KASUN WIJAYARATNA BE, BCOM
Research Associate,
Research Centre for Integrated Transport Innovation, University of New South Wales, Sydney, Australia

kasun.w@unsw.edu.au

KENNETH LAM BE
Commercial Graduate,
Laing O'Rourke, Sydney, Australia

KennethLam@laingorourke.com.au

DISRUPTIONS ON ROAD NETWORKS: IMPACT ON TRAFFIC CHARACTERISTICS

Disruptions are one of the major factors that affect the operation and performance of road networks. This study focuses on the impact of short term disruptions, traffic incidents and crashes, on the performance metrics of road networks and the routing characteristics of road users.

An empirical analysis of speed, traffic volume and geometric characteristic data, obtained from the Roads and Maritime Services, was undertaken to compare incident and non-incident traffic conditions across 5 pairs of competing parallel routes within the Sydney metropolitan. Analysis of the data suggests a stability of mean route travel times across all traffic scenarios. However, the volatility of travel times increased in the presence of disruptions, highlighting the associated unreliability. Disruptions also resulted in adaptive routing with noticeable shifts in route occupancy between the competing routes. These insights support the need for adaptive equilibrium based modelling tools to be developed accounting for the acquisition of information by a user in light of a disruption.

1. Introduction

The reliance and dependence on road transport across the years has resulted in widespread congestion of road networks. Traffic congestion is generally classified into recurrent or non-recurrent events (Rietveld et al., 2001). In the context of road networks, recurrent congestion is related to expected delays as a result of peak hour conditions and seasonal effects that are created from an imbalance between supply and demand within the network. Non-recurrent congestion, on the other hand, is a result of an uncertain event. These events could occur as a result of inclement weather, the presence of traffic incidents or any other impedance of the flow of traffic. These uncertain events are described within this paper as 'disruptions'. Non-recurrent congestion, as a result of disruptions to a network, is a significant part of the total level of congestion. The 2003 Urban Mobility Report by the Texas Institute of Transport states that crashes, vehicle breakdowns, weather conditions, special events and road construction and maintenance activities contribute to 50% of all delays incurred on roads in the United States of America (Schrank and Lomax, 2003). More recently, analysis of freeway travel times in the United States of America suggests that users must allocate 3 times the travel time of free flow conditions to ensure that they can achieve on-time arrival at their destination to account for the possibility of uncertain events occurring (Schrank et al., 2012). Given the immense operational impact on road networks, it is imperative to be able to account for the presence of disruptions when assessing our transport infrastructure.

The forms of disruptions described in Schrank and Lomax (2003) are defined within this study as "short term" disruptions or traffic "incidents". In contrast, "long term" disruptions are generally related to catastrophic events related to the failure of civil infrastructure (bridge and tunnel collapses), natural disasters and terrorist attacks where the impacts on travel behaviour last for several days, weeks, months or even years. These disruptions result in a significant cost to transport authorities and road users, highlighting the importance for research. However, the likelihood of such events is less than that of the presence of day to day short term disruptions and it is evident that short term events also contribute to traffic congestion (TomTom International, 2015, Schrank and Lomax, 2003, Schrank et al., 2012). Thus, it is imperative to understand the behaviour of road users in the presence of traffic incidents in order to develop strategies to mitigate the impacts of short-term disruptions on a road network.

This study conducts an empirical analysis of the impact of traffic incidents on competing parallel routes within Sydney, Australia. Sydney was selected for this study as it has been established as one of the most congested metropolitan areas in Australia. The presence of traffic incidents on Sydney's road network is a daily occurrence for most routes providing a rich data set to analyse. Speed, traffic volume and incident data were obtained for 10 selected routes on the Sydney road network, from Roads and Maritime Services, the road transport authority for the state of New South Wales. As shown in Figure 1, the ten routes selected are from different regions of the metropolitan area providing a diverse data set representative of the Sydney Metropolitan. The data was used to compare the performance of the competing routes as well as understand route choice behaviour in the context of short term disruptions.

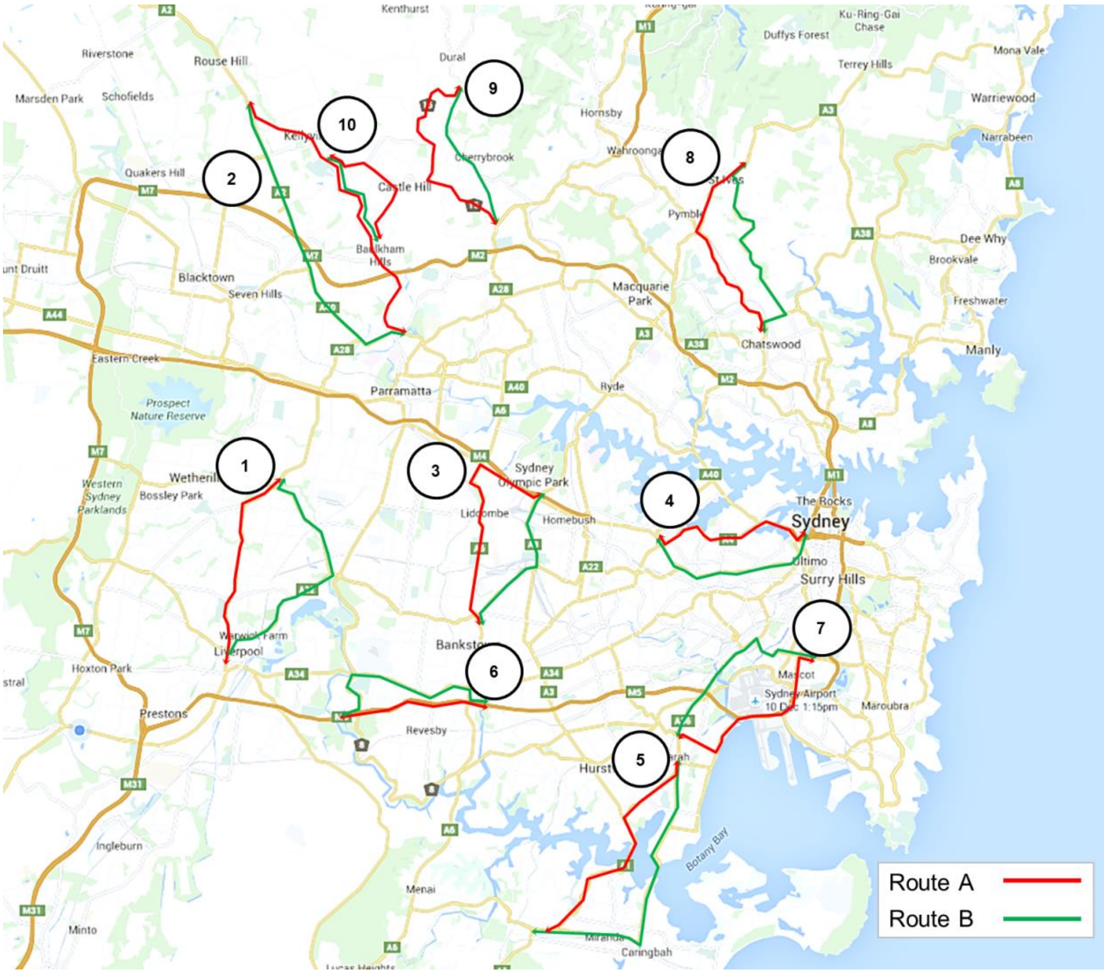

Figure 1: Regions of Sydney considered for Analysis

2. Literature Review

Short term disruptions in the form of traffic incidents on road networks have received considerable attention in the theoretical and empirical domains of transportation research. There have been a number of studies which investigate the causality, classification, severity and prediction of traffic incidents. From an empirical study perspective, this form of research has used field data to develop and validate models that predict the occurrence of incidents and crashes.

Abdel-Aty and Radwan (2000) used a negative binomial modelling technique to model the frequency of accident occurrence and involvement. The research discovered that with '*heavy traffic volume, speeding, narrow lane width, larger number of lanes, urban roadway sections, narrow shoulder width and reduced median width'* (Abdel-Aty and Radwan, 2000) the probability of accident involvement increases. This identifies that the presence of congestion is a leading contributor to the increased frequency of crashes and accidents.

A relationship between the geometric characteristics of a road, traffic volumes and accident rates has been well established by Karlaftis and Golias (2002). The study used a non-parametric statistical methodology, hierarchical tree-based regression. The results show that pavement variables and geometric design have the most influential impact on accident rates. In addition to this study, Golob and Recker (2003) have demonstrated that when weather is taken into consideration the impact of traffic volume has a significant influence on the accident frequency.

Incident duration and severity have generally been studied using analytical approaches such as; Poisson regression(Jones et al., 1991), nonparametric regression (Ozbay and Kachroo, 1999), hazard-based models (Nam and Mannering, 2000), decision trees (Smith and Smith, 2001) and Bayesian methods (Ozbay and Noyan, 2006). Garib et al. (1997) used field data to predict the duration and delay caused by an incident. Furthermore, the study collected incident detection and clearance data with speeds and traffic counts from mainline station of a freeway section in Oakland, Calif to develop a statistical model to forecast delays.

Al-Deek et al. (1995) presented a discussion and an evaluation of analytical methods used to estimate traffic congestion as a result of an incident which reflects the severity of the incident. These methods have been classified into three types, methods based on queuing analysis, methods based on shockwave analysis and methods based on freeway traffic simulation (Al-Deek et al., 1995). For an example, (Wirasinghe, 1978), used shock wave analysis to model total delays upstream of an incident which provides a measure for the severity of the incident itself. In addition Morales (1989) applied queuing theory to develop a program for predicting the impacts of minor incidents such as lane closures. These incident classification and severity studies have provided incredible insight into the impact and prediction of a short-term disruption. However, none of these studies provide comparative performance assessments of 'incident' and 'no-incident' scenarios that may be present on a network, which is the primary objective of this particular component of the research.

The other main research direction investigating short-term incidents is associated with the assessment and determination of reliability concepts. Reliability of a corridor or network is measured using travel time variability. Travel time can be separated into free flow travel time and the additional travel time associated with congestion. The additional travel time may be as a result of predictable delays, such as the presence of excess demand during peak periods, or it could be associated with unpredictable traffic incidents and short-term disruptions. The variance in travel time associated with unpredictable delay defines the reliability of the road corridor of network (Bates et al., 2001). Therefore, it is clear that for studies measuring and valuing reliability, it is essential to understand the impact of short-term disruptions. Comprehensive reviews of studies related to reliability are provided by Noland and Polak (2002) and more recently by Carrion and Levinson (2012). In general, reliability studies have focussed on the development of theoretical frameworks (Jackson and Jucker, 1982, Bates et al., 2001, Small, 1999, Arnott et al., 1990) and empirical studies (Lam and Small, 2001, Small et al., 2005, Ghosh, 2001) which involve either experimental or field data approaches.

Carrion and Levinson (2012) as well as Noland and Polak (2002) have highlighted the reasons for the scarcity of empirical studies within reliability research associated with short term disruptions. The main issues lie with the difficulties in obtaining travel time data, developing methodologies for reasonable controlled experiments and the costs involved in the deployment of surveys to gather data. Furthermore, both review papers suggest that it is difficult to draw generalised conclusions from these studies as data gathered is case specific. In the context of this research, to date there have been no empirical studies which have approached the analysis of short-term disruptions in terms of comparing traffic data which have and have not been affected by incidents. There is a key difference between the mentioned empirical studies and the work described in this paper. These studies consider pooled traffic performance data (considering both incident and non-incident data) to measure mean and standard deviation statistics for a route, corridor or network to assess the reliability. In contrast, the focus of this study is at a more fundamental level. Traffic data have been overlayed with incident data to form separated 'incident' and 'no incident' cases to understand the impact of short-term disruptions on aggregate traffic flow characteristics.

In contrast to the lack of research concerning short-term disruptions, there have been numerous research efforts in assessing the vulnerability and reliability of transport networks in light of long term disruptions (Danczyk et al., 2010, Giuliano and Golob, 1998, Gordon et al., 1998, Tilahun and Levinson, 2008). The review paper, 'Disruptions to Transportation Networks: A review' by Zhu and Levinson (2012) provides a broad overview of theoretical and empirical studies on traffic and behavioural impacts of major long-term network disruptions. The paper discusses the impact of severe infrastructure failure, such as the collapse of a bridge, the shutdown of public transit services (resulting in a significant mode shift and affecting road network performance), or the advent of catastrophic weather events. Research surrounding major catastrophes has been prevalent from a forensic and preventative standpoint. Even though the contexts of the disruptions are significantly different, these empirical studies have provided methodological guidance whilst conducting this research.

3. Data Acquisition

The key objective of the empirical investigation was to investigate the impact of disruptions on parallel commuter routes in Sydney. Initially, ten sets of parallel route sections were selected for the analysis and are presented in Figure 1. The routes were selected based on a commuter perspective and defined as competing commuter routes between origin and destination regions in Sydney. These routes are normally considered from a user perspective and also indicated as alternative routes within GPS navigation tools. The selected routes were;

1. Cumberland Highway Vs Hume Highway - Horsley Drive
2. Windsor Road Vs Old Windsor Road
3. Parramatta Road - St Hillier's Road Vs Centenary Drive - Hume Highway
4. Parramatta Road Vs Western Distributor
5. Princes Highway Vs Rocky Point Road
6. South Western Motorway (M5) Vs Milperra Road
7. General Holmes Drive Vs Princes Highway
8. Mona Vale Road - Pacific Highway Vs Link Road - Archibald Road
9. Old Northern Road - Castle Hill Road Vs New Line Road
10. Old Northern Road - Showground Road Vs Windsor Road

The above route pairs (sets) were selected based on following criteria:

- Each set provides a pair of parallel, competing commuter routes which allow users to alternate between them based on traffic conditions.
- Traffic characteristics such as route lengths and travel times of each pair are comparable.
- Appropriate data such as crash/incident data, traffic volume data and traffic speed data are available from the RMS to undertake a meaningful analysis.

The relevant data sets, necessary for the research tasks, were obtained from Roads and Maritime Services (RMS). Data was collected, across all route sets, for the period between January 2012 and June 2013. RMS provided four sets of data for the selected routes which included; average speed data (aggregated at 15 minute intervals), categorised incident data, hourly traffic volume data and relevant link length data.

RMS utilises Global Positioning System (GPS) data of equipped fleet vehicles to derive the required speed data. Vehicles deployed by RMS for data collection are commercial fleet vehicles involving a diverse range of cars, vans and various sized trucks. The final 15 min average speed data value for each road section is determined by aggregating all signals (broadcasted every 62 seconds) from the fleet. The received signals include information of the position of vehicles, direction of travel and speed (at the second of transmission). These signals are processed with respect to road and subsequent link number combinations and all signals received for that 15 minute block are arithmetically averaged and stored. The travel time data set for each link was calculated using the speed data and the link length data, the route travel times were then determined through an aggregation of link travel times for corresponding trip chains.

Categorised incident data was provided by RMS for the assessment period for all the selected routes. The data included the following features;

- ***Time***: Date and time to the nearest minute of the occurrence of the incident
- ***Location***: Road and link number where the incident occurred
- ***Duration***: A categorisation of the length of time that the incident was present on the road section.

The exact durations of the incidents were not provided by RMS; however the categorisations of duration provided an indication of the severity and impact of the disruption on the network. RMS provided further information regarding the types of information that each duration category could represent, as shown in Table 1.

Table 1: Categorisation of incident data

Duration Category	Type of Incident
1 minute < 15 minutes	Vehicle breakdowns (cars) and minor crashes that do not include more than 2 vehicles
15 minutes < 60 minutes	Larger vehicle breakdowns and crashes
60 minutes < 120 minutes	Significant crashes involving multiple vehicles
120 minutes +	Emergency road works, maintenance works and other construction work zones

RMS uses a range of counters with permanent and sample roadside collection devices to collect traffic volumes. For the purposes of this study, only permanent roadside collection devices were considered, as sample roadside collection devices do not provide continuous data which could be used to correlate with the collected incident data.

3.1 Data pre-processing

Collected raw data was pre-processed to create required data sub-sets for analysis. The pre-processing procedure involved the following;

- Determination of relevant days and time periods of data.
- Removal of outlier data.
- Separation of traffic data to develop ‘incident’ and ‘no-incident’ data-sets.

The focus of the study was an assessment of the peak period commuter traffic; thus all weekend, public holiday and weekday off peak period data were removed from the data set. Some data obtained from GPS and permanent volume counter stations were incomplete, inconsistent or contained errors which were accounted for and removed prior to analysis, if deemed unusable.

Table 2: Incident and no-incident data set combinations

Combination of Scenarios	Red – ‘Route A’	Green – ‘Route B’
C1	No-Incident	No-Incident
C2	Incident	No-Incident
C3	No-Incident	Incident

Table 3: Final routes used for complete analysis

Set ID	Route ID	Route Names	Route Length	Boundary Intersections
Set 1	Route 1A	Cumberland Highway	8.5km	Hume Highway/Cumberland Highway Horsley Drive/Cumberland Highway
	Route 1B	Hume Highway – Horsley Drive	11.4km	
Set 2	Route 2A	Windsor Road	13.9km	Windsor Road/Cumberland Highway Windsor Road/Old Windsor Road
	Route 2B	Old Windsor Road	13.2km	
Set 3	Route 3A	Parramatta Road – St Hillier’s Road	10.5km	Rookwood Road/Stacey Street/Hume Highway Parramatta Road/Centenary Drive
	Route 3B	Centenary Drive – Hume Highway	8.6km	
Set 4	Route 4A	Western Distributor	9.0km	Western Distributor/Kent Street City West Link and Parramatta Road
	Route 4B	Parramatta Road	8.0km	Broadway/Harris Street City West Link and Parramatta Road
Set 5	Route 5A	Princes Highway	16.5km	Princes Highway/Kingsway Princes Highway/Marshall Street
	Route 5B	Rocky Point Road	11.3km	

In addition, as the empirical investigation involved a comparison of ‘incident’ and ‘no-incident’ scenarios for each set of competing routes, the incident data set was matched with all the traffic characteristic data sets. In order to systematically match the data, each set of routes were split into two; one route was denoted by ‘Red’ or ‘Route A’ and the other by ‘Green’ or ‘Route B’. Based on the identification of each route in each set, the matching process considered the following combinations of 'incident' and 'no-incident' scenarios to analyse the data, presented in Table 2.

The review of data obtained from RMS following the 'pre-processing' procedure revealed that some of the selected routes were not viable for further analysis due to an inadequate number of reported incidents along those routes. Accordingly, only five pairs of the initially selected routes were used for further analysis as presented in Table 3.

4. Analysis of Data

A comprehensive methodology was developed to gain an understanding of empirical trends or relationships between short term traffic incidents and fundamental traffic properties such as travel time and traffic flow. In order to investigate the impact on fundamental traffic properties due to short-term incidents, the following tasks were undertaken:

- Hourly traffic volumes on each route were analysed to determine the peak traffic periods.
- Collected data for each route were statistically analysed to interpret the data in a meaningful manner and to establish the impact of incidents on fundamental traffic properties such as speed, travel time and traffic flow.

4.1 Peak Period Determination

The impact of traffic incidents on a commuter route is notably high during peak traffic periods where the greatest numbers of people are travelling on the network. Peak traffic periods are considered as the times throughout the day where the network faces considerably higher demands relative to the average. Accordingly, the traffic volume data obtained from RMS for selected routes was used to define the morning and afternoon peak periods for the purpose of this study. Average hourly, weekday, two-way traffic volumes at midblock locations along the five sets of routes selected for the study are graphically presented in Figure 2.

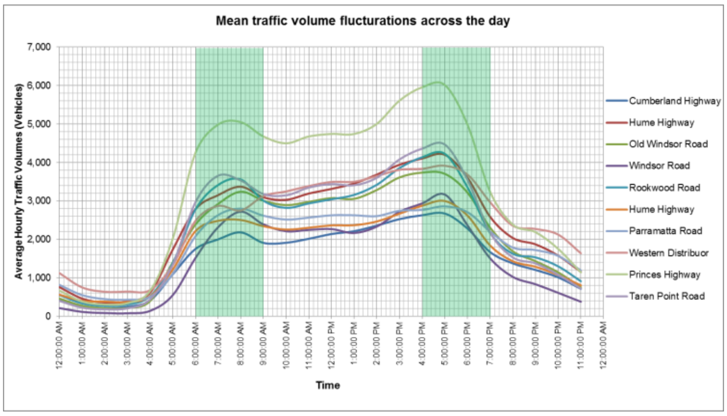

Figure 2: 24 hour fluctuation of traffic volumes

Figure 2 demonstrates that during week days, there is consistent trend across all the selected routes with high traffic volumes from 6am to 7pm. Furthermore, there are definitive peaks within the traffic count distributions on all the selected routes during the morning and afternoon peak periods. Accordingly, the peak traffic periods for all the selected routes for the purpose of this study is defined as: **AM (Morning) Peak Period: 6am - 9am** and **PM (Afternoon) Peak Period: 4pm -7pm.**

4.2 Statistical Analysis

Descriptive statistics of the mean and standard deviation of each of the travel time and volume data sets were calculated and compared to understand the underlying empirical relationships. Furthermore, the principle of equilibrium presented by Wardrop (1952) suggests that travel times on all used paths for each origin and destination pair are equal and minimum. Accordingly, hypothesis testing was undertaken to compare the 'incident' and 'no-incident' travel times of each individual route as well as comparing the competing routes considering the scenario combinations presented in Table 2. In this context, estimated 'incident' and 'no-incident' travel times for the identical time intervals were paired.

The hypotheses considered were as follows;

- The null-hypothesis: $\overline{T_1} - \overline{T_2} = 0$
- The alternative hypothesis: $\overline{T_1} - \overline{T_2} \neq 0$

Where;

$\overline{T_1}$ = the mean route travel time for a specific 'no-incident' or 'incident' scenario

$\overline{T_2}$ = the mean route travel time for an alternative 'no-incident' or 'incident' scenario as compared to $\overline{T_1}$

Due to the limited sample size of incident data for some of the 15 minute time intervals, a Welch's T-test was conducted to test the hypothesis. The conventional pooled T-test for independent means assumes equivalence of standard deviation between samples. As this is not guaranteed within the data sets compared, the more general Welch's T-test was used instead, using the formulation presented in Equation (1).

$$t = \frac{\overline{T_1} - \overline{T_2}}{\sqrt{SE_1^2 + SE_2^2}} \tag{1}$$

Equation (2) calculates the t-statistic by considering the difference of the mean travel time ('b_1' and 'b_2') and their respective standard errors ('SE_1' and 'SE_2'). The t-statistics were compared with the t-critical values for a confidence level of 95% which were determined from the t-distribution with the degrees of freedom, 'v', calculated using Equation (2).

$$v = \frac{(\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2})^2}{\left[\frac{\left(\frac{s_1^2}{n_1}\right)^2}{n_1 - 1} + \frac{\left(\frac{s_2^2}{n_2}\right)^2}{n_2 - 1}\right]} \tag{2}$$

4.3 Route Utilisation

The purpose of this analysis is to understand the impact of disruptions on utilisation of two competing routes under the two scenarios; 'incident' and 'no-incident' scenarios. The metric of 'percentage route occupancy' was used where the proportion (p_A, p_B) of the total traffic using either route A or B was compared. The percentage route occupancy was calculated using Equation (3), where 'V_A' and 'V_B' represent the mean volume on route A and route B respectively for the peak period of analysis considered.

$$p_A = \frac{V_A}{V_A + V_B} \times 100 \;;\; p_B = \frac{V_B}{V_A + V_B} \times 100 \qquad (3)$$

5. Results

The results of the statistical analysis of the final five competing parallel routes are presented within this section of the paper, highlighting the impacts of short term disruptions on travel time and traffic volumes of the competing parallel routes. The presentation of the results is consistent with the route identification described in Table 3.

5.1 Travel Time Assessment

Table 4 and Table 5 present the mean and standard deviation of the route travel times respectively for both the AM and PM peak periods. These tables present the descriptive statistics of the scenario combinations as described in Table 2. In general, the mean travel time on a particular route remains stable in both no-incident and incident scenarios, regardless of which route contains the incident. However, what is evident from these results is that Set 1 is most likely not a pair of competing routes as Route 1B (The Hume Highway and The Horsley Drive) has significantly greater mean travel time values than Route 1A (Cumberland Highway). Even though Route 1B is an alternative route from a commuter perspective, from a performance perspective it is clearly more costly to use in terms of travel time. Excluding this set (pair of routes), the pairs of routes in all other sets have very similar travel times with marginal increases in travel time under disrupted conditions.

Table 4: Mean route travel times

Mean route travel times							
Set ID	**Route**	**AM Peak (6am - 9am)**			**PM Peak (4pm - 7pm)**		
		With No Incidents	***An incident on***		***With No Incidents***	***An incident on***	
			Route A	***Route B***		***Route A***	***Route B***
Scenario Combination		*C1*	*C2*	*C3*	*C1*	*C2*	*C3*
Set 1	Route 1A	10.49	10.59	10.54	10.51	10.64	10.57
	Route 1B	16.47	16.53	16.67	17.19	17.25	17.26
Set 2	Route 2A	19.11	19.32	19.17	18.71	18.90	18.81
	Route 2B	19.16	19.22	19.56	19.09	19.20	20.15
Set 3	Route 3A	10.41	10.98	10.91	11.52	11.62	11.60
	Route 3B	9.94	9.97	9.98	9.69	9.77	9.83
Set 4	Route 4A	13.13	13.60	13.23	12.98	13.10	13.07
	Route 4B	13.44	13.52	13.89	13.76	13.85	13.83
Set 5	Route 5A	15.74	15.89	15.81	16.06	16.27	16.16
	Route 5B	13.26	13.33	13.38	15.95	16.07	16.22

This is an unexpected outcome as in practice disruptions result in delays which should increase the overall travel time. An explanation for this observation could be due to a number of reasons, including:

- Instances of minor disruptions which do not necessarily increase travel time;
- Unrecorded incident resulting in an inflation of travel time within the 'no incident' data sets and a deflation of the 'incident' data sets, and
- Cases where travel times are unusually high due to volatility in demand.

The standard deviation values presented in Table 5 highlight the volatility associated with disrupted transport networks. Even though the mean travel times on competing routes were similar, the standard deviations of the data sets which contain incidents are greater than the no-incident data sets. Thus, it is clear that short-term incidents affect the reliability of a route.

Table 5: Standard deviation of route travel times

Standard Deviation of route travel times							
Set ID	**Route**	**AM Peak (6am - 9am)**			**PM Peak (4pm - 7pm)**		
		With No Incidents	***An incident on***		***With No Incidents***	***An incident on***	
			Route A	***Route B***		***Route A***	***Route B***
Scenario Combination		*C1*	*C2*	*C3*	*C1*	*C2*	*C3*
Set 1	Route 1A	0.79	0.97	0.80	0.75	0.85	0.76
	Route 1B	1.07	1.08	1.15	0.97	0.98	0.98
Set 2	Route 2A	1.03	1.14	1.04	0.83	0.93	0.84
	Route 2B	1.41	1.42	1.42	1.10	1.10	1.33
Set 3	Route 3A	0.77	0.77	0.77	0.78	0.85	0.79
	Route 3B	0.96	0.97	1.11	0.89	0.89	0.93
Set 4	Route 4A	0.93	1.02	0.94	0.79	0.87	0.80
	Route 4B	0.63	0.63	0.64	0.56	0.56	0.60
Set 5	Route 5A	0.94	0.98	0.95	0.76	0.93	0.77
	Route 5B	1.39	1.40	1.49	1.64	1.65	1.67

5.1.1 Hypothesis Testing of Travel Time Data

Hypothesis testing was conducted across the mean travel time results of the 'no-incident' and 'incident' data sets to further investigate the stability of travel time. Table 6 presents the proportion of 15 minute time intervals out of all the time intervals across each AM and PM peak period, that indicated: 'the null hypothesis could not be rejected at a confidence level of 95%'. The results confirm the finding that incident and no-incident scenarios have a limited effect on the performance of the route. Statistically insignificant differences in travel time were observed for a majority of the 15 minute increments with percentage of null hypothesis exceeding 77% for all these cases. However, when comparing the performance of the competing routes it is evident that there are differences in travel times in incident and no-incident scenarios.

Table 6: Summary results of the Hypothesis Testing

T-Test Results (%) for Travel time Assessment				
Set	**Combination of Scenarios**		**% Null Hypothesis**	
	Scenario 1	**Scenario 2**	**Morning Peak**	**Afternoon Peak**
Set 1	Route 1A (No Incident)	Route 1A (Incident)	100%	83%
	Route 1B (No Incident)	Route 1B (Incident)	92%	100%
	Route 1A (No Incident)	Route 1B (No Incident)	0%	0%
	Route 1A (No Incident)	Route 1B (Incident)	0%	0%
	Route 1B (No Incident)	Route 1A (Incident)	0%	0%
Set 2	Route 2A (No Incident)	Route 2A (Incident)	92%	100%
	Route 2B (No Incident)	Route 2B (Incident)	75%	58%
	Route 2A (No Incident)	Route 2B (No Incident)	67%	67%
	Route 2A (No Incident)	Route 1B (Incident)	67%	50%
	Route 2B (No Incident)	Route 2A (Incident)	67%	92%
Set 3	Route 3A (No Incident)	Route 3A (Incident)	83%	100%
	Route 3B (No Incident)	Route 3B (Incident)	92%	92%
	Route 3A (No Incident)	Route 3B (No Incident)	42%	0%
	Route 3A (No Incident)	Route 3B (Incident)	25%	0%
	Route 3B (No Incident)	Route 3A (Incident)	25%	0%
Set 4	Route 4A (No Incident)	Route 4A (Incident)	67%	83%
	Route 4B (No Incident)	Route 4B (Incident)	67%	100%
	Route 4A (No Incident)	Route 4B (No Incident)	67%	33%
	Route 4A (No Incident)	Route 4B (Incident)	75%	33%
	Route 4B (No Incident)	Route 4A (Incident)	75%	42%
Set 5	Route 5A (No Incident)	Route 5A (Incident)	83%	92%
	Route 5B (No Incident)	Route 5B (Incident)	100%	92%
	Route 5A (No Incident)	Route 5B (No Incident)	0%	58%
	Route 5A (No Incident)	Route 5B (Incident)	0%	58%
	Route 5B (No Incident)	Route 5A (Incident)	0%	50%

As described in the previous section, the pair of routes in Set 1 presents statistically significant differences in travel times between both routes. Statistically different travel times have also been observed across a majority of 15 minute time intervals within Set 3 and Set 5 when comparing the competing routes. The statistical difference may not reflect a practical difference in the context of travel time (Devore et al., 2013). A difference of 30 seconds to 2 minutes can suggest that one route has a statistically lower travel time than the other; however from a commuter's perspective both the routes could be considered as feasible alternatives during AM and PM peak periods. This can be further corroborated with a qualitative assessment of the mean travel times in Table 4, where most travel times of one route are within 10% of the other (except for Set 1) which can be perceived by users as equivalent.

5.2 Traffic Volume Assessment

The traffic volume assessment considered hourly traffic volumes at RMS permanent counter stations available across all sets of routes. Table 7 presents the descriptive statistics of mean and standard deviation of volume considering all 'incident' and 'no-incident' scenarios.

Table 7: Descriptive statistics of traffic volumes observed across each data set

Traffic Condition		Parameter	Set 1		Set 2		Set 3		Set 4		Set 5	
			1A	1B	2A	2B	3A	3B	4A	4B	5A	5B
AM Peak Period	No Incident	Sample Size	290	268	169	204	148	155	172	92	225	220
		Mean Traffic Volume (veh/hr)	2612	3904	2897	3596	4592	4111	3832	3875	6284	4208
		Standard Deviation (veh/hr)	181	137	168	98	138	74	88	99	242	191
	Incident on Route A	Sample Size	37	34	13	52	21	31	37	22	38	42
		Mean Traffic Volume (veh/hr)	2568	4118	2679	3678	4497	4162	3776	4029	6219	4311
		Standard Deviation (veh/hr)	262	262	468	88	230	111	218	119	348	244
	Incident on Route B	Sample Size	0	0	91	43	41	48	32	26	19	18
		Mean Traffic Volume (veh/hr)	N/A	N/A	2978	3482	4742	4028	4166	3869	6464	4016
		Standard Deviation (veh/hr)	N/A	N/A	142	99	386	245	138	151	159	398
PM Peak Period	No Incident	Sample Size	290	271	299	268	184	186	164	89	207	211
		Mean Traffic Volume (veh/hr)	2849	4308	3159	3886	4746	4488	4522	3602	6208	4567
		Standard Deviation (veh/hr)	168	252	313	82	91	132	112	122	3280	254
	Incident on Route A	Sample Size	47	42	16	20	21	23	32	21	41	21
		Mean Traffic Volume (veh/hr)	2727	4205	3040	3940	4521	4495	4408	3882	6082	4678
		Standard Deviation (veh/hr)	333	428	339	124	257	140	172	127	592	399
	Incident on Route B	Sample Size	0	0	32	22	30	30	39	23	27	19
		Mean Traffic Volume (veh/hr)	N/A	N/A	3428	3846	4876	4395	4742	3485	6342	4446
		Standard Deviation (veh/hr)	N/A	N/A	286	116	250	315	212	172	428	489

Similar to the process completed with the travel time data, incident data was matched with volume data to derive the incident scenarios. This resulted in situations where there was limited or no relevant volume data, such as what is presented in Set 1 where no incidents were recorded for the green 'Route B' in isolation to the red 'Route A'. The sum of individual routes within a Set remains relatively stable offering the opportunity to understand the impact of disruptions on utilisation of each of the routes. It is evident from Table 7 that the volatility of flow increases in disrupted conditions. This is reflected through the increase in standard deviation of flows experienced throughout the incident scenarios.

Table 8: Percentage occupancy of the competing routes

Percentage Route Occupancy							
Set ID	Route	AM Peak (6am - 9am)			PM Peak (4pm - 7pm)		
		With No Incidents	An incident on		With No Incidents	An incident on	
			Route A	Route B		Route A	Route B
Set 1	Route 1A	40%	38%	N/A	40%	39%	N/A
	Route 1B	60%	62%	N/A	60%	61%	N/A
Set 2	Route 2A	45%	42%	46%	45%	44%	47%
	Route 2B	55%	58%	54%	55%	56%	53%
Set 3	Route 3A	53%	52%	54%	51%	50%	53%
	Route 3B	47%	48%	46%	49%	50%	47%
Set 4	Route 4A	50%	48%	52%	56%	53%	58%
	Route 4B	50%	52%	48%	44%	47%	42%
Set 5	Route 5A	60%	59%	62%	58%	57%	59%
	Route 5B	40%	41%	38%	42%	43%	41%

Table 9: Percentage shift in the occupancy of the competing routes

Route Occupancy Percentage Shift							
Set ID	Route	AM Peak (6am - 9am)			PM Peak (4pm - 7pm)		
		With No Incidents	An incident on		With No Incidents	An incident on	
			Route A	Route B		Route A	Route B
Set 1	Route 1A	0.0%	-1.7%	N/A	0.0%	-0.5%	N/A
	Route 1B	0.0%	1.7%	N/A	0.0%	0.5%	N/A
Set 2	Route 2A	0.0%	-2.5%	1.5%	0.0%	-1.3%	47%
	Route 2B	0.0%	2.5%	-1.5%	0.0%	1.3%	53%
Set 3	Route 3A	0.0%	-0.8%	1.3%	0.0%	-1.3%	53%
	Route 3B	0.0%	0.8%	-1.3%	0.0%	1.3%	47%
Set 4	Route 4A	0.0%	-1.3%	2.1%	0.0%	-2.5%	58%
	Route 4B	0.0%	1.3%	-2.1%	0.0%	2.5%	42%
Set 5	Route 5A	0.0%	-0.8%	1.8%	0.0%	-1.4%	59%
	Route 5B	0.0%	0.8%	-1.8%	0.0%	1.4%	41%

Similar to the process completed with the travel time data, incident data was matched with volume data to derive the incident scenarios. This resulted in situations where there was limited or no relevant

volume data, such as what is presented in Set 1 where no incidents were recorded for the green 'Route B' in isolation to the red 'Route A'. The sum of individual routes within a Set remains relatively stable offering the opportunity to understand the impact of disruptions on utilisation of each of the routes. It is evident from Table 7 that the volatility of flow increases in disrupted conditions. This is reflected through the increase in standard deviation of flows experienced throughout the incident scenarios.

Table 8 and Table 9 present the percentage occupancy of each Set of routes considered. There is relatively even division of traffic between the routes. It is clear that there are shifts in traffic from routes with disruptions to routes without disruptions. Shifts of up to 2.5% were observed, with some isolated data points suggesting even greater variations in traffic flow. These observations indicate that users adapt in the presence of disrupted conditions.

6. Discussion, Limitations and Future Extensions

The analysis of empirical data on the five pairs of competing routes presented the following key findings.

- Concepts of equilibrium modelling cannot be dismissed as travel times on routes are stable between 'incident' and 'no-incident' scenarios.
- The presence of incidents on a route results in adaptive behaviour.

Current traffic assignment techniques consider Wardrop's User Equilibrium, or recent similar variations of the approach, to model traffic within congested scenarios(de Dios Ortúzar and Willumsen, 2011). Equilibrium concepts suggest that travel times on all used feasible routes are equal and a minimum. In general, the competing routes considered in the study presented differences in travel time which do not support the notion of equilibrium. However, this can be an artefact of the statistical testing procedure which is void of the practical difference expected with measures of travel time (Devore et al., 2013).

Support for the feasibility of equilibrium approaches arise from the stability of the route travel times across 'incident' and 'no-incident' scenarios for each individual route. The hypothesis testing suggested that for most 15minute interval data sub-sets, there were no statistical differences between 'incident' and 'no-incident' scenarios across all 10 routes assessed. However, it must be emphasised that this is by no means a proof of the presence of equilibrium itself. The results presented are case specific and empirical in nature and as such cannot be generalised. Nevertheless, this finding is in line with the current overarching idea of equilibrium modelling in traffic assignment.

In saying this, the route occupancy analysis presented in Section 5.2 highlights the current deficiencies of the modelling approach. A majority of equilibrium modelling approaches involve assigning traffic to fixed routes from origin to destination based on the costs observed for each link of a network. Disruptions are accounted for in the modelling paradigm by altering the costs associated with impact on a link by the disruption and re-applying the original traffic assignment technique to define a set of different fixed paths between an origin and a destination. The results of the volume assessment indicate that traffic remains similar across all the different combinations of 'incident' and 'no-incident' scenarios prior to the divergent point between the two competing routes. However, the presence of the disruption results in a reduction in traffic volume on the route with a disruption and a corresponding increase in the volume on the route not containing a disruption. This phenomenon suggests that users adapt routing decisions online after departing from the origin. This empirical finding implies the need to incorporate en route/online adaptive behaviour into traffic assignment techniques to appropriately account for the presence of disruptions, such as User Equilibrium with

Recourse (UER) (Unnikrishnan and Waller, 2009), which cater for information acquisition and the resulting behaviour.

The difficulties and limitations of empirical studies highlighted by (Noland and Polak, 2002) and (Carrion and Levinson, 2012) were faced when conducting this research study. The limitations can be summarised as follows;

- ***Missing and erroneous data***: The data sets obtained from RMS contained missing and erroneous data which required data pre-processing to prevent affecting the overall findings. As mentioned in Section 3, speed data obtained from GPS technology suffered inaccuracy for shorter link lengths when fleet vehicle demands were scarce. However, this was accounted for during the analysis and thus did not affect the final results or conclusions.
- ***Lack of direct travel time data***: The data sets provided by RMS did not include travel time data. Travel time data sets were calculated through the integration of average speed data and link length data along each of the studied routes. Thus, only an approximation of the travel time could be obtained. Nevertheless, these data sources did provide a satisfactory platform to observe general trends and relationships to compare ‘incident’ and ‘no-incident’ scenarios. Future extensions of this study could be the utilisation of detailed field surveys that specifically measure travel times on competing routes during peak periods.
- ***Small sample issues***: The data pre-processing also involved the formation of subsets of data which considered ‘incident’ and ‘no-incident’ scenarios. The incident data were overlayed with the average speed and travel time data sets to create the ‘incident’ and ‘no-incident’ subsets. The size of ‘incident’ subsets was significantly smaller than ‘no-incident’ subsets, as evident through the counts displayed in Appendix B. The small sample size reduced the emphasis of the statistical comparison and more importantly restricted the assessment of the scenario where incidents occur on both routes.
- ***Utilisation of representative volumes***: The volume analysis undertaken in this study obtains representative midblock volumes across the length of the route. A majority of the routes considered have a number of side streets and at times intersections with other major thoroughfares which result in inflows and outflows of traffic from the route. Ideally, use of volume counters at all major connecting arterial roads or the use of loop detector data along the route would allow a more accurate volume data collection and subsequent analysis.
- ***Lack of Origin-Destination data***: Similar to the issues with the volume data, origin and destination data were not available. This means that the data could include users who did not travel on the entirety of the route, but travelled on only a portion of the route. Possible improvements to this issue may include using origin-destination surveys or number plate recognition data collection procedures to get a true understanding of route choice.

Even though there were a number of data limitations, the novelty of the general trends and observations provide valuable insight into the future modelling of disrupted conditions. Alternative modelling approaches which account for the adaptive behaviour of users can lead to improved decision making and ultimately mitigating the negative impacts of delay and congestion arising from disruptions. Furthermore, the novelty of this methodology used to empirically investigate short-term disruptions provides a foundation for similar future studies. Replication of this analysis in other urban cities around the world could provide a more generalised and holistic understanding of the impacts of day-to-day disruptions.

7. Conclusions

This study conducted an empirical investigation of the impact of short-term disruptions on five competing parallel routes within the Sydney metropolitan. Traffic speed, traffic volume, link length and categorised traffic incident data were obtained from the Roads and Maritime Services of New

South Wales for the time period between January 2012 and June 2013. Data pre-processing lead to the formation of data sub-sets which described ‘incident’ and ‘no-incident’ cases for both the travel time and traffic volume performance metrics.

Analysis of the data indicate that the presence of short-term disruptions do not cause a statistically significant impact on the travel time of a route during morning and afternoon peak periods. However, disruptions on routes result in adaptive routing behaviour with noticeable shifts in route occupancy. These observations support the need for adaptive equilibrium based modelling efforts which account for the acquisition of information by users in light of a disruption.

The other primary contribution of this chapter was the presentation of one of the first empirical studies which focussed on the impact of short-term disruptions on road network performance. This methodology could be replicated and enhanced across other regions to further understand the travel behaviour of users under disrupted conditions. Improved understanding in this domain will result in better policies, planning and a more sustainable transport future.

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