MINETA NATIONAL TRANSIT RESEARCH CONSORTIUM

Performance Measures to Assess Resiliency and Efficiency of Transit Systems

MNTRC Report 12-69

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REPORT 12-69

PERFORMANCE MEASURES TO ASSESS RESILIENCY AND EFFICIENCY OF TRANSIT SYSTEMS

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16. Abstract

Transit agencies are interested in assessing the short-, mid-, and long-term performance of their infrastructure with the objective of enhancing resiliency and efficiency. This report addresses three distinct aspects of New Jersey's Transit System: 1) resiliency of bridge infrastructure, 2) resiliency of public transit systems, and 3) efficiency of transit systems with an emphasis on paratransit service.

This project proposed a conceptual framework to assess the performance and resiliency for bridge structures in a transit network before and after disasters utilizing structural health monitoring (SHM), finite element (FE) modeling and remote sensing using Interferometric Synthetic Aperture Radar (InSAR). The public transit systems in NY/NJ were analyzed based on their vulnerability, resiliency, and efficiency in recovery following a major natural disaster.

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EXECUTIVE SUMMARY

Transit agencies, like other transportation agencies, are interested in assessing the short-, mid-, and long-term performances of their infrastructure with the objectives of making better decisions that will enhance their resiliency and efficiency. This report addresses three distinct aspects related to the resiliency and efficiency of New Jersey's Transit System: 1) resiliency of bridge infrastructure, 2) resiliency of public transit systems, and 3) efficiency of transit systems with an emphasis on their disability paratransit service. While the three sections of the report are researched and compiled independently, they are considered important aspects of the resiliency and efficiency of transit systems.

For bridge structures in a transit network, this project proposed a conceptual framework to assess their performance and resiliency before and after disasters. The proposed approach uses structural health monitoring (SHM), finite element (FE) modeling and remote sensing using Interferometric Synthetic Aperture Radar (InSAR). SHM data on various types of bridges would be collected from on-site sensors to validate FE models, which in turn would be applied to assess damage and degree of resiliency post-disasters. On the other hand, using two case studies, it is also shown that InSAR technology is capable of acquiring damage information quantitatively to assess the impact of earthquakes on the bridge performance.

Additionally, this project also analyzed the public transit systems in New Jersey based on their vulnerability, resiliency, and efficiency in recovery following a major natural disaster event such as Hurricane Sandy. Various data-driven models were used to quantify a series of performance measures for the transit network. Analyzing the resiliency and vulnerability of public transit networks is extremely important in the context of natural disasters as these networks serve as important evacuation means. For this purpose, diverse traffic, infrastructure, events and web-based sources of Big Data were analyzed. Due to the sparsity of public transit measures for vulnerability, recovery and resiliency, many measures from existing literature were adapted to public transit. An estimate of the reliability of specific bus routes on the NJ Transit bus network was made. Following Hurricane Sandy, the NJ Transit bus transit network recovered much faster than the rail network, as the most critical link for NJ Transit buses remained intact despite loss of power for driving and signaling rail and subway systems.

Lastly, the third part of the report also presented the discussion about efficiency of the transit system with a specific emphasis on the disability paratransit service. Americans with Disabilities Act (ADA) complementary paratransit is an important service provided by transit agencies nationwide to their registered clients at a fairly high cost and the US Government Accountability Office has already emphasized the importance of improving the efficiency of paratransit service. In order to improve the efficiency of disability paratransit service and optimize the costs of paratransit service, the researchers fully investigated the current and future demand for trips based on available NJ Transit data by the identification of the trip generators, which could assist agencies in allocating resources to service contractors, realigning service regions, and determining location of facilities. The study first identifies the generators of Access Link trips at a macro level by analyzing data at the census block group level. Subsequently, it focuses on the establishments located in the immediate vicinity of drop-off sites to identify the generators of Access Link trips at a micro level. Generalized linear mixed models (GLMM), ordinary least squares (OLS) regression models, and analysis of variance (ANOVA) were used in three components of this study. In addition, factors associated with the efficiency of paratransit were discussed, such as travel time and trip delay, which were recognized as the significant factors affecting the overall efficiency of paratransit systems. The performance measures related to travel time and congestion were also discussed.

This report provides the guidance to bridge engineers and traffic planning engineers from local transit agencies for the improvement of resiliency and reliability of transit infrastructure and the public transit network by the enhancement of proposed performance measures. Local transit agencies would employ remote sensing in assessing post-disaster performance of infrastructure as well as the resiliency of the local public transit network by evaluating the proposed performance measures in this report. This report also will help local transit agencies in optimizing the costs of paratransit service and in improving the efficiency of paratransit service based on the data-driven models.

I. INTRODUCTION

BACKGROUND

The United Nations International Strategy for Disaster Reduction (UN/ISDR) and the Centre for Research on the Epidemiology of Disasters (CRED) annually present official figures of the number of natural disasters and their impacts. Statistics from recent years show that the number of disasters has been increasing significantly. These events (and their devastating consequences) have highlighted the need for an efficient and responsive recovery after disasters. Hurricanes are one of the most dangerous and costly weather-related natural hazards in the United States (US). Considering the fatalities per natural hazard from 1981-2010, hurricanes were responsible on average for about 47 fatalities per year. This is one of the highest fatality rates, as compared to floods, lightning related events, and tornados. Between 2004 and 2013, however, average fatalities per year related to hurricanes increased to 108, which ranks the hurricane and heat as the two most deadly natural hazards.[1]

Public transit plays an important role for evacuating people during extreme events such as Hurricane Sandy. Hurricane Sandy was the second-most devastating storm in the history of United States. In particular, for the state of New Jersey (NJ), at the peak of the storm, more than 2,600,000 customers were without power.[2] There were 43 Hurricane Sandy-related deaths in NJ.[3] Damage in the state was estimated at $36.8 billion.[4]

Public transit in New Jersey (NJ) serves an extremely large urban population. NJ Transit has a service area of 5,325 square miles. With approximately 250,000 average weekday riders, bus customers form 60% of the customer base. Ridership on NJ Transit's rail system averaging about 135,000 customers on a weekday makes up 32% of the customer base. Light rail makes up 8% of the customer base with 35,000 weekday riders.[5]

According to a special report on emergency evacuation, the New York-Newark area has 2,102,874 housing units without cars, 425 cars per 1,000 persons and 18.54 transit vehicles per 1,000 persons.[6] The region also has a travel time ratio, a measure of congestion that is defined as the ratio of peak-period travel time to free-flow travel time, of 1.39.

On the other hand, as an important part of local transit agencies, the disability paratransit service is provided nationwide to their registered clients at a fairly high cost. The United States Government Accountability Office (GAO) emphasized the importance of improving the efficiency of paratransit service by making decisions based on quality data and analysis.[7] All agencies are under pressure to optimize the costs of paratransit service due to its increasing demand. One way to optimize the costs of paratransit service is to fully comprehend the current and future demand for trips. Appropriately forecasting demand for service can assist agencies in allocating resources to service contractors, realigning service regions, and determining location of facilities. An integral part of demand analysis for paratransit service is the identification of trip generators, whether they are defined as space (e.g., census tracts) or establishments (e.g., medical facilities). An extensive part of this report focuses on the identification of trip generators for paratransit service.

This report covers three different areas as the principal investigators (PIs) have different expertise in various areas, such as structural, transportation and paratransit. The PI and his research group performed the research in each area independently to cover the broad view of the efficiency and resiliency of transit systems. The first topic covers infrastructure, the second topic covers mass transit, and the last topic covers paratransit. Links between the three areas are not considered in this report.

OBJECTIVES

The main objective of this project is to assess the efficiency and resiliency of transit systems through the use of data-driven models that take advantage of various transit, traffic and infrastructure data. In order to assess this issue, this report develops different sets of performance measures for infrastructure and transit operations during extreme events such as Hurricane Sandy as well as for one of the important parts of local transit: paratransit service. The research team uses various data-driven models to quantify a series of performance measures. Using the extensive data available to the research team from various sources in NJ, they perform a comprehensive analysis throughout this study.

Other objectives of this report are to characterize the performance, sustainability, resiliency and reliability of transit infrastructure during natural disasters and to make long-term predictions about transit infrastructure. Specifically, this study aims to measure the resiliency of bridge structures, reliability of travel time, and reliability of access during extreme events by evaluating the conditions of pavements and bridges along various routes and also to evaluate transit service reliability during extreme events.

LITERATURE REVIEW

This literature review covers three areas as noted above. The first part covers the resiliency of infrastructure with emphasis on bridge structure to provide a review of state-of-art methodologies for estimating the resiliency of bridges after catastrophic disaster. The second part, about the vulnerability and resiliency of transit systems, assesses the performance of transit systems in the context of their ability to face disruptions. The third part covers the efficiency and reliability of paratransit.

Bridge Resiliency

In a civil infrastructure system, three major components regarding resiliency are used to quantify disaster resiliency. These include 1) system performance during a disaster (system vulnerability), 2) resulting losses, and 3) post-disaster system recovery. Typically, a dimensionless quantity that represents the rapidity of the system to revive from the post-event condition to the pre-event functionality level is used to quantify the bridge resiliency from previous studies. The consequence of extreme natural hazards including earthquake, flood, hurricane, tornado, and landslide leads to economic, human and environmental losses to a society. The Academies defined resiliency of infrastructure system as “the ability to prepare and plan for, absorb, recover from, and more successfully adapt to adverse events,” writing that “enhanced resiliency allows better anticipation of disasters and better planning to reduce disaster losses — rather than waiting for an event to occur and paying for it afterward."[8] To achieve such enhanced resiliency, civil infrastructure systems must not only survive natural disasters, but also recover to functional levels within acceptable time and cost limits.

Drawing from the literature search, various types of structure resiliency assessment models were proposed. The available methods previously proposed regarding the resiliency of structure are listed as following. Eguchi et al. documented the methodological development of preliminary damage detection algorithms for highway bridges.[9] Remote sensing technologies offer near-real post-disaster damage assessment. Deco et al. proposed a probabilistic approach for the pre-event assessment of seismic resiliency of bridges, including uncertainties associated with expected damage, restoration process, and rebuilding/rehabilitation costs.[10] HAZUS presented the restoration curves for highway bridges, based on their observed data from California.[11] Banerjee et al. presented a study on the enhancement of seismic resiliency of bridges through retrofit.[12] A reinforced concrete bridge which was severely damaged during the Northridge earthquake in the Los Angeles region was analyzed. Dojutrek et al. presented a multi-criteria methodology to quantify the resiliency or vulnerability of an infrastructure including bridges to damage, and the consequences of the infrastructure damage.[13]

In particular, the following discussion focuses on the remote sensing and detailed review on SAR (Synthetic Aperture Radar) and InSAR applications that are adopted in this report. Based on previous efforts presented below on the application of remote sensing, the authors present two case studies about InSAR technology in Chapter II.

Review of Previous Research on Infrastructure Applications of Remote Sensing (SAR and InSAR)

The satellite and airborne remote sensing systems currently available for disaster response utilize optical and SAR imaging technologies. Optical systems image the Earth's surface by collecting sunlight that reflects off the surface. On the other hand, SAR systems image the earth's surface by collecting electromagnetic signals which they emit and which are backscattered from the surface.

The main advantages of SAR systems can be summarized as follows:

- They can provide very high-resolution imagery of roads and bridges using the new SAR satellites TerraSAR-X and Radarsat-2 (with 1 and 3 meter spatial resolutions), or airborne SAR systems (with sub-meter resolution). Older SAR satellites (e.g. Envisat) provide only medium resolution imagery (with 20- to 30-meter resolution).

- They can operate day or night and in any weather conditions, making them ideal for disaster response at any time.

In this report the investigators will focus on the use of SAR systems and the advanced InSAR technique due to their significant advantages, especially their ability to be used at any time. The following is a summary of the most relevant studies that have been conducted on the application of SAR and InSAR for post-disaster assessment of transportation infrastructure.

A study by Arciniegas et al., although conducted mainly for the assessment of urban structures after an earthquake, offers useful InSAR methods that may be applicable to the assessment of bridges in the aftermath of an earthquake, provided high resolution SAR data are available.[14] The study involved the use of Envisat satellite SAR images (20 meters ground resolution) to assess the capacity of InSAR data for detecting urban damage caused by the 6.6 magnitude earthquake in Bam, Iran, on December 26, 2003. The researchers analyzed InSAR properties, such as complex coherence and signal amplitude and their sensitivity to changes in ground surface and urban damage, both induced by the earthquake event. These changes lead to quantifiable decorrelation in the InSAR image pixels corresponding to impacted areas on the ground.

The authors analyzed the methods of pre/post-event pixel-by-pixel comparison of SAR amplitude images and change detection of InSAR properties to compare and evaluate both methods for their actual potentials and limitations through validation. They found that coherence works relatively better than amplitude in extracting damaged areas, as it discriminates total destruction better. SAR data have an important sensitivity for measuring surface changes at the range of microwaves. Based on earlier studies, it was assumed that collapsed buildings or heavily damaged areas have different backscattering properties from undamaged areas. Empty spaces, vegetated areas or rubble/debris, however, can also have different backscattering properties that may be similar to those of collapsed buildings. SAR data sets have been previously used to classify urban damage into several levels. In the authors' study, such classification was not achieved. Earthquake destruction lead to high decorrelation on SAR data, but several other factors might also have posed influences that could be wrongly attributed to the event, such as changes in vegetation, atmospheric and seasonal changes, and long temporal baseline.

The authors concluded that it appeared to be a very difficult task to separate earthquake-induced changes from those related to other causes. Moreover, it seemed to be even more difficult to separate damage classes with SAR data. They recommended that further studies be conducted on how to differentiate earthquake-related decorrelation of SAR data quantitatively and qualitatively from other sources of decorrelation of these types of data in urban areas. In addition, they recommended studying how the use of SAR data can complement current methods that use optical images, stressing features that stand out above those of optical images. The SAR backscattering behavior of urban areas with heterogeneous building stock or uniformity in building height should be studied as well. They also noted that it is important to choose pairs of SAR data which are suitable in terms of baseline and time gap, although there is not a definite rule about the optimal values of spatial baselines for the urban domain. Spatial baseline values can be studied with the purpose of defining optimal values for studies related to urban-domain applications for different SAR sensors.

A study by Loh and Shinozuka researched the capabilities of bridge damage and change detection schemes based on simulated complex SAR images of pre- and post-events.[15] They noted that a SAR image, obtained from a coherent and complex imagery system, can be described in three dimensions, whereby two dimensions represent the image and the third dimension represents the phase information which is relevant to the detection of the finer details in the image. The authors' main goal was to compile a library of SAR images related to damage states experienced by common structures such as buildings or bridges.

In this study, simulated SAR images were obtained for two different sets of model bridges. The model bridges were created such that the deck width and length were equal. However, the height and support conditions were varied, and a parapet was added on one of the model bridges. Without any material property differences or other changes to geometry, the SAR simulations captured differences in signal response from these geometrical changes on the bridge models. One of the most obvious observations from the SAR images was seen from the difference between the pre- and post-damage effects. In the damaged bridge models, SAR signal responses were complicated, and the EM (electromagnetic) signature did not represent what a damaged bridge would look like. Since the SAR system measures the reflected EM waves, the planes of material they come in contact with affect these EM waves. When these surfaces are shaped and directed at odd directions, such as in a damaged bridge, reflected waves are measured far beyond the bridge model itself.

A study by Eguchi et al. investigated the use of SAR and optical imagery for structural damage detection following the 1999 Marmara earthquake in Turkey.[16] Their visual comparison of SAR and optical images obtained ‘before’ and ‘after’ the earthquake revealed distinct changes in signal return. They noted that following the earthquake event, surface reflectance on the SPOT satellite optical image increased within the urban center, where numerous buildings collapsed. This suggested that debris piles associated with collapsed structures exhibited a higher signal return than the original standing structure. Trends were more difficult to discern from simple inspection of the ERS (European Remote Sensing) satellite SAR image, with temporal changes dominated by scene-wide variations in signal return. However, from examining derived SAR correlation images, low correlation, indicative of change due to building collapse, was evident throughout central areas of Golcuk city. The preliminary SAR and optical change detection algorithms successfully distinguished between spatial variations in the extent of catastrophic building damage observed in Golcuk. For the optical data, simple subtraction and correlation profiles varied with observed damage. While SAR correlation indices also distinguished trends in the density of collapsed buildings, the subtraction profile was instead dominated by a large radiometric offset between the ‘before’ and ‘after’ scenes. The change detection techniques presented in this paper successfully employed remote sensing technologies to detect and determine the extent of urban building damage.

In summary, several studies have focused on the use of SAR technology in post-disaster urban damage assessment. The main method employed was the generation of change detection maps based on changes in the SAR signal amplitude in corresponding pixels between pre- and post-disaster images. This technique, although useful for providing rough estimates of damaged areas, cannot measure surface deformation and is not as accurate as the more advanced InSAR technique. On the other hand, in most studies involving the use of satellite InSAR for post-disaster urban damage assessment, the method most employed was the use of the coherence image to detect and estimate extent of urban structural damage. Gamba et al. Trianni and Gamba (2008) employed variations of this method in their study on the 2007 Peru earthquake, and Gustavo Arciniegas Lopez in his study on the 2003 Bam earthquake.[17]

It is important to note that the focus of most of those studies has been on trying to detect, estimate and map the extent of damage in built urban areas in general, with no special emphasis on damage assessment in the transportation infrastructure. Moreover, because the SAR imagery utilized in those studies were acquired by SAR satellites that offer medium spatial resolution (around 20-30 meters), the resulting damage assessments were at the city bloc level, which included groups of structures rather than individual structures.

However, in a very recent study by Balz and Haala, the authors showed a number of high-resolution satellite SAR images of damaged bridges in Sichuan province, China, following the 12 May 2008 earthquake. The study shows only post-earthquake SAR amplitude images of the bridges because the high-resolution satellites did not acquire pre-earthquake SAR images. This prevented the authors from performing a change detection analysis on the damaged bridges to estimate the damage or deformation.[18]

So far, most studies on SAR applications in post-disaster damage assessment make use of the amplitude of the return signal (reflected from the ground back to the satellite) and ignore the signal phase data. In this project, the researchers study the feasibility of using the SAR phase information by applying the InSAR technique to detect and assess the conditions of post-disaster transportation infrastructures.

For the purposes of their research work, the investigators have acquired the remote sensing software package ERDAS (Earth Resources Data Analysis System) IMAGINE V.9.3, with an InSAR Module, from Leica Geosystems Company, to allow for the processing of satellite optical and SAR data and generate InSAR data products. The software package was installed on a new high-speed computer that was networked with another UNIX computer (SUN Station) to allow for data processing using different software tools on different platforms. Moreover, the open-source DORIS (Delft Object-oriented Radar Interferometric Software) InSAR software, developed by DEOS (Delft Institute for Earth-Oriented Space Research) Institute of Delft University in the Netherlands, was also installed on the UNIX computer, and used to process the same SAR image data sets to generate InSAR data products.

Assessment of Efficiency and Resiliency of Transit Systems

Transportation infrastructure resiliency has received a lot of attention over the past decade. There are many studies analyzing the reliability of transportation infrastructure. There are myriad performance measures proposed in these studies. For the purpose of assessing the performance of transit systems in the context of their ability to face disruptions, we focus on measures that can be classified into two categories, namely, (a) Vulnerability and (b) Resiliency.

The reason for focusing on the above two measures is that vulnerability considers the potential consequences of a disruption on system performance. It captures a system’s weaknesses or susceptibility to disruptions related to operational performance.[19] Vulnerability does not, however, account for the probability of the disaster event.[20] That is, vulnerability studies recognize that it may be difficult to predict the likelihood of very rare events for many systems, and expectations that incorporate such low probability events may not be very illuminating.[21]

On the other hand, resiliency is generally defined as a system's ability to resist and absorb the impact of disruptions.[22] Resiliency was initially conceptualized and applied in the context of ecological systems.[23] Resiliency measures account for possible interventions that can aid in restoring system performance to near pre-disaster levels. These measures quantify the potential benefits of pre-disruption mitigation actions aimed at increasing the system's ability to cope with the impact of a disruption and post-disruption adaptive actions that aim to restore functionality.

Vulnerability Measures

First the investigators present a few studies that characterize the vulnerability of the transportation network. The objective of this study is to analyze the effect of disruptions on the public transit system. So, the researchers study the applicability of performance measures of vulnerability to public transit networks.

Tampère et al. and Knoop et al. defined three link vulnerability indices (VA_1, VA_2, VA_3) that are dependent on link capacity, flow, length, free flow and traffic congestion density.

$$VA_1 = f_{am}^i/(1 - \frac{f_{am}^i}{C_{am}})$$

Where, f^i_{am} is the flow on link *a* during period time *i* for a travel mode *m*, C_{am} is the capacity of link *a* for a travel mode *m*.[24]

VA_2 identifies the direct impact of link flow with respect to link capacity as defined by:

$$VA_2 = f_{am}^i/C_{am}$$

VA_3 represents the inverse of the time needed for the tail of the queue to reach the upstream junction and is estimated by:

$$VA_3 = f_{am}^i(n_a kj_{am} - \frac{f_{am}^i}{V_{am}})/l_a$$

Where, n_a is the number of lanes of link *a* that have been used by travel mode *m*, kj_{am} reflects congestion density for link *a*, V_{am} is the free flow speed of link *a* for a travel mode *m*, and l_a is the length of link *a*.

El-Rashidy and Grant-Muller extended the above link vulnerability indices by adding network characteristics.[25] VA_4 is calculated from the capacity of link *a* relative to the maximum capacity of all network links in order to reflect relative link importance and the maximum capacity of all network links C_{max}.

$$VA_4 = \frac{C_{am}}{C_{max}}$$

VA_5 simply uses the link length as a physical property representing the level of importance of the link,

$$VA_5 = l_a$$

VA_6 reflects the number of times the link is a component of the shortest path between different OD pairs.

$$VA_6 = \sum_{ij} S_{ij}$$

Where, s_{ij} is given a value of 1.0 if link *a* is a component of the shortest path between origin *i* and destination *j* and a value of 0.0 otherwise.

Ukkusuri and Yushimito developed a methodology for identifying critical links in a transportation network. The authors used a vulnerability measure estimated using the system travel time as the performance measure before and after a disruptive event, by $(MoP_B – MoP_A) / MoP_B$, where MoP is defined as the system travel time.[26]

The vulnerability measures presented above are more applicable to road transportation networks. They cannot, however, directly be applied to study the vulnerability of specific routes in, say, a bus transit network.

Resiliency Measures

Many resiliency measures studied in the literature are also presented below.

Zhang et al. developed a framework for calculating the Measure of Resiliency (MOR) to disaster for intermodal transportation systems.[27] TransCAD was used to model the intermodal network and generate transportation data for the MORs calculation procedure. Intermodal OD (OD) traffic before and after disaster struck was estimated based on the study area's population and employment data. The pre-disaster and post-disaster population and employment data were collected at county level and disaggregated to each traffic analysis zone (TAZ) by using linear equations. A series of indicators in terms of mobility, accessibility, and reliability were selected to evaluate the intermodal system performance based on the TransCAD outputs.

Zhang et al. further introduced a Performance Index (PI) combining some selected indicators to measure the system performance with respect to mobility. The Level of Service (LOS) of highway network and intermodal terminals before and after disaster was also determined according to the Highway Capacity Manual standards.[28]

MOR was defined as the percentage of system performance degradation due to a disaster.

The intermodal network resiliency was defined as the ratio of the reduction of the intermodal system performance after a disaster to the system performance before a disaster.

The proposed methodology for MOR was based on the calculation of the performance indicators.

$$MOR = \frac{(PI_{before} - PI_{after})(1 + t^{\alpha})}{PI_{before}}\%$$

Where:

t = total time required to restore the capacity (year), and

α = system parameter, used $\alpha = 0.5$ in a case study

The parameter α is related with network size, socioeconomic status, government policy, etc. In this study, α was designated as an average value of 0.5. Specific calibration is needed to obtain a more accurate value of α. It is important to note that resiliency comes with a specific system disruption. The lower value of MOR means the system is more resilient to the disruption.

In Murray-Tuite's paper, mobility in the event of a disruption is measured in six different ways. First is the amount of time, *E,* required to evacuate a town's residents. Second is the ability of response vehicles, such as ambulances, to travel from one zone to another. This ability is measured by the average travel time, *RS,* between zones *R* and *S* and the standard deviation of *RS*. Third is the queue length L_a on directed arc *a*, which can be evaluated at various length thresholds d_i. Fourth is the average queuing time *q* per vehicle. Fifth is the amount of time (U_a) link *a* has an average speed lower than a threshold *b* of its posted speed limit (u_a). The final measure is the volume to capacity $(v/c)_a$ for each link *a*.[29]

Jenelius et al. analyzed the vulnerability and reliability of transportation networks from an economics perspective based on the increase in the generalized travel cost when links are closed due to a disruptive event.[30]

Ip and Wang defined resiliency of a transportation network as the number of reliable passageways between any pair of nodes. They argued that this definition represents the ability to recover transportation function once transportation links are partially shut down due to unforeseen events. They introduced a new concept termed "friability," which they define as the reduction in network resiliency caused by the removal of nodes or edges. They see friability as the quantifiable measure of a disaster impact on a network.[31]

Omer et al. proposed a Networked Infrastructure Resiliency Framework (NIRA) based on the road network connecting Manhattan. The resiliency is measured as the ratio of the travel time preceding a disruption to that following a disruption to the network.[32]

Scott et al. (2005) argued that the traditional performance indicator V/C ratio is a localized performance metric, whereas the Gamma Index, which is a network connectivity index relating the actual number of links to the maximum number of possible links, accounts only for the network topology, and neither measure is sufficient when used independently. He therefore proposed a Network Robustness Index (NRI), which is based on the individual capacity of each highway segment, the routing options for the OD pairs using a particular segment, and the topology of the entire network. The NRI is the extra travel time that is imposed on the network because of the removal of a particular link. This is a very valuable measure, because it can be used to identify the most critical links in the network, which may therefore be the best candidates for implementing mitigation strategies. The NRI also tells something about redundancy, because a high NRI means that there is little redundant capacity for the link in question.[33]

The NRI indicates the extent of redundancy, because a high NRI means that there is little redundant capacity for the link in question. It does not, however, tell us which links in the network serve the purpose of providing redundancy. Anderson et al. proposed a network redundancy value (RV) as a useful complement to the NRI.[34] The performance of the road network with both links *a* and *b* removed with travel time t_a and flow x_a is:

$$c_{ab} = t_a x_a \delta_a \delta_b$$

Redundancy support that link *b* provides to link *a* is measured as (c_a is the performance with only link *a* is removed):

$$r_{ab} = c_{ab} - c_a$$

The redundancy value of link *b* to the entire network is then defined as:

$$r_b = \sum_a r_{ab}$$

Chang and Nojima focused on a system-wide highway performance assessment for evaluating post-disaster transportation network health. They claimed that traditionally used measures of overall system-wide performance like total travel time on the network in vehicle hours are not practical, because in a post-disaster situation, the availability of travel time or traffic flow data is very limited. They thus emphasized the need for macroscopic system performance measures, and proposed three such measures: Total Length of Highway Open, Total Distance Based Accessibility and Arial Distance Based Accessibility. They applied these measures to assess the performance of urban rail and the highway transport system after the 1995 Kobe earthquake.[35]

Qiang and Nagurney measured the importance of a network component *g*, *I(g)*, by the relative network efficiency drop after *g* is removed from the network represented by *G*:

$$I(g) = \frac{\Delta\varepsilon}{\varepsilon} = \frac{\varepsilon(G,d) - \varepsilon(G-g,d)}{\varepsilon(G,d)}$$

where *(G-g)* is the resulting network after component *g* is removed from network *G*. The network performance/efficiency measure ε(*G*, *d*) for a given network topology *G* and the equilibrium (or fixed) demand vector *d* is:

$$\varepsilon = \varepsilon(G,d) = \frac{\sum_{w \in W} \frac{d_w}{\lambda_w}}{n_w}$$

where n_w is the number of OD pairs in the network, and d_w and λ_w denote, for simplicity, the equilibrium (or fixed) demand and the equilibrium disutility for OD pair *w*, respectively. Equilibrium disutility is the inverse demand function or disutility of using the OD pair, and the authors assumed it to be known.[36]

In another study by Nagurney, the robustness measure R^γ for a network is defined as the relative performance retained under a given uniform capacity retention ratio γ with $0< \gamma <1$, so that the new capacities are given by *u*.[37] It is a function of the vector of user link cost functions *c*, the vector of link capacities *u*, and the vector of demands *d* (fixed or elastic). Its mathematical definition is:

$$R^\gamma = R(G,c,\gamma,u) = \frac{\varepsilon^\gamma}{\varepsilon} \times 100\%$$

where ε and ε^γ are the network performance measures with the original capacities and the remaining capacities, respectively.

According to this definition, a network under a given level of capacity retention or deterioration is considered to be robust if the network performance stays close to the original level.

Another ratio is the relative total cost index, defined under the user-optimizing (U-O) flow pattern, denoted by I_{U-O}^γ.

$$I_{U-O}^\gamma = I_{U-O}^\gamma(G,c,d,\gamma,u) = \frac{TC_{U-O}^\gamma - TC_{U-O}}{TC_{U-O}} \times 100\%$$

where TC_{U-O} and TC_{U-O}^γ are the total network costs evaluated under the U-O flow pattern with original capacities and the remaining capacities, respectively.[38]

The definition of the index under the system-optimizing (S-O) flow pattern is:

$$I_{S-O}^\gamma = I_{S-O}(G,c,d,\gamma,u) = \frac{TC_{S-O}^\gamma - TC_{S-O}}{TC_{S-O}} \times 100\%$$

where TC_{S-O} and TC_{S-O}^γ are the total network costs evaluated under the S-O flow pattern with original capacities and the remaining capacities, respectively.[39]

This means that the relative total cost does not change much; hence the network may be viewed as being more robust than if the relative total cost were large.

In times of crisis, a system-optimization approach is mandated, because the demands for critical supplies should be met (as nearly as possible) at minimal total cost. However, the ratio of the two indices ("I"s) above gives an insight into the resiliency of the network under U-O vs S-O conditions for different values of the retention ratio.

Adams et al. (2012) studied the measurement of resiliency of transportation links for freight transport.[40] The authors used the resiliency triangle approach proposed in the context of earthquake disaster research (as shown in Figure 1). The recovery and resiliency were measured as the ratio of reduction in performance over time elapsed (i.e. the slopes α and β). In the context of freight resiliency, the slopes boil down to reduction in speed measured from traffic detectors over time elapsed to recover to normal observed speed.

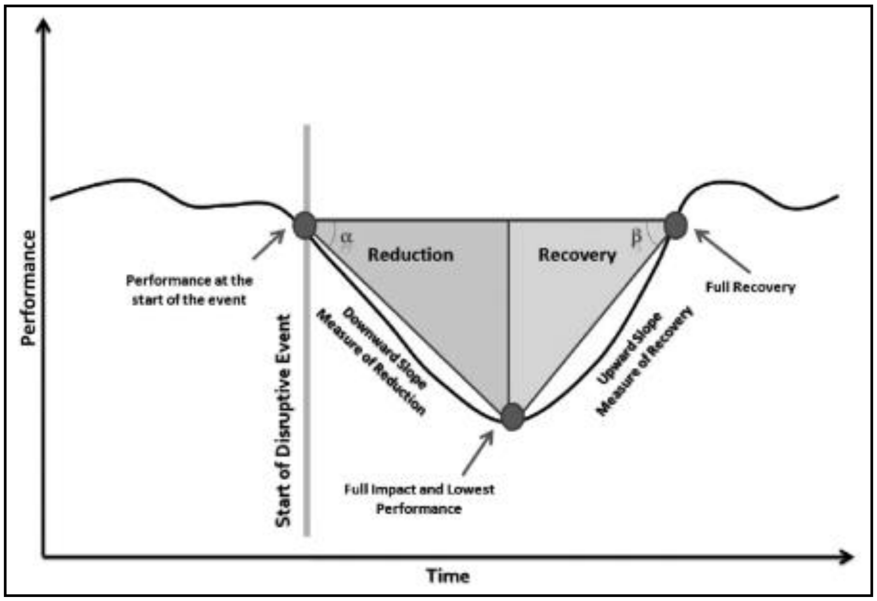


Figure 1. Recovery/Resiliency Triangle

Source: Adams et al. (2012).[41]

The size of community resiliency loss is quantified as the area of the triangle, shown mathematically as:

$$R = \int_{t_0}^{t_1} [100 - Q(t)]dt$$

where *R* is the loss of resiliency and *Q(t)* is the quality of infrastructure.[42] It can be seen that the depth of the breakdown and the slope of the recovery curve determine the size of the triangle.

Turnquist and Vugrin studied the design of distribution networks such as transportation, essential supplies, during the recovery from disruptive events. They formulated the design problem as a stochastic optimization problem to minimize the system cost of recovering from a disruption. They characterized the resiliency and recovery by using the recovery triangle approach similar to one used by Adams et al.[43]

D'Lima and Meddar modeled the system resiliency by characterizing the system performance as an Ornstein and Uhlenbeck (O-U) process with the assumptions that the disruption caused by the shock in the next time interval has a Gaussian distribution with variance equal to the square root of the length of the interval.[44] They essentially used the resiliency triangle as an inspiration in such a way that the O-U process is a mean reverting process. Similarly, the system tried to restore its normal functions following a disruption.

Murray-Tuite used queue length, speed, V/C ratio in her study of resiliency of network links, and investigated whether user-equilibrium or system-optimal assignment works better under disruption.[45]

Chen and Miller-Hooks studied an intermodal freight network design problem to identify the optimal course of action following a disruptive event. The resiliency was measured as a ratio of maximum demand served by the network before and after the disruption, D_B/D_A (before-after max demand satisfied).[46]

Recently there have been few studies focusing on resiliency of the road network utilizing Global Positioning System (GPS) probe data. Donovan and Work utilized taxi data set to measure roadway resiliency of NYC during Hurricane Sandy by measuring the deviation of normalized travel times between four different regions of the city, including three Manhattan regions and one Queens region. Their result shows minor delays for the evacuation period before hurricane landfall, though significant network deterioration after the hurricane impact, and the disruption took more than five days to recover.[47]

Evacuation response and system recovery are two areas on which resiliency studies have focused. In general, evacuation and recovery processes follow similar patterns. That is, the rates of evacuation or restoration follow an S-shape.[48] (Li et al. (2003)) Such behavior can be modeled using a logistic function. The curve describing the logistic function is called a Sigmoid Curve (S-Curve). In 1985, Lewis introduced the concept of S-Curve to represent evacuation rate.[49] Fu et al. improved this curve so that it can reflect intensity of a hurricane, time-of-day, and evacuation order time.[50] Besides Sigmoid curves, researchers also attempted to use other types of curves to represent evacuation demand, including the Rayleigh curve by Tweedie et al. and the Poisson distribution by Cova and Johnson.[51] Li et al. (2003) built an empirical response curve based on traffic data of Cape May County, New Jersey based during Hurricane Irene, and compared it with different types of S-shape curves.[52] Their result shows a better fit to logistic and Rayleigh functions compared to Poisson distribution.

Summary

Similarly, to the vulnerability measures, the resiliency measures need to be adapted in such a way that they can be applied to specific routes. The purpose of this adaptation is for the transit agency to be able to invest resources accordingly to these routes, so that the population targeted by these routes can be served satisfactorily, especially during or following a disruption.

Table 1 provides a summary of the measures of vulnerability and resiliency, their characteristics and data requirements.

Table 1. Summary of Resiliency and Vulnerability Measures

Measure	Characteristic/Application	Requirements
ΔSpeed/Δtime (Adams et al. (2012))	Link/route Resiliency; assessment	Detector speed data
ΔVolume/Δtime (Adams et al. (2012))	Link/route Resiliency; assessment	Detector count data
Queue length (Murray-Tuite (2006))	Link Resiliency; assessment	Simulation output or observed queue data
V/C (Murray-Tuite (2006))	Link Resiliency; assessment	Simulation or Detector count data
D_B/D_A (Chen and Miller-Hooks (2011))	Network Resiliency; Network design	Simulation/Traffic assignment output
TT_B/TT_A (Omer et al. (2011))	Network resiliency measure; assessment	Observed travel time or Simulation/ Traffic assignment output
ΔCost before-after event (Jenelius (2005))	Link/route/network Resiliency; assessment	Observed travel time or Simulation/ Traffic assignment output
r_b, redundancy measure (Anderson et al. (2011))	Network Resiliency; Network design	
Friability, the number of reliable routes between OD pairs (Ip and Wang (2011))	Network Resiliency; Network design/ assessment	Extensive observed travel time or Simulation/Traffic assignment output
$(MoP_B – MoP_A)*(1+t^{\alpha})/MoP_B$ (Zhang et al. (2009))	Link/route/network Vulnerability	
VA_1, VA_2, VA_4, VA_5 (Tampère et al. (2007), Knoop et al. (2012), El-Rashidy and Grant-Muller (2014))	Link Vulnerability	Observed counts
VA_3 (Tampère et al. (2007) and Knoop et al. (2012))	Link Vulnerability	Observed counts at signalized intersections
VA_6 (El-Rashidy and Grant-Muller (2014))	Link/route/network Vulnerability	Simulation/Traffic assignment output

Access Link Trips

Transit agencies provide ADA complementary paratransit at a fairly high cost. Because of the high cost of service with growing demand, all transit agencies nationwide are under pressure to optimize costs of paratransit service. One way to do this is to forecast current and future demand for trips, which can be accomplished by demand analysis for paratransit service. In order to identify the generators of paratransit trips, an analysis of data for the service area of Access Link, the ADA complementary paratransit service provided by NJ TRANSIT, is needed. While most past studies focused on the home end of paratransit trips, this study attempts to identify characteristics of areas where paratransit clients live as well as characteristics of areas and specific locations they visit.

One of the earliest studies to explore methods to estimate demand for ADA complementary paratransit service was by Koffman and Lewis.[53] The article makes reference to two studies – one for King County Metro, Washington State, and the other for New York City Transit Authority – where surveys were conducted to gauge demand for paratransit service. From the description of the studies, it appears that the New York survey was geared towards predicting ridership as a function of service area, fares, eligibility policy, advance reservation policy, fare, etc., whereas the King County survey aimed at estimating the number of potential users and their willingness to travel at different fare levels. Neither of the surveys appeared to have placed emphasis on identifying trip generation for potential origins and destinations.

In recent years, two Transit Cooperative Research Program (TCRP) reports have specifically focused on estimation of ADA paratransit demand.[54] In the first of these studies, Koffman et al. used a statistical model with data from 28 agencies in 15 states to predict ADA paratransit ridership. The study concluded that six variables are associated with paratransit ridership. According to the study, demand for paratransit is positively associated with the size of the service area population, but negatively associated with fare, proportion of population below poverty level, the width of the pickup window, the proportion of applicants that are conditionally eligible to use paratransit, and the practice of determining eligibility on a trip-by-trip basis (instead of determining eligibility for all trips). The statistical analysis in the study did not find any association between paratransit demand and the proportion of elderly persons, incidence of disability in the population at large according to census, availability and quality of fixed-route transit, or ethnicity of population.

The second TCRP report, by Bradley and Koffman, applies sketch planning and regional planning approaches with survey data from 800 ADA paratransit users from the Dallas-Fort Worth area of Texas. The study includes both aggregate and disaggregated models. The aggregate model showed that the proportion of elderly persons in census tracts is positively associated with paratransit registration, but the disaggregate model showed that elderly clients are likely to make fewer trips than younger clients. On the whole, it can be expected from the study that an increase in number of elderly persons will increase the demand for paratransit, although the elderly registrants might use the service less often than younger persons with disabilities. Other relevant results of the study are that higher income and lower poverty in census tracts together with lower poverty among registrants would decrease the number of trips, larger household size in census tracts would decrease the number of trips, increase in travel time would decrease the number of trips, and greater pedestrian access to activities would decrease the number of trips.

The study by Bradley and Koffman also included a trip distribution model, where several zonal variables were considered as trip attractors, namely, number of resident households, number of resident persons, number of retail jobs, number of service jobs, number of other jobs (i.e., non-retail, non-service jobs such as industry and production), number of jobs in shopping malls, and number of jobs in hospitals. Some of these variables were used to measure zonal accessibility.

A study by LaMondia and Bhat (2009) used a linear regression model by combining trip data from a paratransit system in Brownsville, Texas, and census data to identify variables associated with paratransit trips.[55] Based on the model results, the authors came to the conclusion that census block groups with larger population, older populations, larger households, and close proximity to fixed-route transit generate more paratransit trips than other block groups. It may be noted that LaMondia's and Bhat's study's observed relationship between household size and trips is contradictory to the finding in Bradley and Koffman. The study concluded that home ownership, marital status, presence of children in household, etc., could also be associated with trip volume, but the effect of these variables differ when they are used at a regional scale instead of a local scale. The study also included a destination zone assignment model to examine characteristics of places visited by paratransit users. Data from the paratransit travel log that included trip purposes of clients was used for this specific model.

In another study, Kuo et al. used a geographical weight regression model by combining census data with trip data from METROlift, the ADA paratransit service for Houston, Texas, to estimate demand for ADA paratransit trips originating at home.[56] From the modeling effort, the authors concluded that the size of population, the proportion of elderly persons, the proportion of African American persons, and the proportion of persons below the poverty level in census tract were positively associated with outgoing home-based trips. It may be noted that the study's findings on the relationship of persons below poverty and elderly persons with ADA paratransit trips are inconsistent with the study by Koffman et al. An aspect of the study by Kuo et al. that makes it more advanced than some other studies is its recognition that ordinary least squares models may be inappropriate to model paratransit trips when they are geographically clustered. Another study that focused on clustering of ADA paratransit trips was by Bearse et al., which emphasized the importance of accounting for spatial autocorrelation when modeling trip demand.[57]

Other studies have taken different approaches to comprehend and forecast demand for ADA paratransit trips. For example, Orange County, California adopted a time-series model to forecast ridership over a five-year period by using 15 predictor variables. The model, as described in Menninger-Mayeda et al., included census data for the county's 37 census-designated places and included data on age, number of persons with disability, seniors in poverty, and the proportion of ADA certified clients. The study does not indicate whether the model included any information about the trip attractors.[58] Another study that focused on temporal variations in demand for ADA paratransit trips was by Desharnais and Chapleau. The study used space-time budgets with a focus on types of disability.[59]

In addition to finding certain inconsistencies and contradictions in the results of past studies, this literature review found that most past studies involving models of paratransit trip generation focused on trips from home. LaMondia and Bhat and Bradley and Koffman are two rare studies that modeled trip generation for both home and destination ends.[60] The literature review also demonstrated that large-scale surveys of paratransit users to understand their trip patterns have been rare.

Paratransit Service Efficiency

Three streams of literature are pertinent to this research. The first stream pertains to the efficiency of paratransit systems, the second pertains to environmental factors and network characteristics that are associated with congestion and delay, and the third pertains to performance measures related to travel time and delay. The relevant literature in each stream is discussed below.

Because of ADA paratransit's high costs, a number of studies have focused on its service efficiency. Many of these studies were conducted to evaluate the impact of different types of technologies on paratransit service.[61] The technologies considered by these studies varied, but often included computer-aided dispatch, vehicle location, and communication technologies. Other studies on efficiency of paratransit service focused on a hybrid approach to combine fixed-route and demand-response service,[62] optimization of vehicle runs,[63] route choice,[64] service zoning strategies,[65] and optimization of operating conditions.[66] Although examining trip delay is not their explicit objective, reduction of delay is an implicit objective in many of the studies.

Service efficiency of paratransit is usually measured by comparing outputs such as number of passengers and number of passenger miles served with inputs such as total operating cost, number of vehicle hours, or number of employees.[67] Trip duration as well as pickup and drop-off duration can be important factors influencing paratransit service efficiency. As Ben-Akiva et al. noted, when trips can be completed in a short duration, more trips can be completed in a given time period.[68] That, in turn, can reduce the need for additional vehicles, operators, and vehicle storage capacity. Furthermore, reduction of trip delay can save time for clients and enhance their satisfaction. From the environmental perspective, reduction of delay can reduce greenhouse gas emissions.

While most studies on paratransit efficiency considered only system-wide information and avoided the environment of the areas served, only a few studies considered environmental factors. Fu et al. and Min and Lambert studied the association between density of the areas served and efficiency.[69] While the first study compared the service efficiency of 32 paratransit systems in Canada, the second compared the efficiency of 75 paratransit systems in the US. The study by Fu et al. showed that efficiency was significantly and positively associated with density of users in the service areas.[70]

In contrast to the variable on user density used by Fu et al., Min and Lambert developed a density index by combining overall housing density, population density, and commuting time to hypothesize that the index could be negatively associated with efficiency due to the measure's congestion effect but could also be positively associated with efficiency because of its proximity effect.[71] The study could not use paratransit travel time as a measure because of a lack of data. Their statistical model showed that the index was positively associated with efficiency, meaning that areas with high population/housing density are likely to have more efficient paratransit service than low-density areas. Min and Lambert mentioned that their findings are consistent with studies in the context of emergency medical service.[72] For example, Lambert and Meyer found in two studies that emergency medical service (EMS) response time is lower in high-density areas compared to low-density areas.[73] Studies from other countries have also shown similar results regarding EMS response time.[74] However, EMS response time and ADA paratransit response time are not exactly the same, because paratransit trips are typically booked ahead of time, while EMS response is typically instantaneous.

The positive association between density and efficiency in Fu et al. is not surprising, as this study considered user density.[75] Higher user density may reduce average trip time and allow more flexible scheduling opportunities. Min and Lambert most likely found a positive association between a density index based on housing and population density and service efficiency because they compared regions rather than locations. As Min and Lambert noted, the effect of density on service efficiency, especially the speed of service delivery, could be either positive or negative.[76] This is because overall population and housing density, on the one hand, can mean close proximity between clients (and their drop-off and/or pickup locations), but on the other hand, it can also mean greater trip generation and congestion.

To summarize, the review of studies on service efficiency indicated that the environment in which paratransit systems operate has received far less attention than the technologies used by the systems. Most studies on service efficiency have used system-wide or aggregate data on inputs and outputs without specifically focusing on factors such as trip duration, speed, or delay, even though some authors have acknowledged that they affect service efficiency. Although a few studies examined the association between environmental variables such as density and service efficiency, little can be generalized about the effect of environmental characteristics of service areas on efficiency. Finally, little information was found in the literature on the potential association between passenger characteristics and efficiency.

Association between Environmental Factors and Congestion

In the general context of transportation, a number of studies have addressed the association between density, mode-specific trip generation, traffic volume, congestion, and delay. Ewing and Cervero presented evidence from a number of studies that found a negative association between automobile use and population, household, and employment density.[77] Yet lower automobile use in high-density areas does not translate to a lower level of congestion or delay, because a greater number of total trips are generated in such areas than in low-density areas.[78] While Cervero noted that vehicle-operating speed decreases in high-density areas, Levinson and Kumar noted that the direct association between density and congestion makes automobile use unattractive above a certain threshold of density.[79] In view of higher trip generation in high-density areas, reduced automobile use in those areas could be construed as an outcome of traffic congestion, although the availability of transit and shorter distance between activities could be additional reasons.

Literature suggests that intersection density has a greater effect on traffic speed and delay than population and household density. Ewing and Cervero found that intersection density is negatively associated with vehicle miles traveled (VMT) and positively associated with walking. More importantly, they found that intersection density has a greater effect on VMT and walking than population and household density.[80] Since lower VMT is the likely outcome of lower speed and greater delay, their findings possibly indicate that intersection density has a greater effect on delay than population and household density.

Ban et al. noted that intersection delay is the primary contributor to arterial delay.[81] Intersections cause delay not only because of stopped time (idling) at the intersection, but also due to deceleration during approach and lower speed during departure.[82] When intersection density is high, additional delays can be caused by traffic spill-back from one intersection to another and spillover between lanes.[83] Furthermore, variability of traffic at intersections can reduce reliability of a road network in areas with high intersection density.[84]

Intersection density can also contribute to congestion and delay through pedestrian volume. Because of the negative impact of intersections on driving, more individuals are likely to walk between origins and destinations or walk to or from transit stations/stops in areas with high intersection density. A large number of studies found a high positive correlation between density of intersections and walking for children and adults.[85] However, the positive association between intersection density and walking also creates a conflict between vehicles and pedestrians at intersections, thereby causing delay for vehicular traffic.[86] While Schlossberg noted that higher intersection density is attractive to pedestrians because it gives more route options, Guo found in an empirical study that higher intersection density on a route or path attracts more pedestrians to the route.[87]

In areas with high intersection density, the likelihood of crashes involving pedestrians is high because of frequent turns by vehicles.[88] Since drivers typically slow down in such locations to avoid conflicts with pedestrians, intersections can add substantially to vehicular trip duration or travel time in areas with high intersection density.

Delay at intersections is a major issue not only for motorists but also for transit vehicles. While high intersection density allows transit buses a greater choice for route selection, due to the delay at intersections, significant attention has been paid to bus priority by researchers over the years.[89] Although paratransit vehicles are as likely to be affected by intersection delay as transit buses, the effect of intersections on paratransit trips has received little attention in the literature.

In sum, population density, household density, and employment density can all reduce vehicular speed and increase delay because of high trip generation from activities. To the extent that trip duration and delay are inversely related to the efficiency of paratransit, high activity density in a confined space could decrease service efficiency due to congestion. However, if high population and household density is highly correlated with paratransit client density, service delivery could be more efficient because of scheduling ease as well as fewer and shorter deadhead trips. Similarly, if employment density is highly correlated with paratransit trip destination density, service delivery could be efficient.

While the effect of population, household, and employment density on paratransit trip duration and delay could be positive or negative depending on the extent to which they coincide with the density of homes and trip destinations of paratransit users, the effect of intersection density on speed and delay is relatively straightforward. Based on the literature on the effect of intersections on trip duration and delay, traffic spill-back and spillover at intersections, pedestrian trip generation, and pedestrian safety concerns, it can be hypothesized that all vehicles, including paratransit vehicles, are subjected to congestion and delay in areas with high intersection density.

Performance Measures Related to Travel Time and Congestion

The *Highway Capacity Manual* by the Transportation Research Board describes a number of roadway-oriented performance measures pertaining to road intersections and links, often categorizing roads by type of area.[90] On the other hand, the *Transit Capacity and Quality of Service Manual* by the Transportation Research Board describes a number of transit-related performance measures pertaining to various transit modes, including heavy rail, commuter rail, light rail, buses, and ferry services.[91] In both manuals, a large number of performance measures directly or indirectly relate to congestion, trip duration, and delay.

While there is no dearth of performance measures relating to trips by automobile and public transit, the measures are pertinent only in specific contexts. Furthermore, not all measures are equally cost effective, and many cannot be used in real life because of a lack of required data. A host of cost-effective performance measures related to congestion and reliability are described in a report by the National Cooperative Highway Research Program (NCHRP), including individual measures such as travel time, delay per traveler, travel time index, buffer index, planning time index, and area measures such as total delay, congested travel, percent congested travel, congested roadway, and accessibility.[92] Another NCHRP report, by Lomax et al., also provides an inventory of performance measures related to congestion. Reporting from a survey of state departments of transportation and metropolitan planning organizations, the study indicates that delay and speed – the performance measures used in this study – are two of the most commonly used performance measures by the agencies. Specifically, delay ranks second and speed ranks fourth among 17 performance measures considered by the study.[93]

Travel Time Reliability of Access Link Trips

Mobility and reliability are two most commonly used performance measures of transportation systems and networks. While mobility depends on overall travel time or delay, reliability depends on variability of travel time or delay.[94] Thus mobility is primarily associated with typical, usual or recurring congestion, whereas reliability is a function of unforeseen congestion that may occur for a variety of reasons.[95] As mentioned by Carrion and Levinson, a degree of unpredictability of travel time is associated with reliability.[96] In the case of predictable variations of travel time, as experienced in morning and afternoon peak periods compared to off-peak periods, travelers can adjust their departure time to be able to arrive at the destination at the expected time, but when travel time or delay is unpredictable, a traveler cannot make such adjustments. For that reason, public opinion surveys show that travel time variability measures are more meaningful and important to travelers than congestion measures such as average speed and traffic volume.[97] It is therefore not surprising that suggestions have been made to place a greater emphasis on reliability measures than measures of recurring congestion for transportation agencies to become increasingly more focused on the needs of their customers.[98]

Traffic congestion and delay can occur because of a variety of reasons, including physical bottlenecks, roadway crashes, non-crash traffic incidents, work zones, weather, traffic control devices, special events, and day-to-day variability in demand.[99] Many of these factors, especially crashes, traffic incidents, work zones, special events, and day-to-day-variability, can also be causes of unreliability.

In the general context of transportation, the value of reliability for travelers has been the subject matter of a number of studies.[100] Some of these studies compare the value of unreliability with the value of recurring delay. According to a study by Kittleson and

Associates, the value of reliability is high for trips to medical and personal service appointments, for pickups and drop-offs of children, and trips to work; whereas the value is low to moderate for trips to homes and leisure activities, and low for trips to shopping and social activities.[101]

A number of past studies provide insights about the importance of travel time reliability to public transit users.[102] While Wachs noted in the US context that public transit agencies do not pay enough attention to travel time reliability, a study by Börjesson et al. mentioned that travel time reliability is an important consideration for transit agencies in Europe.[103] Noland and Polak also hold the view that transit reliability receives greater importance in Europe than in the US.[104]

Far fewer studies have focused specifically on the reliability of paratransit service than on conventional fixed-route buses and bus rapid transit. In a study on paratransit service for elderly persons and persons with disabilities, Franklin and Niemeier touch upon the importance of reliability, but reliability is not the study's primary focus.[105] Other studies on paratransit, such as those by Lewis et al. (1998), Fu (2002b), and Metaxatos and Pagano (2004), placed a greater emphasis on paratransit reliability, but these studies were primarily concerned with service reliability related to scheduling technology and service denial rate rather than travel time reliability involving actual trips.[106] Other studies, such as those by Wilds and Tally (1984) and Khattak and Yim (2004), concluded that perceived reliability of service is a key factor in people's decision to use paratransit, but since these studies defined reliability rather loosely or generally, it is difficult to determine to what extent the authors were concerned about travel time reliability.[107] Moreover, neither of these studies was specifically focusing on paratransit service for persons with disabilities. In contrast to these studies, a study involving mostly elderly persons and persons with disabilities in Michigan found that reliability associated with on-time pickup and drop-off is highly valued by paratransit users.[108]

Although travel-time reliability of paratransit service has not been widely studied, it can be convincingly argued that reliability of paratransit travel time for persons with disabilities is important because of their distinctive trip purposes. As previously discussed, the value of travel-time reliability is higher for trips to medical-/personal-care destinations compared to trips to many other types of destinations.[109] An analysis of nationwide data from the 2009 National Household Travel Survey by this author showed that 48% of the trips by persons with disabilities using special disability transit service are made for medical/dental appointments.[110] Since conventional fixed-route transit services are not included in special transit service for persons with disabilities, all of these trips are most likely made by paratransit. A study of paratransit service predominantly used by elderly persons and persons with disabilities in four Michigan counties similarly showed that trips for medical visits far outnumber trips for other purposes.[111]

II. BRIDGE RESILIENCY

PROPOSED CONCEPTUAL FRAMEWORK FOR ACCESSING THE RESILIENCY OF BRIDGES

This study proposed a conceptual framework to access the resiliency of bridges before and after disaster. Bridge performance and condition of bridge structure following a terrorist attack or natural disaster can be obtained through comprehensive structural analysis (such as a finite element modeling) or Structural Health Monitoring as well as remote sensing. Figure 2 shows the proposed conceptual framework for accessing the resiliency of bridges. Before disasters happen, Structural Health Monitoring can be employed to update the finite element (FE) model in order to reflect the real condition of the bridges. This will be a starting point for accessing the performance of bridges under major disaster. Once the disaster happens, certain information could be obtained, such as support movement, to update the established FE model. Then the FE model could be used to simulate the bridge performance (response under regular maximum loading) after the disaster to check whether the bridge is functional. Meanwhile, Structural Health Monitoring data, if available post-disaster, could be utilized to check bridge response after the disaster. The proposed damage detection procedure would enable a rapid damage assessment of numerous bridges across a wide geographic area so an optimized management can be scheduled effectively.

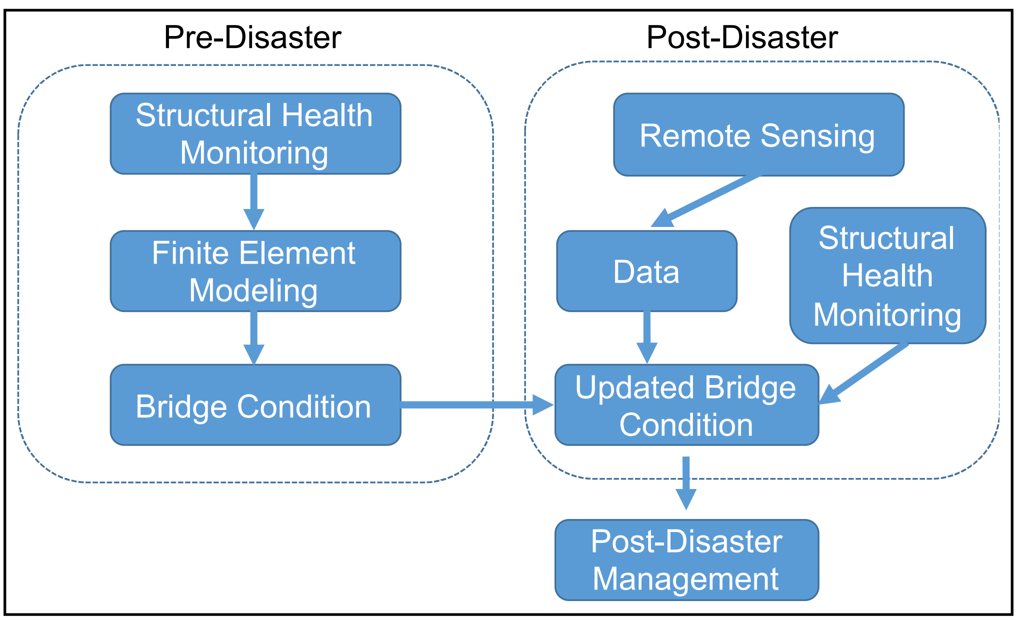


Figure 2. Proposed Framework for Accessing Resiliency of Bridges

BRIDGE PERFORMANCE AND BRIDGE REDUNDANCY (BEFORE DISASTER)

This section describes the evaluation of current bridge-load-carry capacity through field testing and FE modeling. The bridge redundancy was calculated by dividing the bridge capacity by the bridge carrying capacity demanded under current regular loading.

Sensor Instrumentation and Field Testing

The objectives of sensor instrumentation and field-testing are to evaluate the bridge condition before major disaster and calibrate the available analytical model (FE model). Field-testing was performed for two selected bridges in this study. The target bridges were tested to obtain various structural responses such as strain, deflection, and velocity. The testing results will be used to evaluate the performance of the bridge and improve the accuracy of the analytical model.

Testing Equipment

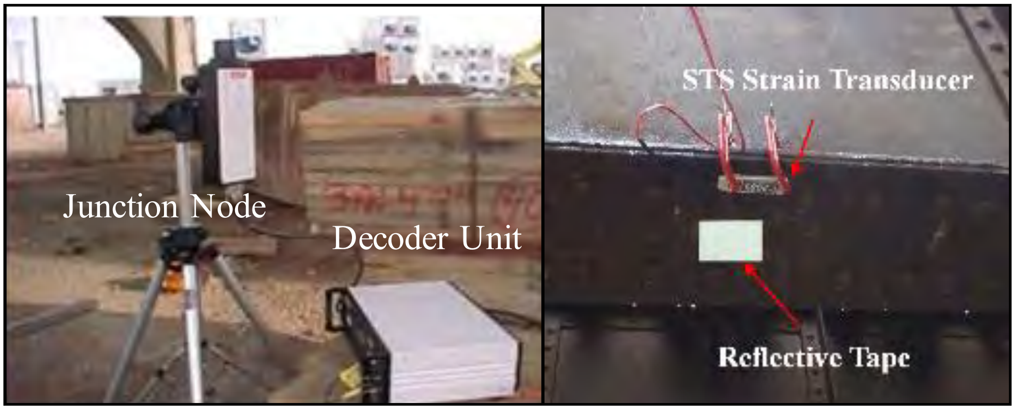
The Structural Testing System (STS) is a modular data acquisition system manufactured by Bridge Diagnostics, Inc. (BDI), of Boulder, Colorado. The system consists of a main processing unit that samples data, junction boxes, and strain transducers. The strain transducers are mounted to structural elements with C-clamps or bolted to epoxied tabs. Each transducer has a unique identification number and a microchip to help identify it easily in the system. The transducer calibration factors are stored in the configuration files and are applied automatically.

The STS consists of strain transducers, junction node, and the main STS unit as shown in Figure 3. Each test is assigned to an automatic file number, and the test is initiated using a trigger button called the clicker. Once the test is completed, the data can be downloaded from the STS unit to a laptop computer.

(a) *(b)* *(c)*

Figure 3. (a) STS Strain Transducer; (b) Junction Node, and (c) Main Unit

The Laser Doppler Vibrometer (LDV), shown in Figure 4, is a non-contact measuring device that measures displacement and the velocity of a remote point. A change in the distance between the laser head and the reflective target will produce a Doppler shift in the light frequency that is decoded into displacement and velocity. The system is composed of three parts: 1) the helium neon Class II laser head, 2) the decoder unit, and 3) the reflective target attached to the structure. The laser head is mounted to a tripod that is positioned underneath the target. The reflective target, typically retro-reflective tape, provides the strongest signal. The signal strength is read on a scale on the laser head. The tripod is adjusted to maximize the signal prior to a test run.



(a) *(b)*

Figure 4. (a) Laser Doppler Vibrometer and (b) Locations of Reflective Targets for Measuring Deflections

Example of Field Testing (NJ Transit Bridge A)

The sensor instrumentation on this selected structure is focused on the center girder on Span No. 2, since this member has the lowest rating based on the Inspection Report. The behavior of the center girder will be evaluated at the cutoff locations and at mid-span. For the exterior girders, strain gage installation was not possible, since the girders were encased in concrete and the girder flanges were not accessible. Figure 5 shows the testing setup and preparation during the installation of the sensors.

Figure 6 shows the location of the 12 strain transducers and five reflective tapes that were instrumented on Bridge A. After the installation of sensors, the tests were conducted with the scheduled passenger trains.

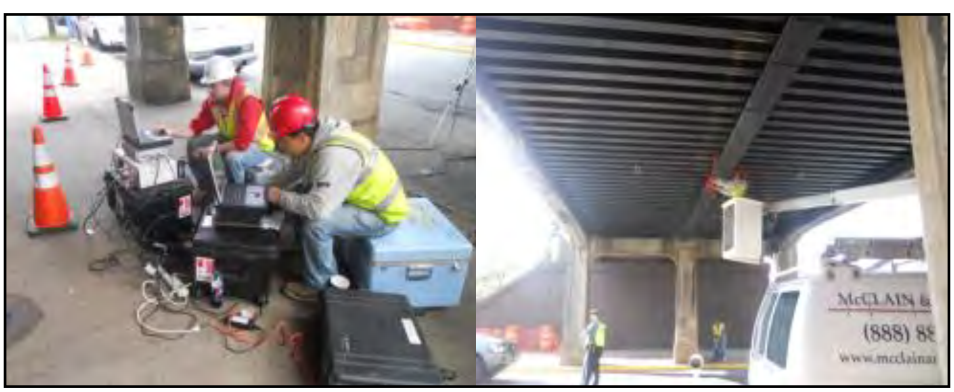


Figure 5. Sensor Instrumentation and Test Equipment at Bridge A

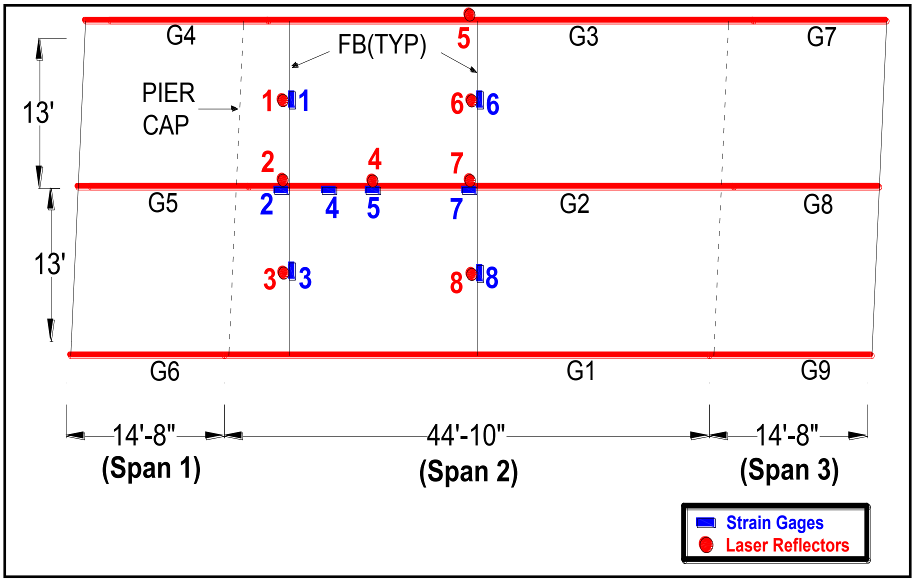
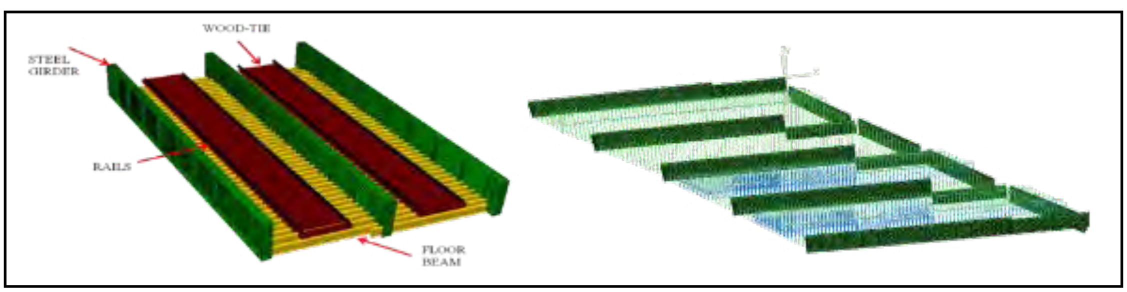


Figure 6. Sensor Locations on the Plan View for Bridge A

Finite Element Bridge Analysis

The selected bridges were modeled and analyzed using the FE program ABAQUS (Version 6.9.1) to simulate the structural behavior of critical members. The ultimate objective of the detailed analysis is to evaluate more accurately the condition of the bridge under current load demand and as a starting point for post-disaster analysis. This section illustrates the FE model in ABAQUS of the selected bridges. Figure 7 illustrates an isometric view of the various FE models for selected bridges. To improve the analysis results, various modeling features were considered in the three-dimensional FE model, such as 1) element types, 2) material behavior, 3) boundary conditions, and 4) interaction between the floor beams and steel girders.



(a) *(b)*

Figure 7. FE Model for Four Selected Bridges: (a) Bridge A, (b) Bridge B

Material Properties

The modulus of elasticity of the steel girder, steel beams and rails, *E*, and Poisson's Ratio, n_s, were considered as 29,000 KSI and 0.3, respectively. It is noted that the steel girders, beams, and rails were expected to undergo deformation within the elastic range only and that therefore the inelastic behavior of the steel material was not considered for a functional bridge. Material properties for wooden-tie members such as modulus of elasticity, *E*, and Poisson's Ratio were considered as 1,600 KSI and 0.3, respectively.

Element Selection and Analysis Procedure

The steel girders were modeled by using a four-node shell element (S4). Element type S4 in ABAQUS is a fully integrated, finite-membrane-strain shell element. Simpson's Rule was used to calculate the cross-sectional behavior of the shell elements. A two-node linear beam element (B31) was selected in the model to simulate the steel floor beams, rails, and wood ties. The element type B31 is a first-order, shear-deformable beam element, which accounts for shear as well as flexural deformations in the analysis. One type of connector element was also used in the FE analysis model to join two nodes. Connection type JOIN, which forces the position of one node to be the same as the second node, was used to idealize the pin connections. The JOIN type of connector was used to idealize the bold connections between steel girders and floor beams.

In the FE model, a set of point loads simulating a railcar was applied on the rail elements. A multiple load case analysis was adopted to apply the railcar loading at various nodes on both tracks of the selected bridge. The accuracy of the model was verified by comparing the strain and deflection results obtained from the FE analysis and field test data, as explained in the next section.

Model Verification

In this section, the verification and calibration were performed for the bridges, and some adjustments to the model were made if needed to improve the accuracy of the model. Since the verified models will be used during the assessing of condition, the maximum structural response under traffic load is the most important issue. Therefore, in this part, the difference in the form of percentage between the FE model and field-testing data was computed at the peak value to verify the models as well as the average value and coefficient of variation (COV). The difference between the FE model analysis results and the field test data can be attributed to various reasons, but is mainly the result of the dynamic impact, the damping effect, and the unexpected restraints at member connections and end supports. Additionally, possible small-dimension differences between the actual bridge sections and the FE model can also help account for the variation between the analysis results and the field test results.

In general, for bridges with ballast deck, another reason for having a variation between FE model results and field-testing data for model simulation may be the idealization of load distribution through the ballast deck. The connectors between wood-tie members and floor beams were modeled in such a way as to help distribute the load applied on the rail element. In reality, however, the load is distributed more evenly to the floor beams and girders through the ballast deck.

Example of FE Model Verification (Bridge A)

Deflections and strains of the structural elements were recorded from the strain transducers and LDV unit as the tested railcars passed over the bridge span. The obtained deflection and strain results of the structural members under the railcar loading were compared with the analysis results.

Figure 8 shows comparison of strain records. The horizontal axis shows the location of the railcar front axle moving from one support of the span. Figure 9 shows a comparison of deflection results between the FE model and field data at mid-span for two testing cases. The horizontal axis shows the front-axle distance from the support in the traveling direction. Overall, it can be seen that the FE model results exhibited good agreement with the testing results under the same railcar loading. After the model was validated and calibrated, accurate condition and response of bridge could be simulated under various scenarios.

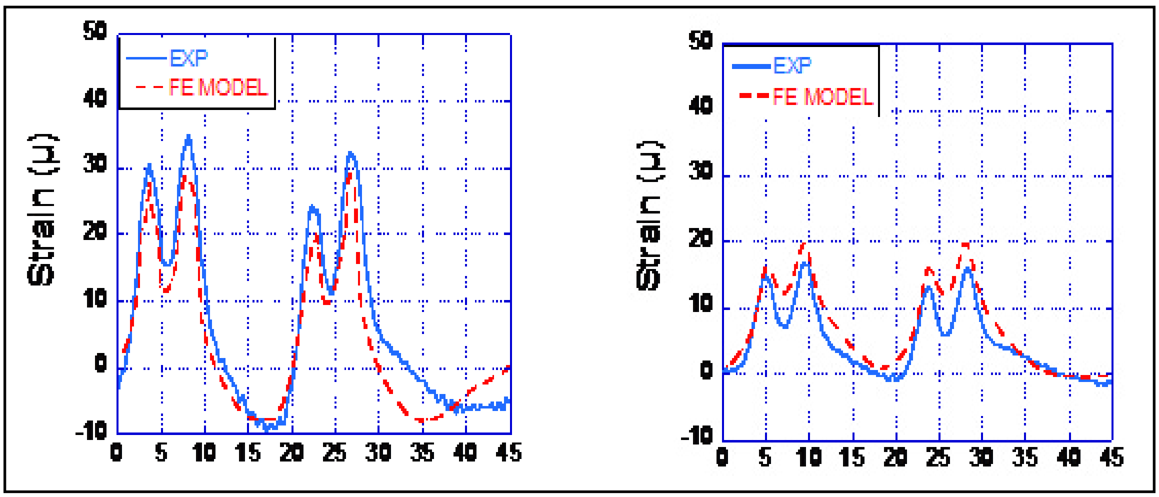


Figure 8. Comparison of Strain Results between FE Analysis and Field-Test Data in Test Run #2 at (a) Sensor 2049 and (b) Sensor 2046, for Bridge A

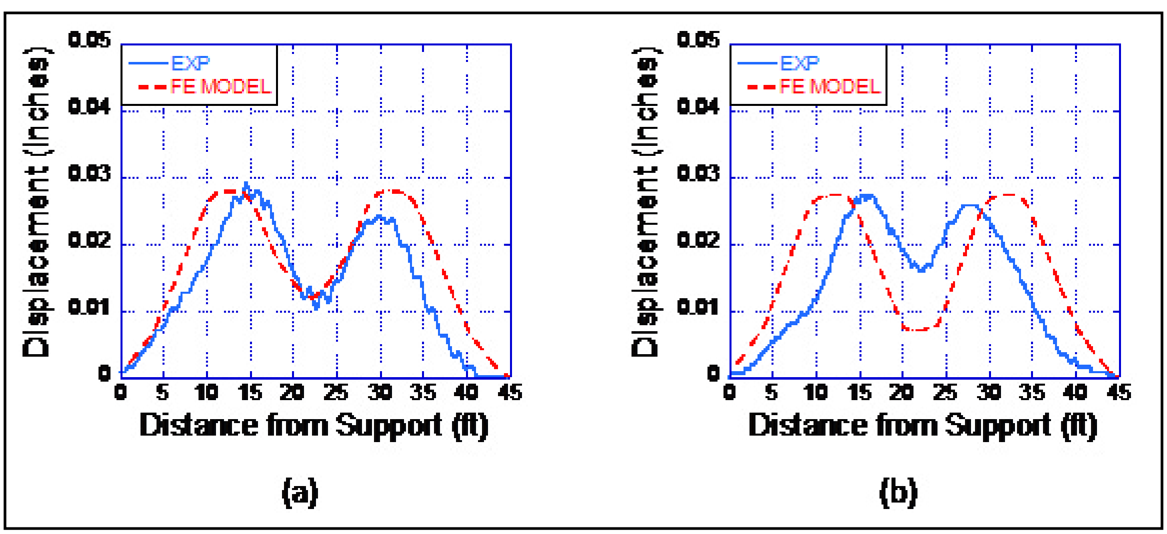


Figure 9. Comparison of Deflection Results between FE Analysis and Field Test Data, for (a) Test Run #1 and (b) Test Run #2, for Bridge A

Safety Margin Based on Field Testing and FE Model

In this section, the safety margin of the bridge was obtained under current maximum loading, 286 kips railcar loading. The safety margin is calculated by dividing the load-carrying capacity by regular demand (response from maximum operating load) expressed as a percentage based on the American Railway Engineering and Maintenance-of-Way Association (AREMA) Manual for Railway Engineering.[112] If the safety margin is greater than 100%, the bridge is safe under operation. The following tables show the assessment of bridge condition under regular maximum loading demand. The results show there is a consistent difference between simple beam analysis and FE analysis. Since the FE models were verified and calibrated with Structural Health Monitoring data, the results from models reflected the actual condition of bridges.

Table 2 shows the results for Bridge A. Two approaches were used to obtain the safety margin: simple beam analysis based on the AREMA design manual and FE analysis. The column “Equivalent Cooper E Load for 286-kip Railcar” represents the current load demanding while the column “Cooper E Rating” can be regarded as the capacity of the selected bridge. Both columns give the results from two approaches mentioned above. Based on the simple beam analysis, the maximum capacity over demand (C/D) ratio is 90%, which means certain repairs are needed to improve the performance of the bridge to accommodate current maximum loading. The FE model, however, shows an unexpectedly high safety margin, 588%, compared to the simple beam analysis, due to the actual boundary condition of the bridge. Data from field tests were used to calibrate the FE model to help provide more accurate results. This model calibration was implemented in changes of the boundary conditions to be fix-pin rather than simply supported as was assumed in the simple beam analysis. The differences between the FE model and simple-beam analysis may come from the boundary condition, member connectivity and load distribution. Table 2 shows all critical locations on this bridge based on inspection reports. Table 3 shows the results for Bridge B.

Table 2. Load Rating Results for the Bridge A

As Inspected		Equivalent Cooper E Load for 286-kip Railcar		Cooper E Rating		Safety Margin	
Rating Type	**Location**	**FE Model (1)**	**Simple Beam Analysis (2)**	**FE Model (3)**	**Simple Beam Analysis (4)**	**Capacity over Regular Demand Ratio (3)/(1)**	**Capacity over Regular Demand Ratio (4)/(2)**
Normal Load Rating	8.65’ from support*	E65	E59	375	53	588%	90%
	11’ from support	E64	E59	247	58	385%	98%
	14.4’ from support	E62	E60	211	62	345%	103%
	Mid-span	E62	E60	199	65	323%	109%
Maximum Load Rating	8.65’ from support*	E65	E59	552	85	833%	145%
	11’ from support	E64	E59	367	93	588%	159%
	14.4’ from support	E62	E60	316	99	500%	164%
	Mid-span	E62	E60	297	103	476%	172%

Note: * Critical location based on simple beam analysis.

Table 3. Rating Results for Bridge B Using As-Inspected Section Properties

As Inspected		Equivalent Cooper E Load for 286-kip Railcar		Cooper E Rating		Safety Margin	
Rating Type	**Location**	**FE Model (1)**	**Simple Beam Analysis (2)**	**FE Model (3)**	**Simple Beam Analysis (4)**	**Capacity over Regular Demand Ratio (3)/(1)**	**Capacity over Regular Demand Ratio (4)/(2)**
Normal Load Rating	G37 10.6’ from support	E44	E58	139	62	313%	106%
	G37 14.5’ from support	E43	E59	108	52	250%	88%
	G37 19.6’ from support	E42	E57	99	53	238%	93%
	G37 Mid-span	E40	E54	77	57	192%	105%
	G28 section 2	E62	E52	175	54	286%	104%
	G28 section 5	E62	E52	188	56	303%	108%
	G28 section 7	E53	E49	124	61	233%	125%
	G28 Mid-span	E47	E47	143	64	303%	137%
	G29 Mid-span	E47	E56	229	78	476%	139%
Maximum Load Rating	G37 10.6’ from support	E44	E58	179	104	400%	179%
	G37 14.5’ from support	E43	E59	183	92	435%	156%
	G37 19.6’ from support	E42	E57	168	94	400%	164%
	G37 Mid-span	E40	E54	129	97	323%	179%
	G28 section 2	E62	E52	282	87	455%	167%
	G28 section 5	E62	E52	303	91	500%	175%
	G28 section 7	E53	E49	199	97	370%	196%
	G28 Mid-span	E47	E47	229	102	476%	217%
	G29 Mid-span	E47	E56	348	119	714%	213%

POST-DISASTER MANAGMENT USING REMOTE SENSING — INTERFEROMETRIC SYNTHETIC APERTURE RADAR (INSAR)

As the investigators had a strong interest in studying the impact of major earthquakes on urban transportation infrastructure, the impacts of two recent earthquakes using available remote-sensing technology and data were investigated. The first case study was on the 6.6 magnitude earthquake that severely damaged the city of Bam in Iran on December 26, 2003. For this study, the researchers selected two Envisat satellite SAR images of the impacted area that were highly suitable for InSAR deformation analysis, with dates of acquisition December 3, 2003 (pre-earthquake) and February 18, 2004 (post-earthquake), respectively. The images were freely available from the European Space Agency (ESA). The second case study was on the 7.9 magnitude earthquake that severely impacted parts of Sichuan province in China on May 12, 2008, including several urban centers. For this study, the researchers selected two Envisat satellite SAR images of the impacted area, which were among only a very few pre/post-earthquake SAR image pairs available and potentially suitable for InSAR deformation analysis. The images' dates of acquisition were February 6, 2006 (pre-earthquake) and May 28, 2008 (post-earthquake), respectively. They were purchased from Eurimage Company, a data distributor for the ESA.

Bam, Iran 2003 Earthquake Case Study

In this study, InSAR processing on two Envisat satellite SAR images of the city of Bam, Iran was performed. This area was severely damaged by a 6.6 magnitude earthquake on December 26, 2003. One image was acquired before the earthquake (December 3, 2003), and the other image was acquired after the earthquake (February 18, 2004). The open-source and advanced software DORIS, developed by Delft University in the Netherlands, was used to perform the InSAR processing. The image products generated were generally of high quality due to the fact that the selected image acquisitions had a relatively short spatial baseline of 2 meters and temporal baseline of around 10 weeks, to maximize the capability for detection of ground deformation patterns.

Arciniegas et al. applied the InSAR technique on similar 20-meter resolution Envisat SAR imagery and tried to assess the building damage distribution at the city block level. The investigators in the present study, on the other hand, focused on trying to detect and assess the conditions of the city's transportation infrastructure. The 20-meter ground resolution limitation, however, made most roads and bridges narrower than 20-30 meters wide undetectable. However, the researchers were able to detect damage to part of the city's airport runway, located a few kilometers east of the city and the earthquake's epicenter, by visually inspecting the InSAR coherence image (Figure 10). This was confirmed by a World Bank report, which stated that the airport runway, with its relatively thin asphalt surface, suffered moderate damage due to the earthquake and the numerous flight landings and takeoffs in the weeks following the earthquake. Due to the spatial resolution limitation, it was not possible to quantify the damage from the generated InSAR images. The following optical and InSAR images show various types of information about the city of Bam's airport runway and the surrounding area.

Figure 10. Satellite Optical Image of Bam, Iran, Showing the City's Airport Runway as Oriented from Northwest to Southeast

Source: Google Inc., 2008.

A number of features in the optical image above, including the airport runway, can be seen in the following InSAR images that the research team generated for this study area.

Figure 11 is the result of pixel-to-pixel multiplication of pre- and post-earthquake SAR amplitude images of the study area, with bright pixels representing strong SAR signal backscatter to the imaging satellite and dark pixels representing weak signal backscatter.

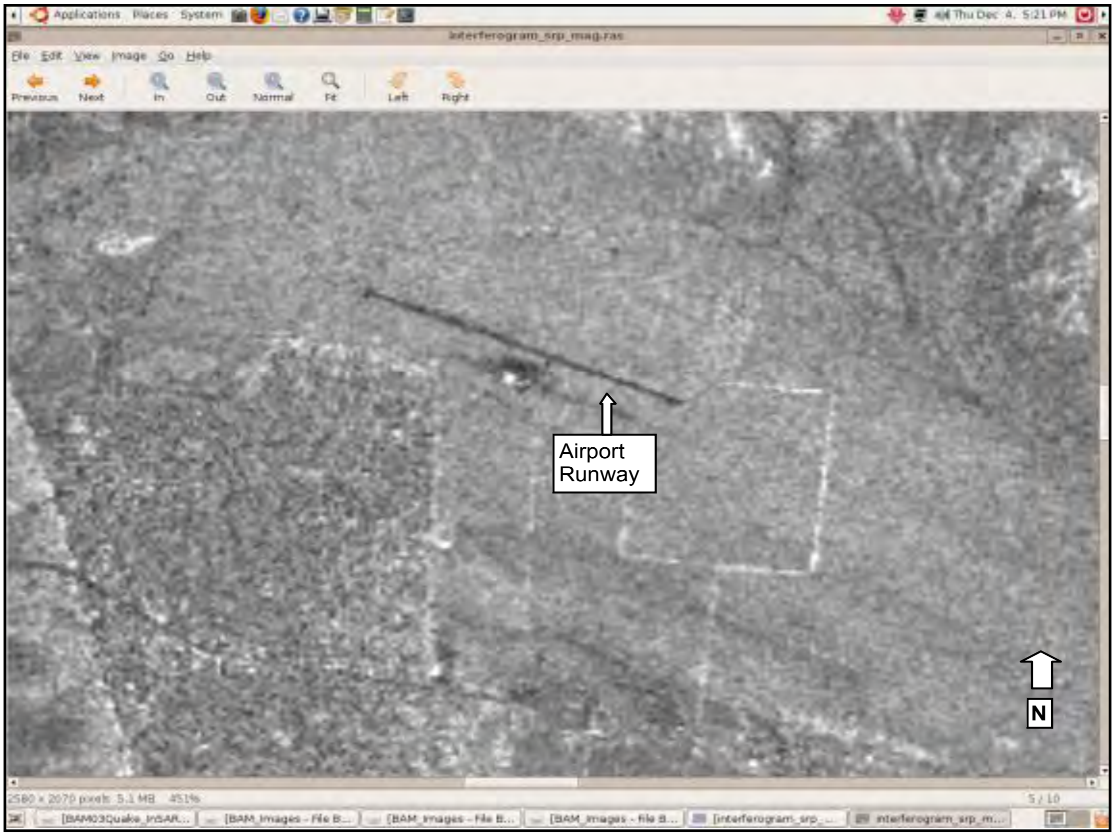


Figure 11. InSAR Magnitude Image Generated with DORIS Software

The InSAR magnitude image above clearly shows the Bam airport runway as a linear feature that is much darker than its surrounding area, an indication that the imaging satellite received very little signal backscatter from the runway. This is due to the fact that the SAR signals from Envisat satellite hit the flat and horizontal runway and reflected away from the satellite as it imaged the area from east to west while on its north to south flight orbit.

Figure 12 is the result of pixel-to pixel phase correlation between pre- and post-earthquake SAR images, where bright pixels indicate high correlation and dark pixels indicate low correlation.

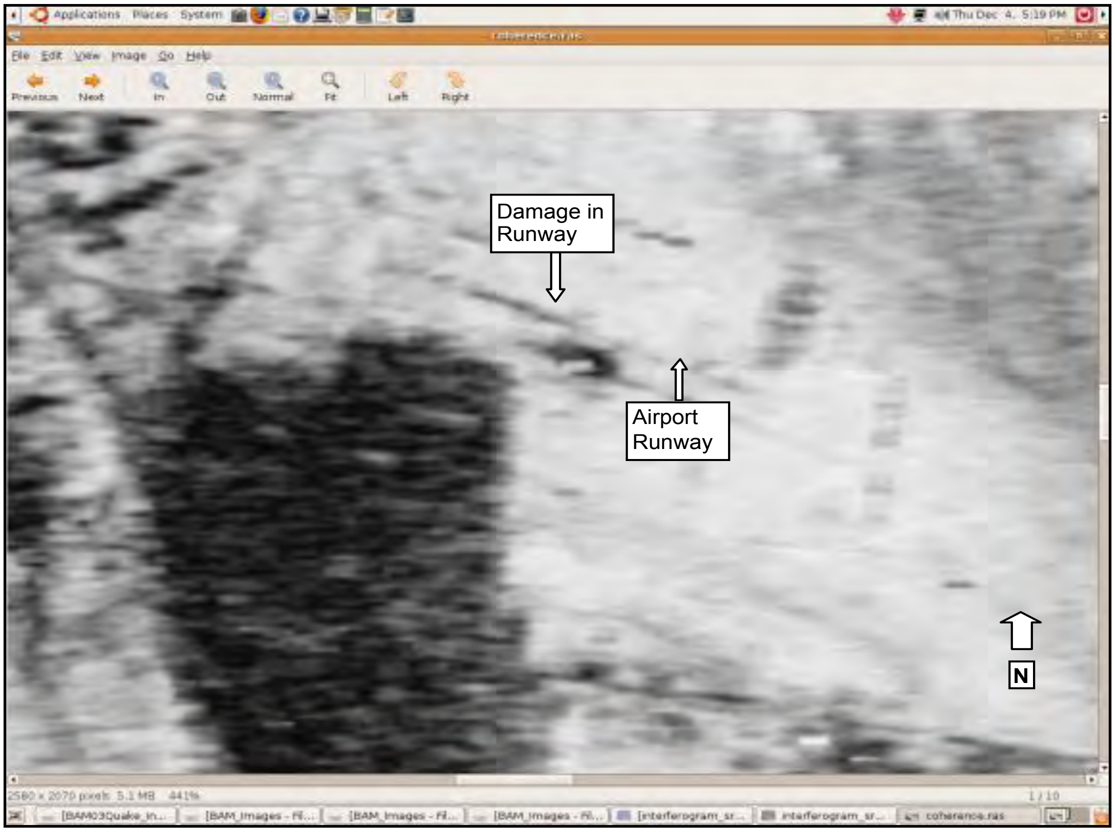


Figure 12. InSAR Coherence Image Generated with DORIS Software

The InSAR coherence image above clearly shows the western part of the Bam airport runway as significantly darker than its surrounding area. This means that those pixels on the runway suffered significant amount of deformation (or damage) due to the earthquake or other effects, which caused significant changes in their backscattered SAR signal phase values as compared to pre-earthquake signal phase values. These significant differences in the runway pixel phase values, between pre- and post-earthquake SAR images, led to low correlation values for those pixels, which therefore made them appear as dark in the InSAR coherence image. Even though the detected deformation on the airport runway appears to be significant, it is difficult to give a more detailed assessment of the runway's operational conditions based on this image alone, due to the 20-meter spatial resolution limitation.

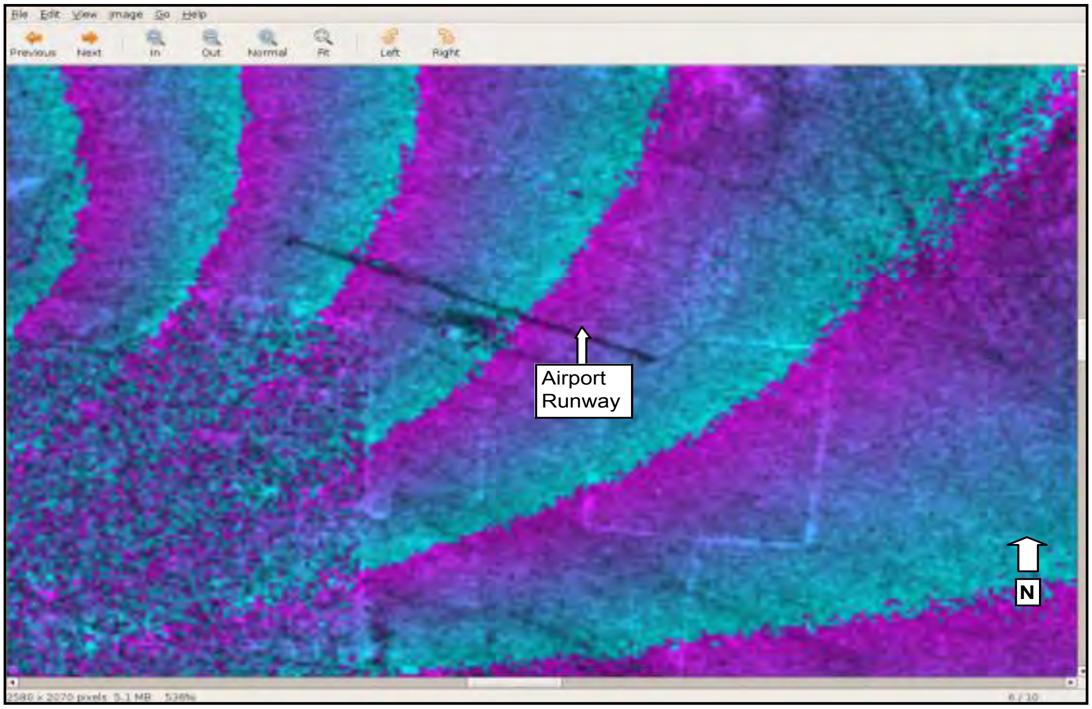


Figure 13. Composite InSAR Image Generated with DORIS Software, Consisting of an InSAR Phase-Difference Image Superimposed on an InSAR Magnitude Image

Figure 13 shows the InSAR phase-difference image superimposed on an InSAR magnitude image showing the Bam airport runway as dark in color. The phase-difference image shows the earthquake-induced ground deformation pattern as color fringes. Note that the deformation pattern (color fringes) caused by the traveling earthquake shock wave traverse the length of the airport runway from west to east. The researchers also note from Figure 11 that the western part of the runway, which is closer to the earthquake epicenter, shows the most noticeable damage.

Sichuan, China 2008 Earthquake Case Study

In this study, the investigators performed InSAR processing on two Envisat satellite SAR images of a selected area of Sichuan province in China that was impacted by a strong earthquake on May 12, 2008. One image was acquired before the earthquake (February 6, 2006), and the other was acquired after the earthquake (May 28, 2008). The open-source and advanced software DORIS, developed by Delft University in the Netherlands, was used to perform the InSAR processing. The generated InSAR image products varied in their quality from high quality for the magnitude image to low quality for the phase and coherence images. This low quality was mainly because the selected image acquisitions had a relatively long spatial baseline of 600 meters and temporal baseline of around 2.25 years, which significantly increased the level of decorrelation between the images and thus severely reduced the capability for detection of ground deformation patterns. The investigators used this image data set, however, because it was among very few data sets that were available for the impacted area that at the same time were suitable for InSAR processing. The generated InSAR magnitude image was the only image that the researchers were able to utilize in their attempt to detect and assess conditions of the transportation infrastructure in the earthquake-impacted area. The following images are first results showing information about the study area.

Figure 14 shows a road-dam structure spanning a river channel from Google Earth. A number of features in the optical image above, including the road-dam structure, can be seen in the following InSAR image that the investigators generated for this study area.

Figure 14. Satellite Optical Image of the City of Mianyang in Sichuan Province, China, which was Impacted by the 2008 Earthquake

Figure 15 is the result of pixel-to-pixel multiplication of pre- and post-earthquake SAR amplitude images of the study area, with bright pixels representing strong SAR signal backscatter to the imaging satellite and dark pixels representing weak signal backscatter.

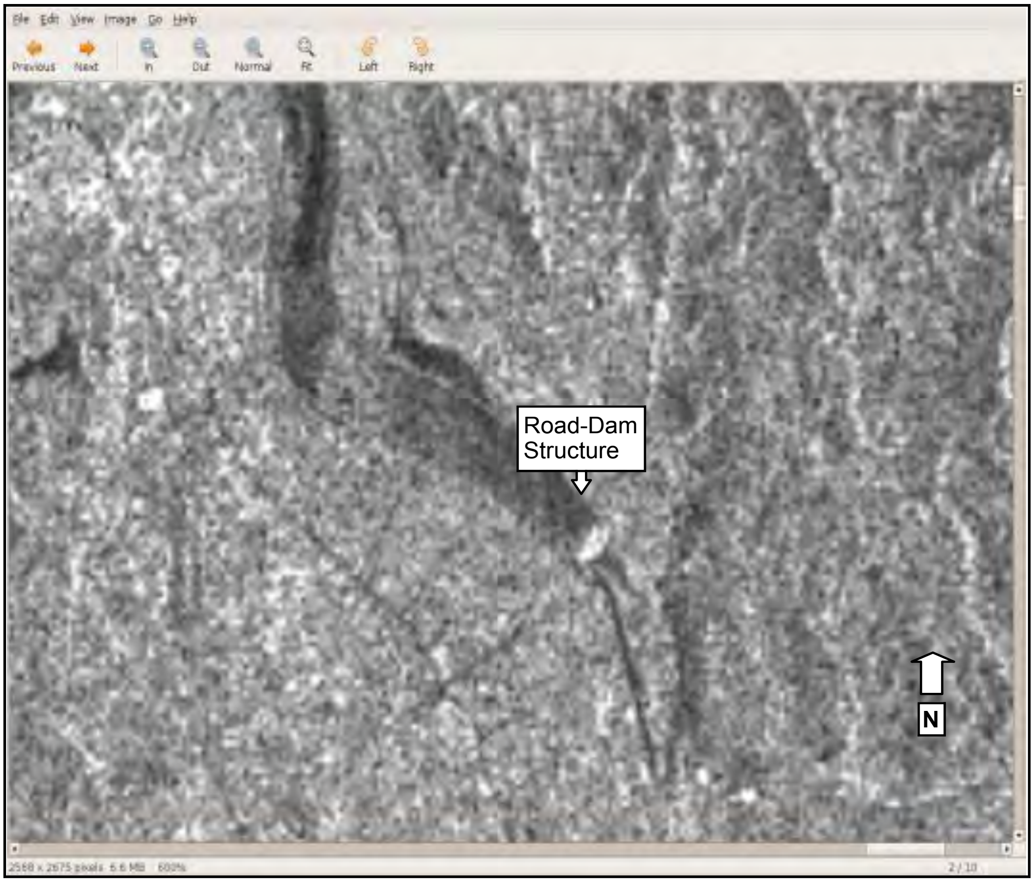


Figure 15. InSAR Magnitude Image Generated with DORIS Software

Note in the image above that the road-dam structure spanning the river channel shows as bright pixels. This means that the SAR signals backscattered from the road-dam structure with high amplitudes due to the fact that the structure is oriented at an almost 450 degree angle with the north-south flight path of the imaging satellite. The other reason for the structure's bright signals is that the width of the structure was estimated at around 50 meters (using a Google Earth tool). That is more than 2 SAR pixels wide, and thus makes it detectable by the SAR system. Based on the brightness of the return signals from the road-dam structure, therefore, the researchers can say that the structure appears to be intact following the earthquake. The investigators cannot determine from this image alone, however, whether the structure has suffered moderate or minor damage, due to the image's 20-meter spatial resolution limitation.

Figure 16 shows a number of bridges spanning a river channel from Google Earth. A number of features in the optical image above, including the bridges, can be seen in the following InSAR image that the investigators generated for this study area.

Figure 16. Satellite Optical Image of the City of Deyang in Sichuan Province, China, which was Impacted by the 2008 Earthquake

Figure 17 is the result of pixel-to-pixel multiplication of pre- and post-earthquake SAR amplitude images of the study area, with bright pixels representing strong SAR signal backscatter to the imaging satellite and dark pixels representing weak signal backscatter.

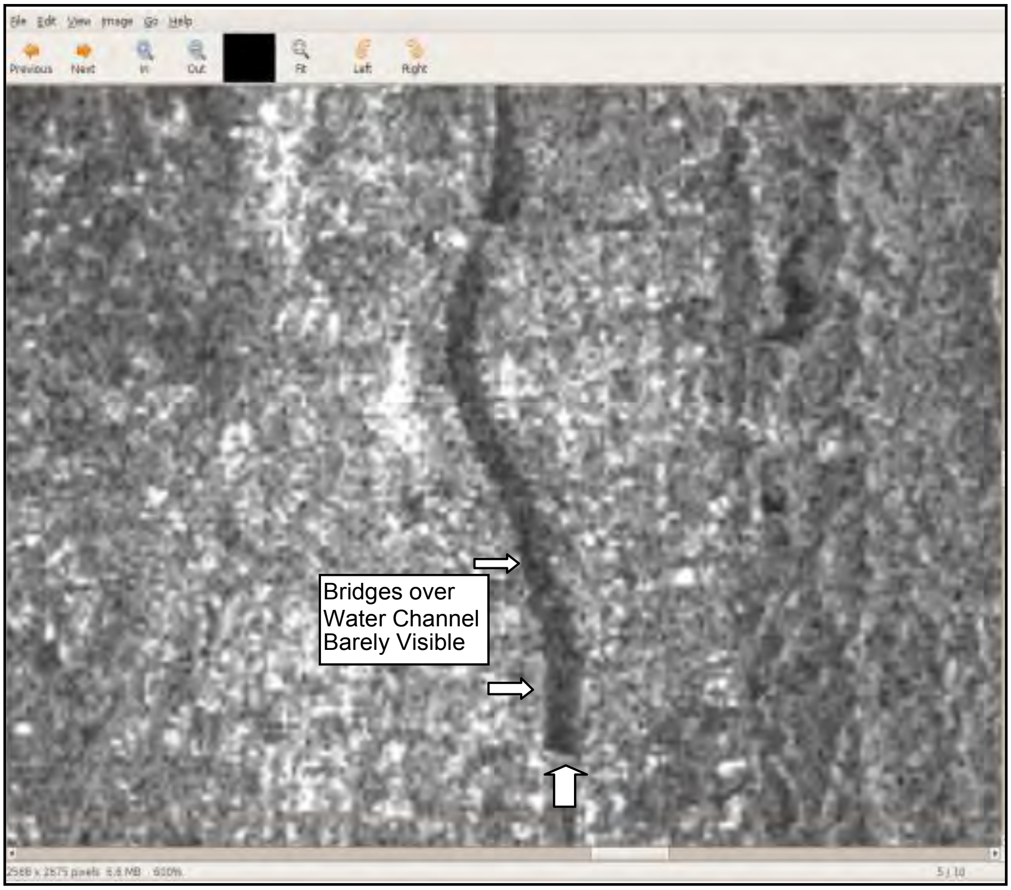


Figure 17. InSAR Magnitude Image Generated with DORIS Software

Note that the bridges showing in the optical image are barely detected in the InSAR image above. One reason for that could be the 20-meter spatial resolution limitation of the SAR system, which means that only structures of width significantly larger than 20 meters can be detected. In this case, the estimated width of those bridges was around 35 meters (estimated using a Google Earth tool), which is less than two SAR pixels wide. The other and most likely reason could be that the bridges are oriented east-west, which is almost perpendicular to the north-south flight path of the imaging satellite. In this case, most of the satellite SAR signals would have hit the flat and horizontal bridge decks and reflected away from the satellite. Therefore only a few low amplitude signals would have backscattered to the satellite, which made the bridges appear much darker on the InSAR magnitude image and therefore barely detectable over the dark water channel.

Hence, in this case, it can be inferred that the following combination of factors prevented us from clearly detecting the bridges and determining if the bridges remained intact following the earthquake: the image spatial resolution limitation, the bridges' perpendicular orientation to the imaging satellite, and the bridges being over a water channel.

SUMMARY

During normal operation of the bridge, the FE model can be developed to assess its performance and current condition throughout the comprehensive structural analysis. The model can be validated and calibrated using data from field tests and sensors using the SHM system. Thereafter, when a disaster happens, a quick evaluation of the bridge condition in a post-disaster mode can be re-evaluated using InSAR technology for the bridge network looking at factors such as support movement, member failure, etc. Two case studies were presented to test the feasibility of this proposed approach. Additionally, the bridge SHM system, if still operational post-disaster, would be utilized for further confirmation of the bridge response after the disaster. This proposed damage-detection procedure would enable a rapid damage assessment for numerous bridges on the bridge network basis, and thus provide rapid, optimized, and cost-effective management of road and bridge network post-disasters. With the proposed approach, transit agencies could assess the load-carrying capacity of their bridge structures promptly and efficiently. Major decisions could be made based on the results of proposed approach.

III. ASSESSMENT OF EFFICIENCY AND RESILIENCY OF TRANSIT SYSTEMS

The objective of the study is to characterize the sustainability/resiliency/reliability of transit infrastructure after natural disasters and make long-term predictions. Specifically, the researchers aim to measure public transit infrastructure when subject to disruptions, in terms of travel time, speed, speed of recovery, and reliability of access during extreme events, by evaluating the conditions of pavements and bridges along various routes and also by evaluating transit service reliability during extreme events.

DATA SOURCES

Public transit infrastructure consists of numerous components such as bus stations, road network, road bridges, train stations, train tracks, train signal control systems, tunnels, paratransit facilities, etc. In order to measure the performance of all these components, varied kinds of data are necessary.

With the advent of new technologies, there is a massive amount of available data sources in various facets of transportation and infrastructure. Most of these observed and model data were obtained in the context of other evacuation and emergency management projects as well as New Jersey Department of Transportation (NJDOT) research projects conducted by the Rutgers research team in the past. The following are the lists of data sources available in NJ for infrastructure, traffic and various events with references to the studies that used these data sets.

Infrastructure data sources used in this study include the following:

1. NJ Straight line diagrams are used in Ozbay et al. (2012a) and in Nassif et al. (2015).[113]

2. The New Jersey State-Wide Planning Model (NJSWM) and the North Jersey Regional Transportation Model - Enhanced (NJRTM-E) are used in Ozbay et al. (2012b), Demiroluk et al. (2016), Yang et al. (2016).[114]

3. Google transit data archived by the research team is used in several research projects conducted by Rutgers team researchers.

Traffic data sources used in this study include the following:

1. Anonymized Electronic Toll Collection (ETC) data is in Ozbay et al. (2012b), Demiroluk et al. (2016), Yang et al. (2016).[115]

2. INRIX travel time data is used in Ozbay et al. (2012b) and Rutgers Intelligent Transportation Systems Laboratory (RITS) (2011).[116]

3. NJDOT Weigh-in-motion (WIM) data is used in Ozbay et al. (2012a), Nassif et al. (2015).[117]

4. Traffic Monitoring System (TMS) continuous traffic count data integrated with NJ straight line diagrams are used in Ozbay et al. (2016a).[118]

5. New York City (NYC) subway turnstile data is used in Zhu et al. (2016).[119]

Events data sources used in this study are as follows:

1. Transportation Operating Coordinating Committee (TRANSCOM) event data is used in Ozbay et al. (2012b), Demiroluk et al. (2016), Yang et al. (2016), and Ozbay et al. (2016b).[120]

    a. Hurricane Irene events

    b. Hurricane Sandy events

2. NJ Transit recovery information is obtained from online sources such as Twitter, advisory notices, etc.

Brief Description of Data Sources

NJ Straight Line Diagrams

The straight line diagrams provide many details about the road infrastructure in NJ.[121] They are maintained by the NJ Department of Transportation (NJDOT). The straight-line diagrams include detailed GIS-based data up to local roads. Other data in the straight-line diagrams include, milepost, AADT, number of lanes, road type, surface condition, etc.

NJSWM and NJRTM-E

These data sources are used for long-term predictions of various transportation related investments. The level-of-detail is up to county-level road geometry. These data sets include, milepost, average peak and off-peak volume, speed and travel time by vehicle class. Aside from highway data they also include transit network data and planning-level ridership data.[122]

Google Transit Data

NJ Transit provides some transit data for public access for various transit application developers. This data set includes coverage of the transit routes, station locations and service timings. This data source is useful in geo-locating various transit lines with respect to highway and other infrastructure data.

ETC Data

The ETC data are collected for all toll-ways in NJ: New Jersey Turnpike (NJTPK), Garden State Parkway (GSP) and Atlantic City Expressway.[123] The NJTPK is spread over 150 miles with 28 interchanges and 366 toll lanes. The GSP is about 170 miles long with 50 toll plazas and 236 toll lanes. Each freeway carries up to 400,000 vehicles per day.[124] The ETC data set is collected at toll plazas on these freeways.[125] The ETC data set consists of the individual vehicle-by-vehicle entry and exit time data. It also consists of the information regarding the lane through which each vehicle was processed (both E-ZPass and Cash users), vehicle types, number of axles, etc. Since this data set is extremely detailed, it can be used to analyze changes in volumes, travel time and vehicular composition not only on a daily basis, but also as a response to extreme events.

INRIX GPS Travel Time Data

INRIX Inc. collects and compiles GPS traces collected from GPS devices in cars and mobile phones.[126] INRIXTM monitors traffic flows across more than 260,000 miles of US and Canadian highways and provides real-time traffic information for 32 countries across North America and Europe that comes from 800,000 vehicles equipped with GPS devices (INRIX (2013)).[127] In addition, INRIX receives information from road sensors located in about 9,000 miles of highways. It is a crowd-sourced traffic network, and it receives information from commercial fleets – taxicabs, delivery vans and long-haul trucks – and mobile devices. INRIX also reports incidents and unique local variables (INRIX (2013)).[128] INRIX offers developers real-time traffic and routing information using application programming interface (API) access. Using GPS traces, the company provides historical and recent travel-time information and also traffic forecasts in the near future. Although the level of detail is not as much as the ETC data set's, the INRIX GPS data is richer in its geographical expanse. It is collected over county-level highways, state highways, interstates and freeways.

NJDOT WIM Data

Weigh-in Motion (WIM) sites are used for monitoring the heavy vehicles operations on roadways. The types of data available through WIM are: traffic volume, speed, directional distribution, lane distribution, date and time of passage, axle spacing, and vehicle classification.[129]

TRANSCOM Event Data

Several agencies collect event data related to all the accidents, incidents, crashes and other road-related events.[130] For example, TRANSCOM, an agency that coordinates the activities of all of the transportation agencies in the New York – NJ region, collects volume, speed, and travel time data through electronic readers, known as TRANSMIT data (TRANSCOM (2013)).[131] TRANSCOM also provides data specific to distinct events in the transportation network. Events such as major constructions activity, major accidents, hurricanes, sporting events, conventions, etc. may cause disruptions in the transportation network. Information on disruptions on roadway network is collected by, traffic incidents, type of incident, flooding, other traffic blockage events such as tree falls, down poles, etc. The event data can be generated from an XML feed from the TRANSCOM database. Around 5,000 event records are obtained on an average in a month. For this study the event data during hurricane Sandy (October through December 2012) are used.

NJ Transit Online Data

Recovery effort of various bus and rail lines is constantly updated by NJ Transit on their web site and using their twitter account. This data set is compiled and used to estimate the recovery effort.

These extensive data sets are very useful in estimating various data-driven performance measures for the transit infrastructure. Some of these performance measures, as studied in the relevant literature, are discussed in the next section.

METHODOLOGY FOR RESILIENCY, VULNERABILITY AND RECOVERY MEASUREMENT

The transportation vulnerability, recovery and resiliency measures in the literature described in the previous section are mostly network-level measures. However, for assessing the resiliency of public transit network, it may also be needed to evaluate these measures at route- and link-levels. Route-level measures may be used to determine the resiliency of specific bus routes. Link-level measures may be useful in identifying particularly vulnerable links in the public transit network. Hence, in this study the resiliency measures mentioned in the literature above are customized so that they can specifically be quantified for transit routes.

Table 4 lists the adapted performance measures classified into different categories, a brief definition and data to be used to quantify these measures with New Jersey-specific data.

Table 4. Adapted Performance Measures Estimated in this Study

Vulnerability Measures	Data Used
Vulnerability index VA_6: number of times a link is a part of the route on route map[132]	Google Transit
Change in bus route travel time[133]	INRIX
Number of critical links (links with high VA or links with events) on specific bus routes	Google Transit/TRANSCOM
NRI – extra travel time / distance imposed on the route by removing a particular link on a route[134]	NJRTM-E
Recovery Measures	**Data used**
Bus transit recovery in number of days	ETC data
Rail transit recovery in number of days	Advisory information from internet
Change in speed[135]	INRIX
Resiliency Measures	**Data to be used**
Change in travel times or generalized transportation cost between ODs[136]	NJRTM-E
Δtravel time/Δtime[137]	ETC data
Δvolume/Δtime[138]	ETC data
Friability (number of reliable routes) for select bus routes[139]	Google Transit/TRANSCOM NJRTM-E

Since most of the available New Jersey-specific traffic data are for the highway network, the measures are generated for the bus transit network in this study. In order to evaluate these measures for transit, the Google transit data is used as the basis for geo-location. The traffic and event data are superimposed and mapped onto the bus transit network. The bus transit network is made discrete based on bus routes, whereas the traffic data are available on the basis on links. Thus each bus route has to be mapped onto the corresponding highway links in order to obtain the appropriate traffic data. An example of this process is shown in Figure 18.

Figure 18. Google Transit Network + NJRTM-E Loaded Network for Bus Route 139

It may not be possible to estimate the measures for all the links in the bus transit network. Therefore, a set of links with high vulnerability index, $VA_{6,}$ is used. In this study, however, for the case of transit, VA_6 is modified as the number of times a link is a part of different bus routes. Additionally, the event data is also mapped onto the highway network. The links associated with disruption events are also added to the set of links chosen above. All other link-level measures are estimated for these links.

For estimating network-level measures such as NRI and NIRA, the links chosen above are used in cases of disruption. These measures require estimating the travel times without specific links as a part of the network. For this purpose, the NJRTM-E loaded network is used. In specific cases, the travel time information for the ETC data of NJTPK or INRIX, if available during the event, is used.

For the analysis of travel times, the investigators use a software application developed by the Rutgers team specifically to analyze four-step planning process' output data from Northern NJ's demand forecasting model, namely, NJRTM-E. This application software application titled ASSIST-ME (Advanced Software for State-wide Integrated Sustainable Transportation System Monitoring and Evaluation) is developed on a customized version of the ArcGIS 9.2 Developer Engine in Microsoft.NET Framework, as a tool to visualize and analyze the output of transportation planning models in a GIS environment. Various functionalities of ASSIST-ME are described below briefly. For a detailed presentation of the tool please refer to Ozbay et al. (2014).[140]

The major functionalities of ASSIST-ME are:

1. Visualization of data such as link speed and volume-to-capacity (V/C) ratio, including side-by-side visual comparison of two network model runs.

2. Calculation of macroscopic statistics such as VMT, vehicle hours traveled (VHT), or average network speed, travel time, and delay.

3. Analysis and comparison of OD demand between various zones in the network.

4. Calculation of shortest paths between origins and destinations on a loaded network.

5. Estimation of travel costs for user-defined/all network links, or for trip paths based on:

    - Vehicle Operating Cost

    - Congestion Cost

    - Accident Cost

    - Roadway Maintenance Cost

    - Air Pollution Cost

    - Noise Cost

6. Benefit/Cost analysis of various policies and planning decisions.

7. Creating and selectively exporting analyses into a report.

The workflow of ASSIST-ME is shown in Figure 19. Users select the analysis method and feature-selection method using the graphical user interface of ASSIST-ME. Corresponding database(s) are accessed depending on the method of analysis chosen using appropriate queries and programs. This information can be presented in the form of color schemes and tables that can also be saved for future reference and reporting.

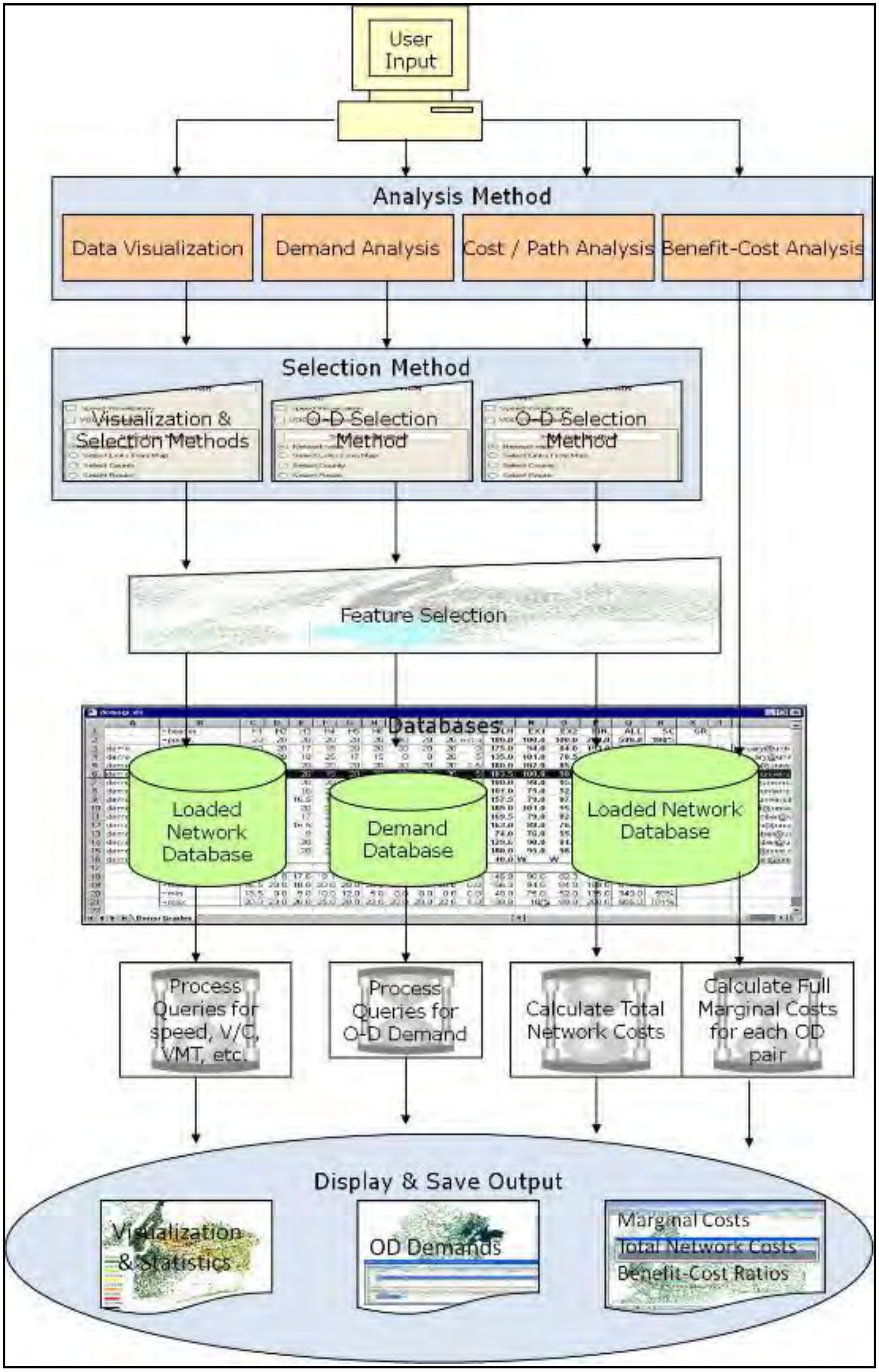


Figure 19. ASSIST-ME Workflow[141]

For this study, path analysis and trip-cost estimation are the applicable functionalities. ASSIST-ME can track changes in travel times and paths and function as a quick analysis tool to visualize the shortest path between an OD pair and calculate its model-estimated travel time. This module of ASSIST-ME does not perform the traffic assignment process, but estimates shortest path(s) and corresponding travel times between selected OD pairs based on the output of the traffic assignment process. The methodology used to find the multiple trips between OD pairs is based on the *k-th* shortest path algorithm developed by Ozbay et al.[142] Beyond changes to travel times and travel paths, network changes result in wide-ranging effects on the complete system. These effects can be represented as "costs" incurred by various entities of the system.

In addition, due to the availability of detailed turnstile ridership data from the NYC subway, the spatio-temporal resiliency characteristics of the NYC subway system are also included as a part of this study.[143] Recover curves are also built for the subway system in New York City in the aftermath of Hurricanes Irene and Sandy.

Subway ridership data was obtained from the turnstile data set from the Metropolitan Transportation Authority (MTA). This data set includes subway turnstile information since May, 2010 and is updated every week. The data is stored in txt format and is available through an official data feed.[144] The data is organized by weeks, remote units (stations) and control areas (turnstiles). Each station can have multiple control areas, and for each turnstile, there are two increment counters used to record numbers of entries and exits. In each weekly file, a row contains one read of entry and exit counters, time of the read, station and turnstile IDs. Typically, counter readings of each turnstile are recorded every four hours, but each station may have a different time of reading. In order to obtain daily ridership of each station, first it is necessary to convert values of counters to turnstile ridership by subtracting last reading and first reading of the day, and then calculate the sum of all turnstiles.

The processed data sets were then incorporated into Neighborhood Tabulation Areas (NTA). The NTA is a set of polygons created by the New York City Department of City Planning, used for presenting data from Census and American Community Survey.[145] There are overall 195 NTAs in NYC, and each NTA corresponds to one Neighborhood with a unique ID and name. There are two reasons for selecting NTAs. First, the sizes of NTAs are appropriate for analysis, especially for subway data. These areas are neither so big as to cover more than one category of evacuation zones, nor so small as to not include even one subway station. Second, as mentioned above, unlike TAZs or Census Tracts, each NTA also has a familiar name, so it is much easier to follow travel patterns based on these names. Data for the present study periods were extracted from taxi and subway data sets, and NTA attributes are associated with each trip's origin and destination.

Subway ridership data during the study period is compared with data for the same period of the previous year. Daily ridership for each NTA is obtained as the sum of ridership for all stations located in the NTA. For both hurricanes, the researchers choose the days before evacuation orders as the start days of study, and durations are 15 days. Study periods of hurricanes and normal conditions are shown in Table 5.

Table 5. Study Period of the Empirical NYC Subway Data

Cases	Start Date (Day 1)	Evacuation Order	Hurricane Landfall	End Date (Day 15)
Hurricane Irene	Aug. 25, 2011 (Thurs.)	Aug. 26, 2011 (Fri.)	Aug. 28, 2011 (Sun.)	Sept. 8, 2011 (Thurs.)
Reference Irene	Aug. 26, 2010 (Thurs.)	-	-	Sept. 7, 2010 (Tue.)
Hurricane Sandy	Oct. 27, 2012 (Sat.)	Oct. 28, 2012 (Sun.)	Oct. 29, 2012 (Mon.)	Nov. 10, 2012 (Sat.)
Reference Sandy	Oct. 29, 2011 (Sat.)	-	-	Nov. 8, 2011 (Tue.)

There are several important issues in processing taxi and subway turnstile data. The first is the filtering of noisy or erroneous data. For subway trips, errors including extremely low or high ridership values (caused by counter reset due to maintenance) need to be filtered out. Besides, for normal days, daily subway entrance and exit counts are close. However, in the first two days of November 2012, entrance counts were significantly lower than exit counts. That is because fare was not collected in the initial recovery period of the system, and entry data was not recorded at all.[146] For comparison purposes, therefore, ridership in terms of exit data only is used.

ESTIMATION OF PERFORMANCE MEASURES AND ANALYSIS

Various performance measures listed in Table 4 are estimated and presented in this section in three categories, namely, vulnerability, recovery and resiliency.

Vulnerability Measures

VA_6, the number of times a link is a part of the route, is an important characteristic of the network. In the context of this study, it indicates the number of times a link occurs in a bus route in the bus network.[147] In other words, VA_6 indicates which links are more important for the operating agency. Table 6 lists VA_6 for the NJ Transit bus network. Note that VA_6 is a property of the network, and independent of any critical event it may be subject to.

Table 6. VA_6 Number of Times a Link is a Part of a Bus Route on NJ Transit

Link	VA_6	Link	VA_6
Lincoln Tunnel	63	I-80 before NJ 17	12
NJTPK exit 16E	21	NJ 3 between 16W & NJ-495	11
NJ 3 before NJ-495	21	George Washington Bridge	8
NJTPK exit 17	21	US9 before GSP	7
NJTPK exit 14-15E	18	I-280	6
NJTPK exit 13A-14	17	NBHCE exit 14A-14C	5
NJTPK exit 13-13A	16	US 1 south of Princeton	3
Ben Franklin Bridge	15	NJTPK exit 9-10	2
NJTPK exit 11-12	14	Holland Tunnel	2
GSP before NJTPK 11	12		

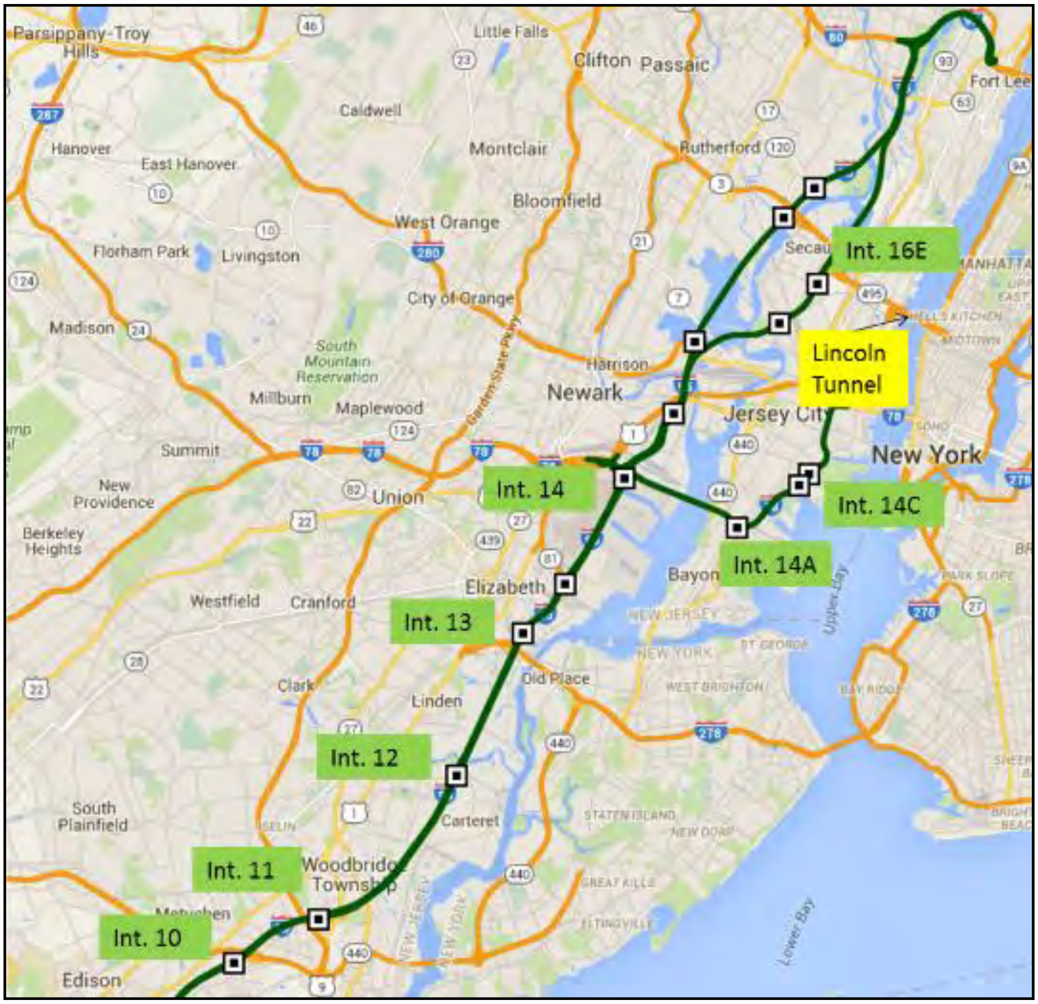


Figure 20. Interchanges of NJTPK on Google Maps

Table 7. Comparison of Changes in Travel Time

	Interchange 11-16E		Interchange 14-16E	
	Travel time (min.)	Percent change	Travel time (min.)	Percent change
Average Regular Days	20.47		8.42	
Average during Hurricane Evacuation	28.90	41%	13.73	63%
Maximum during Evacuation	39.72	94%	35.73	325%

Change in Travel Time on Routes with Critical Links

Change in travel time is another link-level vulnerability measure.[148] In this study, change in travel time is estimated using the ETC data on NJTPK and travel time data from INRIX for the few critical links that carry most of the buses. In other words, the change in travel time is estimated for critical links with a high VA_6 from Table 6. Travel time between major interchanges is a good indication of how critical events, in this study hurricane Sandy, have affected the network and the bus routes.

Travel time is estimated from ETC data between Interchange 11 and 16E and Interchange 14 and 16E (see Figure 20 for the location of the interchanges) for three days before and five days after evacuation for Hurricane Sandy began.

Two levels of comparison of travel times are performed. The first level includes the difference between average travel times before the hurricane and the maximum travel time during the evacuation and hurricane period. The second level includes the difference between the average travel times before the hurricane and the average travel times during the evacuation and hurricane period. Table 7 shows the comparison of the travel time measures.

Number of Events on Routes (October 29-30, 2012)

The number of events is a critical input in determining which routes were affected by Hurricane Sandy. The event data during Hurricane Sandy are provided by TRANSCOM. A general classification of events before, during and after Hurricane Sandy is shown in Figure 21.

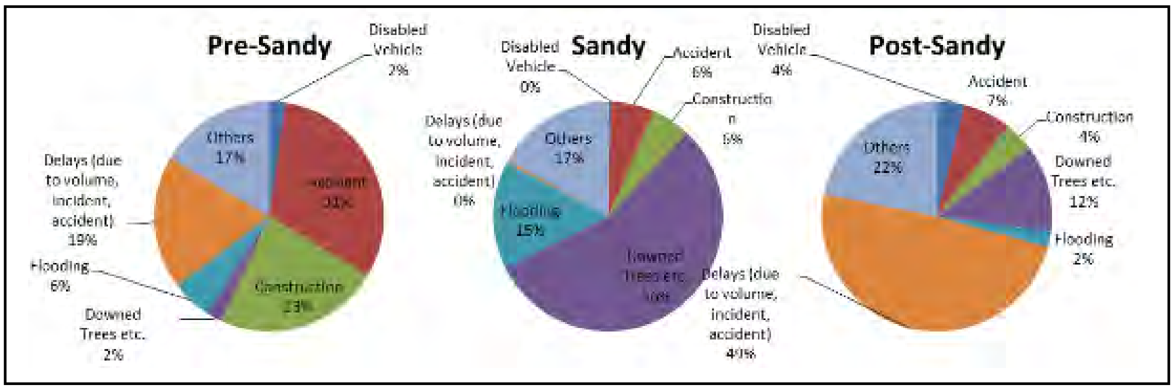


Figure 21. Event Classification Before, During and After Hurricane Sandy

For the purpose of evaluating bus routes affected by Sandy-related events, the event data from TRANSCOM is mapped onto Google Transit's bus network. The intersection data set is used to obtain the frequency of number of routes versus number of critical Sandy-related events beginning October 29-30, 2012.

The intersection data set is used to obtain the frequency of number of routes versus number of critical Sandy-related events beginning October 29-30, 2012. Figure 22 shows the number of routes with {0, [1-4], [5-8], [9-12], [13-16], [17-20], [21-24], 24-more} events.

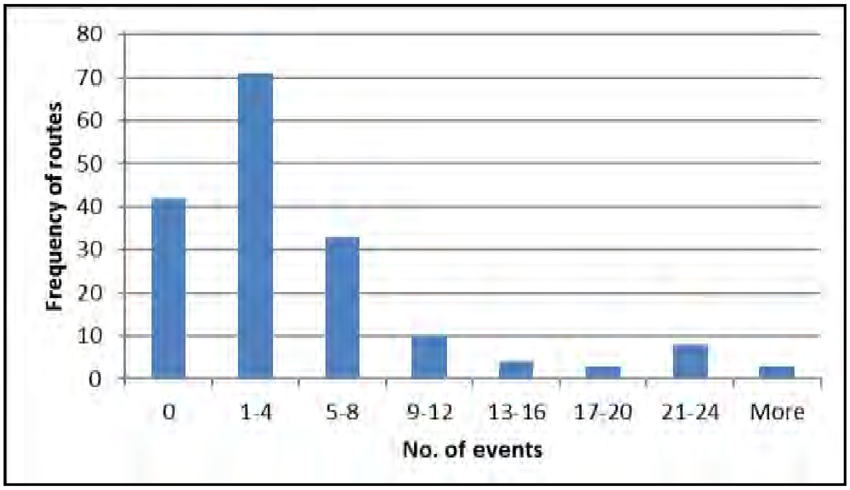


Figure 22. Frequency of Routes with Critical Sandy-Related Events

Note: Beginning Oct. 29-30.

Figure 23 shows a map of the ten routes with the most Sandy-related critical events beginning October 29-30, 2012. From Figure 23, it can be inferred that Sandy generally affected most of the routes that pass along the coast in the southern and eastern parts of NJ.

Figure 23. Routes with the Most Sandy-Related Critical Events

Notes: More than 20. Beginning Oct. 29-30.

Network Robustness Index (NRI)

The NRI is a measure of vulnerability of a particular link and its impact on the network. Note that VA_6 is a property of the network and independent of any critical event it may be subject to. In other words, it is dependent on the design on the transportation network. In this study, as an illustration, the investigators demonstrate the effect of removing the most critical link (in terms of VA_6: number of times a link is a part of the bus route on bus network), namely, the Lincoln Tunnel. For estimating this measure, the researchers use ASSIST-ME to estimate the extra travel time imposed on operating the route by removing the link representing the Lincoln Tunnel.[149] The researchers study the extra travel time imposed on operating the route by removing the link representing the Lincoln Tunnel that runs from or upstream of (a) Middletown, NJ – PABT, Manhattan, (b) Newark Airport – PABT, Manhattan. Note that in this case, since only three bus routes are analyzed, the traffic assignment is not performed without the critical link. Instead, only the shortest path is re-estimated between the few important origins and destinations that form a part of the majority of the bus routes. For a similar analysis for all bus routes in the NJ TRANSIT bus network, a full cycle of the four-step planning process will be performed with the critical link removed.

Table 8. Change in Travel Time When the Lincoln Tunnel is Removed

Origin-Destination	Travel Time under Normal Conditions (*hr*)	Travel Time when Lincoln Tunnel is Removed (*hr*)	Percent Increase in Travel Time
Middletown, NJ – PABT, Manhattan	2.06	2.09	1.4%
Newark Airport – PABT, Manhattan	1.07	1.04	-2.3%
Clifton, NJ – PABT, Manhattan	0.95	1.15	21.1%

The result in Table 8 shows that the network is fairly reliably able to compensate for the loss of a critical link. Note that the current route followed by buses traveling from Newark Airport – PABT, Manhattan is via Lincoln Tunnel. Since only three bus routes are analyzed, the traffic assignment is not performed. When the full four-step planning process is performed with the Lincoln Tunnel removed, the possible options would involve:

- traffic (including buses) shifting to other routes which could be of a shorter travel time as seen in Table 8,
- a modal shift of passengers traveling to New York City such as a shift from bus to PATH from Newark Penn station or a shift from bus to PATH to Jersey City and ferry to Manhattan, etc.

Recovery and Resiliency

Hurricane Sandy caused extensive damage to the rail transportation infrastructure in particular and to the road infrastructure in general. The following are a few examples of the damage.[150]

1. NJ Transit's rail operations center was submerged, damaging the backup power supply systems, emergency generator, and the computer system that controlled train movement and power supply.

2. Numerous downed trees damaged overhead and signal wires.

3. The North Jersey Coast line experienced washouts and damage to the Morgan drawbridge.

4. Downed tree limbs and power lines made roads impassable.

5. Nine of NJ Transit's bus garages operated on backup generator power.

6. The Hudson-Bergen Light Rail experienced track washouts at Port Imperial and West Side Avenue Stations, as well as trees in the overhead wire in Weehawken and flooding in Hoboken.

7. The River Line sustained no significant damage to equipment or infrastructure; due to a loss of commercial power in downtown Camden, however, there was no power to operate the signals and switches.

The impact of Sandy on the Port Authority Trans-Hudson (PATH) was also significant. The PATH suspended all services at midnight on 10/28. Storm surge from the hurricane caused significant flooding to PATH train stations in Hoboken and Jersey City, as well as at the World Trade Center on 10/29. The subway tunnel between Manhattan and NJ was also flooded.[151]

In the next subsection, the researchers analyze the recovery of transit in NJ and estimate a few resiliency measures.

RECOVERY

The recovery of public transit systems such as rail, light rail and bus is determined by the time each mode is brought back into service in the aftermath of extreme events. Figure 24 shows a map of various rail, light rail and subway lines operated by NJ Transit and Port Authority colored according to their recovery (full or part) time.

Table 9 shows the recovery time of various rail, light rail and subway lines operated by NJ Transit and Port Authority in number of days. It shows that light rail infrastructure can recover more quickly than regular rail lines. The possible reason for this could be that since regular rail infrastructure carries much higher load at higher speeds, the structural strengthening of the damaged tracks and bridges could require a greater amount of time. The guideway for light rail is usually on or close to existing roads, so the recovery is closely correlated to the recovery of road infrastructure. Light rail recovery, however, additionally depends on the recovery of systems such as signal control, power supply, etc.

Recovery of underground subway systems such as the PATH system operated by Port Authority are very dependent on the extent of flooding of the underground tunnels.

On October 27, 2012 the Governor of New Jersey announced preparations for potential shut down of NJ Transit bus, rail, light rail and Access Link Service effective October 29 and system-wide cross-honoring from Monday through Wednesday. The Holland Tunnel and the Battery Tunnel were preemptively closed at 2 p.m. on October 29 due to vulnerability to flooding. The George Washington Bridge was closed to traffic at 7 p.m. The Holland Tunnel experienced significant flooding. By the end of October 29, the Lincoln Tunnel was the only Manhattan entry point that remained open. The Lincoln Tunnel and Port Authority Bus Terminal (PABT) remained open since there was no flooding there.[152]

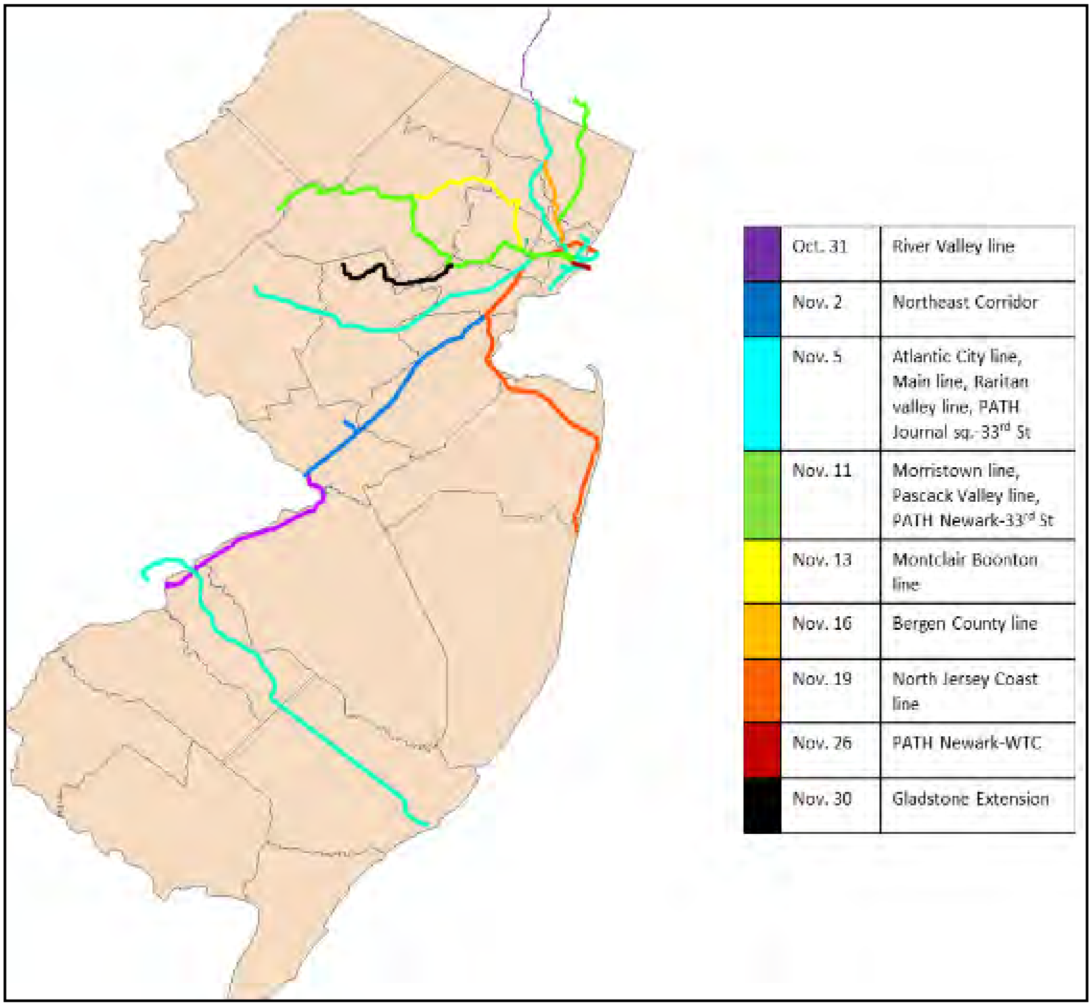


Figure 24. NJ Transit Rail, Light Rail and PATH Recovery Map

Source: NJTRANSIT (2015).

Table 9. Recovery Time of Various NJ Transit Rail, Light Rail and PATH

Rail Line	Recovery Time
River Valley Line	2 days
Northeast Corridor	4 days
Atlantic City Line, Main Line, Raritan Valley Line, Hudson Bergen Light Rail	7 days
PATH Journal sq.-33rd St.	8 days
Morristown Line, Pascack Valley Line, PATH Newark-33rd St.	13 days
Montclair Boonton Line	15 days
Bergen County Line	18 days
North Jersey Coast Line	21 days
PATH Newark-WTC	28 days
Gladstone Extension	32 days

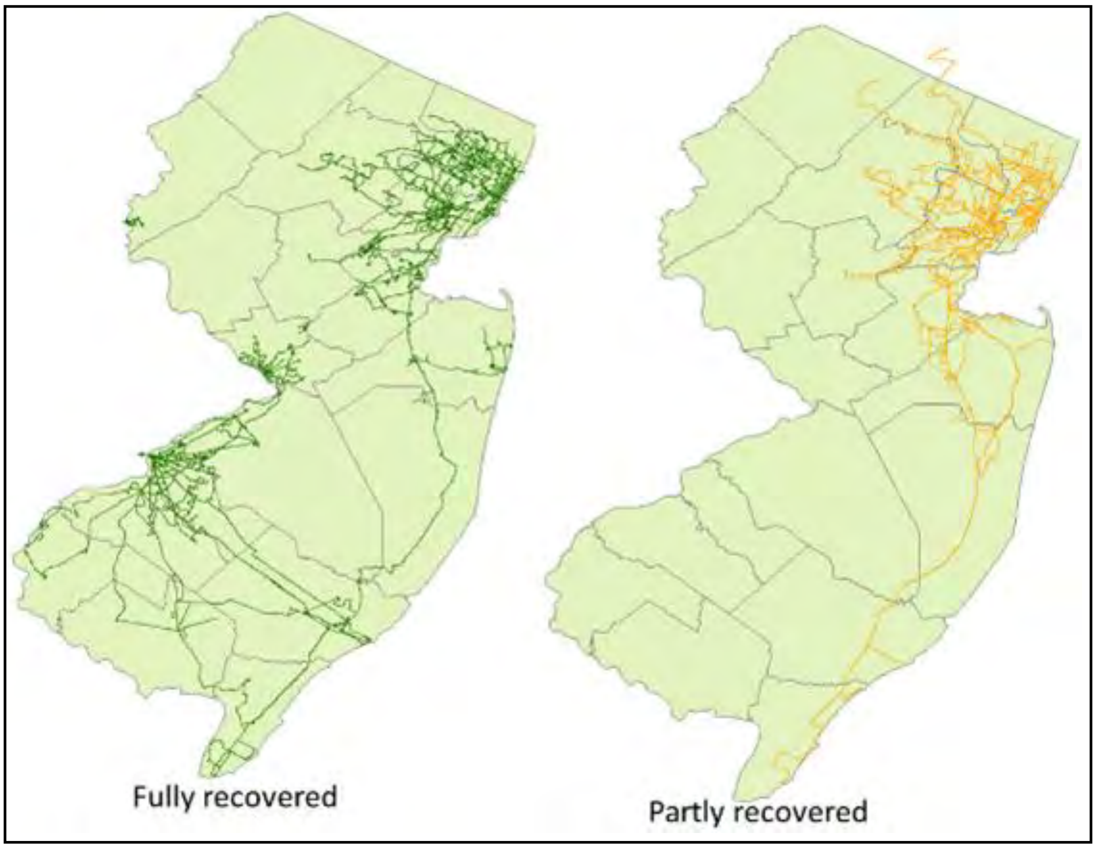


Figure 25. Recovery of Bus Routes as of November 1, 2012
Source: NJTRANSIT (2015).

Once Hurricane Sandy was over on October 31st, dozens of buses started to operate again, and specific routes were restored. As of November 1st, less than 40% of the gas stations in NYC metropolitan region were functioning due to loss of power supply. Access Link - ADA Paratransit service resumed in some regions. Starting November 9th, free shuttle buses were in service for the Morris & Essex Lines, Montclair-Boonton, North NJ Coast, and Northeast Corridor Lines.

Recovery of the bus transit system depends directly on the recovery of the highway system. Figure 25 shows the routes fully and partly recovered as of November 1st. One primary reason why the bus system recovered faster than the rest of the NJ Transit services is that the Lincoln Tunnel was not affected by the storm. Additionally, PABT was also unaffected. Since the Lincoln Tunnel is the most critical of the links in the bus route network as shown in Table 6, the bus transit system was able to recover quickly. Additionally, other critical links (Table 6) were also unaffected by the storm, as of November 1st:

- 167 routes recovered fully
- 83 routes partly recovered

Analysis of Sandy-related events on the routes provides a better idea on recovery time. The event data from TRANSCOM is used for this analysis. Considering the events with start time on October 29-30,

- partly recovered routes as of November 1st had 138 events, and
- fully recovered routes as of November 1st had 236 events.

However, the average duration for the events on fully recovered routes was 17.7 hours, whereas it was 20.7 hours for partly recovered routes. This observation confirms the fact the routes with shorter duration events, on average, recover faster than routes with longer duration events.

CHANGE IN SPEED

NIRA is defined as ratio of travel time before and after a disruption. Instead of travel time if speed is used in NIRA, the measures is similar to 1/NIRA. Thus the investigators calculate the NIRA measure using speed as:

$$NIRA_{speed} = speed_{after}/speed_{before}$$

The closer $NIRA_{speed}$ is to 1 the more recovered is the route.[153]

The researchers use anonymous location and speed data collect from many GPS-equipped vehicles and smart phones by INRIX to estimate $NIRA_{speed}$. The speed data are averaged for each hour for five days before and after hurricane Sandy made landfall on October 29, 2012. The investigators estimate the measure $NIRA_{speed}$ for three routes. The three bus routes are chosen such that they originate from (a) southern NJ, (b) central NJ and (c) northern NJ.

Table 10. Route Speed Information

Route	Average Speed before (mph)	Average Speed Immediately after	$NIRA_{speed}$	Average Speed Few Days after (from Nov. 1, 5 PM)	$NIRA_{speed}$
Southern NJ	59.54	53.23	0.89	59.19	0.99
Central NJ	50.69	42.63	0.84	49.29	0.97
Northern NJ	49.51	48.60	0.98	48.1	0.97

$NIRA_{speed}$ for route (c) recovers to normal levels immediately after hurricane Sandy, while $NIRA_{speed}$ for routes (a) and (b) does not recover as much. The reason is that route (c) travels in northeastern NJ, where roads and highways are not affected by Sandy as much as in southern and central NJ where routes (a) and (b) pass. This also supports the result from Figure 23, which shows that most of the events are in the southern part of NJ, and routes in the northern parts do not pass through highways with as many events as the southern parts.

RESILIENCY MEASUREMENT

Resiliency indicates a system's ability to resist and absorb the impact of disruptions.[154] Resiliency measures account for possible interventions that can aid in returning system performance to nearly pre-disaster levels. They quantify the potential benefits of pre-disaster mitigation actions aimed at increasing the system's ability to cope with disaster impact and of post-disaster adaptive actions that aim to restore functionality.

In this study the researchers use two important resiliency measures to study the impact of Hurricane Sandy on the bus transit system in NJ. The measures are (Adams et al. (2012)):

(a) Travel time over time, and,

(b) Traffic volume over time.[155]

Unfortunately, due to the lack of ridership or real-world travel time data for rail, light rail and subway services in NJ, the above-mentioned measures could not be estimated for the system.

Recovery of travel time to pre-disaster levels indicates the speed of recovery of the highway infrastructure, whereas recovery of volume over time indicates the speed at which the agency can provide the same level of service as the pre-disaster level.

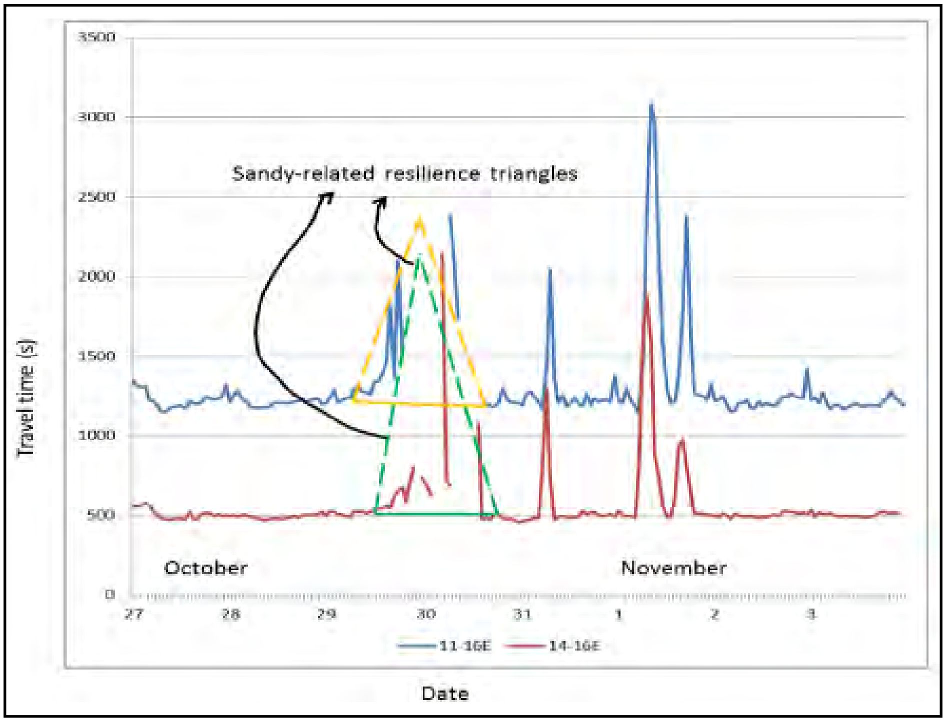


Figure 26. Sandy-Related Resiliency Triangles for Travel Times on NJTPK

In this study, the investigators use the ETC data from NJTPK for three days before and five days after hurricane Sandy made landfall on the coast of NJ to study travel time and volume resiliency measures. As noted in Table 6, the link ending at Interchange 16E is the second most critical link to the bus route network. Additionally, since the NJTPK is a closed system, travel times to and traffic volumes exiting Interchange 16E can be accurately estimated. Hence, the travel time to Interchange 16E is used as a benchmark for highway recovery. Figure 26 shows the average travel time between Interchange 11 and 16E, and between Interchange 14 and 16E (see Figure 20 for the location of interchanges on NJTPK). Figure 26 also indicates resiliency triangles for travel time. The line segments joining the top vertex of these triangles (Figure 26) are dashed, since there was no data on vehicles exiting interchange 16E during and immediately after hurricane Sandy. The reason could be that there were not enough vehicles or the tolls were suspended during this period.

Figure 27 shows the average hourly bus volume at interchange 16E. Figure 27 also depicts a resiliency triangle for volume.

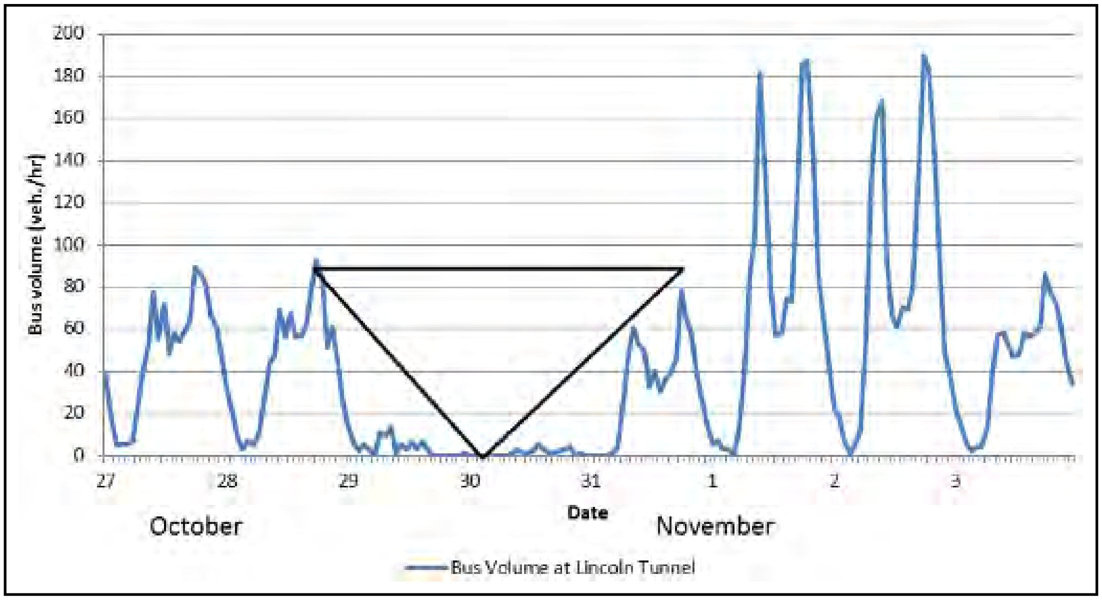


Figure 27. Sandy-Related Resiliency Triangle for Bus Volumes

From the resiliency triangle in Figure 26, it can be inferred that infrastructure required 27 hours to recover to pre-Sandy levels. Figure 27 indicates that NJ Transit could operate buses at pre-Sandy levels within 70 hours.

Friability

Friability, defined as number of reliable routes between OD pairs, provides another measure of resiliency of the bus network. The notion of "friability" expressed in this section is based on (a) incidents due to an extreme event, and (b) travel time in a normal network without an extreme event.[156] Friability based on an extreme event can be presented as a comparison of durations of incidents caused by the extreme event along alternate routes for a given bus route. In this study, the extreme event is Hurricane Sandy. Friability can also be studied based on travel-time reliability on alternative routes for a given bus route. However, obtaining real-world data for such analysis is very difficult. The researchers thus present friability based on travel time as a comparison of travel times on alternative routes using the NJRTM-E demand forecasting model output.

In this study, the investigators present two or three alternate routes to three bus routes passing through the top-three critical links (from Table 6) of the bus transit network. The three bus routes are chosen such that they originate from (a) southern NJ, (b) central NJ and (c) northern NJ. Table 11 lists the alternate routes for the routes for which friability is studied.

Table 11. Routes Considered for Friability

Bus Route	Critical Link	Original Route	Alternate Routes
Middletown, NJ – PABT	Lincoln Tunnel and NJTPK exit 16E	1. GSP – NJTPK – Lincoln Tunnel	2. GSP – NJTPK – I-78 – Holland Tunnel 3. GSP – NJTPK – Goethals Bridge I-278
Newark Airport – PABT	Lincoln Tunnel and NJTPK exit 16E	1. I-78 – NJTPK – Lincoln Tunnel	2. I-78 – Holland Tunnel 3. I-78 – NJTPK – George Washington Bridge – Henry Hudson Parkway
Clifton, NJ – PABT	NJ 3 before NJ-495	1. NJ 3 – Lincoln Tunnel	2. NJ-3 – NJTPK Holland Tunnel 3. NJ-3 – NJTPK – George Washington Bridge – Henry Hudson Parkway

Figure 28, Figure 29 and Figure 30 illustrate the origin, destination, original route, alternate routes and few important crossings from NJ to NYC.

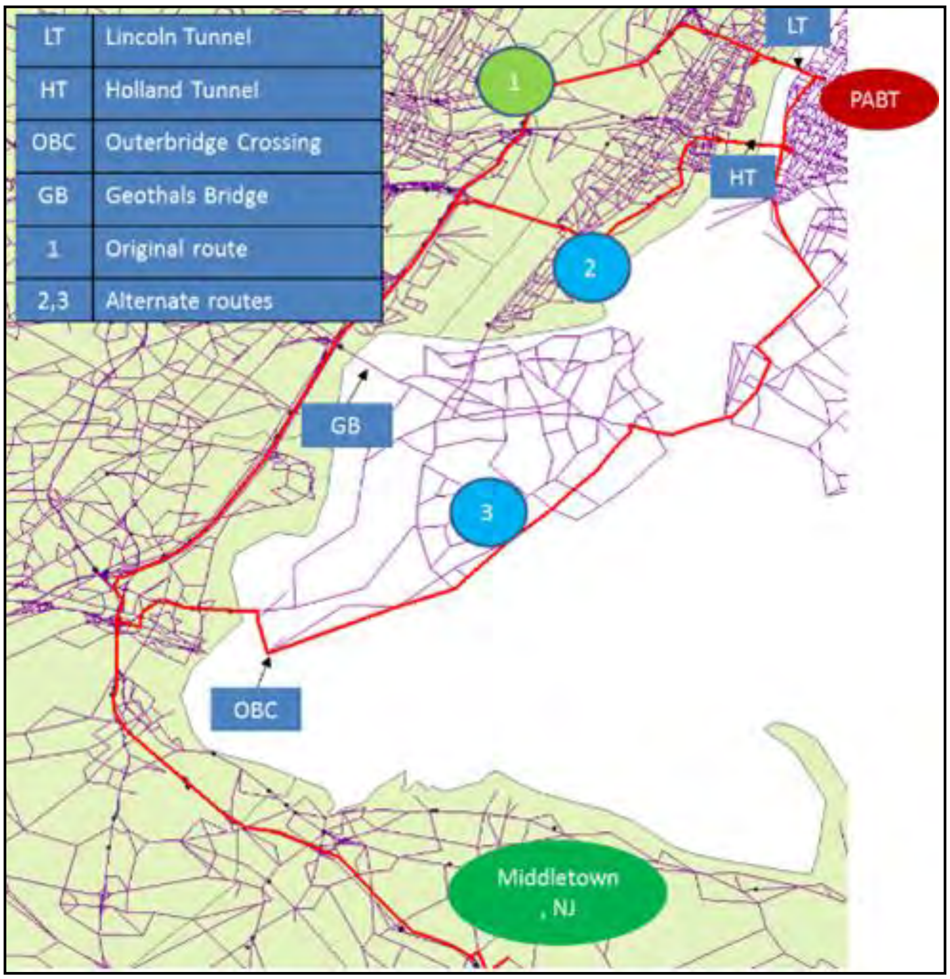


Figure 28. Original and Alternative Path Visualization for Middletown, NJ to PABT

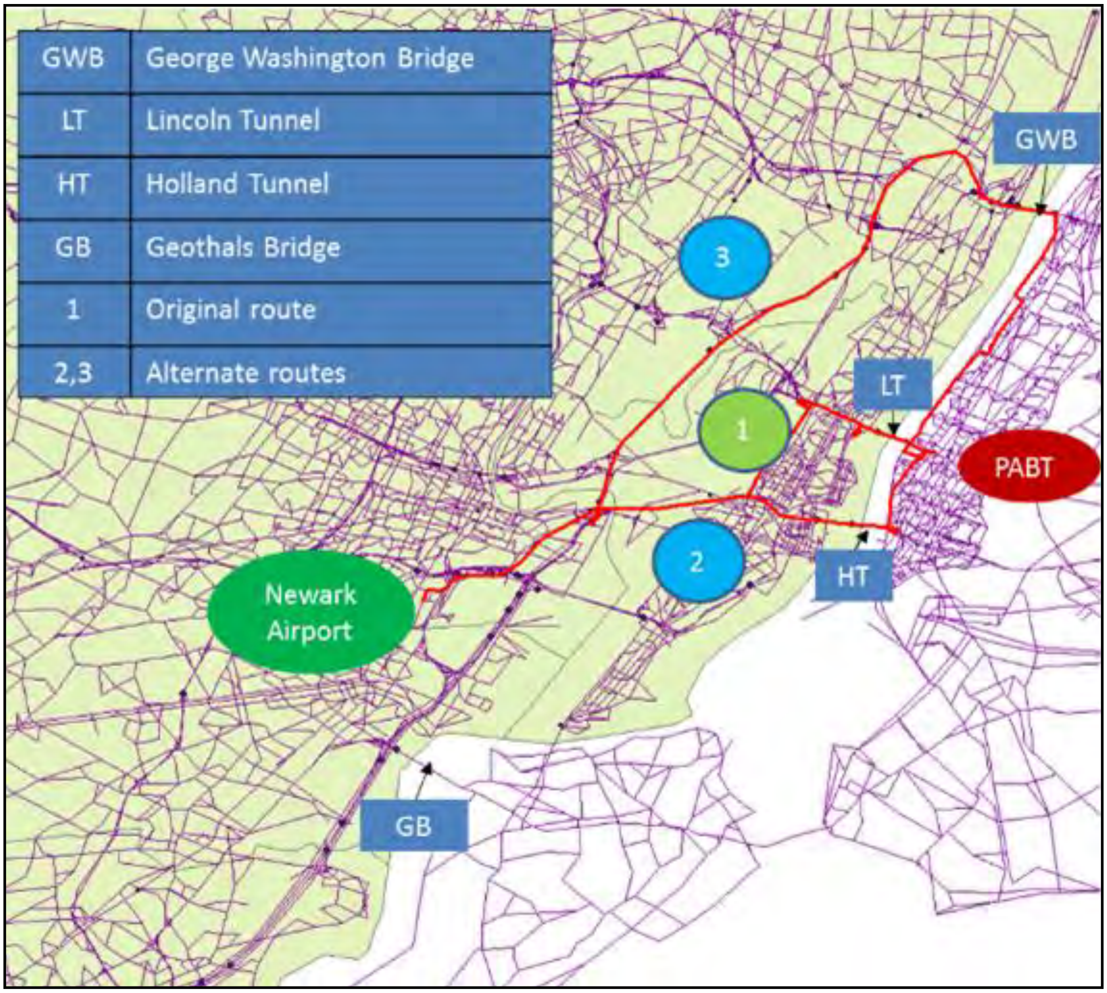


Figure 29. Original and Alternative Path Visualization for Newark Airport to PABT

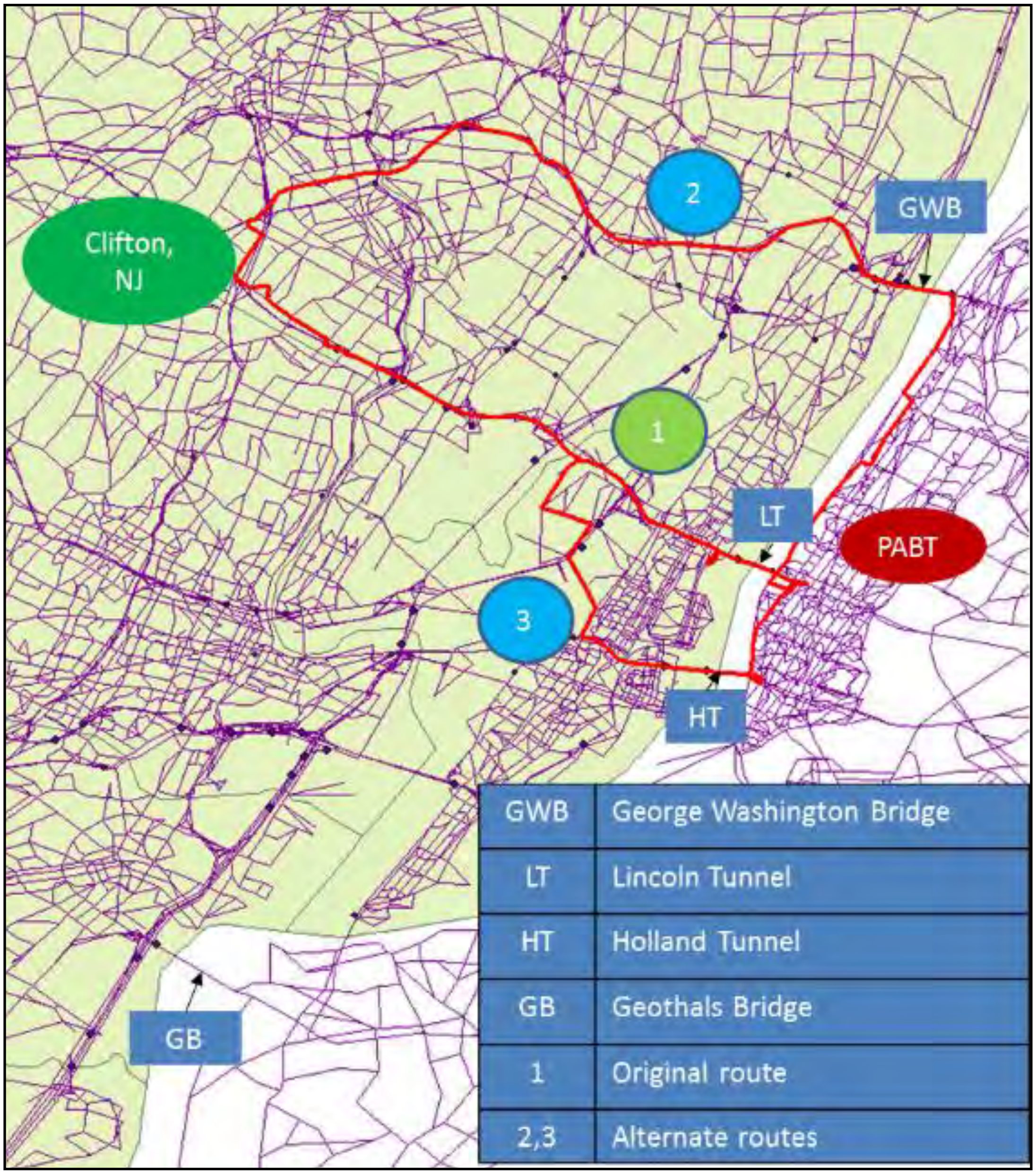


Figure 30. Original and Alternative Path Visualization for Clifton, NJ to PABT

For friability based on events, the researchers use event data from TRANSCOM to estimate the number of Sandy-related incidents on alternative routes between two major origins and PABT as the destination. From these definitions of friability, the greater the friability the more resilient are the routes. Table 12 shows the maximum duration of an incident on the critical link on the route and total number of incidents on each of the alternate routes for the three bus routes listed in Table 11. From the perspective of the total number of events:

1. Middletown, NJ – PABT has three reliable routes, i.e., friability of 3.

2. Newark Airport, NJ – PABT has two reliable routes, i.e., friability of 2.

3. Clifton, NJ – PABT has one reliable route, i.e., friability of 1.

However, in terms of maximum duration of a Sandy-related incident, there is only one reliable route for all three-bus routes. However, the basis of reliability based on maximum duration of a Sandy-related incident may not be rational. Hurricane Sandy is a once in a 100-year storm, and designing a transportation network for such a rare event is not an economically viable approach.

Table 12. Friability Based on Incidents Caused by an Extreme Event

Bus Route	Routes	Max. Duration of Incident on Critical Link	Total Incidents
Middletown, NJ – PABT	GSP – NJTPK – Lincoln Tunnel	0	24
	GSP – NJTPK – I-78 – Holland Tunnel	3.5 days	22
	GSP – NJTPK – Goethals Bridge – I-278	1.3 days	28
Newark Airport – PABT	I-78 – NJTPK – Lincoln Tunnel	0	9
	I-78 – Holland Tunnel – Henry Hudson Parkway	3.5 days	8
	I-78 – NJTPK – George Washington Bridge – Henry Hudson Parkway	1.3 days	13
Clifton, NJ – PABT	NJ 3 – Lincoln Tunnel	0	6
	NJ-3 – NJTPK Holland Tunnel	3.5 days	13
	NJ-3 – NJTPK – George Washington Bridge – Henry Hudson Parkway	1.3 days	11

Table 13 shows friability based on travel time. Similarly to the above definition of friability, the greater the friability the more resilient the routes are. Friability is estimated based on percent increase in travel time of alternative routes (considering routes within 5% of travel time of the original route to be good enough):

1. Middletown, NJ – PABT has three reliable routes, i.e., friability of 3.

2. Newark Airport, NJ – PABT has one reliable route, i.e., friability of 1.

3. Clifton, NJ – PABT has one reliable route, i.e., friability of 1.

Table 13. Friability Based on Travel Time

Bus Route	Routes	Travel Time (*hr*)	Percent Change
Middletown, NJ – PABT	GSP – NJTPK – Lincoln Tunnel	2.06	
	GSP – NJTPK – I-78 – Holland Tunnel	2.09	1.4%
	GSP – NJTPK – Goethals Bridge – I-278	2.18	5.8%
Newark Airport – PABT	I-78 – NJTPK – Lincoln Tunnel	1.07	
	I-78 – Holland Tunnel – Henry Hudson Parkway	1.04	-2.8%
	I-78 – NJTPK – George Washington Bridge – Henry Hudson Parkway	1.25	16.8%
Clifton, NJ – PABT	NJ 3 – Lincoln Tunnel	0.96	
	NJ-3 – NJTPK Holland Tunnel	1.31	36.4%
	NJ-3 – NJTPK – George Washington Bridge – Henry Hudson Parkway	1.16	20.8%

Based on both measures of friability, among the three bus routes studied, the bus route from Middletown, NJ to PABT is seen as a very resilient route. Newark Airport, NJ to PABT is the next resilient route followed by Clifton to PABT.

Because of the fixed infrastructure of rail systems, finding alternate routes for rail routes is not possible. However, users of the rail system can find alternative paths by using different routes in the rail system. Users of, for instance, Northeast Corridor (NEC), NJ Coast Line (NJCL), and the Morris & Essex Line can find an alternative route from Newark Penn station by using PATH to Manhattan. Similarly, users of PATH from Newark Penn station can switch to NEC or NJCL.

Following Hurricane Sandy, NEC recovered in four days. This was the fastest recovery time among all the rail routes to Manhattan. However, PATH service from Newark Penn station took 28 days to recover. Thus, users starting their trips from Newark Penn station had a reliable route in NEC. Note that the notion of “reliability” expressed in this section is Hurricane Sandy-specific and cannot be generalized for future cases. Additional service reliability data during regular times and extreme events would provide a much better indication of reliability in general.

RESILIENCY AND RECOVERY OF THE NYC SUBWAY

Given the availability of detailed ridership data for the NYC subway, unlike NJ Transit, the spatio-temporal analysis of recovery of demand for the NYC subway is possible for Hurricanes Irene and Sandy. Figure 31 shows a summary of citywide transit counts and comparison with the previous year’s data[157] (Zhu et al. (2016)).

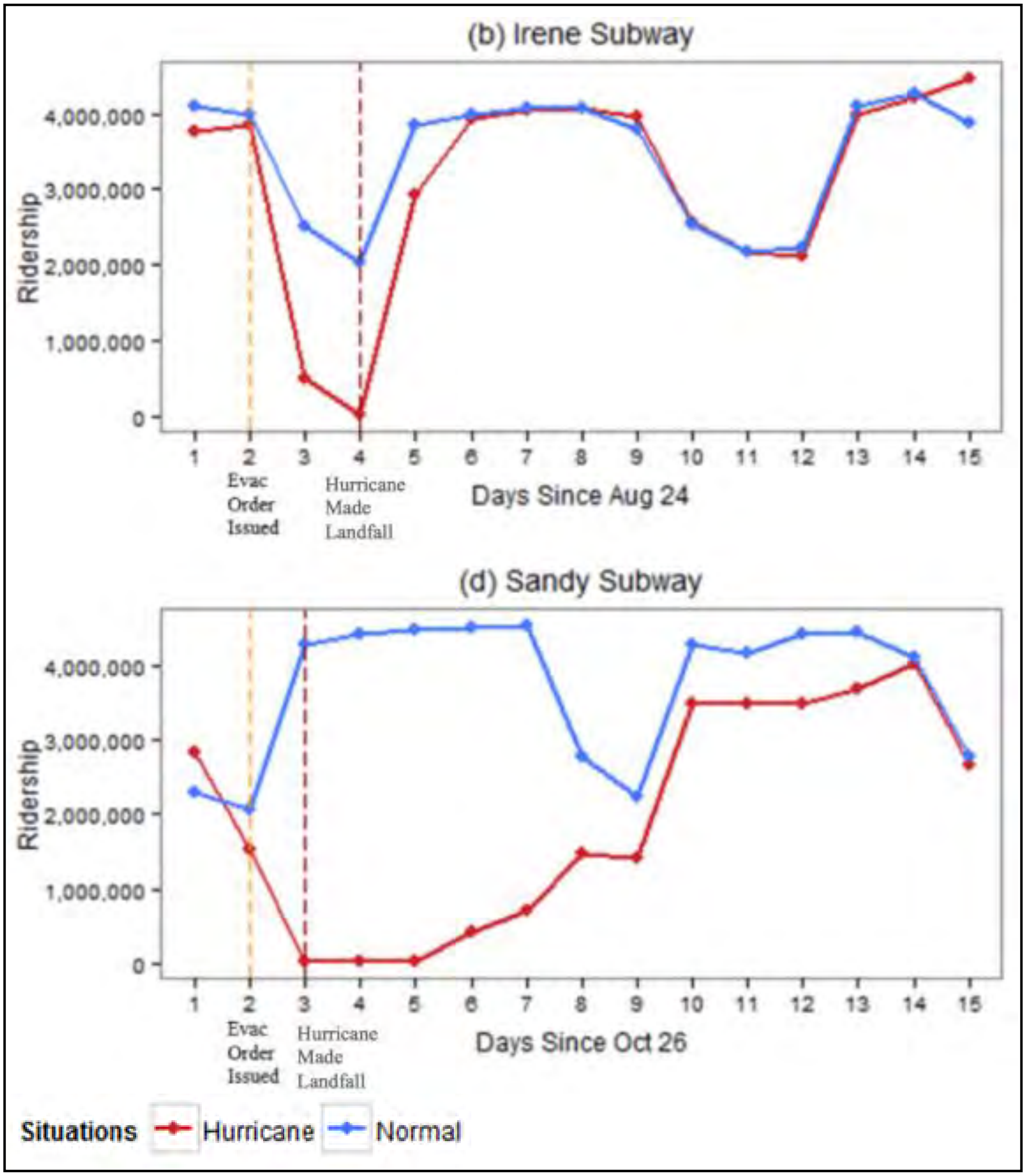


Figure 31. Comparison of Trips During Hurricane Periods with Those During Normal Conditions[158]

For both hurricanes, there are significant decreases from the day of evacuation, but the recovery speeds of two storms are quite different from each other. After *t* Hurricane Irene, the subway trips were restored to normal levels in two days, while recovery took much longer after Hurricane Sandy. There are multiple reasons for these differences. First, Hurricane Sandy caused more damage to the transit infrastructure, resulting in a suspension of the entire subway network for three days. It took nearly ten additional days for the ridership to return to normal.

Besides in volume, comparison is also made in terms of recovery rates. The rate of recovery is defined as the quotient of trips during a certain hurricane period divided by trips during a corresponding normal (control) period. In this study, the recovery rate for each NTA in NYC is calculated. Results of recovery rates in 50 NTAs of highest volumes are selected out of 195 NTAs for the purposes of visualization. The reason for selection based on volumes is that characteristics of most critical zones, and criticalities for different NTAs, are directly related to the volumes of the area. If the recovery rate reached 100%, the investigators assume the area is fully recovered and keep the rate at 100%. For modeling purposes, this assumption is also applied to the researchers' methodology of recovery-curve modeling, which will be discussed later.

Figure 32 and Figure 33 illustrate the recovery rates for Hurricanes Irene and Sandy respectively, for 50 neighborhoods, ordered by the number of daily subway trips for normal conditions.[159] These heat maps mainly focus on general patterns of the city, and also on characteristics of most critical zones. The subway ridership's resiliency heavily depends on service status of transit infrastructure. It can be seen from Figure 32 that during Hurricane Irene, ridership of the subway system in most NTAs started to drop on Day 3, since the system shut down at noon. On Day 4, Irene made landfall in the morning, and the subway system remained closed for another day. Then the subway ridership quickly returned to the levels of before the hurricane for most areas. Moreover, on Days 10 to 12, recovery rates for Washington Height North dropped to 30%. That is because all subway stations in Washington Height North are Line 1 stations, and during the Labor Day holiday, ridership reduced due to the service change caused by the construction work on Subway Line 1.[160]

It is evident from Figure 33 that Hurricane Sandy caused far more serious disruption to the subway operations than Hurricane Irene. The ridership decreased on Day 2, and subway stations remained closed until Day 6 of the study period, when initial recovery began for upper sections of Manhattan. The recovery rate, however, is relatively small. This is because the number of lines that were in service was quite limited. Moreover, the subway connections between Queens, Manhattan and Brooklyn were still not operational. On Day 8, inter-borough subway connection was partially restored, and recovery rates for more than half of NTAs came back to at least 50% of the original, while other areas include Lower Manhattan, Southern Brooklyn and Williamsburg. On Day 10, there was a major increase in ridership for most areas, since it was the first Monday after Sandy, and multiple lines were back into service[161] Due to extensive damage to the system infrastructure, post-Sandy rehabilitation for stations in specific NTAs took longer than the time covered by the study period, especially Whitehall Street and South Ferry Station for Lower Manhattan and Far Rockaway Stations.[162]

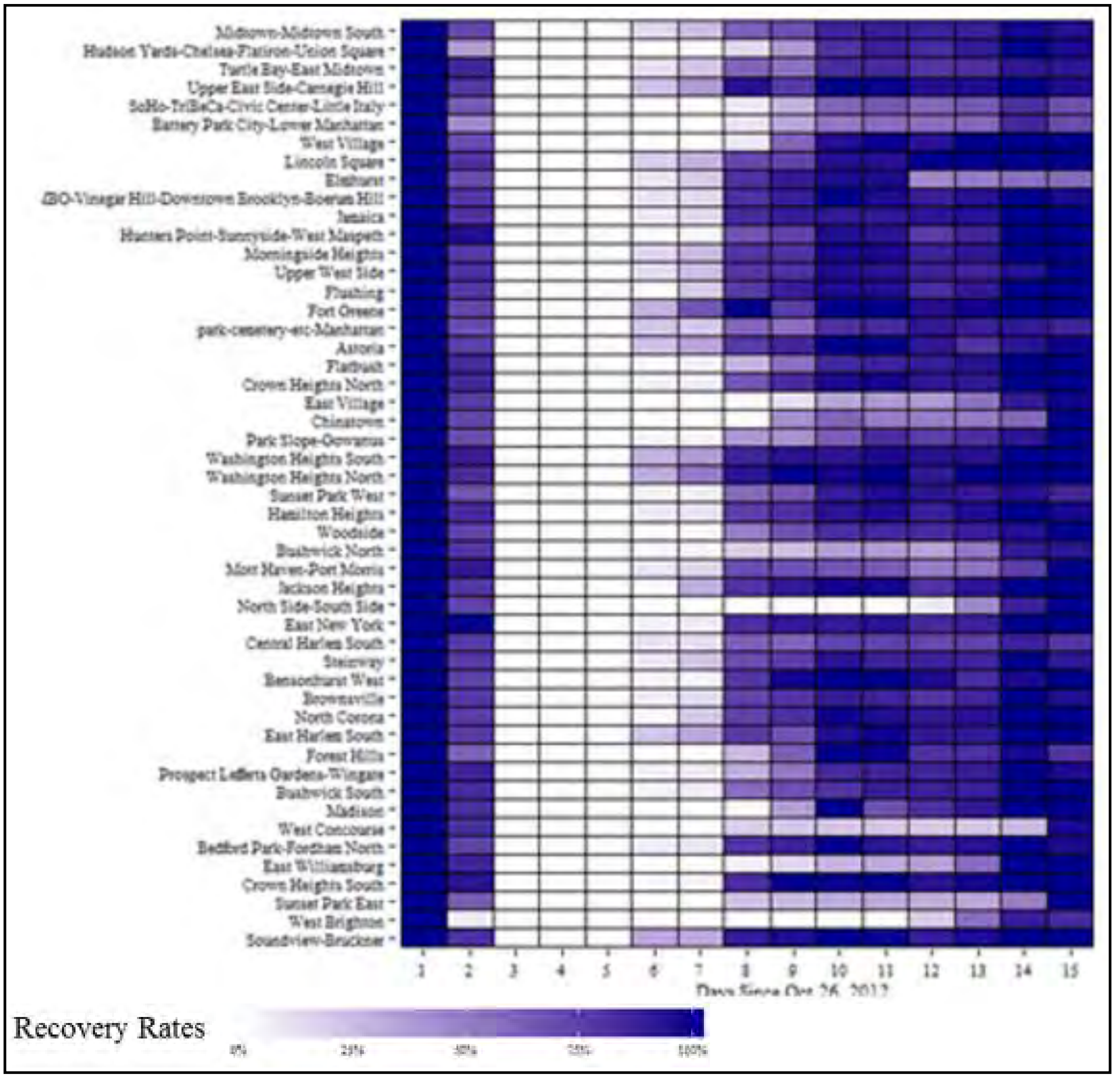


Figure 32. Subway Recovery Rates for NYC Neighborhoods for Hurricane Irene[163]

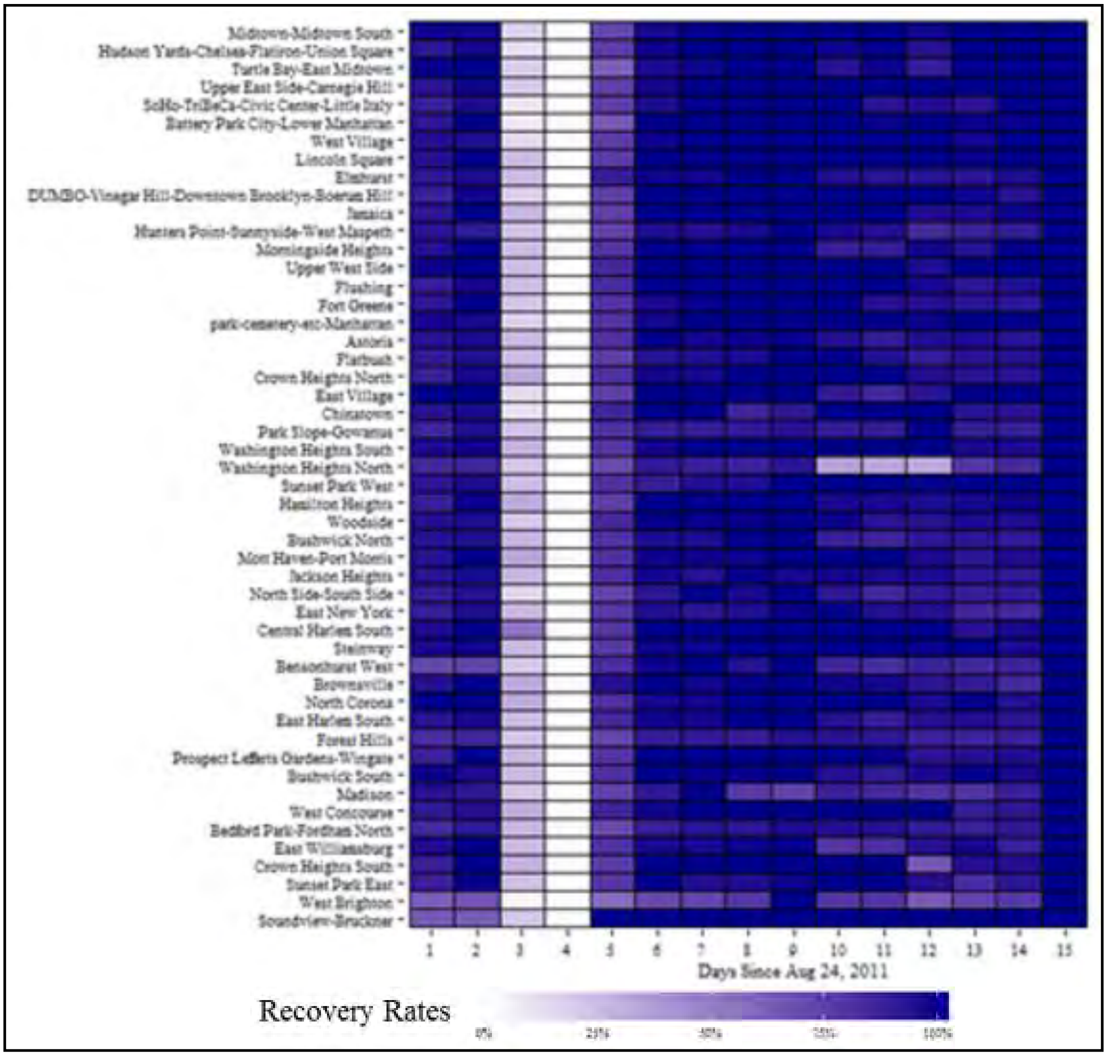


Figure 33. Subway Recovery Rates for NYC Neighborhoods for Hurricane Sandy[164]

SUMMARY AND CONCLUSIONS

In this study, the researchers analyzed the public transit systems in NJ based on their vulnerability, resiliency and efficiency in recovery following a major natural disaster event. Specifically, the investigators conducted their analyses based on Hurricane Sandy, which took place in October 2012. They used a diverse set of data sources to estimate many data-driven performance measures for the transit network.

After performing a thorough review of the relevant literature on performance measures for transportation-network efficiency, resiliency, vulnerability and recovery, we categorized various measures to be estimated for the transit network in NJ into vulnerability, recovery and resiliency. The research team adapted some of the general road transportation vulnerability and resiliency measures proposed in the literature to public transit infrastructure. Since most of the available infrastructure data are that of the highway network, most measures estimated in this study were those corresponding to the bus-transit network. The performance measures were adapted as route-based measures so that they could be applied to specific bus routes. Such estimates will be useful for agencies to plan their resources accordingly to cater to the needs of the population served by said routes.

For the bus transit network in NJ, the investigators determined that the top three most critical links were Lincoln tunnel, NJTPK link to Interchange 16E, and NJ-3 before merging to I-495, based on the vulnerability measure VA_6.[165] This implies that the three most critical links need to be reinforced so that bus service can be maintained even during a disruption without the need for re-routing. For transit buses using the NJTPK, average and maximum travel time increased by 41-63% and 95%-300% (Table 4), respectively. This increase in travel time could be due to (a) increased congestion due to evacuation orders or (b) Sandy-related events on the NJTPK. The distribution and duration of Sandy-related events were analyzed with respect to the bus transit network. The bus routes had an average of five events with an average duration of 19 hours. The ten routes with most Sandy-related critical events showed that the routes along the coast in the southern and eastern parts of NJ were most affected by Hurricane Sandy. Hence, it is important to plan for providing alternative means of transportation for the population dependent on transit along the coast during a disruption such as a hurricane.

Another measure of vulnerability in this study is NRI, the measure of criticality of a link: i.e., the effect of removing the link from the network. In order to investigate NRI, the investigators used the most critical link (based on adapted VA_6 vulnerability measure) for the bus network, the Lincoln tunnel, and analyzed the effect of removing it from the network.[166] The analysis entailed the comparison of travel times of the original route with those of possible alternate routes of three selected bus routes originating from southern, central and northern NJ. The alternate routes were estimated using a customized software application namely, ASSIST-ME, previously developed by the authors to analyze the output of various regional planning models.[167] The increase in travel times ranged from 2.8% to 21% among alternate routes. This methodology of using NRI can be used by the transit agency for other vulnerable links so that the possibility of rerouting can be explored if the vulnerable links are disrupted.

The researchers analyzed the recovery of the transit system in NJ following Hurricane Sandy. Recovery of the rail network took two to 32 days, whereas more than 65% of bus network was restored to full service in two days, and the rest of the bus network was partly operational. Recovery of the bus transit system directly depends on the recovery of the highway network. One primary reason that the bus system recovered faster than other NJ Transit rail services is that the Lincoln Tunnel was not affected by the storm. Additionally, the Port Authority bus terminal was also unaffected. Since the Lincoln Tunnel is the most critical of the links in the bus route network, the bus transit system was able to recover quickly.

Resiliency triangles for travel time (Figure 26) and bus volumes (Figure 27) were created to estimate the rate of recovery of the bus-transit network. Recovery of travel time to pre-disaster levels indicates the speed of recovery of the highway infrastructure, whereas recovery of volume over time indicates the speed at which the agency can provide the same level of service as the pre-disaster level. From the resiliency triangles, infrastructure recovery to pre-Sandy levels required 27 hours, and NJ Transit was able to operate buses at pre-Sandy levels within 70 hours. Unfortunately, due to the lack of ridership or real-world travel time data for rail, light rail and subway services in NJ, the above-mentioned measures could not be estimated for the rail system.

Given the availability of detailed ridership data for NYC subway, unlike NJ Transit or the PATH subway system, the spatio-temporal analysis of recovery of demand for NYC subway is possible for Hurricanes Irene and Sandy. The demand recovery for the NYC subway post-Hurricane Sandy took 11 days, as can be seen from Figure 31. The inter-borough subway connection was partially restored, and recovery rates for more than half of the NYC subway system came back to at least 50% of the original after eight days. There was a major increase in ridership for most areas in ten days after Hurricane Sandy made landfall. However, due to extensive damage to the system infrastructure, post-Sandy rehabilitation for a few stations, especially Whitehall Street and South Ferry Station for Lower Manhattan and Far Rockaway, is still underway at the date of this study. As a comparable service to the NYC subway, the PATH subway system had most lines recovered in 13 days, though one particular line, namely the PATH line from Newark to World Trade Center (WTC), took 28 days to recover (Table 9). Rail services on the NJ Transit system, however, took 32 days to recover. Among these, the rail lines closer to the NJ coast (Bergen, NJ Coast line) and those lying close to the path of Hurricane Sandy (Morristown, Pascack valley, Montclair-Boonton and Gladstone extension) took more than 13 days to recover.

Bus and light rail infrastructure recovered within a week of Hurricane Sandy's landfall. Bus and light rail infrastructure can recover more quickly than regular rail and subway lines. A possible reason could be that since regular rail infrastructure carries much higher load at higher speeds, the structural strengthening of the damaged tracks and bridges could require a greater amount of time. The guideway for light rail is usually on or close to existing roads, so the recovery is closely correlated to the recovery of road infrastructure. However, light rail recovery additionally depends on the recovery of systems such as signal control, power supply, etc. Recovery of underground subway systems such as the PATH system and the NYC subway are very dependent on the extent of flooding of the underground tunnels.

Friability, defined as the number of reliable routes between OD pairs, was estimated for three selected bus routes in the bus transit network, viz., Middletown, NJ to PABT; Newark Airport, NJ to PABT; and Clifton to PABT. Two alternate routes were estimated for each selected bus route. Friability was estimated in two ways for the bus transit network: (a) by comparing the number of incidents and maximum duration of an incident caused by Hurricane Sandy for a given bus route, and (b) by comparing the travel times on the two alternate routes to the original route's travel time for a given bus route. From these definitions of friability, the greater the friability the more resilient are the routes. Based on the total number of events, the friability of the three bus routes was three, two and one, whereas using maximum duration, the friability was calculated as one for all three routes. Based on an assumption that routes within 5% of travel time of original route can be considered acceptable, friability of three, one and one is estimated for the three selected bus routes. Based on both measures of friability, among the three bus routes studied, the bus route from Middletown, NJ to PABT is seen as a very resilient route. Newark Airport, NJ to PABT is the next resilient route followed by Clifton to PABT.

Friability based on event characteristics can also provide an estimate on the possible routes onto which buses can be rerouted if the original route is disrupted. Additionally, friability based on travel time is similar to NRI in its ability to understand the alternative routes available for a given route. These two measures can help the agency plan possible rerouting plans for affected bus routes.

IV. IDENTIFICATION OF TRIP GENERATORS AND FACTORS ASSOCIATED WITH TRIP DELAY AND RELIABILITY OF DISABILITY PARATRANSIT

GENERATORS OF ACCESS LINK TRIPS

ADA-complementary paratransit is provided by transit agencies nationwide to their registered clients at a fairly high cost. Citing the cost differential between paratransit trips and fixed-route trips, a recent report by the United States Government Accountability Office emphasized the importance of improving the efficiency of paratransit service by making decisions based on quality data and analysis.[168] The high cost of ADA paratransit service has been the subject matter of other studies as well.[169] Despite the high cost of service, however, some researchers have concluded that the benefits of ADA paratransit service exceed the associated costs.[170]

Yet all transit agencies nationwide are under pressure to optimize costs of paratransit service because of its growing demand. One way to optimize costs of paratransit service is to fully comprehend the current and future demand for trips. Appropriately forecasting demand for service can assist agencies in allocating resources to service contractors, realigning service regions, and determining location of facilities. An integral part of demand analysis for paratransit service is the identification of the trip generators, whether they are defined as space (e.g., census tracts) or establishments (e.g., medical facilities).

In order to identify the generators of paratransit trips, this research examines the characteristics of census block groups and finer geographic locations that generate paratransit trips by analyzing data for the service area of Access Link, the ADA-complementary paratransit service provided by NJ Transit. While most past studies focused on the home end of paratransit trips, this study attempts to identify the characteristics of the areas where the paratransit clients live as well as the characteristics of the areas and specific locations they visit. The study first identifies generators of Access Link trips at a macro level by analyzing data at the census-block-group level. Subsequently, it focuses on the establishments located in the immediate vicinity of drop-off sites to identify generators of Access Link trips at a micro level.

Selection of Methods

Homes of clients are indeed the most easily identifiable trip generators of Access Link trips. It is more challenging and important, however, to identify trip generators away from home for demand analysis. To be able to identify trip generators away from home, pickups and drop-offs of Access Link trips in the data set were distinguished into two classes, at-home and non-home. For this classification, all pickups and drop-offs within a 300-foot radius of clients' homes were considered as at-home, and all others were considered non-home. Since many Access Link clients live in multi-family homes and apartment complexes, matching exact locations of homes with curbside pickups and drop-offs was considered inappropriate. Therefore, the number of pickups and drop-offs were examined for 100-foot, 200-foot, 300-foot, 400-foot, and 500-foot circles. Areas beyond 500 feet were not considered because all Access Link clients have disability. The 300-foot circle was chosen for the delineation because of a steep decrease in the number of at-home pickups and drop-offs beyond that point.

Access Link trip data were supplemented by demographic and socioeconomic data at the census-block-group level from the 2006-2010 American Community Survey (ACS) and employment (jobs) data from the 2010 Longitudinal Employer-Household Dynamics (LEHD). While the ACS provided data on total population, household income, household size, race, ethnicity, etc., the LEHD provided number of jobs in block groups for 20 different industry types. The GIS shape files of the Access Link service area and transit routes in the region were obtained from NJ Transit and combined with other data. Network distances between each OD pair in the data set were estimated by using the network analyst of ArcGIS.

Two broad sets of data analysis were undertaken. The first set consisted of an OLS model and five spatial GLMM to identify the characteristics of census block groups that are associated with the volume of resident clients as well as pickups and drop-offs. Pickups and drop-offs were modeled separately for at-home and non-home trip ends. GLMM was used in several models instead of OLS because of the presence of spatial autocorrelation in the data. As noted in two studies in the literature review, because of the clustering of trip origins and destinations over space, models need to take into account spatial autocorrelation.[171]

Spatial autocorrelation has been defined as the property of random variables that are positively or negatively correlated compared to randomly associated pairs of observations when they are located at certain distances from each other.[172] For example, variables may have similar characteristics when observations pertain to adjacent or nearby locations but dissimilar characteristics when they are far apart. In the presence of spatial autocorrelation, standard statistical tests of hypothesis are impaired, and the usual least squares estimators are unsatisfactory.[173] Studies have often suggested variations of mixed models instead of ordinary least squares models in the presence of spatial autocorrelation.[174] GLMM is one of several types of mixed models recommended for situations involving spatial autocorrelation.[175]

It makes intuitive sense to hypothesize that variables such as number of paratransit pickups and drop-offs would be spatially correlated because service levels and characteristics of areas would be more similar in nearby areas than areas far apart. Prior to the estimation of the GLMM, however, efforts were made to check for the presence of autocorrelation in the data. These efforts included inspection of the data through maps and the use of Moran's I statistical tests.[176] Following a common practice in empirical studies, OLS models were run, the residuals were obtained, and Moran's I tests were run on the residuals to check for the presence of spatial autocorrelation.[177]

The second set of analysis in the paper focuses on the types of establishments located in the immediate vicinity of non-home drop-offs. The objective of this analysis was to identify activities potentially visited by the Access Link clients and to assess the relationship between the characteristics of drop-off locations and the characteristics of clients who were dropped off. Geocoded Dun & Bradstreet data on establishments with one or more employees were used for this analysis.

Models on Number of Clients and At-Home Pickups and Drop-offs

Due to the nature of the data, it was important to examine whether spatial autocorrelation was present. When spatial autocorrelation is present, OLS regression models are considered to be inappropriate. Analysis began with an inspection of maps showing the spatial clustering of Access Link registered clients' and active clients' residences as well as pickup and drop-off locations. Clustering was particularly obvious for certain areas, especially in Camden, Mercer, and Essex Counties. Subsequent analysis consisted of Moran's I tests. In order to check for this possibility, OLS models were run on the variables by using the independent variables shown in Table 14 and Table 15, the residuals were saved, and Moran's I tests were run on the residuals. The tests clearly indicated the presence of spatial autocorrelation. Based on the results, it was determined that GLMM would be more appropriate than OLS models.

The results of the GLMM with dependent variables pertaining to the block groups where the Access Link clients live, namely, the number of registered clients, the number of active clients, the number of at-home pickups, and the number of at-home drop-offs, are presented in Table 14 and Table 15. Table 14 shows the model results on total number of registered clients and active clients, whereas Table 15 shows the model results on at-home pickups and at-home drop-offs.

Understanding the characteristics of the areas where paratransit clients live is important, because a large proportion of trips originate at home. For this reason, most empirical studies considering the association between trip demand and spatial characteristics focused on areas where the clients live. Some of the independent variables for the models described in Table 14 and Table 15 were selected on the basis of previous empirical studies on demand estimation. It was important to include these variables not only because they make intuitive sense, but also because of apparent inconsistencies in the findings of past studies. Models in one or more past studies included total population of the area, proportion of elderly persons, proportion of African American population, proportion of ethnic minorities, and average household size. While certain past studies considered persons in poverty, the models in Table 14 and Table 15 include a dummy variable on annual per capita income less than $15,000 to represent low-income persons. Poverty rate could not be included because at the time of the analysis, data were available only for census tracts but not for block groups. Median household income was not included in the model because it is highly correlated with two other variables included in the models, namely median home price and median contract rent. It was expected that places with high home value and rent would be negatively associated with Access Link trips.

Table 14. Generalized Linear Mixed Model (GLMM) Results on Resident Registered Clients and Resident Active Clients

	Total Registered Clients Living in Block Group		Total Active Clients Living in Block Group	
Independent Variables	**Coefficient**	**t Value**	**Coefficient**	**t Value**
Intercept	7.90[a]	6.74	4.13[a]	7.11
Total population (in 1,000)	2.49[a]	14.78	0.90[a]	10.67
Proportion of persons 65 and over	11.81[a]	9.41	3.86[a]	6.23
Proportion of African American persons	7.84[a]	14.97	2.10[a]	8.26
Proportion of Hispanic persons	-0.91	-1.30	-0.30	-0.83
Average household size	-0.66[a]	-2.41	-0.21	-1.54
Median home value (in $100,000)	-0.22[a]	-2.59	-0.11[a]	-2.36
Median monthly contract rent (in $1,000)	-1.22[a]	-3.73	-0.49[a]	-2.92
Per capita income less than $15,000 (1=yes, 0=no)	-0.93[a]	-2.19	-0.37[b]	-1.73
Percent owned dwelling units	-1.00	-1.17	-1.03[a]	-2.37
Percent single detached dwelling units	1.85[a]	2.57	0.80[a]	2.24
Percent dwellings with 2-9 units in structure	0.56	0.70	-0.53	-1.33
Percent dwelling with 10-19 units in structure (referent)				
Percent dwellings with 20 or more units in structure	8.90[a]	9.15	1.92[a]	4.01
Percent households with zero vehicles	2.74[a]	2.49	0.46	0.82
Percent resident workers who took rail to work	8.55[a]	3.51	2.35[b]	1.83
Percent resident workers who took bus to work	-1.39	-1.03	-0.83	-1.22
Percent resident workers who walked or biked to work	-3.51[a]	-1.99	-0.44	-0.49
Estimated average commute time of residents in minutes	-0.10[a]	-5.15	-0.04[a]	-3.94
Impedance score of block group vis-à-vis jobs in selected sectors	-0.59[a]	-4.81	-0.10[b]	-1.65
Number of block groups (N)	3,526		2,520	
-2 Res Log Likelihood	22,661		11,934	
Akaike information criterion (AIC)	22,667		11,940	

[a] *Significant at the 5% level;*
[b] *Significant at the 10% level.*

Table 15. Generalized Linear Mixed Model (GLMM) Results on At-Home Pickups and Drop-Offs

	Total Registered Clients Living in Block Group		Total Active Clients Living in Block Group	
Independent Variables	**Coefficient**	**t Value**	**Coefficient**	**t Value**
Intercept	418.63[a]	5.47	396.11[a]	5.59
Total population (in 1,000)	82.18[a]	7.32	75.89[a]	7.31
Proportion of persons 65 and over	288.47[a]	3.06	271.02[a]	3.11
Proportion of African American persons	312.03[a]	9.37	270.14[a]	8.77
Proportion of Hispanic persons	-8.01	-0.17	-9.46	-0.22
Average household size	-51.40[a]	-2.75	-41.10[a]	-2.38
Median home value (in $100,000)	-8.61	-1.36	-9.14	-1.56
Median monthly contract rent (in $1,000)	-18.36	-0.80	-15.09	-0.71
Per capita income less than $15,000 (1=yes, 0=no)	-30.60	-1.09	-24.54	-0.95
Percent owned dwelling units	-95.84[b]	-1.66	-94.42[b]	-1.77
Percent single detached dwelling units	68.38	1.38	68.17	1.49
Percent dwellings with 2-9 units in structure	13.30	0.25	2.15	0.04
Percent dwelling with 10-19 units in structure (referent)				
Percent dwellings with 20 or more units in structure	230.21[a]	3.63	187.95[a]	3.20
Percent households with zero vehicles	-27.32	-0.38	-30.42	-0.45
Percent resident workers who took rail to work	534.36[a]	3.18	538.28[a]	3.46
Percent resident workers who took bus to work	-88.99	-1.01	-76.95	-0.95
Percent resident workers who walked or biked to work	-225.92[b]	-1.91	-226.54[a]	-2.07
Estimated average commute time of residents in minutes	-3.76[a]	-2.86	-4.10[a]	-3.38
Impedance score of block group vis-à-vis jobs in selected sectors	-35.34[a]	-4.60	-32.09[a]	-4.51
Number of block groups (N)	2,282		2,282	
-2 Res Log Likelihood	32,711		32,358	
Akaike information criterion (AIC)	32,717		32,364	

[a] *Significant at the 5% level;*
[b] *Significant at the 10% level.*

In addition to the variables mentioned above, several variables were included in the models that represent home ownership, vehicle ownership, type of dwelling, and commuting pattern of workers in each block group. It was expected that high home ownership would be negatively associated with trips whereas the proportion of zero-vehicle households would be positively associated. The variables on dwelling type were included with the expectation that the proportion of single detached homes would be negatively associated and the proportion of apartments with a large number of units would be positively associated. The proportion of commuting trips by train, bus, and walk/bike were included with the hypothesis that they might be negatively associated with Access Link trips, because in some instances they could be perceived as alternatives to paratransit. Finally, a variable representing the impedance of the block groups vis-à-vis the activities they might travel to was included with the hypothesis that, all else being equal, Access Link clients would be less likely to live in areas that are far from the activities they usually travel to compared to areas that are closer to the activities. The impedance score was obtained at the municipal level and assigned to block groups within the respective municipalities.

According to the model results in Table 14 and Table 15, the independent variables that are consistently and significantly associated with the dependent variables of the four models are total population, proportion of persons age 65 and over, proportion of African American persons, proportion of dwellings with 20 or more units, proportion of workers who took rail to work, average commute time of residents, and the impedance score vis-à-vis jobs. The positive sign of total population is consistent with all past studies. The proportion of elderly persons was found to be positive in all four models. Although some past studies did not find a positive association between the proportion of elderly persons and paratransit trips,[178] the model results are consistent with two studies.[179] The observed positive relationship between proportion of African American population and paratransit trips in the current study is consistent with one of those two studies.[180]

The four models in Table 14 and Table 15 also consistently show a positive association of the proportion of dwellings with 20 or more units and the proportion of workers who commute to work by train with the dependent variables, indicating that Access Link clients are more likely to live and make trips from areas with very high dwelling density and areas with a high level of rail service. The significant positive sign of the variable on proportion of rail commuters in all four models could be due to the fact that Access Link service is mandatory within 0.75 miles of all rail stations, and the proportion of rail commuters is likely to be high in areas around stations.

The dependent variables in all four models have a negative association with average commuting time of workers living in a block group and with the impedance score. Since average commute time is often very high in fringe areas because of long trip distances, the negative sign of the variable in all four models could indicate that Access Link clients are not very likely to live or make trips from fringe areas. The results on the impedance score indicate that, all else being equal, Access Link clients are more likely to live in areas that are closer to places with activities associated with jobs in the health, retail, administrative, and food and accommodation sectors.

A few other independent variables in Table 14 and Table 15 are statistically significant in more than one model with identical signs. These variables are average household size, median home value, median monthly contract rent, per capita income, percent owned homes, and percent resident workers who walked or bicycled to work. The variable on average household size shows a negative sign in the model on registered clients as well as the models on at-home pickups and drop-offs, indicating that Access Link demand could be higher in areas with small household size. The negative association of household size found in the models is consistent with one study[181] but inconsistent with another study.[182] Since a person with disability in a larger household is more likely to be transported by other persons in the household compared to a similar person in a smaller household, it makes intuitive sense to hypothesize that places with larger average household size would generate fewer paratransit trips.

The negative association between walking/bicycling commuting trips and paratransit pickups and drop-offs is consistent with the study by Bradley and Koffman.[183] The variables on home value and rent indicate that Access Link clients are less likely to live in affluent areas. The negative sign of the variable on percent owned homes is consistent with these results. The variable on per capita income, however, indicates that Access Link clients are also not likely to live in the poorest parts of the study area. One might be tempted to conclude from these results that there would be more Access Link demand in middle-income areas than in areas with the highest and lowest incomes. As the variables on home value and income are not statistically significant in the models for at-home pickups and drop-offs, however, the relationship between income and actual trips remain unclear from the models.

Models on Non-Home Drop-Offs

To comprehend the overall demand patterns of paratransit trips, it is as important to identify the characteristics of the places visited by clients as it is to identify the characteristics of the places where they live. Identifying characteristics of the places visited by clients is more challenging, however, because past studies have examined non-home trip ends less often than at-home trip ends.

Two models were tested to examine characteristics of the places visited by the Access Link clients, one with non-home pickups and the other with non-home drop-offs as the dependent variable. Since the results of the two models were virtually identical, only the results from the drop-off model are presented in Table 16. Two versions of the model, one OLS and the other GLMM, are presented in Table 16. According to the Moran's I test on residuals, the OLS model in Table 16 is not significantly affected by spatial autocorrelation. Therefore, a GLMM model is not necessary. However, for the sake of consistency with the models in Table 14 and Table 15, a GLMM version of the model is also presented in Table 16. Since all 15 variables included in the two models have identical signs, and only one variable (the dummy variable on Camden County) that is significant in one model is not significant in the other, the discussion below practically describes both models in Table 16.

For the selection of independent variables of the model in Table 16, it was hypothesized that Access Link clients would primarily visit places to attend work, receive services, purchase food and retail goods, and visit friends and family. Since little is known about the occupations of working Access Link clients or the types of industries where they work, total block group jobs for all 20 industry categories in LEHD were tested with various combinations of other variables. This assessment indicated that jobs in only four industry categories are significantly associated with Access Link drop-offs.

Table 16. Ordinary Least Squares (OLS) and Generalized Linear Mixed Model (GLMM) Results on Non-Home Drop-Offs of Access Link Trips

	OLS Model		GLMM Model	
Block Group Characteristics	**Coefficient**	**t Value**	**Coefficient**	**t Value**
Intercept	152.27	1.47	220.24[a]	2.06
Total population of block group (in 1,000)	55.88[a]	2.48	61.57[a]	2.72
Health Care and Social Assistance jobs in block group	0.25[a]	6.81	0.25[a]	6.82
Retail Trade jobs in block group	0.37[a]	5.84	0.37[a]	5.85
Administrative and Support, Waste Management & Remedial jobs in block group	0.73[a]	8.79	0.73[a]	8.83
Accommodation and Food Services jobs in block group	0.42[a]	5.30	0.41[a]	5.29
Average household size	-58.09[a]	-2.05	-52.99[b]	-1.87
Percent of African American population in block group	79.18	1.22	75.00	1.16
Percent persons age 65 and over in block group	109.03	0.63	113.06	0.66
Median home value of block group in $100,000	-11.96	-1.22	-12.49	-1.27
Impedance score of block group vis-à-vis number of resident registered clients	-0.82[b]	-1.67	-1.22[a]	-2.36
Number of blocks in block group bisected by bus line	11.22[a]	4.80	11.13[a]	4.76
Block group in Essex County	172.89[a]	3.84	155.11[a]	3.40
Block group in Union County	169.43[a]	3.43	237.23[a]	4.24
Block group in Mercer County	206.73[a]	3.08	211.08[a]	3.15
Block group in Camden County	144.48[a]	2.08	108.77	1.53
Block group in Hudson County	49.21	1.01	48.84	1.01
Number of block groups (N)	4,192		4,192	
F	28.65		NA	
Adjusted R-square	0.096		NA	
-2 Res log likelihood	NA		68,554	
Akaike information criterion (AIC)	NA		68,560	

[a] *Significant at the 5% level;*
[b] *Significant at the 10% level;*
NA = Not applicable.

The association between block group jobs in these four categories with Access Link drop-offs is shown in Table 16. It is not surprising that jobs in healthcare and social assistance, retail trade, food and accommodation, and administrative support are positively associated with number of drop-offs, whereas jobs in other sectors such as manufacturing and construction are not. The statistical significance of jobs in the four industry categories does not necessarily mean, however, that the clients visit the areas with high concentration of these jobs for work purposes. It may instead mean that many visit those areas to receive healthcare service or social assistance, purchase retail goods, purchase food products, or to eat out. For social trips, or trips to visit friends and family, it was hypothesized that the persons visited by the Access Link clients would have similar characteristics to the clients themselves, because people often socialize within their own reference group. With this hypothesis, a few variables found to be significant in the models on number of registered and active clients in Table 14 and Table 15 were also included as independent variable in the model in Table 16. Among these variables, average household size was found to be significant with the expected sign, but the other variables were not significant. Most of the socioeconomic variables included in the model were highly sensitive to model specification, however, indicating that some of them may be marginally associated with non-home drop-offs even though they are not significant in the model presented in Table 16. On the whole, the effect of jobs on non-home drop-offs appears to be stronger than the effect of socioeconomic variables.

It may be noted that the independent variable on impedance score in the models in Table 16 was computed by weighting the distances to other municipalities by registered clients of the other municipalities instead of number of jobs, because the concern here is the impedance of drop-off sites from the homes of Access Link clients. Similarly to the variable on impedance vis-à-vis jobs in the models in Table 14 and Table 15, the variable on impedance vis-à-vis registered clients in the models in Table 4 shows that Access Link clients are more likely to travel to places that are closer to their homes than farther. The two distance variables in the models in Table 14, Table 15 and Table 16 together indicate that a distance-decay function is also relevant in the case of paratransit trips.

A variable representing number of census blocks bisected by local buses within a block group was included in the model with the hypothesis that block groups with a larger number of bisected blocks would have a larger geographic area served by Access Link, and that more drop-offs would occur in block groups that have more extensive service area. As expected, the variable has a significant positive sign, providing some evidence in support of the hypothesis. Finally, to account for urban activities not represented by jobs in the four industry categories, separate dummy variables were included representing each of the heavily urban counties of the region. Four of these five variables in the OLS model (three in the GLMM) showed significant positive signs, indicating that non-home drop-offs might be more likely in urban environments than suburban environments, even after controlling for other variables.

Establishments in the Immediate Vicinity of Drop-Offs

This analysis consists of an effort to identify the types of non-residential activities that are present in the immediate vicinity of Access Link drop-off sites. In addition to providing insights about the type of activities visited by Access Link clients, this effort was considered important to test the validity of the results of the non-home drop-off model in Table 16. As a part of the effort, each non-home drop-off was matched with establishments by using 2010 Dun & Bradstreet establishment data. This data set contains all establishments with one or more employees in the entire Access Link service area. All addresses in the establishment data set were geocoded with high precision, and subsequently the establishments within 75 feet of each drop-off location were recorded together with their Standard Industry Classification (SIC) codes. The 75-feet buffer was selected based on the precision of the geocoded X-Y coordinates of the two data sets. In a small proportion of cases, when multiple establishments were present around a single drop-off location, only the establishment with the highest employment was included in the data set to reduce arduous GIS work.

The frequency of Access Link drop-offs by clients' gender and the classification of establishments near drop-offs are shown in Table 17. The frequencies are shown, in descending order, for only the top 25 establishment types together with their two-digit SIC codes.

It is evident from Table 17 that health services and social assistance services rank first and second, respectively, in terms of frequency of Access Link drop-offs in their vicinity. Together, they account for almost 25% of the drop-offs, potentially indicating that a large proportion of Access Link clients make their trips to receive healthcare and social assistance services. These results are consistent with the block group level results in Table 16. When classified by age, almost 27% of the drop-offs for clients age 65 and over have health services establishments in vicinity, whereas only 12% of clients below age 65 have such establishments. The number of drop-offs near other types of establishments provides insights about the types of activities clients might frequently visit.

Table 17. Number of Access Link Drop-Offs by Type of Establishment within 75 Feet of Drop-Off Site

	Female		Male		Total	
Industry Category (Two-digit SIC Code)	**Drop-offs**	**Percent**	**Drop-offs**	**Percent**	**Drop-offs**	**Percent**
Health Services (80)	49,150	16.89%	30,740	14.37%	79,890	15.8%
Social Assistance Services (83)	27,071	9.30%	18,659	8.72%	45,730	9.1%
Business Services (73)	16,871	5.80%	10,603	4.96%	27,474	5.4%
Membership Organizations (86)	18,433	6.34%	8,508	3.98%	26,941	5.3%
Educational Services (82)	17,174	5.90%	9,482	4.43%	26,656	5.3%
Wholesale Trade - Durable Goods (50)	13,833	4.75%	11,773	5.50%	25,606	5.1%
Food Stores (54)	14,131	4.86%	10,362	4.84%	24,493	4.9%
Miscellaneous Retail (59)	11,138	3.83%	6,844	3.20%	17,982	3.6%
Construction - Special Trade Contractors (17)	7,758	2.67%	9,339	4.37%	17,097	3.4%
Building Construction - General Contractors & Operative Builders (15)	8,723	3.00%	6,790	3.17%	15,513	3.1%
Engineering, Accounting, Research, Management & Related Services (87)	6,065	2.08%	9,352	4.37%	15,417	3.1%
Printing, Publishing and Allied Industries (27)	7,309	2.51%	8,094	3.78%	15,403	3.1%
Eating and Drinking Places (58)	7,545	2.59%	6,411	3.00%	13,956	2.8%
Real Estate (65)	7,362	2.53%	4,614	2.16%	11,976	2.4%
Personal Services (72)	6,701	2.30%	3,626	1.69%	10,327	2.0%
Wholesale Trade - Nondurable Goods (51)	5,205	1.79%	4,879	2.28%	10,084	2.0%
Amusement and Recreation Services (79)	5,838	2.01%	3,831	1.79%	9,669	1.9%
Apparel and Accessory Stores (56)	5,137	1.77%	4,156	1.94%	9,293	1.8%
Automotive Dealers and Gasoline Service Stations (55)	4,784	1.64%	3,852	1.80%	8,636	1.7%
Legal Services (81)	4,766	1.64%	2,280	1.07%	7,046	1.4%
General Merchandise Stores (53)	4,148	1.43%	2,577	1.20%	6,725	1.3%
Depository Institutions (60)	2,961	1.02%	2,709	1.27%	5,670	1.1%
Transportation Services (47)	2,843	0.98%	2,513	1.17%	5,356	1.1%
Automotive Repair, Services and Parking (75)	2,581	0.89%	2,234	1.04%	4,815	1.0%
Chemicals and Allied Products (28)	2,347	0.81%	2,112	0.99%	4,459	0.9%
Drop-offs with Establishments within 75 Feet in Top 25 Categories	259,874	89.32%	186,340	87.10%	446,214	88.38%
Total Drop-offs with Establishments within 75 Feet	290,962	100.00%	213,932	100.00%	504,894	100.00%

Summary

By using trip data for NJ Transit's ADA-complementary Access Link service and data from ACS, LEHD, and Dun and Bradstreet, this part of the research examined the characteristics of areas where the Access Link clients live and the locations they visit. While most past empirical studies focused on the home end of paratransit trips, this research also made an effort to identify the characteristics of the block groups visited by the paratransit clients and the activities in the immediate vicinity of the drop-off locations.

The models on resident clients in block group and at-home pickups and drop-offs indicated that total population and the proportions of elderly and African American population are positively associated with number of clients and trips, whereas average household size, median home value, and median rent are negatively associated. Furthermore, evidence was found that places with large apartment complexes are likely to generate more trips while places with long average commuting time are likely to generate fewer trips. Evidence was also found that at-home trip generation is higher in areas that are closer to typical trip destinations compared to places that are far from the destinations.

One of the most significant contributions of this study is the identification of potential trip generators away from home. A modeling effort with block group data showed some of the characteristics of places associated with Access Link trip generation. The frequency of non-home drop-offs showed the types of establishments that are most commonly located in the vicinity of drop-offs. The analysis of data on establishments in close proximity of Access Link drop-offs showed that certain types of establishments, such as health services, social services, and educational establishments are more common around drop-off sites than other types of establishments.

Some of the key findings of this component of the research provide useful insights about potential future demand for Access Link. For example, the results suggest that the growth of elderly persons will be a key factor influencing the future demand for the service. While persons age 65 and over constitute 14% of the population in the 18 counties where Access Link service is available, 52% of the Access Link's active clients are of age 65 or over, and their trips constitute 21% of total trips. According to projections by the New Jersey Department of Labor, persons age 65 and over will grow from 1.14 million in 2010 to 1.82 million in 2030 in the counties served by Access Link.[184] On the one hand, this growth will potentially increase the total number of persons with disability, and on the other hand, it will potentially increase the number and/or size of health facilities providing them service. The growth and spatial distribution of the elderly and health facilities could greatly influence the number and OD patterns of Access Link trips in the future. Although the New Jersey Department of Labor projections do not indicate a significant growth of minority populations, changes in their residential location patterns could also influence future trip patterns. Finally, if the trend of diminishing household size continues, there could be more demand for Access Link trips in the future.

This research showed that by combining trip data with data from other secondary sources, useful insights could be obtained about the generators of ADA paratransit trips. Although this method is relatively inexpensive compared to client surveys, considering the large sums of money expended to provide paratransit service, this type of analysis should be accompanied by a survey of clients for a better understanding of trip generators and their relative importance to clients. Such surveys will be particularly useful to understanding the specific reasons for which clients visit trip generators. This understanding, in turn, will help to make better forecasts of trip patterns.

FACTORS ASSOCIATED WITH PARATRANSIT TRIP DELAY

The primary objective of this component of the research is to examine how local environmental characteristics and personal characteristics of passengers are associated with travel time and delay of paratransit trips by persons with disabilities. Although it has been recognized by past studies that trip delay significantly affects overall efficiency of paratransit systems, efforts have been made only rarely to study the effect of environmental characteristics such as population, employment, and intersection density on service efficiency. A limited number of past studies examined the association between regional density and aggregate service efficiency to compare the efficiency of systems located in different parts of a country, but efforts to examine how local environmental characteristics affect service efficiency have been rare. Furthermore, since past studies generally focused on economic efficiency, little is known about performance measures such as travel time and delay, even though these performance measures ultimately affect overall efficiency of service. Considering that persons with different types of disabilities and demographic characteristics may have different travel patterns and needs in terms of mobility equipment, operator’s attention, etc., this study also examines how these characteristics influence trip delay and pickup/drop-off duration.

It is not difficult to hypothesize that local conditions such as congested roads affect vehicle speed and delay of paratransit trips. Because of variations in population density, employment density, and network characteristics, there is often a wide variation in traffic congestion between different parts of the same region. The variations in the level of congestion can conceivably lead to variations in travel time and delay of paratransit trips. Similarly, because of variations in the local built environment, such as distance between homes and curbside pickup and drop-off locations, pickup and drop-off durations may be different in different parts of a region.

One of the reasons for the limited emphasis of past studies on the association between local environmental conditions and paratransit service efficiency is the difficulty quantifying delay at a local level. Although overall traffic congestion and delay are often reported for metropolitan regions, obtaining such data for numerous locations within a large region is difficult. In the case of paratransit for persons with disabilities, duration of trips can be easily measured from data recorded by operators at the pickup and drop-off sites. However, estimating speed and delay is usually difficult because actual trip distance cannot be estimated in the absence of route-specific movement of vehicles. This study overcomes this obstacle by obtaining and using a proxy distance variable. This proxy variable was obtained by estimating network distances of approximately 1.91 million paratransit trips with the ArcGIS Network Analyst extension.

The trip data used by this research pertain to Access Link, a complementary paratransit service provided by NJ Transit pursuant to the Americans with Disabilities Act (ADA) of 1990. These trips were made by the system's registered clients between October 1, 2010 and September 30, 2012. Access Link service is provided in 18 of 21 counties of New Jersey, but not in three counties in the northwestern part of the state.

The statistical analysis of this component of the research consists of ANOVA and regression models. The analyses pertain to trip performance measures such as minutes per mile (MPM) of travel and delay per mile (DPM) of travel. The analysis begins with ANOVA to examine how the characteristics of pickup and drop-off locations relate to MPM and DPM. This simple analysis with grouped data is followed by regression models with disaggregate data that examine the association of pickup and drop-off location characteristics, vehicle characteristics, mobility equipment characteristics, companion characteristics, and client characteristics with trip delay. The models are tested with the full data set for the entire study area, 10% and 1% random samples of the study area data, and data for three specific regions.

Data and Methods

Data

This research uses data for approximately 1.91 million trips made by Access Link clients in a 24-month period. The data set, acquired from NJ Transit, includes each trip's pickup and drop-off coordinates determined by GPS equipment located in the vehicles, as well as the time at which a vehicle arrives at and departs from a location. It includes information on the type of vehicle used for the trip and the type of mobility equipment used by the clients during the trip. It further indicates whether someone accompanied the client during a trip. The trip data can be used to determine whether a trip segment involved a shared ride by two or more clients who booked trips independently. A complementary data set, also obtained from NJ TRANSIT, includes clients' age, gender, and disability type, as well as the coordinates of their home locations. Socioeconomic data such as household income and race are not included in the client data set. The two data sets were merged by using the clients' coded identification numbers.

The census block group for each pickup and drop-off location was identified by GIS. Socioeconomic data from the 2006-10 ACS and employment data from the 2010 LEHD were downloaded from the Census Bureau's web site and combined at the block group level with the Access Link trip data. The duration of each trip was computed by subtracting the vehicle departure time at the pickup location from the arrival time at the drop-off location. The pickup duration for each trip was obtained by subtracting the vehicle arrival time at the pickup location from the departure time at the same location. Similarly, drop-off time was obtained by subtracting the arrival time at a drop-off location from the departure time from the same location.

A street network map for the state was obtained in GIS format from the New Jersey Department of Transportation (2013) to estimate intersection density.[185] After eliminating the ramps of all limited-access highways, the number of intersections in each block group was divided by the area of the block group to obtain the intersection density for all block groups within the Access Link service area. Finally, by using the ArcGIS Network Analyst extension, network distances between the origins and destinations of each of the 1.91 million trips were obtained. Since the network analyst uses a shortest-path algorithm to estimate network distance between a pair of points on map, the estimated network distances may not be exact for some trips (e.g., a vehicle might take a longer route because of congestion on the shortest path). However, in the absence of actual trip distance between origin and destination pairs, this variable can be considered the closest proxy.

Measures and Methods

The first part of the analysis is aimed at identifying the variables that are associated with trip delay. It focuses on two performance measures, namely, MPM and DPM. As described in the literature review, speed and delay are two of the most commonly used performance measures in congestion analysis. While MPM is the inverse of speed, DPM represents the difference between the time it took to travel a mile and the time it should have taken to travel a mile under ideal conditions. Mathematically, MPM and DPM are expressed as follows:

$$MPM_{ij} = \frac{R_{ij}}{D_{ij}}$$

$$DPM_{ij} = \frac{R_{ij}}{D_{ij}} - \frac{N_{ij}}{D_{ij}} = \frac{R_{ij} - N_{ij}}{D_{ij}}$$

where, R_{ij} is the recorded or actual trip duration (minutes) between origin *i* and destination *j*, D_{ij} is the network distance (miles) between *i* and *j* by the shortest-path algorithm without intersection delay, and N_{ij} is the estimated trip duration (minutes) based on trip distance and posted speed on roads between *i* and *j*. For this study, the values of R_{ij} were obtained from time recorded from Access Link vehicles at trip origin and destination, whereas the values of D_{ij} and N_{ij} were obtained by the ArcGIS Network Analyst extension.

To identify the variables associated with MPM and DPM, two types of statistical methods were used: ANOVA and OLS regression models. One-way ANOVA was used to examine how the characteristics of pickup and drop-off locations relate to MPM and DPM. One-way ANOVA is a simple but useful statistical technique that shows how a variable is associated with another variable based on grouped data of one variable. This analysis was followed by a series of OLS regression models with disaggregate trip data to identify variables that are associated with MPM and DPM. Since the results were similar, only the results from the models on DPM are presented in this paper. The DPM models were tested with the full data set for the entire study area, a 10% sample of the data, a 1% sample of the data, and separate data sets for three Access Link regions that are different in terms of location characteristics. For the analysis of MPM and DPM, shared-ride trips, constituting less than 5% of all Access Link trips in the data set, were excluded because of the complexity in estimating their duration.

It may be noted that Seemingly Unrelated Regression (SUR) was tested as an alternative to the OLS regression models because of the method's ability to account for correlation between model residuals. However, SUR was not used because the correlation between the residuals of the region-specific OLS models was found to be extremely low.

The second part of the analysis consists of OLS regression models to identify variables associated with pickup and drop-off duration. These models were also tested for the entire study area, for 10% and 1% random samples, and for specific regions. Since the results of the models on drop-off duration were virtually identical to the models on pickup duration, only the results from the models on pickup duration are presented.

Heteroscedasticity and multicollinearity, two major concerns with OLS models, were properly addressed for all models presented in this paper. To account for potential heteroscedasticity, only the robust t-values, estimated on the basis of heteroscedasticity-consistent standard errors, are presented in all tables with model results. Because of the seemingly collinear nature of some independent variables included in the models, such as density of population, jobs, and intersections, variance inflation factors (VIFs) were estimated for all variables. Although VIF is not a statistical test, standard textbooks suggest that VIF>5 is a sign of unacceptable multicollinearity.[186] The analysis showed that all variables in the models presented in this paper had a VIF far below 5.

Analysis and Results

Identification of Variables Associated with Speed and Delay

As mentioned in the previous section, one-way ANOVA and OLS regression models were used to identify the variables associated with MPM and DPM. For both sets of analysis, it was hypothesized that variables pertaining to the characteristics of the pickup and drop-off locations, the vehicles used, the trip makers, the companions of the trip makers, and the mobility equipment used by the trip makers could be associated with MPM and DPM. Although ANOVA was undertaken to examine the association of all of these variables with MPM and DPM, only the results of the variables pertaining to pickup and drop-off locations are presented in this paper because of space limitations and a special emphasis of the paper on location characteristics.

ANOVA Results on MPM and DPM

Table 18 shows the ANOVA results for the association between MPM and the characteristics of the pickup and drop-off locations. Table 19 shows the ANOVA results for the association between DPM and the same location characteristics. In both tables, the left panel pertains to the pickup location and the right panel pertains to the drop-off location. The variables included in the two tables are population density, job density, intersection density, and per capita income, as well as one variable indicating whether the pickup or drop-off occurred within a ¾-mile buffer along the bus route, and another variable indicating whether the pickup or drop-off occurred near a client’s home. The mean MPM and DPM of each category of the variables, their standard errors, and the F statistics from the ANOVA are presented in both tables. The F statistics, computed on the basic of inter-group and within-group comparison, show that the association of all the variables in the table with MPM and DPM are statistically significant.

Table 18. ANOVA Results on Minutes per Mile (MPM) for Characteristics of Pickup and Drop-off Locations

	Pickup Location		Drop-Off Location	
Characteristics of location	**Mean MPM**	**Standard error**	**Mean MPM**	**Standard error**
Block group population density (persons/acre)				
Less than 2	3.93	0.006	3.99	0.006
2 to 5	5.10	0.006	5.00	0.006
5 to 10	5.58	0.006	5.60	0.006
10 to 20	6.30	0.008	6.29	0.008
20 to 30	7.26	0.013	7.32	0.014
30 to 50	7.28	0.013	7.21	0.014
50 or more	8.47	0.022	8.50	0.022
F*	21,127		21,465	
Block group job density (jobs/acre)				
Less than 0.5	4.89	0.006	5.06	0.007
0.5 to 0.99	5.32	0.010	5.32	0.010
1 to 1.99	5.56	0.008	5.57	0.008
2 to 3.99	5.77	0.008	5.99	0.012
4 to 6.99	5.74	0.010	5.64	0.010
7 to 9.99	6.59	0.011	6.34	0.010
10 or more	6.77	0.010	6.73	0.010
F*	5,972		4,611	
Block group interaction density (intersections/acre)				
Less than 0.05	4.41	0.007	4.38	0.007
0.05 to 0.10	5.02	0.006	5.04	0.006
0.10 to 0.15	5.24	0.008	5.23	0.007
0.15 to 0.20	5.98	0.009	6.00	0.009
0.20 to 0.30	6.81	0.008	6.76	0.008
0.30 or higher	6.93	0.009	6.90	0.009
F*	17,870		17,604	
Block group per capita income				
Less than $15,000	7.04	0.014	6.93	0.013
$15,000-20,000	6.82	0.010	6.63	0.010
$20,000-30,000	5.85	0.006	5.83	0.006
$30,000-40,000	5.20	0.006	5.22	0.006
$40,000-50,000	5.08	0.009	5.22	0.009
$50,000 or higher	4.95	0.008	4.95	0.008
F*	8,981		7,216	
Whether location within 3/4 mile buffer				
Not in ¾-mile buffer	6.07	0.004	6.09	0.004
In ¾-mile buffer	3.88	0.006	3.81	0.006
F*	66,124		72,144	
Whether at home location				
Away from home	5.66	0.005	5.48	0.005
At home	5.73	0.005	6.00	0.004
F*	122		5,938	

** All F statistics are significant at 1% level.*

Table 19. ANOVA Results on Delay per Mile (DPM) for Characteristics of Pickup and Drop-off Locations

	Pickup Location		Drop-Off Location	
Characteristics of location	**Mean DPM**	**Standard error**	**Mean DPM**	**Standard error**
Block group population density (persons/acre)				
Less than 2	2.40	.006	2.47	.006
2 to 5	3.53	.006	3.43	.006
5 to 10	3.96	.006	3.99	.006
10 to 20	4.68	.008	4.67	.008
20 to 30	5.62	.013	5.70	.013
30 to 50	5.65	.013	5.57	.013
50 or more	6.83	.022	6.87	.022
F*	20,818		21,109	
Block group job density (jobs/acre)				
Less than 0.5	3.31	.006	3.47	.006
0.5 to 0.99	3.77	.009	3.77	.009
1 to 1.99	3.95	.008	3.95	.008
2 to 3.99	4.18	.008	4.40	.012
4 to 6.99	4.12	.010	4.05	.010
7 to 9.99	4.97	.011	4.71	.010
10 or more	5.17	.010	5.13	.010
F*	6,014		4,637	
Block group interaction density (intersections/acre)				
Less than 0.05	2.88	.007	2.86	.007
0.05 to 0.10	3.44	.006	3.47	.006
0.10 to 0.15	3.64	.008	3.63	.007
0.15 to 0.20	4.35	.009	4.36	.009
0.20 to 0.30	5.18	.008	5.14	.008
0.30 or higher	5.31	.009	5.28	.009
F*	17,344		17,054	
Block group per capita income				
Less than $15,000	5.43	.013	5.32	.013
$15,000-20,000	5.22	.010	5.04	.010
$20,000-30,000	4.26	.006	4.24	.006
$30,000-40,000	3.60	.006	3.62	.005
$40,000-50,000	3.49	.008	3.63	.009
$50,000 or higher	3.36	.008	3.37	.008
F*	9,215		7,440	
Whether location within 3/4 mile buffer				
Not in ¾-mile buffer	4.46	.004	4.48	.004
In ¾-mile buffer	2.38	.005	2.32	.006
F*	62,170		67,914	
Whether at home location				
Away from home	4.08	.004	3.90	.004
At home	4.13	.005	4.38	.005
F*	63		5,335	

** All F statistics are significant at 1% level.*

It is evident from Table 18 and Table 19 that mean MPM and DPM values are higher for pickup and drop-off locations with higher population, employment, and intersection density, suggesting that these variables are positively associated with both MPM and DPM. The results in the two tables also show that MPM and DPM are higher in areas with lower per capita income and lower in areas with high per capita income, indicating a negative association between income and the two performance measures. The results in the two tables also indicate that a lower level of trip delay is involved when pickups and drop-offs occur in ¾-mile buffers than when pickups and drop-offs occur in urban core areas. Finally, a comparison between trips with pickups and drop-offs near home and trips with pickups and drop-offs away from home indicates that trips beginning or ending near clients' homes may involve a little more delay than trips beginning or ending away from home.

Although the ANOVA results in Table 18 and Table 19 provide useful insights about the association of individual characteristics of pickup and drop-off locations with MPM and DPM, the analysis does not control for potential effects of other variables. For example, the ANOVA results show that both population density and intersection density are positively associated with MPM and DPM, but they do not show how MPM and DPM vary with intersection density after controlling for the effects of population density and the other variables.

Regression Results on DPM

In order to examine the effects of all variables that can be conceivably associated with the two performance measures, OLS regression models were run with MPM and DPM as the dependent variables. An advantage of a regression model over ANOVA is that its shows the association of each independent variable with MPM and DPM after controlling for the effects of the other independent variables. The variables used in the regression models on MPM and DPM are shown in Table 20. The means and standard deviations of the variables estimated from the full data set, as well as a 10% sample and a 1% sample, are also shown in the table.

Although the regression models were run for both MPM and DPM, only the DPM model results are presented because (a) the direction of association and significance level of the variables in the MPM and DPM models were very similar, and (b) delay is a more commonly used measure of congestion than speed. The results of six regression models on DPM are presented in Table 21 and Table 22.

Table 20. Mean and Standard Deviation of Variables Used in Regression Models

	Full Data Set		10% Sample		1% Sample	
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Log of delay per mile (dependent variable)	1.09	0.909	1.09	0.90	1.09	0.90
Log of pickup duration (dependent variable)	1.04	0.80	0.99	0.77	0.95	0.78
Jobs per acre in pickup block group	7.20	20.49	7.27	20.78	7.23	20.68
Jobs per acre in drop-off block group	7.48	21.26	7.51	21.22	7.70	22.17
Population per acre in pickup block group	12.89	15.68	12.89	15.64	12.84	15.78
Population per acre in drop-off block group	12.77	15.58	12.79	15.54	12.89	15.74
Intersections per acre in pickup block group	0.18	0.13	0.18	0.13	0.18	0.13
Intersections per acre in drop-off block group	0.18	0.13	0.18	0.13	0.18	0.13
Pickup location in 3/4-mile buffer	0.17	0.37	0.17	0.37	0.17	0.37
Drop-off location in 3/4-mile buffer	0.17	0.37	0.17	0.37	0.17	0.37
Pickup at home	0.46	0.50	0.46	0.50	0.46	0.50
Drop-off away from home	0.58	0.49	0.58	0.49	0.58	0.49
Per capita income in pickup block group (in $10,000)	3.08	1.40	3.07	1.39	3.07	1.39
Per capita income in drop-off block group (in $10,000)	3.08	1.41	3.07	1.40	3.08	1.41
Pickup between 7 and 9 AM	0.20	0.40	0.20	0.40	0.20	0.40
Pickup between 2 and 4 PM	0.22	0.41	0.22	0.41	0.22	0.41
Pickup between 4 and 6 PM	0.10	0.30	0.10	0.30	0.09	0.29
Used subscription booking	0.46	0.50	0.46	0.50	0.45	0.50
Weekend trip	0.13	0.34	0.13	0.34	0.13	0.34
Vehicle is sedan	0.00	0.04	0.00	0.03	0.00	0.03
Used oversized chair	0.00	0.05	0.00	0.05	0.00	0.05
Used wheelchair	0.16	0.37	0.16	0.37	0.17	0.37
Accompanied by personal care attendant	0.08	0.27	0.08	0.27	0.08	0.28
Accompanied by child	0.00	0.04	0.00	0.04	0.00	0.03
Age 65 or over	0.21	0.40	0.21	0.41	0.21	0.41
Female	0.54	0.50	0.54	0.50	0.54	0.50
Has physical disability	0.23	0.42	0.23	0.42	0.24	0.42
Has medical disability	0.29	0.46	0.30	0.46	0.29	0.46
Has mental illness	0.09	0.29	0.09	0.29	0.09	0.28
Has cognitive or learning disability	0.26	0.44	0.26	0.44	0.26	0.44
Has visual disability	0.23	0.42	0.23	0.42	0.22	0.42
Region 2	0.07	0.25	0.07	0.25	0.07	0.25
Region 3	0.26	0.44	0.26	0.44	0.26	0.44
Region 4 West	0.06	0.25	0.07	0.25	0.07	0.25
Region 4 East	0.07	0.26	0.07	0.26	0.08	0.26
Region 6	0.18	0.38	0.18	0.38	0.18	0.39
Sample size (N)	1,754,997		175,485		17,342	

Table 21. Regression Models on Delay per Mile (DPM) for the Entire Access

	Full Data Set		10% Sample		1% Sample	
	Coefficient	Robust t Value	Coefficient	Robust t Value	Coefficient	Robust t Value
Intercept	1.0366	282.02	1.0357	88.90	0.9772	26.40
Jobs per acre in pickup block group	0.0007	24.71	0.0006	7.44	0.0007	2.63
Jobs per acre in drop-off block group	0.0006	21.73	0.0006	7.64	0.0008	3.32
Population per acre in pickup block group	0.0040	80.22	0.0038	24.27	0.0045	9.21
Population per acre in drop-off block group	0.0047	95.46	0.0049	31.41	0.0050	10.03
Intersections per acre in pickup block group	0.4992	92.42	0.4980	29.35	0.4575	8.51
Intersections per acre in drop-off block group	0.4687	86.68	0.4539	26.71	0.4367	8.02
Pickup location in ¾-mile buffer	-0.2392	-98.96	-0.2374	-30.91	-0.2698	-11.06
Drop-off location in ¾-mile buffer	-0.2244	-92.23	-0.2278	-29.57	-0.2371	-9.68
Pickup at home	0.0350	16.36	0.0329	4.89	0.0160*	0.74
Drop-off away from home	-0.0619	-29.17	-0.0585	-8.77	-0.0562	-2.62
Per capita income in pickup block group (in $10,000)	-0.0475	-99.76	-0.0469	-31.29	-0.0416	-8.52
Per capita income in drop-off block group (in $10,000)	-0.0314	-66.33	-0.0313	-20.91	-0.0219	-4.61
Pickup between 7 and 9 AM	0.2804	153.80	0.2894	50.25	0.3052	16.64
Pickup between 2 and 4 PM	0.3051	172.33	0.3097	55.32	0.3165	17.51
Pickup between 4 and 6 PM	0.1771	82.14	0.1772	25.95	0.1733	7.96
Used subscription booking	0.0584	42.31	0.0573	13.14	0.0681	4.84
Weekend trip	-0.1219	-62.24	-0.1199	-19.27	-0.0959	-4.90
Vehicle is sedan	-0.1836	-13.07	-0.1572	-3.32	-0.2727*	-1.62
Used oversized chair	0.3773	32.48	0.3766	10.04	0.4651	2.93
Used wheelchair	0.2673	148.81	0.2703	47.51	0.2599	14.18
Accompanied by personal care attendant	0.0501	21.91	0.0463	6.45	0.0487*	2.07
Accompanied by child	0.0816	5.24	0.1621	3.25	-0.0225	-0.14
Age 65 or over	0.1202	73.21	0.1149	22.13	0.1458	8.71
Female	0.0597	48.38	0.0604	15.47	0.0581	4.66
Has physical disability[a]	0.0272	18.30	0.0300	6.34	0.0148*	0.97
Has medical disability[a]	0.0358	24.81	0.0310	6.77	0.0332*	2.24
Has mental illness[a]	0.0731	34.49	0.0722	10.77	0.0523	2.48

	Full Data Set		10% Sample		1% Sample	
	Coefficient	Robust t Value	Coefficient	Robust t Value	Coefficient	Robust t Value
Has cognitive or learning disability[a]	0.0139	9.39	0.0120	2.56	0.0126*	0.85
Has visual disability[a]	-0.0946	-60.98	-0.0905	-18.36	-0.0919	-5.79
Region 2[b]	-0.1850	-75.51	-0.1791	-23.26	-0.1779	-7.14
Region 3[b]	-0.2369	-137.34	-0.2402	-44.03	-0.1932	-11.18
Region 4 West[b]	-0.3817	-89.25	-0.3897	-28.94	-0.2998	-6.86
Region 4 East[b]	-0.3040	-109.13	-0.3141	-35.77	-0.2922	-10.21
Region 6[b]	-0.1979	-116.61	-0.1964	-36.42	-0.2190	-12.84
N	1,754,997		175,485		17,342	
F	16,008		1,615		154	
Adjusted R-square	0.237		0.238		0.231	

*All coefficients without * are significant at the 1% level;*

[a] *Referent category is "Other types of disability";*

[b] *Referent category is "Region 5."*

Table 22. Regression Models on Delay per Mile (DPM) for Specific Access Link Regions

	Region 3		Region 4		Region 5 (10% Sample)	
	Coefficient	Robust t Value	Coefficient	Robust t Value	Coefficient	Robust t Value
Intercept	-0.3881	-5.48	0.5367	35.85	1.2046	64.46
Jobs per acre in pickup block group	0.0008	2.69	0.0060	16.37	0.0008	7.96
Jobs per acre in drop-off block group	0.0004*	1.41	0.0036	12.77	0.0006	5.89
Population per acre in pickup block group	0.0135	10.40	0.0026	6.76	0.0021	8.48
Population per acre in drop-off block group	0.0051	4.32	0.0007*	2.04	0.0041	16.19
Intersections per acre in pickup block group	0.5361	13.24	0.0726	2.71	0.5641	21.84
Intersections per acre in drop-off block group	0.5966	15.12	0.2789	11.28	0.4524	17.16
Pickup location in ¾-mile buffer	0.1139	3.62	-0.1284	-16.63	-0.3509	-18.49
Drop-off location in ¾-mile buffer	0.1318*	2.15	-0.1140	-14.71	-0.2531	-13.65
Pickup at home	-0.0837	-8.61	0.3545	40.11	0.0194*	1.83
Drop-off away from home	0.0199*	2.07	-0.3596	-41.74	-0.0029*	-0.27
Per capita income in pickup block group (in $10,000)	0.0137	5.08	-0.0025*	-1.16	-0.0747	-35.17
Per capita income in drop-off block group (in $10,000)	0.0332	12.47	-0.0122	-5.89	-0.0605	-28.13
Pickup between 7 and 9 AM	0.2410	26.90	0.0402	5.68	0.2796	31.44
Pickup between 2 and 4 PM	0.2345	27.78	0.1635	26.42	0.2897	32.23
Pickup between 4 and 6 PM	0.1623	16.74	0.1498	19.78	0.1514	13.88
Used subscription booking	0.0515	8.10	-0.1417	-28.46	0.0790	11.41
Weekend trip	-0.0977	-12.19	-0.0597	-9.37	-0.1319	-13.62
Vehicle is sedan	-0.2320*	-0.43	0.5070	3.24	0.3265*	0.77
Used oversized chair	0.5897	15.43	1.2221	23.73	0.2679	4.88
Used wheelchair	0.2669	38.32	0.5684	86.02	0.2214	23.50
Accompanied by personal care attendant	0.0592	3.94	0.0541	6.20	-0.0476	-4.26
Accompanied by child	0.6120	11.49	-0.1231*	-1.67	0.1895	2.56
Age 65 or over	0.1138	14.38	0.0301	5.05	0.1244	16.82

	Region 3		Region 4		Region 5 (10% Sample)	
	Coefficient	**Robust t Value**	**Coefficient**	**Robust t Value**	**Coefficient**	**Robust t Value**
Female	0.0293	4.76	0.1437	30.33	0.0791	13.18
Has physical disability[a]	0.2145	31.34	-0.0160	-2.76	-0.0180*	-2.46
Has medical disability[a]	0.0929	12.14	0.0582	10.87	0.0110*	1.66
Has mental illness[a]	-0.0355	-3.60	0.1399	11.98	0.1520	15.64
Has cognitive or learning disability[a]	-0.3211	-36.95	-0.0409	-6.32	0.0740	10.78
Has visual disability[a]	-0.0982	-11.69	0.0013*	0.24	-0.0533	-7.06
N	113,866		130,891		61,594	
F	414		936		577	
Adjusted R-square	0.095		0.172		0.213	

*All coefficients without * are significant at the 1% level;*
[a] Referent category is "Other types of disability."

The three models in Table 21 were estimated from the full data set for the entire study area, a 10% random sample of the data set for the whole study area, and a 1% random sample of the data set. The models with the 10% and 1% samples were necessary, as the full data set contains an extremely large number of observations. When the number of observations is very large, regression model coefficients are highly likely to be significant merely because t-values increase with an increase in number of observations.[187] The models with the 10% and 1% data were run with the anticipation that some variables that are statistically significant in the model with the full data set would not be significant when the data set size is substantially reduced. That, in turn, would provide a greater degree of confidence about the variables significantly associated with the dependent variable in all three models.

In addition to the three models on DPM for the entire study area, three separate models were tested with data for three specific regions to examine if the variables found to be significant in the models for the entire study area continue to be significant in different environments. Region 3, Region 4, and Region 5 were chosen for the models because of the differences in their characteristics. Region 5 has extremely high population density, Region 4 has moderate density, and Region 3 has low density. Similar differences exist between the three regions in terms of job density and intersection density as well. The results of the models on DPM with data from the three regions are shown in Table 22. It may be noted that, because of the large number of trips in Region 5 (over 650,000), data from a random sample of 10% trips were used for the model pertaining to this region.

On the basis of the reviewed studies, it was hypothesized that Access Link trip delay would be higher when pickup or drop-off locations have a higher density of population, employment, and intersections. A positive association between delay and population/employment density is expected because of higher pedestrian volumes, whereas a positive association between delay and intersection density is expected because of control delay at intersections, blockage, spill-back, and conflicts with pedestrians. Based on the ANOVA results, two variables representing median per-capita income of the pickup and drop-off block groups were included with the expectation that they would be negatively associated with delay.

Since a large proportion of Access Link clients live in high-density and low-income areas, it was hypothesized that trips with pickup and drop-off locations near home would be associated with greater delay than were trips with pickups and drop-offs in areas away from home. Similarly, since most of the ¾-mile buffers along bus routes are in low-density suburban highway corridors, it was hypothesized that trips with pickups or drop-offs in the buffers would involve a lower level of delay than other areas.

Three dummy variables were included in the models that pertain to trip time, namely, 7-9 AM, 2-4 PM, and 4-6 PM, with the expectation that trip delay would be higher at these time periods compared to other time periods. The afternoon peak period was divided into two parts, because Access Link trips peak between 2 and 4 PM while regular traffic in the region peaks between 4 and 6 PM. A variable on trip-booking type was included with the expectation that subscription-booking trips would be positively associated with delay compared to demand-booking trips because a large proportion of the subscription trips are expected to be made by individuals commuting to or from work. A dummy variable on weekend trip was included with the anticipation that weekend trips would involve a lower level of delay because of lower traffic volume on roads.

A few dummy variables were included in the models that represent other characteristics of the trips. They include a dummy variable on the use of sedans (versus ambulatory vehicles or vans), two variables on equipment used by the trip maker (wheelchair and oversized chair) and two variables on companion (personal care attendant and child). The expectation was that delay would be lower when a sedan was used and higher when the two types of equipment were used or when a trip maker was accompanied by others. It was hypothesized that when equipment or multiple passengers were onboard, vehicle operators would be more careful, especially when accelerating, decelerating, and turning a vehicle.

A few independent variables were included in the models for mostly exploratory purposes to examine if personal characteristics of the passengers had any association with trip delay. These variables pertained to age, gender, and disability type. Delay could be associated with these variables because of differences in trip patterns (e.g., different destinations), passenger behavior (e.g., variations in time taken to occupy a seat once inside a vehicle), as well as driver behavior (e.g., driving more slowly or turning more carefully when an elderly person is onboard). Since past studies provide little insight about the association of these variables with paratransit trip delay, there was no clear expectation about the relationship of these variables with delay. However, it was anticipated that trips involving elderly persons and persons with physical disability might be positively associated with delay because of a potentially longer time taken by these trip makers to occupy seats and more careful driving by the operators when such persons were onboard.

The results of the regression models on DPM with the full data set for the entire study region, the 10% sample, and the 1% sample are presented in Table 21. The dependent variable of these models is the natural log of DPM. The variable was transformed because of extreme dispersion. In addition to the independent variables mentioned above, dummy variables on five regions were included to control for differences between the regions. Region 5 was used as the referent category, because it is the largest and most distinct from the other regions. Since this region is located close to New York City and has a substantial volume of interstate through traffic on its roadways, it was expected that the other five regions would have a lower delay than this region.

The models in Table 21 show generally expected results. Considering that the models use disaggregate data on trips, the adjusted R-square values are acceptable. In the first model, the model with the full data set, all variables are statistically significant, and the variables included with a clear expectation of relationship with DPM had coefficients with expected signs. However, the significance of some of the variables in the model is potentially due to the extremely large number of observations used.

In the model with 10% sample data, all variables are also statistically significant, but in the third model, where only 1% of data was used, six variables cease to be statistically significant (at the 1% level). These variables are at-home pickup, vehicle type, presence of personal care attendant, physical disability, medical disability, and cognitive or learning disability.

Although a large number of variables continue to be significant even in the model with 1% data, to examine how generalizable the model results are, the regression model on DPM is repeated for three Access Link regions with vastly different characteristics. The results of the models with the full data set for Regions 3 and 4, as well as a 10% sample data set for Region 5, are presented in Table 22. A few important observations can be made from the model results. First, the adjusted R-squares of the models for Region 3 and Region 4 are substantially lower than the model with 10% data from Region 5, even though a larger number of observations are used in the first two models than in the last model. This indicates that the model results for the entire region in Table 17 are significantly affected by Region 5, where almost one-third of all trips take place. Conversely, it indicates that the model results for the entire region are more replicable in Region 5 than in the other regions because of the differences in their characteristics. Second, despite the differences in the outcomes for several variables in the models for Region 3 and Region 4, a number of variables in these two models show results similar to model results for Region 5.

The variables that are statistically significant with identical signs in all six models in Table 21 and Table 22 are (a) Job density in pickup location, (b) population density in pickup location, (c) intersection density in pickup and drop-off locations, (d) pickup location within the ¾-mile buffer along bus routes, (e) pickup and drop-off in morning and afternoon peak periods, (f) weekend trip, (g) use of oversized chair and wheelchair by trip maker, (h) elderly trip maker, and (i) female trip maker. In addition, the models in Table 21 consistently show that, compared to Region 5, delay is lower in the other five regions. In sum, the model results indicate that the characteristics of the pickup locations, time of day, day of week, mobility equipment used by trip makers, age of trip maker, and gender of trip maker are consistently associated with delay. In contrast, the variables on companion characteristics, type of vehicle, and type of disability show inconsistent results.

Summary

This part of the research helped to identify some of the variables pertaining to local environmental characteristics and personal characteristics of trip makers that are associated with speed, delay, and pickup duration of Access Link trips. Most notably, it showed that a certain degree of delay is involved when trips are made to and from areas with a high density of population, employment, and intersections. Although the reviewed literature shows that having a high population density regionally can make paratransit service more efficient, this research showed that service provision may be inefficient locally in areas with high population density because of trip delay. The model results also show that the association between employment density and delay is significant and positive. The empirical findings strongly indicate that Access Link vehicles experience greater delay in areas with a high intersection density even after population and employment density are accounted for.

The observed relationship between density and paratransit trip delay has implications for transportation and land-use planners. While general transportation studies often mention lower VMT and higher share of transit and pedestrian trips as benefits of high density, paratransit trips experience more delay in such environments. Since a large proportion of ADA-paratransit clients live in urban centers where population, employment, and intersection density are high, a large proportion of trips are affected by high density. In contrast to urban core areas, trips beginning in ¾-mile buffers along bus routes, mostly located in suburban areas, experience a significantly lower level of delay. However, far fewer clients live in those areas.

Density and ADA-paratransit service both have societal benefits. Density benefits are seemingly enjoyed by society in general, whereas the benefits from paratransit are directly enjoyed by persons with disabilities but are also indirectly enjoyed by society at large. Given that both density and paratransit are beneficial to society, transportation planners and traffic engineers should consider strategies that can reduce delay of paratransit vehicles in high-density areas. Regular adjustment of signal timing at critical intersections, based on up-to-date traffic data, could be one such strategy. A second strategy could be network-based optimization of signal timing in high-density areas. A third strategy would be to implement bus priority at intersections in high-density areas and to afford paratransit vehicles the same privileges as buses. Urban planners perhaps can do little about where paratransit clients live and where they travel. When opportunities arise to develop activities that generate a substantial amount of trips, however, or to increase population or employment density through new construction, planners should also bear in mind the potential negative effects of density and congestion on bus and paratransit.

This research also showed the association between certain passenger characteristics and paratransit speed and delay. Although one might not suspect that speed decreases and delay increases when particular types of passengers are on board, this research showed that vehicle speed, on average, is lower when a passenger with a wheelchair is on board or when an elderly person is on board. While operators are not instructed to drive slower or faster on the basis of passenger characteristics, it appears that operator behavior may have an influence on trip duration and speed. It is possible that, because of the need for an operator to activate a mechanism to indicate arrival and departure from a location, a portion of the pickup and drop-off duration is attributed to the duration of the trip.

Finally, this research afforded an opportunity to compare service efficiency in the six Access Link regions. In terms of trip delay, Region 5 appears to be worse off than the other five regions. After other variables are controlled for, trip delay is greater in Region 5 compared to the other regions. While it is not possible to conclude from this research whether the region suffers from any kind of provider-related inefficiency, the location and other attributes of the region could also be contributory factors. On the one hand, the region contains a number of municipalities with high population and employment density; on the other hand, its highways and major roads are perpetually congested because of a high volume of intra- and inter-regional traffic. The region's relatively large size may also lead to complexities in providing efficient service. If NJ TRANSIT considers a re-alignment of service regions, this research suggests that Region 5 should be the top candidate.

TRAVEL TIME RELIABILITY OF ACCESS LINK TRIPS

Reliability is the inverse of variability; when travel time for a given roadway segment or trip time between an origin and a destination fluctuates widely, travel time reliability is low. With the growing recognition that travel time variability is a more serious concern for travelers than delay caused by everyday congestion, recent studies in the general sphere of transportation have suggested a greater emphasis on reliability than recurring delay. Compared to the general public, travel-time reliability is seemingly more important for travelers with disabilities who use paratransit service provided in accordance with the Americans with Disabilities Act (ADA). The reason is that a large proportion of those trips are made for medical and other essential appointments. Moreover, since many users of such services belong to low-income households, they often do not have any other means to travel.

The primary objective of this component of the research is to provide insights about the factors associated with ADA-paratransit's travel-time variability. It places a special emphasis on the potential effect of roadway crashes on travel-time variability. It hypothesizes that the characteristics of the locations where pickups and drop-offs occur, including the occurrence of crashes, influence paratransit's travel-time variability. It seeks to examine if locations with high crash incidents can be empirically linked to the variability of paratransit's travel time or trip speed. The underlying principle of the research is that, if locations with high crash incidents could be statistically linked to paratransit's travel time variability, trip scheduling could be improved by adding additional travel time to (i.e., imposing time penalties on) trips beginning or ending in such locations. Since it is impossible to predict if a particular paratransit trip's travel time will be affected by a motor vehicle crash in the origin or destination location, can a travel time penalty be measured and imposed on the trips to and from locations with a history of high crash volumes so that the unpredictability of travel time can be minimized? This is the primary question around which this research resolves.

Addressing travel-time variability issues can benefit paratransit riders and providers alike. While riders would have more realistic expectation about arrival time at destinations, service providers would have better control over vehicle availability at different moments of time. Unfortunately, paratransit reliability has received little attention in past studies. Although a limited number of studies dealt with issues related to paratransit reliability, they were conducted from the perspective of service providers, often with an emphasis on scheduling technology. In contrast, this study addresses reliability in terms of travel time variability experienced by paratransit users in real life.

The study area for this research is an 18-county region of the State of New Jersey where NJ Transit provides ADA-compliant Access Link paratransit service. Two large data sets, one on Access Link trips and the other on motor vehicle crashes, were used in conjunction with data from the ACS and the LEHD of the US Census Bureau. Data analysis was conducted for the entire study area as well as for six Access Link regions. Pursuant to recent literature, the study focuses on four measures of travel-time variability: Standard Deviation, Percent Variation, Buffer Index, and Misery Index. The analysis includes basic statistical tests and regression models. The first major analytical component of the paper includes regression models on the four measures of travel time variability with crash density in the pickup and drop-off locations as the key variables and other variables as controls. To validate the findings of the four models on travel-time variability, a second set of regression models was used to examine if Access Link trips ending in locations that experienced crashes before a drop-off required significantly longer time than trips that ended in locations that did not experience crashes prior to a drop-off. The models provided strong evidence of a significant effect of crash density and crash incidents on paratransit's travel time variability.

Measures of Reliability

In the general context of highway performance, a number of reliability measures have been discussed in past studies.[188] The measures that are of most relevance for this study are:

Standard Deviation: $s = \sqrt{\frac{\sum(X_i - \overline{X})^2}{N}}$

Travel Time Window: $TTW = \overline{X} \pm s$

Percent Variation: $PV = \frac{S}{\overline{\overline{X}}} * 100$

Misery Index: $MI = \frac{\overline{X}_{Top20\%}}{\overline{X}} - 1$

Buffer Index: $BI = \left(\frac{X_{95} - \overline{X}}{\overline{X}}\right) = \frac{X_{95}}{\overline{X}} - 1$

All of these measures can be used to estimate paratransit's travel-time reliability. These measures are often described in the literature in terms of travel time (minutes) for a highway segment of a given length (miles). Standard Deviation is a measure defined in minutes. When travel time on a highway segment varies widely, Standard Deviation will be high and reliability will be low. On the other hand, when all trips on the highway segment take more or less the same time, Standard Deviation will be low and reliability will be high. By adding and subtracting the Standard Deviation to the mean trip time, one can obtain the Travel Time Window, which is defined as a range of minutes. Percent Variation is a measure of variability obtained by multiplying the coefficient of variation by 100. This unit-less measure is high when the Standard Deviation is high and low when the mean is high. Standard Deviation and Travel Time Window are likely to be more meaningful to travelers than Percent Variation, because travelers are concerned about minutes delayed instead of unit-less measures. On the other hand, Percent Variation may be more meaningful to transportation agencies, because its unit-less-ness allows comparison across different components of a transportation network or system.

Standard Deviation, Travel Time Window, and Percent Variation place equal emphasis on trips involving different amounts of travel time. In contrast, Buffer Index and Misery Index place a greater emphasis on trips involving extreme travel time. The premise in using these two measures instead of the other measures is that it is the trips that take an inordinately long time compared to the mean time that are important to travelers, whereas trips that take slightly longer than the mean trip time are of no significance. In the case of Buffer Index, the concern is the difference between the mean travel time for all trips and the 95th percentile trip time, whereas in the case of Misery Index, the concern is the difference between the mean travel time for all trips and the mean travel time for the 20% trips that take the longest time. In both cases, the greater the difference between the mean travel time and the trips involving extreme travel time, the lower is the travel time reliability.

Data, Analysis, and Results

Data Used

The empirical analysis in this paper is based on several data sources. First, 24-month Access Link trip data described previously is the core data for the analyses. This data set contains the actual location coordinates and arrival and departure time at each pickup and drop-off location, as well as information on vehicle type, mobility equipment used by riders, etc., for a total of approximately 1.9 million trips. A complementary data set containing information on demographic characteristics of the riders was combined with the trip data. The second major data source for this research is the Plan4Safety (P4S) crash data set compiled by the Center for Advanced Infrastructure and Transportation of Rutgers University on behalf of the New Jersey Department of Transportation.[189] This data set contains all recorded vehicle crashes in the State of New Jersey as well as the time and location coordinates of each occurrence. When restricted to the 18-county Access Link service area and the 24-month period for which Access Link trip data are available, the data set contains information on 93,479 motor vehicle crashes. Figure 2, where the density of crashes is shown at the census-tract level, provides an indication about the location of the areas where crashes are most concentrated.

Third, in order to estimate intersection density of geographic areas, a street network map for the study area was obtained in GIS format from the New Jersey Department of Transportation (2013). Fourth, data on socioeconomic and demographic characteristics of population at the census block group level were downloaded from the 2006-2010 American Community Survey by using the US Census Bureau's web site.[190] Finally, employment data at the census block group level were compiled from the 2010 LEHD web site of the US Census Bureau.[191]

Travel Time Reliability of Access Link Regions

Although travel-time reliability is often defined in terms of travel time for a given segment of a roadway, such a measure does not have much relevance when comparing Access Link trips, because vehicles travel between multiple origins and destinations using multiple road segments. It was therefore necessary to use a standardized measure of travel time that could be compared across regions. This measure is MPM, derived by dividing the actual travel time of Access Link trips by the corresponding network distance (in miles) between the origins and destinations. The travel time for each trip was obtained by subtracting the vehicle departure time at the trip origin from the arrival time at the destination. At both ends, time was recorded by an in-vehicle technology. Since actual route-specific travel information for vehicles is not available, the distance between each OD pair was obtained by using the ArcGIS network analyst. Although distance measurements by this method are not exact because it uses the shortest-path algorithm, it is the closest proxy of actual distance between the origins and destinations.

The MPM estimates were obtained for almost all 1.9 million Access Link trips. The MPM estimates were used to compute and compare four reliability measures across the six regions. The estimates of these measures, namely, Standard Deviation, Percent Variation, Misery Index, and Buffer Index of MPM for the six regions, are presented in Table 23. A fifth measure, the MPM Window, can be obtained by adding and subtracting the Standard Deviation from the mean MPM for each region.

Table 23. Variability of Travel time (MPM) for Access Link Regions According to Four Measures

Regions	Number of Trips	Mean MPM (Rank)	Standard Deviation of MPM (Rank)	Percent Variation (Rank)	Misery Index (Rank)	Buffer Index (Rank)
Region 2	496,506	5.12(3)	4.22(3)	82.31(2)	0.74(6)	1.17(6)
Region 3	123,941	3.62(6)	2.71(6)	74.90(4)	0.75(5)	1.18(5)
Region 4-West	139,623	4.98(4)	3.82(5)	76.75(3)	0.83(1)	1.32(1)
Region 4-East	151,147	4.18(5)	3.68(4)	87.97(1)	0.76(4)	1.24(4)
Region 5	654,133	6.79(1)	5.03(1)	74.14(5)	0.81(2)	1.26(3)
Region 6	336,262	6.12(2)	4.46(2)	72.87(6)	0.78(3)	1.27(2)

Note: Since Rank 1 is given to the highest value and 6 to the lowest, Rank 1 has the highest variability and lowest reliability.

As evident from Figure 34, mean MPM is lowest in Region 3 and highest in Region 5. In region 3, mean MPM is 3.62, which translates to approximately 17 miles per hour (mph) average speed. In contrast, mean MPM in Region 5 is 6.79, which translates to an average of only 9 miles per hour. If actual trip distance could be used in place of network distance estimated by the ArcGIS network analyst, the mean MPM for the regions could be somewhat lower (and mean mph could be somewhat higher) because the network analyst uses the shortest-path algorithm, whereas some trips presumably take a longer route because of congestion on the shortest path. Yet the differences in MPM between the six regions make sense because the regions known to have highly congested roads and high volumes of through traffic have higher MPM than the other regions.

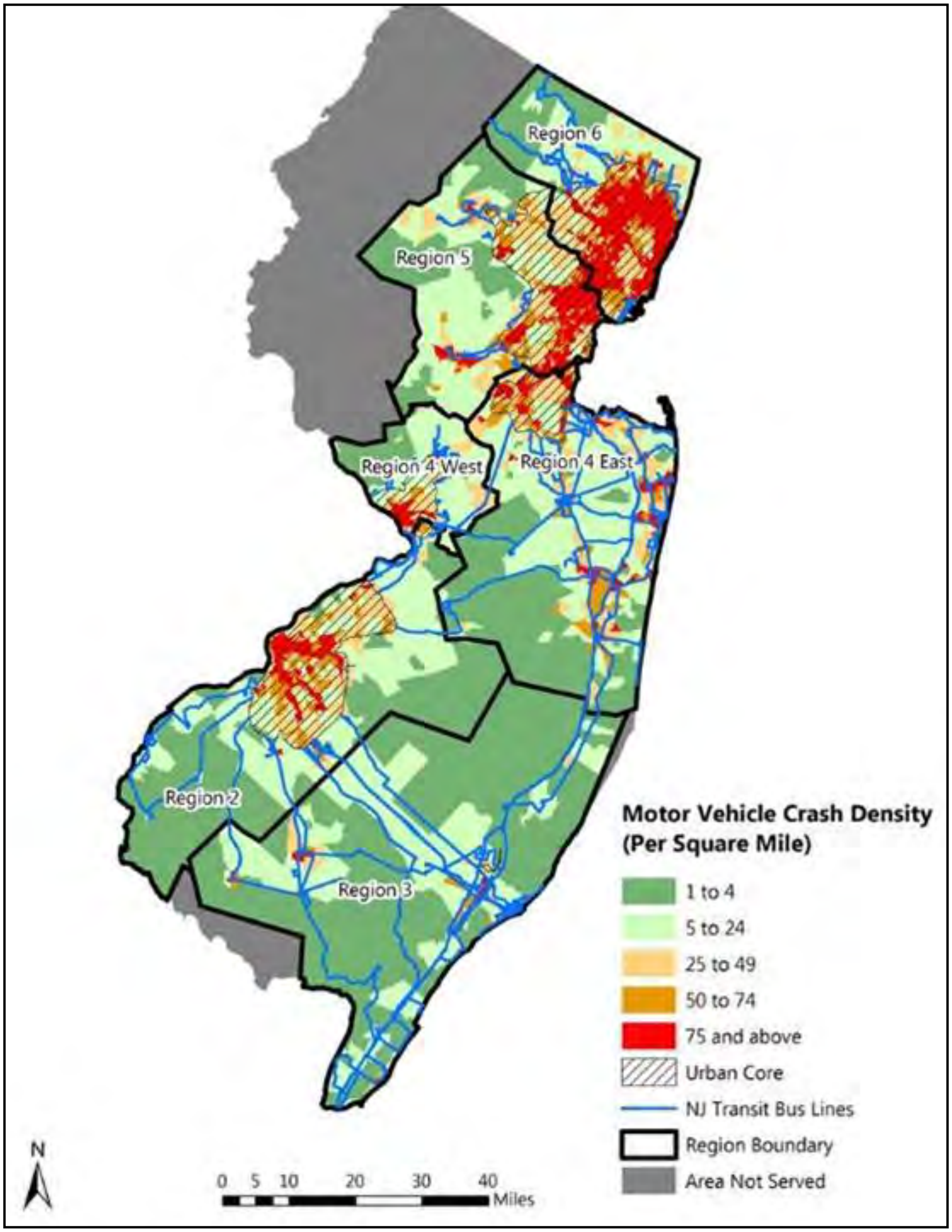


Figure 34. Crash Density in the Access Link Service Area

The regions with high mean MPM also have larger MPM Windows, but that is because (all else being equal) a high value of Standard Deviation can be expected when a distribution has higher values compared to a distribution with lower values. When one considers Percent Variation of MPM, Region 5 moves to the bottom and Region 4-East, a relatively low-density region with a small part designated as urban core, moves to the top. Despite the high value of Percent Variation, however, trip makers in the region experience higher reliability in terms of absolute minutes compared to four other regions because the region's MPM Standard Deviation is low. Yet another picture emerges when one considers Buffer Index or Misery Index, the measures that compare extreme MPM values to the mean. By both these measures, travel time reliability is the lowest for Region 4-West, a small region having areas with fairly high density. By both these measures, reliability is low in Region 5 and Region 6 also, where MPM Windows are the largest.

The analysis of trips at the regional level shows that travel time reliability varies according to measures used. When MPM Standard Deviation or MPM Window is considered, Regions 5 has the lowest reliability followed by Region 6; when Percent Variation is considered, Region 4-East has the lowest reliability followed by Region 2; and when Misery Index and Buffer Index are considered, Region 4-West has the lowest reliability followed by Region 5 and Region 6, respectively. Thus, whether a region is better off than the other regions is dependent on which measure of travel time reliability is used to compare the regions.

Regression Models on the Measures of MPM Variability

Although the basic comparison of regional MPM variability in the previous section is insightful, it has certain limitations. One limitation is that the trips included in the analysis were made between different origins and destinations, with different types of vehicles, at different times of day, and in different seasons. Furthermore, the analysis does not provide any insights about the variables that may be associated with travel-time variability of trips. To address these limitations, OLS regression analysis is carried out in this section by considering MPM variations of trips for OD pairs with sufficiently large number of trips and examining the association of trip- and location-related variables with the MPM variations for the OD pairs. The premise of the analysis is that trip MPM fluctuates differently for different OD pairs, and the degree of fluctuation is associated with the characteristics of the pickup and drop-off locations and the characteristics of the trips. For example, if MPM varies widely for trips between origin i and destination j, but varies little between origin k and destination l, by comparing the characteristics of i and k, and j and l, after controlling for other characteristics of trips t_{ij} and t_{kl}, one should be able to tell why greater MPM variability occurs between i and j than between k and l.

In order to estimate variability of trip MPM through regression models, only those OD pairs were selected between which 30 or more trips were made in the 24-month study period. It was decided to estimate MPM variability for OD pairs with 30 or more trips because (a) the 5% level of significance is achieved on a t-distribution at 30 degrees of freedom, and (b) setting a margin greater than 30 would limit the number of OD pairs substantially for regions with relatively smaller number of trips (e.g., Region 3 and Region 4-West) and thus reduce the geographic representation of the analysis. A total of 9,799 OD pairs were found to have 30 or more trips in the entire 18-county study area. Despite defining origins and destinations as exact locations or addresses, it was possible to obtain such a large number of OD pairs because (a) the data set includes a total of 1.9 million trips, and (b) riders often make trips between the same origins and destinations because the home end of trips remains the same unless households move and a large number of travelers evidently repeat trips to identical destinations.

Regression models were used to estimate all four measures of travel-time variability described previously. The results of the regression models on Standard Deviation and Percent Variation are presented in Table 24, and the results of the models on Misery Index and Buffer Index are presented in Table 25. As can be seen in the two tables, the independent variables of the models pertain to the origin and destination locations as well as to characteristics of the trips between the OD pairs. Since the observations for the models are OD pairs, several trip-related variables are expressed as proportions. For example, seasonal variability of trips between OD pairs is accounted for by including a variable on proportion of trips in winter months. The variables that pertain to origin and destination locations have been treated differently, however, since they remain constant for each OD pair.

The first independent variable of the models shown in Table 24 and Table 25, the network distance between the origins and destinations, was included with the hypothesis that it would be negatively associated with travel-time variability because vehicle operators have a greater opportunity to make up lost time for those trips than for shorter trips. The second variable, the number of trips between OD pairs, was included with the hypothesis that a greater number of trips would involve smaller variability because of the familiarity of operators with the routes and the pickup and drop-off locations. A variable on proportion of subscription-booking trips was included with the hypothesis that subscription trips would involve a lower variability than demand-response trips because of the familiarity of both operators and riders with routes and the pickup and drop-off locations. A variable on proportion of trips during the winter months (December-February) was included with the hypothesis that a greater proportion of winter trips would increase variability because of variations in winter weather conditions. A variable on proportion of trips in summer months (June-August) was included with the opposite hypothesis. A variable on proportion of weekend trips was included with the hypothesis that it would be negatively associated with overall variability (as expressed by the Standard Deviation) because of lower overall traffic volume on weekends, but could be positively associated with Misery Index and Buffer Index because of sporadically high traffic volumes generated by special events (e.g., football games) and activities in the Jersey-shore areas and other recreational areas. Three variables on morning and afternoon/evening peak periods were included with the opposite expectation.

Two location-specific variables that are of utmost interest for this research are density of crashes in the pickup and drop-off census tracts. Although day-to-day driving experiences tell us that crashes cause unpredictable delays and travel-time variability, the objective of the modeling effort here is to examine if a high variability of travel time is observed for places that experience large volumes of crashes. The expectation obviously is that the two variables would be positively associated with MPM variability.

Intersection density, population density, and job density of pickup and drop-off block groups were included in the models with the hypothesis that they would be positively associated with overall variability, as expressed by the Standard Deviation, because these variables can potentially increase MPM. When MPM is high, its variability in absolute terms is also likely to be high. The variables were included in the other models for the sake of consistency across the models rather than any definite expectation. Similarly, two variables indicating whether pickups and drop-offs take place in ¾-mile buffers along bus routes (against urban core areas) were included with the hypothesis that absolute variability would be low in the buffers because of low MPM resulting in those areas due to proximity to high-speed roads. Two variables on per-capita income were also included with the expectation that they would be negatively associated with MPM, and hence also with absolute fluctuations of MPM, because high-income neighborhoods are out in the suburbs with good freeway access. Because of its potential to increase absolute MPM and variability, a variable on proportion of trips using wheelchair was included. Although a very small proportion of trips are made by sedans, a variable on the proportion of trips by this type of vehicle was included with the opposite expectation, namely, that it would be negatively associated with absolute MPM and its variability.

Table 24. Regression Models on Standard Deviation and Percent Variation of MPM

	Y=Standard Deviation		Y=Percent Variation	
Variables	**Coeff.**	**t Value**	**Coeff.**	**t Value**
Intercept	2.5206[a]	25.22	42.9239[b]	53.13
Network distance between origin and destination (mile)	-0.0611[a]	-39.23	-0.3141[b]	-24.94
Number of trips between OD pair	0.0002	1.63	0.0020[c]	1.80
Proportion of trips using subscription booking	-0.1780[a]	-4.47	-4.1140[b]	-12.79
Proportion of trips made during winter months	0.6388[a]	3.39	5.6304[b]	3.69
Proportion of trips made during summer months	0.1226	1.11	0.0449	0.05
Proportion of trips made on weekend	-0.0391	-0.72	0.9937[b]	2.27
Proportion of trips between 7 and 9 AM	0.2166[a]	4.32	-3.2229[b]	-7.96
Proportion of trips between 2 and 4 PM	0.4382[a]	9.32	-0.6653[c]	-1.75
Proportion of trips between 4 and 6 PM	0.2911[a]	4.76	0.6920	1.40
Crashes per acre in pickup census tract	0.9515[a]	8.82	3.5764[b]	4.10
Crashes per acre in drop-off census tract	0.8691[a]	8.07	4.7654[b]	5.48
Intersections per acre in pickup block group	0.0406	0.30	-0.4555	-0.42
Intersections per acre in drop-off block group	0.3723[a]	2.82	-0.3171	-0.30
Population per acre in pickup block group	0.0054[a]	4.23	-0.0062	-0.61
Population per acre in drop-off block group	0.0049[a]	3.85	-0.0193[c]	-1.90
Jobs per acre in pickup block group	0.0001	0.17	-0.0016	-0.26
Jobs per acre in drop-off block group	0.0000	-0.06	0.0033	0.55
Pickup location within 3/4 mile of bus route	-0.1451[a]	-2.83	-2.0676[b]	-4.99
Drop-off location within 3/4 mile of bus route	-0.1543[a]	-3.01	-0.5066	-1.22
Per capita income in pickup block group (in $10,000)	-0.0699[a]	-6.07	-0.0244	-0.26
Per capita income in drop-off block group (in $10,000)	-0.0472[a]	-4.13	0.0040	0.04
Proportion of trips using wheelchair	0.2672[a]	6.91	-2.8247[b]	-9.04
Proportion of trips using sedan	-0.4852	-1.12	-1.2932	-0.37

Variables	Y=Standard Deviation Coeff.	t Value	Y=Percent Variation Coeff.	t Value
Proportion of trips by persons age 65+	0.1968[a]	5.49	0.3644	1.26
Proportion of trips by female trip maker	0.1138[a]	3.95	-0.0433	-0.19
Region 2 - Dummy	-0.1560[b]	-2.52	3.6152[b]	7.23
Region 3 - Dummy	-0.1378[a]	-3.23	1.9503[b]	5.66
Region 4-West - Dummy	-0.3542[a]	-4.18	2.9178[b]	4.26
Region 4-East - Dummy	-0.4054[a]	-6.69	0.0789	0.16
Region 5 – Dummy (Referent)				
Region 6 – Dummy	-0.3557[a]	-8.60	-0.8699[b]	-2.60
N (number of OD pairs)	9,421		9,421	
F	140.0		48.3	
Adjusted R-square	0.307		0.131	

[a] *Significant at the 1% level;*
[b] *Significant at the 5% level;*
[c] *Significant at the 10% level.*

Table 25. Regression Models on Misery Index and Buffer Index of MPM

Variables	Y=Misery Index Coeff.	t Value	Y=Buffer Index Coeff.	t Value
Intercept	0.5786[a]	44.00	0.8746[a]	45.69
Network distance between origin and destination (miles)	-0.0030[a]	-14.45	-0.0075[a]	-25.25
Number of trips between OD pair	0.0000[b]	-2.32	0.0000[c]	-1.78
Proportion of trips using subscription booking	-0.0648	-12.38	-0.1017[a]	-13.34
Proportion of trips made during winter months	0.0505[b]	2.04	0.1559[a]	4.32
Proportion of trips made during summer months	-0.0179	-1.23	0.0334	1.58
Proportion of trips made on weekend	-0.0030	-0.41	0.0354[a]	3.41
Proportion of trips between 7 and 9 AM	-0.0297[a]	-4.50	-0.0991[a]	-10.33
Proportion of trips between 2 and 4 PM	-0.0117[c]	-1.88	-0.0391[a]	-4.34
Proportion of trips between 4 and 6 PM	0.0126	1.57	-0.0157	-1.34
Crashes per acre in pickup census tract	0.0609[a]	4.29	0.0702[a]	3.40
Crashes per acre in drop-off census tract	0.0623[a]	4.40	0.0856[a]	4.15
Intersections per acre in pickup block group	-0.0034	-0.20	-0.0039	-0.15
Intersections per acre in drop-off block group	-0.0265	-1.53	-0.0104	-0.41
Population per acre in pickup block group	0.0002	0.97	-0.0001	-0.42
Population per acre in drop-off block group	-0.0002	-1.33	-0.0003	-1.22
Jobs per acre in pickup block group	0.0000	0.13	0.0000	0.09
Jobs per acre in drop-off block group	0.0001	0.89	0.0001	0.39
Pickup location within 3/4 mile of bus route	-0.0370[a]	-5.48	-0.0420[a]	-4.27
Drop-off location within 3/4 mile of bus route	-0.0143	-2.12	0.0032	0.32
Per capita income in pickup block group (in $10,000)	0.0002	0.12	-0.0001	-0.04
Per capita income in drop-off block group (in $10,000)	-0.0011	-0.70	-0.0020	-0.91
Proportion of trips using wheelchair	-0.0450[a]	-8.83	-0.0647[a]	-8.74
Proportion of trips using sedan	-0.0690	-1.22	0.0313	0.38
Proportion of trips by persons age 65+	0.0059	1.25	0.0111	1.61

Variables	Y=Misery Index Coeff.	Y=Misery Index t Value	Y=Buffer Index Coeff.	Y=Buffer Index t Value
Proportion of trips by female trip maker	-0.0027	-0.71	0.0049	0.89
Region 2 - Dummy	0.0441[a]	5.41	0.0560[a]	4.72
Region 3 - Dummy	0.0208[a]	3.71	0.0371[a]	4.54
Region 4-West - Dummy	0.0528[a]	4.74	0.0804[a]	4.95
Region 4-East - Dummy	-0.0147	-1.84	0.0088	0.75
Region 5 – Dummy (Referent)				
Region 6 – Dummy	-0.0086	-1.58	-0.0190[b]	-2.40
N (number of OD pairs)	9,421		9,421	
F	31.3		53.1	
Adjusted R-square	0.088		0.142	

[a] *Significant at the 1% level;*
[b] *Significant at the 5% level;*
[c] *Significant at the 10% level.*

Since no information is available on the actual trip purpose of the trip makers, two variables representing demographic characteristics, namely, proportion of trips made by persons aged 65 and over and female persons, were included with the expectation that they could be associated with variability due to latent trip purposes. It was hypothesized that these variables would serve as proxies for trip purposes if elderly or female persons visit particular types of activities that are latently associated with MPM variability.

Finally, a set of five dummy variables on Access Link regions were included in the four models in Table 24 and Table 25 by using Region 5 as the referent region. These variables were included to capture the effect of geographic diversity of variability that is not captured by the other variables. Their inclusion in the models would also help to examine if the rankings of the regions by the four performance measures shown in Table 23 are consistent.

Several important observations can be made from the results of the four models in Table 24 and Table 25. First, the larger size of the adjusted R-square of the model on MPM Standard Deviation compared to the other three models indicates that predicting absolute variability of MPM may be easier than predicting variability normalized by the mean (i.e., Percent Variation) or predicting travel-time reliability defined by the difference between the mean and extreme values, as in the case of the Buffer Index and Misery Index. It is not surprising that extreme travel-time variability is more difficult to predict than overall variability because extreme travel times are mostly experienced because of specific events or incidents.

Second, only six variables included in the models are consistently significant with expected signs in all four models. These variables are crash density in the pickup census tract, crash density in the drop-off census tract, distance between pickup and drop-off locations, proportion of trips by subscription booking, proportion of trips in winter months, and pickup in ¾-mile buffers along bus routes. The consistency of the relationship of these variables with all four measures reveals their importance in predicting travel time reliability.

The positive relationship between crash density of census tracts and MPM variability should be noteworthy for both researchers and practitioners. The results are convincing because the association between crashes and MPM variability remains significant with expected signs in all four models even when crash density is measured at the level of municipalities instead of census tracts. Although it is common-sense knowledge that roadway crashes cause unpredictable delays and thus increase travel-time variability, considering that this analysis is place-based instead of being event-based, it is an important finding of this research. It shows that even place-based aggregated crash data can provide insights about the potential effect of crashes on travel-time variability.

The model results can be used to estimate how much each measure of variability will change with changes in number of crashes in a census tract in a 24-month period. For example, using the coefficient for crash density in drop-off location in Table 24, it can be estimated that an increase in number of crashes from 40 to 60 in a 500-acre tract would increase MPM Standard Deviation from 0.07 to 0.10.

The negative association between trip distance and travel-time variability in all four models provides credence to the hypothesis that vehicle operators have a greater opportunity to make up lost time in long trips than short trips. The results of the variable on winter travel also shows what is usually believed, that travel time fluctuations are more common in winter conditions because of occasional ice and snow. Similarly, the result of the variable on subscription booking shows that familiarity of riders and operators with the trip and the origin and destination locations can reduce MPM variability. The negative association between pickups in ¾-mile buffers and MPM variability in all four models is also consistent with expectation.

Third, many more variables are significant with expected signs in the model on MPM Standard Deviation than in the other three models. For example, the model shows that MPM Standard Deviation is high when trips are made in the morning and afternoon peak periods, when trips are generated in locations with high population density and low income, when the proportion of trips with wheelchairs onboard is high, and when a greater proportion of trips are made by older persons and women. However, these variables fail to remain significant or become significant with the opposite sign in the other models. In some cases, as in the case of peak period trip share, the change in the direction of relationship makes intuitive sense. The MPM Standard Deviation is potentially high for peak period trips because absolute MPM is high in peak periods, but when the variation is normalized by the mean to estimate Percent Variation, variability would be low because of a high mean MPM in peak periods. Peak period variability measured by Misery Index and Buffer Index may be low because the high lower bound of peak period trip MPM due to high traffic volume can reduce the gap between extreme values and the mean. Similarly, trips with wheelchairs onboard may have high MPM Standard Deviation because of high MPM of those trips, but when the focus is on a normalized MPM or extreme values of MPM, they may have low variability. It would not be surprising if travelers requiring wheelchairs deliberately avoided trips that could potentially experience extreme delays, such as trips in the Jersey-shore areas during summer weekends or trips on special-event days.

Finally, the dummy variables on the Access Link regions show more or less expected results, as the regions that topped three measures of variability in Table 23 (Region 5 for Standard Deviation and Region 4-West for both Buffer Index and Misery Index) continue to be at the top according to the model coefficients. However, the ranks of the regions changed for Percent Variation. Overall, despite continuing to have the highest MPM Standard Deviation, Region 5 appears to be better off according to the model results than it appeared from the direct comparison in Table 23. On the other hand, Region 2 appears worse off according to the model results than it appeared from the direct comparison.

The Effect of Crash Incidents on Trip MPM

The regression models with aggregated data for trip origins and destinations provided evidence that a higher volume of crashes in places is positively associated with MPM variability of Access Link trips. However, the analysis did not show a causal connection, as crashes were not directly linked to MPM of specific trips. Analysis is carried out in this section to examine if specific crash incidents in drop-off locations can be directly linked to individual Access Link trips. It is possible to test the direct link between specific crashes and MPM for specific trips by combining Access Link trip data and P4S crash data, because the first data set provides time and location coordinates of each drop-off and the second data set provides time and location of each crash.

The primary hypothesis for this analysis is that a trip ending at a location that had a crash a short while before the drop-off experiences greater MPM compared to a similar trip ending at a location that did not experience a crash prior to the drop-off. Two types of geographic areas and three time periods were considered at the outset: census tracts and municipalities for geographic areas and 30-minute, 60-minute, and 90-minute windows prior to a drop-off as the effective period. Since the results based on census tracts and municipalities were virtually identical, only the results from the models based on census tracts are presented. Among the three time periods considered, a 60-minute window prior to a drop-off was considered to be the most effective. Thirty minutes was considered inappropriate because of the possibility of approximation of time entered by law-enforcement personnel at crash sites and insufficient traffic spillover and blockage within that time frame. Ninety minutes was considered too long because traffic spillover and blockage may dissipate towards the end of the time period.

Of the 1.9 million Access Link drop-offs in the full data set, 176,948 (9.3%) occurred in a census tract that experienced a crash on the day of the drop-off, but only 10,468 (0.55%) occurred in a tract that experienced a crash within a 60-minute window prior to the drop-off. When the census tracts were restricted to those that experienced a crash at any time during the day of a drop-off, the mean MPM for trips with a drop-off within 60 minutes of a crash was 5.82, whereas the mean MPM for the rest of the trips was 5.53, a difference that is statistically significant at the 1% level. This difference translates to 5.3% greater MPM for trips with drop-offs preceded by a crash in a 60-minute window compared to the rest of the trips. Although the crashes might have affected some Access Link trips by a significantly greater margin, considering that some trips might not have been affected at all because the vehicles entered the tracts from a direction not affected by the crashes, the mean difference has to be considered substantial.

Since the 5.3% greater MPM for trips with drop-offs in a tract that experienced a crash within a 60-minute period prior to the drop-off could be because of a number of factors other than the crash, an OLS regression model was used to compare the MPM of such trips with the MPM of other trips after controlling for the potential effects of the other factors. To maintain consistency with the models on MPM variability in the previous section, only those trips were included in the model that constituted the OD pairs in Table 24 and Table 25. In order to exclude census tracts where crashes are extremely rare, only those trips were included that had a crash on the day of the drop-off. Thus, a trip involving a drop-off within 60 minutes of a crash in the drop-off tract was coded 1, and a trip involving a crash in the drop-off tract at some other time of the day was coded 0. For example, if a crash occurred at 2 PM in a tract and the drop-off occurred between 2 PM and 3 PM, the trip was coded 1, but if a crash occurred in another tract at 2 PM and a drop-off occurred there before 2 PM or after 3 PM, the trip was coded 0. Although several other independent variables were included in the model, this variable is of utmost interest because it can demonstrate whether, or to what extent, crashes affect paratransit-trip MPM.

The results of the MPM model are presented in Table 26. The dependent variable, MPM, was included in its natural-log form to compress extreme variations. Most of the variables included in the models in Table 26 represent the same trip characteristics as the variables in Table 24 and Table 25. However, they are used as dummy variables in the trip MPM model because the observations are trips, whereas they were used as proportion of trips in MPM variability models because the observations were OD pairs. Two variables in the MPM variability models were not included in the MPM Model. The variable on number of trips between OD pairs was dropped because it is irrelevant for the MPM model in Table 26. The variable on trip distance was dropped because the dependent variable of the model in Table 26, MPM, is directly estimated from this variable.

Although many of the variables included in the MPM model represent the same trip characteristics as the variables in the models in Table 24 and Table 25, they were not necessarily included with the same hypothesis or expectation. For example, the variable on subscription booking was included in the MPM variability models with the expectation that such trips would have lower variability because both riders and operators are likely to be more familiar with the trips, but in the case of the model in Table 26, subscription booking trips were expected to have a positive association with MPM because such trips are more likely to be made to travel to work and school compared to demand-response trips. In contrast, weather conditions were expected to affect MPM and MPM variability in the same way. MPM of winter trips was expected to be higher because of adverse driving conditions, whereas the MPM of summer trips was expected to be lower because of favorable conditions. Similarly, MPM of weekend trips was expected to be lower because of lower traffic volumes, whereas MPM of morning and afternoon/evening peak period trips was expected to be higher because of high traffic volumes.

Density of intersections, jobs, and population were expected to be positively associated with MPM. Frequent stops and turns in areas with high intersection density can reduce speed. Similarly, high pedestrian volumes in areas with high population and employment density can lower trip speed. Trips with pickups and drop-offs in ¾-mile buffers along bus routes were expected to have lower MPM, because these buffers are typically in suburban corridors with good access to freeways. Similarly, pickups and drop-offs in high-income areas were expected to have lower MPM, because these areas are also typically in suburbs with good freeway access. Trips with sedans were expected to have lower MPM, because they can weave through traffic more easily than ambulatory vehicles. In contrast, trips with wheelchairs onboard were expected to have higher MPM, because of extra care taken by vehicle operators. For the same reason, trips with elderly riders onboard were expected to have higher MPM. The variable on female riders was included for the sake of consistency with the MPM variability models. The variation of MPM among the regions was expected to be consistent with the mean MPM shown in Table 23, i.e., Region 5 would have the highest MPM, Region 3 would have the lowest MPM, and the other regions would follow the same ranking as in Table 23.

The first trip MPM model in Table 26 was estimated from the data set for the entire study area with trips that matched the selection criteria. For the second and third models in the table, the data set was further restricted to Regions 2 and 6 to show results at the regional level. Similar models were run for all six regions, but the results of the other regions are not shown because of space limitation.

Table 26. Regression Models on Trip MPM for the Entire Study Area and Two Specific Regions

	Entire Study Area		Region 2		Region 6	
	$Y=\log_e(MPM)$		$Y=\log_e(MPM)$		$Y=\log_e(MPM)$	
	Coeff.	t Value	Coeff.	t Value	Coeff.	t Value
Intercept	1.5663[a]	176.74	1.4391[a]	83.74	1.2926[a]	70.00
Crash in tract within 60 minutes before drop-off	0.0423[a]	7.00	0.0372[a]	3.26	0.0565[a]	3.73
Subscription booking trip	0.0383[a]	12.07	0.0695[a]	11.33	-0.0250[a]	-3.36
Trip made in winter (Dec., Jan., Feb.)	-0.0060	-1.40	-0.0283[a]	-3.39	-0.0045	-0.44
Trip made in summer (June, July, Aug.)	-0.0234[a]	-6.75	-0.0291[a]	-4.47	-0.0330[a]	-3.86
Weekend trip	-0.0755[a]	-14.14	-0.0845[a]	-7.45	-0.0689[a]	-5.51
Pickup between 7 and 9 AM	0.1840[a]	49.36	0.1896[a]	26.81	0.1503[a]	15.81
Pickup between 2 and 4 PM	0.2133[a]	52.51	0.2729[a]	34.87	0.1109[a]	10.87
Pickup between 4 and 6 PM	0.1089[a]	19.48	0.0526[a]	4.54	0.1173[a]	9.53
Intersections per acre in pickup block group	0.3661[a]	27.61	0.2797[a]	8.75	0.0952[a]	3.19
Intersections per acre in drop-off block group	0.4324[a]	30.79	0.5225[a]	14.48	0.3548[a]	11.72
Population density per acre in pickup block group	0.0009[a]	6.98	-0.0005	-0.82	0.0023[a]	12.35
Population density per acre drop-off block group	0.0039[a]	26.52	-0.0040[a]	-5.60	0.0061[a]	28.36
Jobs per acre in pickup block group	0.0001	0.87	0.0026[a]	5.68	-0.0009[a]	-4.67
Jobs per acre in drop-off block group	0.0000	-0.66	-0.0009[c]	-1.81	-0.0009[a]	-4.79
Pickup location within ¾-mile buffer of bus route	-0.1699[a]	-31.70	-0.2887[a]	-32.55	-0.0581[a]	-4.34
Drop-off location within ¾-mile buffer of bus route	-0.1122[a]	-19.14	-0.2229[a]	-22.84	-0.0598[a]	-3.69
Per capita income in pickup block group (in $10,000)	-0.0364[a]	-29.02	-0.0354[a]	-11.56	-0.0159[a]	-5.37
Per capita income in drop-off block group (in $10,000)	-0.0251[a]	-20.35	-0.0102[a]	-3.28	0.0061[c]	1.90
Wheelchair onboard during trip	0.1906[a]	44.21	0.1074[a]	13.33	0.1419[a]	12.58
Sedan used for trip	-0.1415[a]	-4.09	-0.2318[b]	-2.49	-0.0791[b]	-2.12

	Entire Study Area		Region 2		Region 6	
	Y=$\log_e$(MPM)		Y=$\log_e$(MPM)		Y=$\log_e$(MPM)	
	Coeff.	**t Value**	**Coeff.**	**t Value**	**Coeff.**	**t Value**
Trip maker age 65+	0.0697[a]	17.25	0.0680[a]	7.23	0.1070[a]	12.06
Female trip maker	0.0336[a]	11.57	0.0215[a]	3.90	0.0164[b]	2.36
Region 2	-0.1359[a]	-32.19	NA	NA	NA	NA
Region 3	-0.2347[a]	-26.38	NA	NA	NA	NA
Region 4-West	-0.1522[a]	-25.08	NA	NA	NA	NA
Region 4-East	-0.1690[a]	-25.59	NA	NA	NA	NA
Region 5 (Referent)						
Region 6	-0.1946[a]	-44.32	NA	NA	NA	NA
N	123,074		32,202		21,041	
F	1363.8		280.12		146.55	
Adjusted R-square	0.230		0.1602		0.1321	

[a] *Significant at the 1% level;*
[b] *Significant at the 5% level;*
[c] *Significant at the 10% level;*
NA Not applicable as variable not included in model.

With a few exceptions, the variables in the models showed expected signs. Since the reasons for their inclusion are already described, the results of the statistically significant variables other than the variable on crash are not elaborated further. The variable on crash occurrence within 60 minutes before a drop-off had a positive sign in all three models shown. When the model was repeated for the other regions, the variable was statistically significant at the 1% level for Region 5 and at the 10% level for Region 4-East. However, it was not statistically significant for Region 3 and Region 4-West. Although the variable had the expected positive sign in both models, it was significant only at the 12% level for Region 4-West and at the 29% level for Region 2. A reason for the variable not being significant in the two regions could be that they have the smallest number of trips among the regions.

According to the results of the model for the entire study region, trips ending in a tract that experienced a crash in a 60-minute window prior to the drop-off had 4.3% greater MPM than the other trips. Although this is lower than what was observed from a direct comparison, it is still significant. The other models indicated that MPM for trips involving a crash within the 60-minute window was 3.7% greater in Region 2 and 5.7% greater in Region 6. Similarly, the models for Region 4-East and Region 5 showed that MPM for trips involving a crash within the 60-minute window was 3.6% and 3.5% greater, respectively, than the other trips.

The three variables that did not show expected results are job density in pickup location, job-density in drop-off location, and winter trip. When these variables were dropped in additional runs, the models continued to show results similar to those shown in Table 26. It may also be noted that the variables that are significant in the models in Table 26 continued to be significant when the models were run without log-transforming the dependent variable, although the adjusted R-square of the models decreased modestly.

Summary

The paper focused on travel-time variability, or reliability, of paratransit trips with a special emphasis on the potential effect of motor vehicle crashes on reliability. It showed through basic comparisons the differences among the six Access Link regions according to four variability measures and identified variables associated with paratransit reliability through regression models. It showed that a number of characteristics of the trips and the pickup and drop-off locations are associated with travel-time variability. Although reliability can vary according to the measures used, the models showed that six variables are consistently associated with expected signs with reliability irrespective of the measures used. The most important among the variables is crash density, which seems to affect reliability at both ends of paratransit trips.

From the regression models on the four measures of travel-time variability, it became evident that Standard Deviation can be predicted more effectively by trip and place characteristics than the measures that are focused on extreme travel time, such as Misery Index and Buffer Index. Yet it was found that crash density of pickup and drop-off locations is associated even with the reliability measures that focus on extreme variation of travel time.

The subsequent regression models showed that the occurrence of a crash in a location prior to a drop-off is positively associated with trip MPM, providing evidence of a potentially causal link between individual crashes and individual trip MPM. The model showed that MPM is about 4-5% higher when a crash occurs in a location prior to a drop-off. Considering that a paratransit vehicle can enter a census tract or a municipality from any direction and therefore does not have to be affected by each crash that occurs prior to a drop-off, 4-5% greater MPM for an average trip is substantial. When thousands of paratransit trips are made per month in areas with high crash incidents, as in the Access Link service area, even 4-5% higher MPM can lead to a substantial amount of unexpected delay. Consequently, such delays can also lead to scheduling difficulties.

The findings of this study should be of interest to both paratransit service providers and agencies funding such services. It showed that crashes and a number of other location-related, trip-related, and seasonal factors can influence paratransit's travel-time variability. By conducting similar analysis for their own areas, service providers can determine what level of travel-time penalties should be imposed on trips to and from specific locations based on crash density and other location characteristics so that vehicle runs can be scheduled optimally. That, in turn, will increase reliability, reduce frustration of riders because of unexpected delays, and make paratransit service more efficient. As geocoded crash data have become increasingly available for states and metropolitan areas, utilization of such data for trip-scheduling purposes can enhance paratransit's travel-time reliability, customer satisfaction, and efficiency.

V. CONCLUSIONS AND FUTURE WORKS

This report could provide guidance and help for bridge engineers and traffic and planning engineers from local transit agencies regarding the improvement of resiliency and reliability of transit infrastructure, and of the public transit network based on the enhancement of proposed performance measures. Local transit agencies would employ the potential application remote sensing in assessing post-disaster performance of infrastructure. They would also be able to assess and improve the resiliency of the local public transit network by evaluating the proposed performance measures in this report. This report also would help local transit agencies optimize the costs of paratransit service and improve the efficiency of paratransit service based on the data-driven models. The following conclusions can be drawn from the previous analysis:

POST-DISASTER MANAGEMENT USING REMOTE SENSING - INSAR

- Based on field-testing and finite element modeling of bridge structure, performance of bridges before the disaster could be simulated and verified. Quick evaluation of bridge condition in a post-disaster mode can be re-evaluated using InSAR technology for the bridge network due to various effects such as support movement, member failure, etc. Additionally, the bridge SHM system, if still operational post-disaster, would be utilized for further confirmation to check bridge response after the disaster. This proposed damage-detection procedure would enable a quick damage assessment for numerous bridges on a bridge network basis, thus providing rapid, optimized, and cost-effective management of road and bridge network post-disasters. With the proposed approach, transit agencies could assess the load-carrying capacity of their bridge structures promptly and efficiently. Major decisions could be made based on the results of proposed approach.

- Based on visual inspection of generated InSAR images in the case studies discussed earlier, the Envisat satellite's 20-meter spatial resolution only allows for detection of bridge structures, roads, and airport runways that are at least 20 to 30 meters wide, by using the InSAR magnitude image. Bridge structures over water channels, however, can only be detected if they are oriented in a non-perpendicular direction with respect to the imaging satellite. Moreover, only significant level of deformation or damage in these structures can be detected by using the InSAR coherence image. Therefore, the extraction of detailed and quantifiable post-disaster damage information about the transportation infrastructure is not feasible while using 20-meter spatial resolution SAR imagery. Hence, the need for much higher spatial resolution SAR data that allows for detailed post-disaster damage assessment becomes very obvious.

IDENTIFICATION OF TRIP GENERATORS AND FACTORS ASSOCIATED WITH TRIP DELAY AND RELIABILITY OF DISABILITY PARATRANSIT

- Demand for paratransit for persons with disabilities has been steadily increasing over time. Because of the high cost of the service, transit agencies nationwide are under pressure to make their services as efficient as possible without compromising service quality or customer satisfaction. This research considered ways to increase paratransit's service efficiency by identifying its potential trip generators and the factors associated with trip delay and travel time reliability.

- This research used a large data set containing more than 1.9 million trips made by Access Link disability paratransit service provided by NJ TRANSIT in 18 New Jersey counties. The first component of this study focused on identifying potential trip generators of Access Link trips. Identifying trip generators is important for appropriately estimating and forecasting demand for trips. Travel surveys can provide useful information about the generators of paratransit trips. However, the literature review showed that travel surveys involving disability paratransit trip riders have been rare. This research showed that, in the absence of travel surveys, using statistical models with trip data could provide some insights about the places that are likely to generate more trips than others. In the case of Access Link, it was found that places with a high proportion of elderly persons, minority populations, and multi-family residences are more likely to produce home-end trips than other places, whereas places with large amounts of jobs in health care services, retail services, food and accommodation services, and administrative support services are likely to generate more non-home trips. The analysis with establishment-level data showed that non-home drop-offs occur more frequently near health services, social services, educational services, and membership services (i.e., religious service) establishments than other types of establishments. The analyses carried out at the Census Block Group level and establishment level together indicate that the number and distribution of elderly persons and minority persons as well as jobs in the health care services, social services, and educational services will have a substantial impact on where the demand for Access Link will increase in the future. Forecasting future demand on the basis of these variables could increase the service's efficiency.

- While analysis of trip generators showed that places with low-to-moderate median home value, a high proportion of minority population, a high proportion of multi-family homes, and a large number of jobs in the health care sector, the retail sector, the food and accommodation sector, and administrative support sector are likely to generate more Access Link trips than other places, the analysis of delay showed that places that have a high density of population, jobs, and intersections experience greater delay than other places. Since places that have a greater propensity to generate Access Link trips also happen to have the characteristics that are typically associated with trip delay, such as high density of population and jobs, keeping Access Link service efficient is an inherent challenge. If the places that generate more trips had different characteristics, such as lower density of population, jobs, and intersections, it would be far less challenging and more efficient to provide the service.

- The relationship between density and paratransit trip delay has implications for transportation and land-use planners. While mainstream transportation studies perceive lower VMT and higher share of transit and pedestrian trips associated with high density as desirable, paratransit trips experience more delay in dense environments. Since a large proportion of paratransit clients live in urban centers where population, employment, and intersection density are high, a large proportion of trips experience delay due to high density. In contrast to urban core areas, trips beginning in ¾-mile buffers along bus routes, mostly located in suburban areas, experience a significantly lower level of delay. However, far fewer clients live in those areas.

- Since both density and paratransit are beneficial to society, transportation planners and traffic engineers should consider strategies that can reduce delay of paratransit trips in high-density areas. Regular adjustment of signal timing at critical intersections based on up-to-date traffic data could be one such strategy. Another strategy could be network-based optimization of signal timing in high-density areas. Yet another strategy would be to implement bus priority at intersections in high-density areas and to afford paratransit vehicles the same privileges as buses. When opportunities arise to develop activities that generate a substantial amount of trips, or to increase population or employment density through new construction, urban planners should also bear in mind the potential negative effects of density and congestion on bus and paratransit.

- The third and final component of this research focused on travel-time reliability of paratransit trips with an emphasis on the effect of motor vehicle crashes. It considered travel-time reliability according to four commonly used measures: Standard Deviation, Percent Variation, Misery Index, and Buffer Index. It helped identify a number of characteristics of the trips and the pickup and drop-off locations that are associated with travel-time variability. Although reliability varies according to the measures used, statistical models showed that six variables are consistently associated with reliability irrespective of which measure is used. The most important among the variables is crash density, which affects reliability at both ends of paratransit trips.

- The regression models showed that Standard Deviation could be predicted more easily and effectively by trip and place characteristics than the measures that are focused on extreme travel time, such as Misery Index and Buffer Index. Yet it was found that crash density of pickup and drop-off locations is associated even with the reliability measures that focus on extreme variation of travel time.

- Additional regression models showed that a motor vehicle crash in a location prior to a drop-off is positively associated with trip duration (MPM), providing evidence of a potentially causal link between individual crashes and individual trip MPM. The analysis showed that MPM could be 4-5% higher when a crash occurs in a location prior to a drop-off. Since a paratransit vehicle can enter a census tract or a municipality from any direction and therefore does not have to be affected by each crash that occurs prior to a drop-off, 4-5% greater MPM for an average trip is substantial. Since thousands of trips are made per month by Access Link vehicles in areas with high crash incidents, even a 4-5% higher MPM leads to a substantial amount of unexpected delay.

- In many ways, this research helped to bridge gaps in existing literature. Although several studies have already been published on the factors affecting paratransit trip demand, their findings had often been contradictory. This study provides another set of results on factors associated with trip demand from an area where research on disability paratransit had been limited. Other researchers can compare the results of this research with previously conducted studies and make better judgments about the factors associated with trip generation and demand for service.

- Compared to studies on demand for paratransit trips, studies on trip delay and travel-time reliability have been less common. One of the reasons for the scarcity of studies on paratransit trip delay and reliability is that acceptable measures of delay and reliability cannot be had without having estimates of network trip distance. However, trip distances are not usually available from transit agencies, because they usually keep record of travel time only. A substantial amount of time and energy were spent in this research to estimate network distances for approximately 1.9 million trips by using the ArcGIS network analyst. Estimation of trip distances allowed the development of measures to represent delay and reliability. Analysis with these measures helped identify factors that are associated with trip delay and travel time reliability. It is expected that, by taking a cue from this study, other researchers will conduct similar studies elsewhere and provide additional insights helpful to transit agencies, paratransit providers, and researchers.

ACRONYMS AND ABBREVIATIONS

AASHTO	American Association of State Highway and Transportation Officials
ACEC	American Council of Engineering Companies
ACI	American Concrete Institute
ACS	American Community Survey
ADA	Americans with Disabilities Act
ANOVA	Analysis of Variance
API	Application Programming Interface
AREMA	American Railway Engineering & Maintenance-of-Way Association
ASCE	American Society of Civil Engineers
ASSIST-ME	Advanced Software for State-Wide Integrated Sustainable Transportation System-Monitoring and Evaluation
BDI	Bridge Diagnostics, Inc.
COV	Coefficient of Variation
CRED	Centre for Research on the Epidemiology of Disasters
CUSP	Center for Urban Science and Progress
DEOS	Delft Institute for Earth-Oriented Space Research
DORIS	Delft Object-Oriented Radar Interferometric Software
DPM	Delay per Mile
EECS	Electrical Engineering and Computer Science
EM	Electromagnetic
EMS	Emergency Medical Service
ERDAS	Earth Resources Data Analysis System
ERS	European Remote Sensing (satellite)
ESA	European Space Agency
ETC	Electronic Toll Collection
FE	Finite Element
GAO	Government Accountability Office
GIS	Geographic Information System
GLMM	Generalized Linear Mixed Model
GPS	Global Positioning System
GSP	Garden State Parkway
InSAR	Interferometric Synthetic Aperture Radar
ITS	Intelligent Transportation Systems
IVHS	Intelligent Vehicle-Highway Systems
KAIST	Korea Advanced Institute of Science and Technology
KSI	Kilograms per Square Inch
LDV	Laser Doppler Vibrometer

LEHD	Longitudinal Employer-Household Dynamics
LOS	Level of Service
LRFD	Load and Resistance Factor Design
MOR	Measure of Resiliency
MPH	Miles per Hour
MPM	Minutes per Mile
MTA	Metropolitan Transportation Authority
NBHCE	Newark Bay - Hudson County Extension
NCHRP	National Cooperative Highway Research Program
NEC	Northeast Corridor
NIRA	Networked Infrastructure Resiliency Framework
NJ	New Jersey
NJCL	NJ Coast Line
NJDOT	New Jersey Department of Transportation
NJRTM-E	North Jersey Regional Transportation Model - Enhanced
NJSWM	New Jersey State-Wide Planning Model
NJTPK	New Jersey Turnpike
NRI	Network Robustness Index
NSF	National Science Foundation
NTA	Neighborhood Tabulation Areas
NYC	New York City
NYU	New York University
OD	Origin-Destination
OLS	Ordinary Least Squares
P4S	Plan4Safety
PABT	Port Authority Bus Terminal
PATH	Port Authority Trans-Hudson
PI	Principal Investigator of Performance Index
RITS	Rutgers Intelligent Transportation Systems Labratory
SAR	Synthetic Aperture Radar
S-Curve	Sigmoid Curve
SHM	Structural Health Monitoring
SIC	Standard Industry Classification
STS	Structural Testing System
SUR	Seemingly Unrelated Regression
TAC	Techinical Activity Committee
TAZ	Traffic Analysis Zone
TMS	Traffic Monitoring System
TRB	Transportation Research Board
TRCP	Transit Cooperative Research Program

TRANSCOM	Transportation Operation Coordinating Committee (metro New York, New Jersey, and Connecticut)
UN/ISDR	United Nations International Strategt for Disaster Reduction
US	United States
UTRC	University Transportation Research Center
V/C	Volume-to-Capacity
VHT	Vehicle Hours Traveled
VIF	Variance Inflation Factor
VMT	Vehicle Miles Traveled
VTC	Alan M. Voorhees Transportation Center
WCTRS	World Conference on Transportation Research Society
WIM	Weigh-in-Motion
WTC	World Trade Center

NOMENCLATURE

C_{am}	Capacity of Link *a* for a Travel Mode *m*
C_{max}	Maximum Capacity of all Network Links
ΔCost	Difference in Cost before and after Event
d	Equilibrium (or fixed) Demand Vector
D_A	Demand after Event
D_B	Demand before Event
$\varepsilon(G,d)$	Network Performance/Efficiency Measure
f^i_{am}	Flow on Link *a* during Period Time *i* for a Travel Mode *m*
G	Network Topology
k_{jam}	Congestion Density for Link *a*
l_a	Length of Link *a*
MoP_A	Measure of Performance after Event
MoP_B	Measure of Performance before Event
n_a,	Number of Lanes of Link *a*
r_b	Redundancy Measure
TC_{S-O}	Total Network Costs Evaluated Under the System Optimal Flow Pattern with Original Capacities
TC^{γ}_{S-O}	Total Network Costs Evaluated Under the System Optimal Flow Pattern with Remaining Capacities
TC_{U-O}	Total Network Costs Evaluated Under the User Optimal Flow Pattern with Original Capacities
TC^{γ}_{U-O}	Total Network Costs Evaluated Under the User Optimal Flow Pattern with Remaining Capacities
TT_A	Travel Time after Event
TT_B	Travel Time before Event
VA_i	Vulnerability Index i (i = 1,…6)
V_{am}	Free Flow Speed of Link *a* for a Travel Mode *m*
V/C	Volume-to-Capacity Ratio

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PEER REVIEW

San José State University, of the California State University system, and the MTI Board of Trustees have agreed upon a peer review process required for all research published by MNTRC. The purpose of the review process is to ensure that the results presented are based upon a professionally acceptable research protocol.

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