Changes in Service Elasticity of Travel Demand during Disaster: A New Indicator of Phase Transition

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SHORT SUMMARY

The resilience studies often discussed phases of a system under disrupted conditions. However, these phases are arbitrary defined. In this study, we propose to use the elasticity as an indicator to identify the phase transition of transport system conditions under the disaster. The elasticity here refers to the service elasticity of travel demand, which indicates the degree of necessity of transport service. We use the multilevel log-log linear model to calculate the service elasticity and its temporal changes. We also use the change point detection algorithm to identify the timing of phase transition. Results show that the service elasticity becomes more elastic, indicating that the people may tend to stop making non-emergent travel in the first phase of the disruption, but after some time, people start to adapt with the disrupted condition (less elastic). The changes in the elasticity would help policymakers to decide the timing of phase transition of disaster management, e.g., when they can open the road for non-emergent travel needs.

Keywords: Change Point Detection, Disaster, Elasticity, Phase Transition.

1. INTRODUCTION

In recent years, the discussion of transport network performance under disrupted conditions has become an important topic. Some studies focus on the changes in demand and/or transport supply of the transport network performance under disrupted conditions (Bevilacqua et al., 2017; Gu et al., 2020; Ouyang et al., 2012; Safitri & Chikaraishi, 2021). This discussion also involves the temporal changes of the network performance and its phases. Existing studies define the phase of a system when it gets disrupted (Bawankule et al., 2021; Bešinović, 2020; Bevilacqua et al., 2018; Hossain et al., 2021; Najarian & Lim, 2019; Pant et al., 2014) as normal, disruption, adaptation, and recovery. However, these phase transitions are arbitrary defined and we argue that these phases must be defined not sorely based on supply but rather based on supply-demand interactions. Having an indicator to explore both supply and demand is necessary to understand the situation under disrupted conditions.

We propose to use the elasticity as an indicator to identify the phase transition of disaster management. Borrowing the economic definition, the elasticity refers to the percentage change in demand due to a 1% change price increase (Stock & Watson, 2015), while in this study, the elasticity refers to the service elasticity of travel demand, which indicates the degree of necessity of transport service. The changes in the elasticity would help policymakers to decide the timing of phase transition of disaster management, e.g., when they can open the road for non-emergent travel needs.

In order to address this point, the study attempt to explore the changes in the service elasticity as one of the indicators looking at the reaction of the demand when the transport supply change under the disrupted condition and to identify the phase transition. Specifically, this study aims to:

1) calculate the service elasticity and its temporal changes under disrupted conditions, and 2) identify the timing of phase transition using the service elasticity.

The structure of this study is as follows: the following section discusses the methodology used to determine the elasticity changes and detect the transition point. The third section discusses the results, and finally, we conclude our research by discussing the findings, contributions, policy implications, and future possible research.

2. METHODOLOGY

We first calculate the expected minimum generalized cost using the recursive logit model to obtain the accessibility index (Eq. (1)) based on the available links in a given network condition (see the details in Safitri and Chikaraishi, (2021)). We then straightforwardly compute the expected minimum generalized cost from origin i to destination j on date δ time τ ($x_{ij\delta\tau}$) (Eq. (2)).

$$ac_{ij\delta\tau} = \ln \left(\sum_{a\in A(k)} \exp \left(\frac{1}{\mu}(v\left(a\middle|k;\beta\right) + V^j(a;\beta)\right)\right) \tag{1}$$

$$x_{ij\delta\tau} = \frac{1}{\beta_c}\left(ac_{ij\delta\tau}\right) \tag{2}$$

Where $ac_{ij\delta\tau}$ represents the accessibility index from origin i to destination j on date δ time τ; β_c is the cost parameter in units of 100 Japanese Yen borrowed from Oka et al. (2018) that is -18.45; a is the next link that can be chosen from link k; A denotes all real links; β shows the vector parameter; $V^j(a;\beta)$ is the expected maximum utility; and μ is the scale parameter.

We then set the hypotheses as follow:

(a) *H1: In the condition just after the disaster, the service elasticity of travel demand becomes been more elastic. Being more elastic might be because people tend to stop travel and stop doing leisure activities (non-emergent activities).*

(b) *H2: After some time of the disaster, the service elasticity of travel demand becomes less elastic. Being less elastic might be because of the recovery activities conducted.*

The first hypothesis may naturally occur in the disruption phase of the disrupted system. In this phase, the number of available links decreases, people may tend to stop making non-emergent trips and give space to the emergency vehicles. Meanwhile, the second hypothesis may occur in the phase of adaptation and recovery.

To confirm these hypotheses, we use the multilevel log-log linear model, which is one of the regressions to calculate the elasticity (Stock et al., 2015). This method allows us to identify the temporal changes of the service elasticity. By using the multilevel log-log linear model, both Y and X are specified in logarithms, where $\beta_1$is the elasticity value of Y with respect to X, meaning that the percentage change in Y corresponds to 1% change in X (Gujarati, 1995). As the dependent variable Y, we use the log of travel demand from origin i to destination j on date δ time τ ($Q_{ij\delta\tau}$) and for the independent variable X (or x_1), we use the log of expected minimum generalized cost ($\ln\left(x_{1ij\delta\tau}\right)$) from equation (2).

$$Q_{ij\delta\tau} = \beta_o + \beta_1(x_{1ij\delta\tau}) + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + (u_{0ij\delta} + u_{1ij\delta}x_{1ij\delta\tau} + \varepsilon_{ij\delta\tau}) \tag{3}$$

Where the $\beta_o, \beta_1, \beta_2, \beta_3, \beta_4, \beta_5$ are the estimated parameters; x_2, x_3, x_4, x_5 show the time, dummy variables for Saturday, Sunday, and Obon (お盆) week, respectively. $u_{0ij\delta}$, $u_{1ij\delta}$, represent random variables/effects representing the deviation of the intercept for ID of origin i and destination j on date δ. By using this random effect, we can generate the elasticity value over time while $\varepsilon_{ij\delta\tau}$ is the white noise (residual), $var(\varepsilon_{ij\delta t}) = \sigma_{e0}^2$. In this study, Obon (お盆) week which is Japanese holiday that occurs in the middle of August is considered, because people may have different trip behavior.

3. RESULTS AND DISCUSSION

We focus on the heavy rain disaster July 2018 Japan in Hiroshima Area as the case study. Th dats that we use are 1) the travel demand data obtained from Mobile spatial statistics data, and 2) main links (including railroad) of road network data in the Hiroshima, Higashi-Hiroshima, Kure, and Aki District (Figure 1), consisting of 24 small areas. Based on the data availability, the analysis period is from June 1, 2018, to October 31, 2018, where the starting time of regulations or road closure and disaster occurred on July 6-7, 2018.

Before starting to analyze the service elasticity, we identify the affected and non-affected areas by using the information of the severity of each area, which we obtained from the city municipality. The classification of affected and non-affected areas will be used identify the to identify whether the change in service elasticity is the same or not. And thus, the policymakers could have the same or different reaction to these situations, e.g., when they can open the road for non-emergent travel needs for affected and non-affected area.

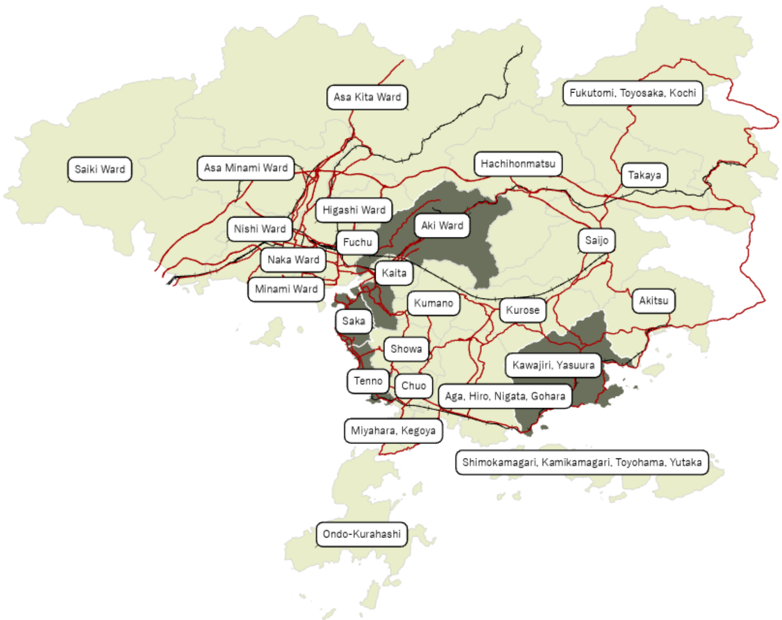

Figure 1. Network map and four affected areas.

The affected and non-affected classification is based on the information of the number of houses completely destroyed (d_1), number of houses half destroyed (d_2), number of houses partially damaged (d_3), number of houses underfloor flooded (d_4), and death (d_5). As a result, there are four severe areas, and the rest (20 areas) are not too severe. The affected areas are showed by dark green color on the map (See Figure 1).

The study employs a multilevel log-log linear model to get the temporal changes of service elasticity. Table 1 shows the estimation results, where β_1 reflects the elasticity value, meaning that 1% changes in the service elasticity are associated with 1.0423% changes in the travel demand. In this condition, the changes of service elasticity almost have the same proportion with the demand. However, some changes in the demand as the reaction to the changes of transport supply can be seen after we obtain the temporal changes from the random effect.

Table 1: Estimation Results of Service Elasticity

	β	**t-value**	σ^2	**Std. Dev**
	Fixed effects			
(Intercept)	3.1225	725.110		
Expected Minimum Generalized Cost	-1.0423	-184.314		
Time	0.0295	189.213		
Sunday	-0.0681	-8.778		
Saturday	-0.0287	-3.806		
Obon (お盆) week	-0.0073	-3.795		
	Random effects			
Origin-Destination-Date (Intercept)			0.197	0.444
Origin-Destination-Date (Expected Minimum Generalized Cost)			0.489	0.699
Residual			0.723	0.850
Final log-likelihood		-1,270,258		
Number of observations		953,255		

We then perform the random effect function to get the temporal changes of service elasticity. We also assign four distinctive O-D (Origin-Destination) pair based on the affected and non-affected area, i.e., 1) affected to affected, 2) affected to non-affected, 3) non-affected to affected, and 4) non-affected to non-affected. Figure 2 shows the temporal changes of the elasticity values of each O-D pair. Some elasticity values in the O-D pair between affected areas cannot be identified, given that some areas are not connected in the disrupted situations (just after the disaster). However, we can see that the service elasticity is relatively more elastic on the day when the disaster occurs (July 7, 2018). Almost all O-D pair show more elastic under disrupted conditions, except in non-affected to non-affected pair, where in this O-D, the service elasticity value is less elastic. This finding partially confirms the first hypothesis *H1: In the condition just after the disaster; the service elasticity of travel demand becomes been more elastic. Being more elastic might be because people tend to stop travel and stop doing leisure activities (non-emergency activities).* It provides an interpretation that people associated with the affected areas tend to stop travel and stop doing activities, which may be because people tend to give space to emergency vehicles.

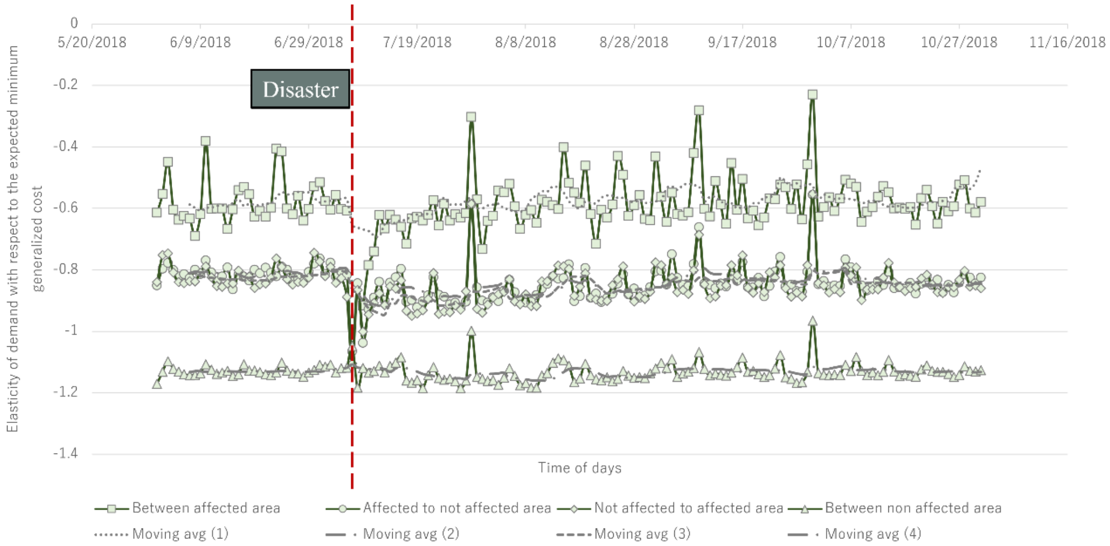

Figure 2. Temporal changes of service elasticity values based on four distinctive O-D pair.

Subsequently, sometime after the disaster, all O-D pairs show less elastic, supporting the second hypothesis *H2: After some time of the disaster; the service elasticity of travel demand becomes less elastic. Being less elastic might be because of the recovery activities conducted.* The recovery activities may already be started, and people start to adapt to the condition. We identify that the service elasticity becomes less elastic, more stable, and not too fluctuating in the third month after the disaster, at least on October 6, 2018 (91 days after the disaster). Note that some fluctuation identified in the graph showing the following disaster in the study area (typhoon 12) and Obon (お盆) week.

We then perform the change point detection to detect the timing of phase transition. The phase transition defines as the point of time when the characteristic of the temporal data shows a change. We consider some phases based on the existing studies, i.e., normal, disrupted/disruption, adaptation, and recovery. We then decide to merge these last two phases, believing that adaptation and recovery could occur simultaneously since the recovery phase may start in the middle of the adaptation phase (Najarian et al., 2019).

We generate the phase transition using the change point detection as one of the functions to generate the change point in the time series data by using mean and variance (Killick & Eckley, 2014). Additionally, we also use other methods. i.e., environmental time series change point detection, segmented, Bayesian analysis of change point problem, and cumulative sum. However, the change point detection analysis shows persistent results. Note that the length of the data may also influence the phase transition analysis.

We set the change point detection to three different phases as stated previously. Figure 3 displays the result of change point detection, where the first change is detected in point 36 (July 6, 2018), reflecting the starting point of the disruption, where the heavy rain disaster broke some links in the transportation network. The second transition is on August 10, 2018, one month after the disaster. The changes in the mean and variance increase along with the less elastic condition on that day. Additionally, we can conclude that more elastic condition occurs in the disruption phase.

Whereas the less elastic condition likely occurs in the adaptation and recovery phase. Again, note that the results may have different timing of phase transition depending on the number of phase transition we want to achieve and the length of the data.

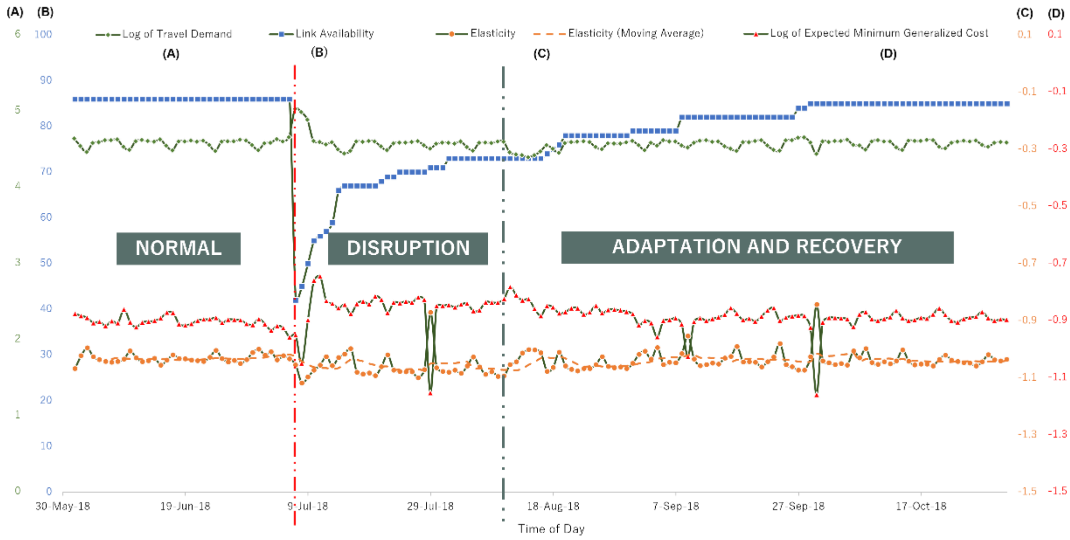

Figure 3. Phase Transition based on Change Point Detection

Figure 3 also shows some other graphs, i.e., log of travel demand, link availability, elasticity, moving average of the elasticity and log of expected minimum generalized cost. In heavy rain July 2018, Tenno (Kure), as one of the affected areas, experienced congestion due to high travel demand, from July 12, 2018 and it continued for several months (Chikaraishi et al., 2019). Considering the disrupted condition identified in this study, people might tend to consider transportation services as necessity travel demand even though the network was disrupted and total travel cost was higher, where in fact, the congestion could not be avoided. In this condition, it is better to prioritize the emergency vehicles, e.g., the policymakers could open the road for emergent travel needs only. While then, in the adaptation and recovery phase, the policymakers could open the road for non-emergent travel needs.

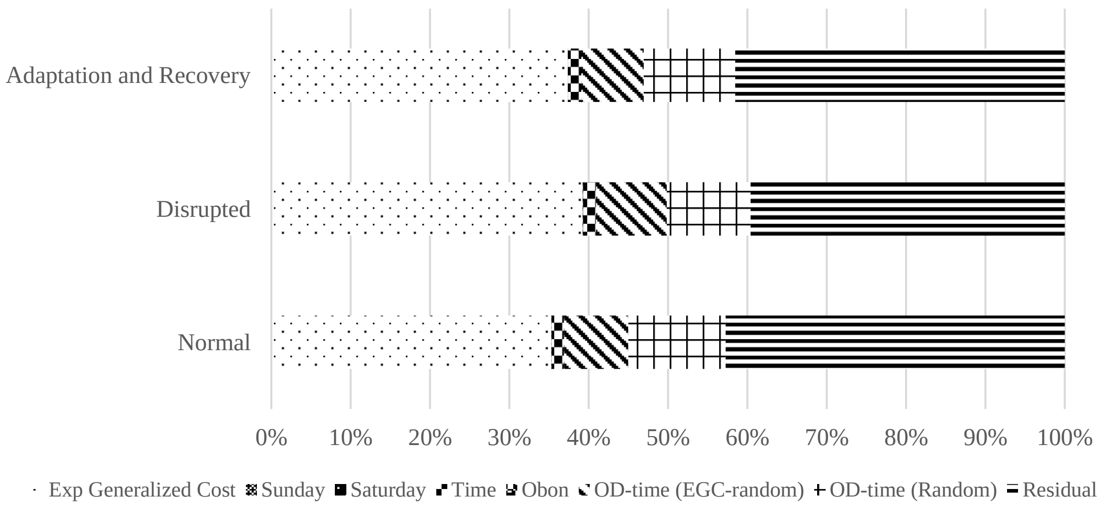

Figure 4. Variance Decomposition

Furthermore, we also analyze the variance decomposition to check the variance of the variables affecting the demand. Figure 4 shows the variance of fixed effects and random effects. The random effects, including residual, play an important role and have a higher proportion in all phases. Meanwhile, if we compare the fixed effects, i.e., the expected minimum generalized cost, Sunday, Saturday, time, and Obon (お盆) week by its phases, it has a higher proportion of influence on disrupted conditions (40.93%), followed by adaptation and recovery (39.08%). Likewise, in the normal condition (no disruption occurred), that only has a 36.90% proportion of fixed effects. Hence, this study shows that the unobserved components still play an important role to the changes of service elasticity.

4. CONCLUSIONS

This study proposes to use elasticity as an indicator to identify the phase transition of disaster management, indicating the degree of necessity of transport service. We partially confirm the first hypothesis, indicates that the service elasticity of travel demand becomes been more elastic just after the disaster and becomes less elastic sometime after the disaster. It shows that people may tend to stop travel and stop doing activities to give pace to the emergency vehicles in severe areas. Whereas then, people may start to adapt to the condition. Additionally, using the change point detection methods, we identify the timing of phase transition based on mean and variance. The results show that the more elastic condition occurs in the disruption phase, while the less elastic is likely occurring in the adaptation and recovery phase. The changes in the elasticity would help policymakers to decide the timing of phase transition of disaster management, where they could prioritize the emergent vehicles under disrupted situations. Furthermore, the variance decomposition indicates that the random effects, including residual, play an important role in changes of the service elasticity.

However, there are some limitations to this study. First, the computation of the service elasticity does not consider the congestion aspect, which we are currently trying to work on. Second, although the current empirical results can indicate three different phases in the study area, and we also try other methods, a deep analysis must be conducted to detect the change point more precisely, given that the analysis depends on the length of the data and the number of change points that need to be detected.

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