accident (Kyungbu)	# of accident (Total)	Proportion (%)
2010	1,839	10,406	17.7
2011	1,767	9,813	18.0
2012	1,864	10,358	18.0
2013	1,633	9,703	16.8
2014	1,784	9,900	18.1
Total	8,890	50,180	17.7

Figure 19. VDS installation in Kyungbu Expressway

Seohaean, Yeongdong, and Joongang Expressways cover 18% of entire expressways in Korea (total length of 864.0km). 11,803 accidents occurred between 2010 and 2014 (23.5% of total number of accidents in all domestic Expressway).

Table 11 summarize the descriptions of the selected sites.

Table 11. Summary of selected sites, 2010–2014

Contents	Number of accidents	Total length (km)
Selected sites	20,693	1,289
All Expressways	50,180	4,767
Proportion (%)	41.2	27.0

4.2 Dataset Construction

Dataset contains accident type, traffic flow, weather, and geometric features related information from various data sources between 2010 and 2014. Main data sources are accident report, vehicle detection system (VDS), and automatic weather station (AWS).

Collected data was segmented and integrated to 5–minute time interval and at around 500m spatial interval according to VDS zone. Figure 20 describes the basic concept of VDS zone. For example, VDS zone #1 can be determined as $(l_3 - l_1)/2$.

Figure 21 illustrates the data filtering process. Throughout the process, data integrity (e.g. no missing data), significance of the accident impact, and the main cause for the congestion can be checked. Based on this, 420 accident sample data were finally filtered out to investigate the accident induced congestion property.

Table 12. Data sources and available information

Source	Available data
Accident report	Date, time, location, fatality, injury, facility type, lane, speed, cause, weather, accident type, number of accident vehicles, pavement material, road geometry, surface condition, lighting, roadwork, vehicle type, accident clearance time, occupied road, accident descriptions
VDS	Traffic volume, speed, occupancy
AWS	Wind direction, wind speed, temperature, humidity, local air pressure, sea level air pressure, precipitation, hourly precipitation, daily precipitation
Others	number of lanes, lane type, speed limit

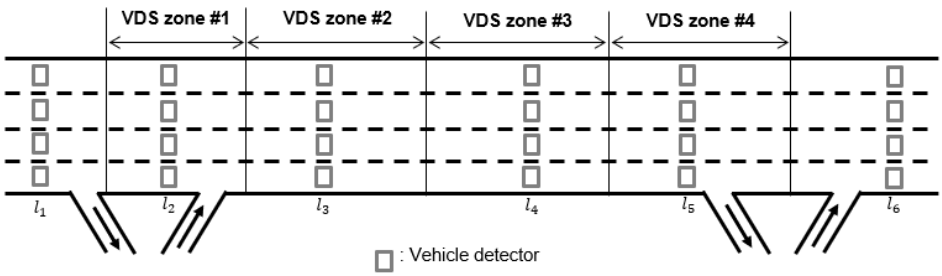


Figure 20. Basic concept of VDS zone

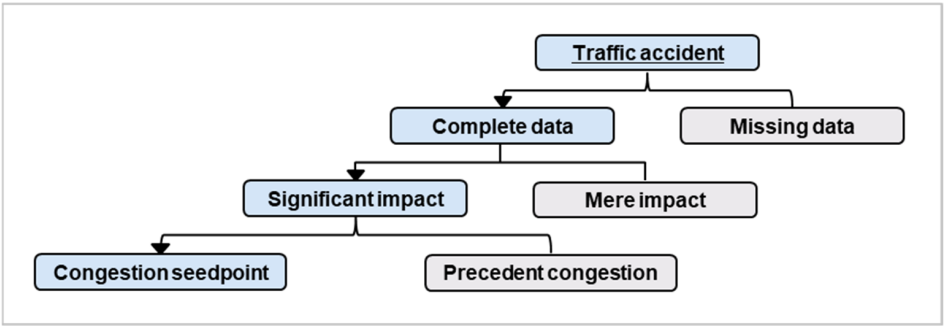


Figure 21. Data filtering process

4.3 Accident Impact Region

Traffic state classification analysis utilizing GMM revealed that the accident impact persists for 86.4 minutes on average. In addition to this, spatial range of the accident impact is measured as 4.5 km on average. Table 13 explains the spatiotemporal range of freeway accident impact region.

From the analysis results, traffic accident impacts on freeway network seems to be insignificant. Most of the accident impact ranges within a link (e.g. IC to IC) and the cases of the range over multiple links are less than 10% from the accident sample data. It was also revealed that accident occurrence spots are located at middle to downstream of the freeway link (located at 33 percentile downstream point of link, on average).

Based on the results, Freeway link is selected as an applicable spatial unit to conduct accident impact analysis. The term link utilized here is defined as a freeway section between adjacent interchanges. Route change is not allowed within a link; hence, it can be argued that a link is one of the major interests for traffic operators to implement efficient traffic control measures.

Table 13. Accident impact region

Accident impact	Unit	Mean	Standard deviation
Temporal range	Minute	86.36	50.32
Spatial range	km	4.53	2.82

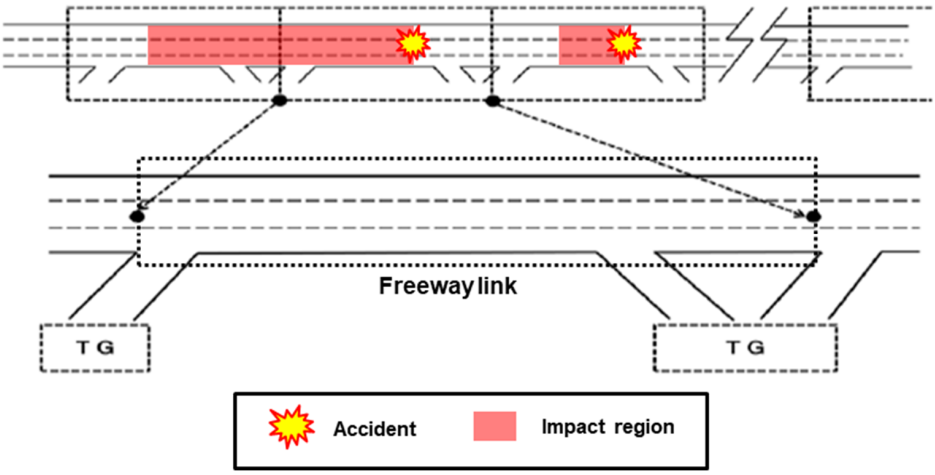


Figure 22. Accident impact on freeway link

Figure 23 illustrates the typical case of speed reductions caused by traffic accident. GMM utilized here to determine the accident impact region as shown. In figure 24, accident impact region can be easily discovered along the spatiotemporal boundary.

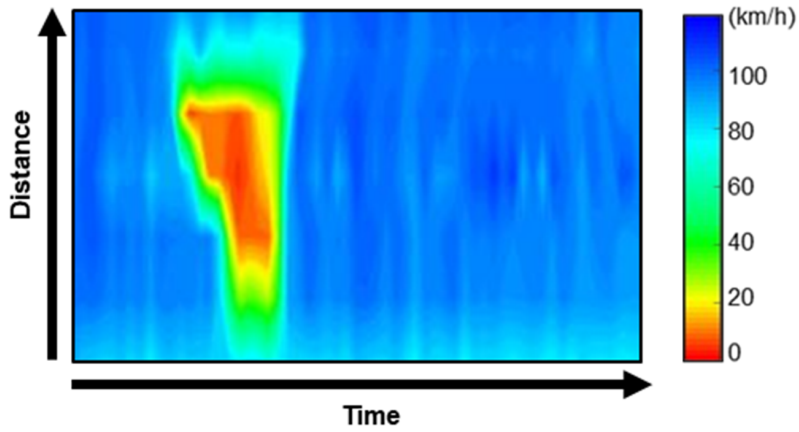
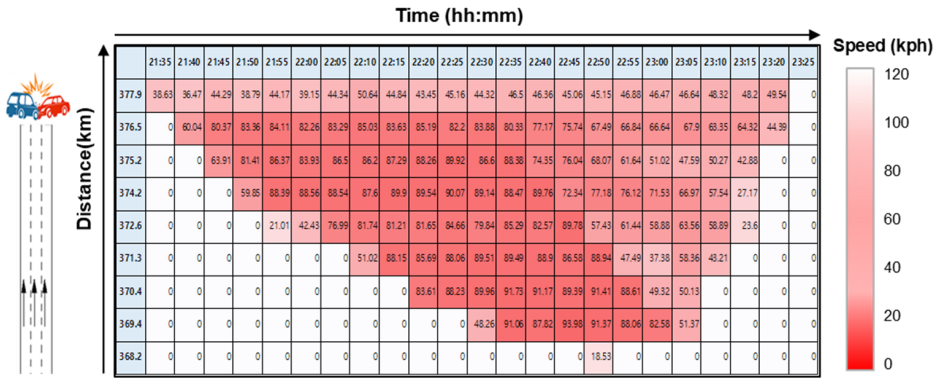


Figure 23. Spatiotemporal impact of traffic accident



	21:35	21:40	21:45	21:50	21:55	22:00	22:05	22:10	22:15	22:20	22:25	22:30	22:35	22:40	22:45	22:50	22:55	23:00	23:05	23:10	23:15	23:20	23:25
377.9	38.63	36.47	44.29	38.79	44.17	39.15	44.34	50.64	44.84	43.45	45.16	44.32	46.5	46.36	45.06	45.15	46.88	46.47	46.64	48.32	48.2	49.54	0
376.5	0	60.04	80.37	83.36	84.11	82.26	83.29	85.03	83.63	85.19	82.2	83.88	80.33	77.17	75.74	67.49	66.84	66.64	67.9	63.35	64.32	44.39	0
375.2	0	0	63.91	81.41	86.37	83.93	86.5	86.2	87.29	88.26	89.92	86.6	88.38	74.35	76.04	68.07	61.64	51.02	47.59	50.27	42.88	0	0
374.2	0	0	0	59.85	88.39	88.56	88.54	87.6	89.9	89.54	90.07	89.14	88.47	89.76	72.34	77.18	76.12	71.53	66.97	57.54	27.17	0	0
372.6	0	0	0	0	21.01	42.43	76.99	81.74	81.21	81.65	84.66	79.84	85.29	82.57	89.78	57.43	61.44	58.88	63.56	58.89	23.6	0	0
371.3	0	0	0	0	0	0	0	51.02	88.15	85.69	88.06	89.51	89.49	88.9	86.58	88.94	47.49	37.38	58.36	43.21	0	0	0
370.4	0	0	0	0	0	0	0	0	0	83.61	88.23	89.96	91.73	91.17	89.39	91.41	88.61	49.32	50.13	0	0	0	0
369.4	0	0	0	0	0	0	0	0	0	0	0	48.26	91.06	87.82	93.98	91.37	88.06	82.58	51.37	0	0	0	0
368.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	18.53	0	0	0	0	0	0	0

Figure 24. Spatiotemporal impact of traffic accident

4.4 Resilience Index Measurement

4.4.1 Resistance

To measure the resistance, capability of a freeway link is assumed as the 95-percentile values of throughput flow according to traffic occupancies. In Figure 25, yellow circles broadly depict the capability of freeway section. Trend line can be drawn to represent the link capability at any points of traffic occupancies.

From this analysis, it was found that the freeway link capability varies with different physical characteristics (e.g. length, number of lanes, speed limit, and other geometry related factors). Figure 26 illustrates the different shapes of flow-occupancy curves on freeway links. Measurement of resistance is generally described in Figure 27.

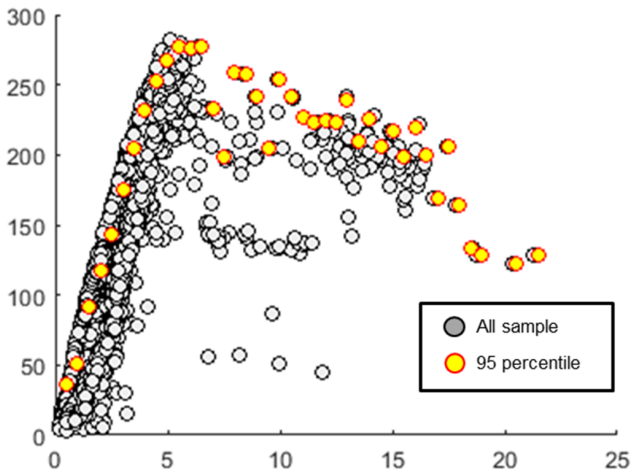


Figure 25. Flow-occupancy curve

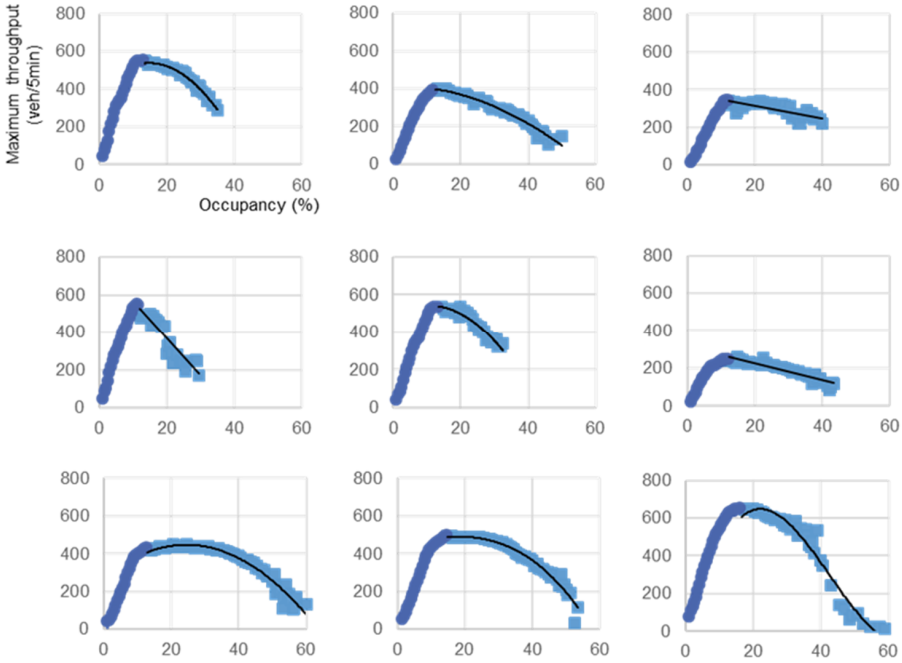


Figure 26. Flow−occupancy curves at different links

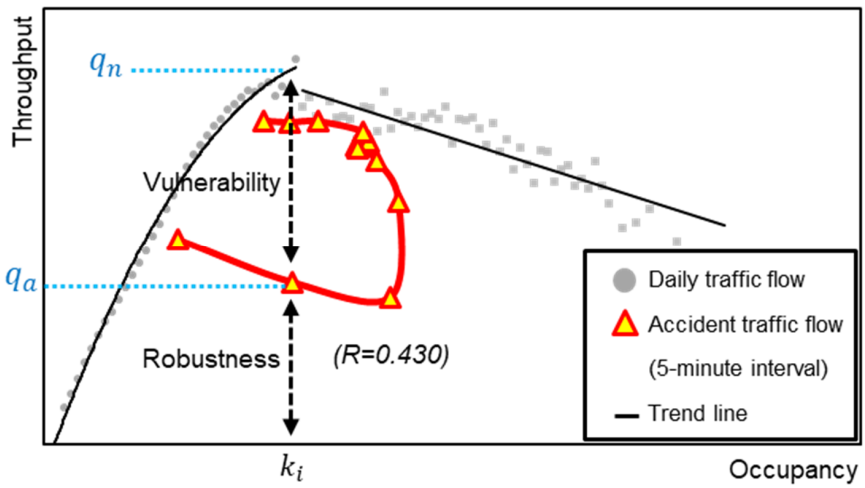


Figure 27. Measurement of resistance

4.4.2 Total delay

Traffic state classification, by utilizing GMM, conducted again to figure out temporal range of freeway accident impact. The point is that the spatial unit here is fixed as a freeway link where the accident is occurred. Figure 28 illustrates the traffic state classification on freeway link.

From the GMM analysis, normal state speed can be represented as $\hat{V}_{ji}^{n}$ and then speed reductions due to accident can be simply calculates as $\hat{V}_{ji}^{n} - V_{ji}^{a}$ (see Figure 29). As length of freeway link and traffic volume are given from data sources (e.g. accident report and VDS), total delay can be measured as stated in Section 3.2.2.

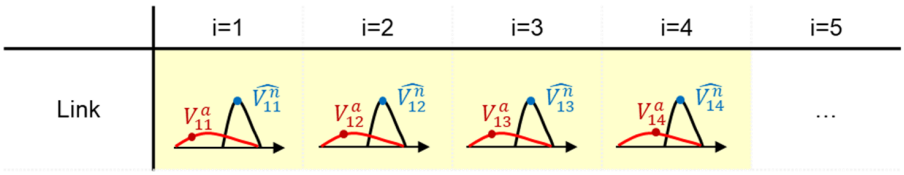


Figure 28. Traffic state classification on freeway link

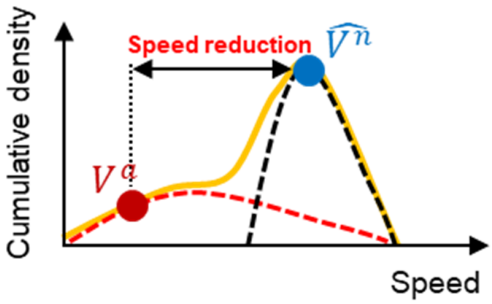


Figure 29. Speed reductions acquired from GMM analysis

4.4.3 Measured indices

Suggested resilience indices were measured as shown in Table 14. Mean values of the indices are 0.49 and 221.48 for resistance and total delay, respectively. Other descriptive statistics are also given in Table 14 below. To interpret the indices, probability density functions of the distributions are fitted as follows:

- Resistance evenly distributed follows the Beta distribution
- Distribution of total delay follows the lognormal distribution that is highly skewed to the right

Table 14. Descriptive statistics of resilience indices

Index	Observation	Mean	Standard deviation	Min	Max
Resistance	420	0.49	0.21	0.02	0.95
Total delay	420	221.48	387.22	0.05	2,393.78

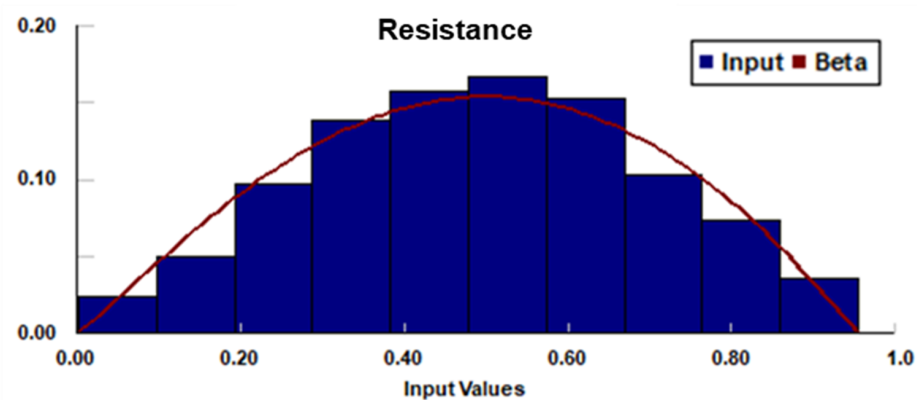


Figure 30. Distribution fitting: resistance

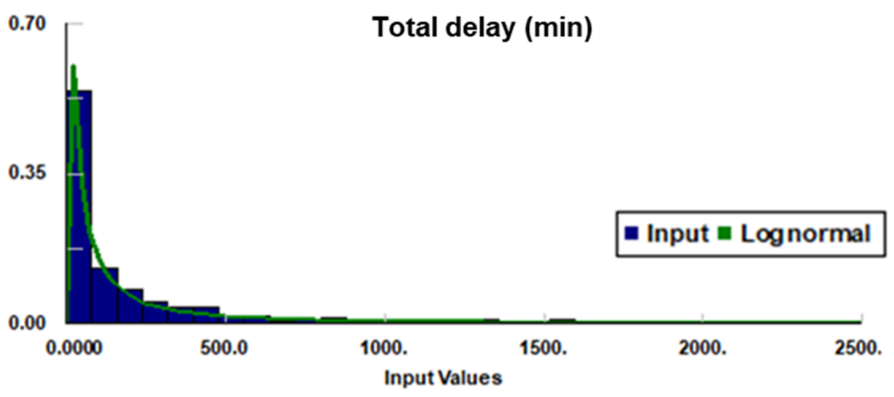


Figure 31. Distribution fitting: total delay

4.4.4 Resistance vs. total delay

This section investigates the relationship between resistance and total delay. From the scatter plots (see Figure 32), four different types are classified as follows:

- Type I (most undesired): shorter length of link & higher V/C
- Type II: longer length of link & higher V/C
- Type III: shorter length of link & lower V/C
- Type IV (most desired): longer length of link & lower V/C

Resistance is sensitive to the length of the freeway link, whilst total delay is found to be sensitive to volume capacity ratio (V/C). Based on this, it can be thought that the resistance index is closely related to the improvement of geometries as long-term efforts. In the case of total delay index, operational aspects to improve traffic

management could be more effective.

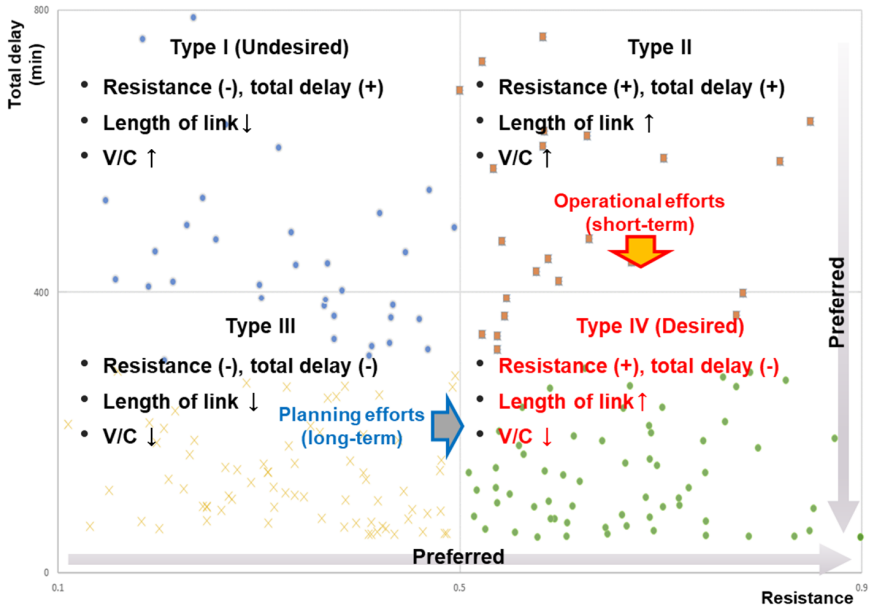


Figure 32. Resistance vs. total delay

4.5 Regression Analysis

4.5.1 Descriptive statistics

From the data sources and available information, as illustrated in Table 12 (p.33), expected influential factors on resilience indices are considered with its descriptive statistics. Influential factors are categorized as geometry, accident, and others. Selected variables are length, slope, speed, tunnel, vehicle, curve, bus-lane, truck, laneblock, vehicle, V/C, roadwork, and day. Descriptions of the variables are provided in Table 15 and Table 16.

Table 15. Expected influential factors: resistance

Index	Variable		Unit	Description	Potential impact	Mean	Std. Dev.
Resistance	Geometry	Length	km	Length of congestion zone	Positive	8.49	5.02
		Slope	%	Vertical slope of roadway section	Positive	0.33	1.44
		Speed	Km/h	Speed limit	Negative	103.60	5.10
		Tunnel	km	Tunnel length in a con-zone	Negative	0.19	0.61
	Accident	Vehicle	number	Number of vehicles involved in accident	Negative	0.47	0.50
		Truck	(dummy)	Truck involvement (no:0, yes:1)	Negative	0.47	0.50
		Laneblock	(dummy)	Mainlane block (no:0, yes:1)	Negative	0.61	0.49
	Others	V/C	Ratio	Volume capacity ratio	Positive	0.48	0.19
		Roadwork	(dummy)	Roadwork (no:0, yes:1)	Negative	0.01	0.11

Table 16. Expected influential factors: total delay

Index	Variable		Unit	Description	Potential impact	Mean	Std. Dev.
Total delay	Geometry	Curve	(dummy)	Length of curve section (0: 0m, 1: <0.5km, 2: <1km, 3: ≥1km)	Positive	0.45	1.01
		Tunnel	km	Tunnel length in a con-zone	Negative	0.19	0.61
		Bus-lane	(dummy)	Bus-lane (no: 0, yes: 1)	Positive	0.35	0.45
	Accident	Vehicle	number	Number of vehicles involved in accident	Negative	0.47	0.50
		Truck	(dummy)	Truck involvement (no:0, yes:1)	Negative	0.47	0.50
	Others	V/C	Ratio	Volume capacity ratio	Positive	0.48	0.19
		Day	(dummy)	Day or night (day: 0, night: 1)	Negative	0.16	0.37

4.5.2 Multivariate multiple linear regression

Multivariate multiple linear regression analysis is conducted in this section to explore the impact of selected factors on resilience indices. The multivariate multiple linear regression model has the form as Equation (10):

$$y_k = b_{0k} + \sum_{j-1}^{p} b_{jk} x_{ij} + e_k \tag{10}$$

for $i \in \{1, \dots, n\}$ and $k \in \{1, \dots m\}$ where,

- $y_k \in R$ is the k−th real−valued response for the i−th observation
- $b_{0k} \in R$ is the regression intercept for k−th response
- $b_{jk} \in R$ is the j−th predictor's regression slope for k−th response
- $x_{ij} \in R$ is the j−th predictor fot the i−th observation
- $(e_{i1}, \dots, e_{im})^{iid} \sim N(0_m, \Sigma)$ is a multivariate Gaussian error vector

Table 17 summarizes the results of the regression analysis. Resistance was analyzed to be affected by the length of the link, vertical slope, speed limit and the length of the tunnel. Number of vehicles involved in accidents, truck involvement, lane block, V/C,

and roadwork also influences on resistance. Correspond to the discussions in Section 4.4.4, length of the link is positively proportional to resistance.

Total delay is influenced by the length of curve, length of tunnel, and the presence of the bus lane. Number of vehicles involved in accidents, truck involvement, V/C, and day also affect the total delay. Correspond to the discussions in Section 4.4.4, traffic management related factor (e.g. buslane) is positively proportional to total delay.

Table 17. Results of multiple linear regression

Variables		Resistance (%)	Total delay (min)
Geometry	Length	0.44**	1.56
	Slope	0.51*	10.64
	Curve	0.23	32.33**
	Speed	−0.42**	2.50
	Tunnel	−2.69*	40.30*
Accident	Buslane	−2.19	72.00*
	Vehicle	−1.13*	90.53***
	Truck	−4.73**	22.08*
	Laneblock	−7.53***	36.02
Others	V/C	0.63***	331.29***
	Day	2.13	−158.59***
	Roadwork	−1.59**	142.69
Constant		6.77***	−389.96
R−Squared		0.535	0.273

Note: * p <0.1, ** p<0.05, *** p< 0.01

Multicollinearity issue between the variables are checked as well. Correlations between the independent variables were checked (see Table 18) and variation inflation factor (VIF) less than 2.5 threshold was applied in Table 19.

Table 18. Correlations between independent variables

	Length	Slop	Curve	Speed	Tunnel	Buslane	Vehicle	Truck	Laneblock	V/C	Day	Roadwork
Length	1.000											
Slop	0.084	1.000										
Curve	0.142	0.107	1.000									
Speed	−0.092	−0.036	−0.198	1.000								
Tunnel	0.249	0.040	0.002	−0.107	1.000							
Buslane	−0.010	−0.132	−0.109	0.560	−0.226	1.000						
Vehicle	−0.115	−0.020	−0.155	0.078	−0.104	0.034	1.000					
Truck	−0.047	−0.019	0.046	−0.009	−0.048	−0.031	0.149	1.000				
Laneblock	−0.091	−0.072	−0.060	−0.102	−0.020	−0.104	0.317	0.218	1.000			
V/C	0.025	0.008	−0.031	0.025	−0.066	0.171	−0.072	−0.125	−0.135	1.000		
Day	−0.012	−0.042	0.035	−0.032	−0.114	0.016	−0.038	0.000	0.004	−0.226	1.000	
Roadwork	0.034	−0.109	0.017	−0.035	0.017	0.011	0.029	−0.015	0.042	0.068	0.011	1.000

Table 19. Variation inflation factors

Variable	Length	Slop	Curve	Speed	Tunnel	Buslane	Vehicle	Truck	Laneblock	V/C	Day	Roadwork	Mean VIF
VIF	1.12	1.06	1.10	1.55	1.16	1.63	1.17	1.08	1.20	1.15	1.09	1.03	1.19
1/VIF	0.89	0.95	0.91	0.64	0.86	0.61	0.85	0.93	0.83	0.87	0.92	0.98	

Chapter 5. Discussions

5.1 Implications of Results

In this section, we consider several implications of this study findings regarding the assessment framework of freeway traffic resilience for policy makers and transport engineers.

For policy makers, suggested framework can be applied to plan, develop, and evaluate traffic management policies. For example, resilience indices suggested in Section 3.2 can be utilized to figure out vulnerable links against potential risk due to random disturbances on traffic flow. Effectiveness of traffic management policies can be evaluated by utilizing the indices.

Transport engineers could refer the results stated in Section 4.5 that provides deeper understandings on accident induced congestion property. Influential factors and their impacts on resilience indices would be considered for roadway design. As a pioneer research, this study lays the foundation stone for further researches on freeway traffic resilience.

Specific applications of this study will be discussed in Section 5.2.

5.2 Possible Applications

5.2.1 Assessment of existing infrastructure

Resilience indices can be co-utilized with existing indicators (e.g. number of accidents) to assess the existing infrastructures. Table 20 shows the freeway links where traffic accident occurred the most frequently. It can be seen that the values of resilience indices are not always corresponding to the number of accidents.

Table 20. Accident blackspots based on number of accidents

Line	Segment	# of accident (2010-2014)	Resilience Index	
			Total delay	Resistance
Kyungbu	Chungju IC – Mokchun IC	267	654.23	0.39
Kyungbu	Kumho JC – Bukdaegu IC	239	7152.05	0.18
Yeongdong	Munmak IC – Yeoju IC	224	2930.57	0.41
Kyungbu	Mokchun IC – Chungju IC	223	304.71	0.48
Kyungbu	Namgumi IC – Weguan IC	204	674.97	0.24
Kyungbu	Jyungsa IC – Yungchun IC	185	15.15	0.43
Kyungbu	Weguan IC – Namgumi IC	183	303.60	0.31
Joongang	Sinrim IC – Namwonju IC	183	51.10	0.37
Kyungbu	Dongdaegu JC – Kyungsan IC	178	217.97	0.75
Seohaean	Muan IC – Mokpo IC	175	186.96	0.42

5.2.2 Effectiveness analysis of traffic facilities

Resilience index can be also utilized for effectiveness analysis of traffic management facilities. Hard shoulder running (HSR), section speed enforcement (SSE), variable speed limit, and ramp metering are the possible facilities for the effectiveness analysis.

In table 21, HSR reduces 40% of total delay induced by accident. In the case of SSE, accident induced total delay is reduced by 57% (see Table 22). Correspond to the discussions in Section 4.4.4, traffic management facilities are more likely to improve total delay rather than resistance.

Table 21. Effectiveness evaluation of HSR

Line	Segment	Total delay		Resistance	
		Before	After	Before	After
Kyungbu	Bukcheonan IC – Ansung IC	1,379	458	0.28	0.31
	Ansung JC– Osan IC	2,109	1,504	0.58	0.49
	Osan IC – Dongtan JC	910	427	0.21	0.56

Table 22. Effectiveness evaluation of SSE

Line	Segment	Total delay		Resistance	
		Before	After	Before	After
Kyungbu	Ansung JC – Osan IC	1,504	638	0.49	0.44

5.2.3 Guidelines for roadway design

In Table 23, current guidelines for roadway section design suggest proper length between interchanges (Ministry of Land, Infrastructure, and Transport, 2016). However, geometry features (e.g. slope, horizontal curve, tunnel, etc.) discussed in the study are not considered in the design manual.

Therefore, comprehensive guideline considering the impact of geometry features on traffic resilience can be suggested. Appropriate traffic management facilities (e.g. HSR, SSE, VSL, and RMS) and their impact can be provided as well.

Table 23. Guidelines for length between interchanges

Region	Standard gap (km)
Urban freeway	2 – 5
Urban industrial area	5 – 10
Small city	15 – 25
Rural area	20 – 30

Chapter 6. Conclusions

6.1 Summary

This study developed a framework to quantitatively assess the freeway traffic resilience on link caused by random disturbances (e.g. traffic accident) throughout the following contents:

- Reviews the existing literatures on transport system resilience and accident impact analysis to investigate the research trends and further research opportunities
- Constructs a definition of freeway traffic resilience and designs freeway traffic resilience indices based on the literature reviews
- Develops a resilience quantification method based on traffic state identification technique by utilizing multivariate GMM
- Conducts an experimental analysis including site selection, dataset preparation, and influential factor analysis to assess and characterize the freeway traffic resilience on link
- Provides implications and possible applications of the assessment framework of freeway traffic resilience on link

6.2 Limitations & Opportunities

6.2.1 Limitations of this study

Limitations of this study can be summarized as follows:

- Data sample size is not enough to fully investigate the accident induced congestion property. Only 420 accident sample data can be utilized for the analysis due to missing data, insignificant impact on traffic flow, and existing congestion from precedent period or upstream location.
- Limited implications were derived from total delay analysis. As stated in Section 3, total delay could be further divided as deterioration state and recovery state. Deterioration delay might be highly influenced by road clearance time, whilst recovery delay would influenced by physical features of roadways. These issues are not covered in this study.
- Although VDS data is one of the best options to conduct spatiotemporal analysis, it has limitations in representing traffic flow characteristics such as density and space mean speed.
- This study does not investigate the network level resilience as the accident impact region was found to be ranged within a link.

6.2.2 Applications & further research opportunities

Despite the limitations mentioned above, this study is still valuable to provide more comprehensive approach to enlarge the concept and understanding of the accident induced congestion property.

Potential applications of this study lie in investment policy of freeway facilities which currently concentrated in tackling chronic congestions. It can be expected that customized solutions to improve the freeway traffic resilience on accident can be developed based on this study. Developed traffic resilience assessment framework would be also applicable to other type of roadways, other transport systems (e.g. subway, airline, and maritime), or even different systems (e.g. electric grid, water supply, etc.).

As further research opportunities, traffic resilience studies can be expanded to network level and multimodal systems (e.g. link → line → unimodal network → multimodal network). In addition to this, much detailed dataset from the environment of cooperative intelligent transport systems (C-ITS) can be considered. More indicators can be also considered to conduct deeper analysis on traffic resilience. For example, deterioration state, oscillation state, recovery state, and post recovery state can be considered within the resilience property.

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국문 초록

교통사고로 인한 고속도로 링크 회복탄력성 평가

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본 논문은 교통사고와 같은 임의의 유고 상황에 대한 고속도로 시스템의 회복탄력성 평가 방법론을 개발하였음. 교통류의 특성을 반영하여 고속도로 시스템의 회복탄력성을 정의하였으며, 교통사고에 대한 고속도로 구간의 저항 및 회복 능력을 정량적으로 평가하기 위한 지표를 개발하였음. 기존 교통사고 영향분석 연구에서 교통상태 분류 시 주관적 기준을 사용했던 한계를 개선하기 위해 확률적 모형 기반 교통상태 분류 방법을 제시하였으며, 이를 교통사고 영향 범위 설정 및 회복탄력성 지표 산정에 활용하였음.

제시된 방법론을 적용하여 국내 고속도로 링크의 교통사고에 대한 회복탄력성 평가지표를 산정하고, 각 지표 값의 분포적 특성 및 지표 간 관계를 분석하였음. 또한, 통계적 모형 기반 분석을 통해 기하구조, 교통량, 교통사고 특성 등 다양한 변수가 고속도로 구간의 회복탄력성에 미치는 영향을 규명하였음.

본 연구는 향후 교통안전 개선사업 대상지점 선정 및 가변차로, 구간단속, 가변속도제어, 램프 미터링 등 교통 운영관리 시설물의 효과평가 시 보조지표로 활용 가능하며, 이 외에도 다양한 교통정책의 개발 및 평가 측면에서 다양한 활용방안을 가짐. 또한 본 연구에서 제시한 교통 시스템 회복탄력성 평가 방법론은 네트워크 레벨의 다수단 교통 시스템으로 그 범위를 확장할 수 있으며, 고속도로 외에도 다양한 유형의 교통 및 타 시스템의 회복탄력성 평가에도 적용할 수 있음.

주요어: 회복탄력성 지표, 성능평가, 고속도로 교통사고, 교통상태 분류

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