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Quantifying the impacts of traffic incidents on urban freeway speeds

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Abstract

Planning for traffic related congestion during peak periods continues to be one of the most important challenges facing road managers. Congestion may be thought of as either recurrent or non-recurrent. The latter is caused by factors such as incidents, work zones, weather, and special events. Traffic incidents are reported as the cause of 25 per cent of total delays in the US. However, its effect varies from place to place due to the local conditions.

Different types of traffic incidents affect drivers' behaviour and the performance of vehicles. In an incident situation, the average headway between vehicles and the speed variability increases. The resultant impact on road speed profile is the main topic of the paper. The paper describes the methodology of extracting the impacts of traffic incidents including duration and delay on traffic speed for an urban freeway network.

The analysis of data from a case study in Brisbane is reported here. A section of an urban freeway has been studied in detail using inductive loop detector data and traffic incidents related variables for a period of 12 months. A variety of probability distribution functions were employed in order to test the best model for the duration and delay frequency distribution for each category of incident. The findings of this research will be used to put forward improved predictive delay models and travel time reliability models for urban freeway conditions.

Key words: *traffic factors, vehicle speed, traffic incident, recurrent and non-recurrent congestion*

1. Introduction

Urban networks are becoming more and more congested as a result of population growth and increased urban density and motorisation. This has reduced transport mobility and consequently has resulted in millions of hours of vehicle delays, air pollution and fuel consumption that lead to social, economical and environmental problems.

Congestion may be considered as either recurrent or non-recurrent. Recurrent congestion relates to everyday peak period traffic flow when demand exceeds capacity. Conversely, non-recurrent congestion is due to unsteady and unpredictable changes from time to time or day to day; and also to the unexpected occurrences such as incidents, work zones, weather, stationary vehicles and special events, where peak demands are higher than normal (Lomax et al., 2003).

The Bureau of Transport and Regional Economics (2007) estimated that urban congestion from capital cities in Australia cost the economy a total of $9.4 billion in 2005. Brisbane's share of this total was 12.8% which equates to $1.2 billion. By 2020, the overall costs of congestion to the Australian economy are expected to be $20.4 billion, with the cost to Brisbane of $3 billion, more than twice of the base year. Thus Brisbane's share of congestion costs will increase by 14.7%, while its population growth is estimated to increase by only 9%

over the 15 years to 2020. Brisbane is expecting the greatest increase of congestion costs among capital cities in Australia.

In a study by Ikhrata and Michell (1997), it was estimated that as much as 50% of the delay experienced on US highways was caused by non-recurrent congestion. In a later study, an investigation was undertaken to evaluate the congestion levels in 85 large metropolitan areas representing a national estimation in the U.S. from 1982 to 2003 (CamSys/TTI, 2005). The results showed that non-recurrent congestion contributed up to 60% of all congestion, while traffic incidents accounted for 25% of all congestion. Thus, traffic incidents appear as a major contributor to a lack of reliability, and hence have led to an increasing research interest in traffic incident management. However, the importance and impacts vary from place to place due to the local conditions.

Acknowledging the effects of incidents on congestion, incident management techniques have been implemented in order to minimise incident delay by quickly reinstating the capacity of a road network in the case of an incident event (Charles and Higgins, 2002). Systematic understanding of incident characteristics and its patterns are essential to restore a road network to full capacity. Therefore, the collection and analysis of traffic incident data and its components including traffic impacts is crucial. Hence, predicting traffic incident components, for example, incident duration, is a very important aspect for improving traffic incident management so that appropriate strategies can be implemented to alleviate the traffic impacts of incidents through the allocation of equipment and personnel (Konduri, Labi and Sinha, 2003). In addition, predicting incident components is vital for providing reliable traffic information and improving travel time reliability (Lyman and Bertini, 2008).

When an incident happens, a bottleneck forms and consequently congestion takes place when demand exceeds capacity. However the size and the impact of incidents vary. In this regard, one of the important issues is to identify the impact of non-recurrent congestion caused by incidents from regular recurrent congestion. This step is essential to extract the possible effect of incidents.

This paper summarises the findings of a study aimed at developing a method to identify incident components to facilitate the improvement and optimisation of incident management strategies for South-east Queensland (SEQ) in Australia. This would allow improved predictive travel time reliability models to be put forward.

This paper begins with a brief review of previous research on incident analysis. This is followed by a description of the methodology used in this study. Also, incident data and its components will be described. Attention is then directed towards the results of employing the methodology and extract traffic incident components. In addition, the extracted results are analysed from different points of view along with categorising the data into homogenous patterns for data grouping analysis purposes. Furthermore, traffic incident components, such as duration and delay for different categories are assessed. The last section draws conclusions based on the results of analysis and discusses areas for future research.

2. Background

The lack of extensively distributed equipment by which travel time (TT) can be measured directly has pushed researchers to use estimated travel from traffic data measures collected from widespread available traffic data collection technologies (Liu et al., 2006). Inductive Loop Detectors (ILDs) are the primary technology currently employed in many cities around the world especially on freeways to collect actual traffic data which make them the best source of traffic data over a wide area. In spite of recent advances in technology for collecting traffic measures particularly travel time directly, ILD is still popular due to its low cost compare to other methods as well as the advantage of providing traffic data on a continuous basis over a long period of time(Vanajakshi, 2004). However, ILD has inherent flaws mostly due to the prevalence of equipment malfunctions (Robinson, 2006).

ILD data has been used in a number of studies in order to estimate congestion delay. In the early study by Skabardonis, Petty and Varaiya (1999), the impacts of incidents including frequency, duration and delay have been investigated using a large comprehensive database on incidents and freeway characteristics in Los Angles. Delay caused by incidents has been extracted based on the incident location on speed and density contour plots for the segment which came from field data including loop detectors and probe vehicle speeds. The results indicate that only 37 per cent of all types of incidents lead to delay to the traffic movement and depend on the incident severity and duration. However, this approach is based on the availability of probe vehicle data. In addition, compatibility and calibration of the two data collection system is an issue. Abdel-Aty and Pande (2005) demonstrate the applicability of loop detector data for identifying crash prone conditions using probabilistic neural network (PNN). The results show that at least 70% of the crashes on the evaluation dataset could be identified.

In the study by Saberi and Bertini (2010), freeway segments are prioritized based on travel time reliability measures using archived loop detector data from five freeways in Portland and Oregon in US. It is found that the buffer index and the coefficient of variation are more consistent among other measures. Although travel time reliability measures are analysed, the contributory factors on unreliability are not identified. Therefore, the impact of incidents cannot be investigated separately through this approach.

Kwon, Mauch and Varaiya (2006) employ a method to calculate total delay based on the comparing the free-flow speed and actual speed using freeway loop detector data from the San Francisco Bay Area for morning and afternoon peak periods. Then, a number of components of non-recurrent congestion, namely: incidents, special events, lane closures, and weather, are used as explanatory variables in the linear regression analysis to estimate the total delay of each non-recurrent congestion and consequently calculate total recurrent delay. As a result, this method is not capable of estimating delay for individual recurrent and non-recurrent congestion.

Since early 1970, a number of Automatic Incident Detection (AID) algorithms have been developed to analyse traffic data and detect incidents. These algorithms are based on traffic flow theory, pattern recognition, statistics techniques and recently using artificial intelligence and fuzzy logic (Liu et al., 2006; Guiyan et al., 2010).

In the study by Venkatanarayana and Smith (2008), normal traffic pattern is defined as “a representative time-series of the largest subset contacting similar traffic data”.

Pattern recognition is a very powerful tool in automated data analysis and it is implemented in many different fields. In the area of transport, there is a widespread acceptance of the inherent existence of rhythmic patterns on traffic characteristics i.e. flow and speed, from day to day and through seasons (Garber and Hoel, 2010; Chung and Recker, 2012). Simple historic average is a common and popular approach to get the traffic pattern due to its simplicity and the ability to manipulate the final results statistically. However, this method can lead to significant bias in the case of abnormal situations (Garber and Hoel, 2010).

The literature demonstrates that traffic data from ILD when combined with information of non-recurrent congestion, are capable of estimating congestion delay. However, estimation of each individual recurrent and non-recurrent congestion delay and in particular delay due to traffic incidents remains unclear from the literature. In addition, estimation of recurrent congestion delay is an important factor in the process of identifying non-recurrent congestion delays. In this regard, pattern recognition techniques can be examined as effective tools to estimate recurrent delay.

3. Methodology

This section presents the procedure to estimate non-recurrent congestion delay on freeway networks using historical loop-detector data, as well as to identify traffic incident delay. The delay consists of recurrent delay, as well as non-recurrent delay caused by different forms of random events such as incidents, work zones, inclement weather, and special events. The total delay can be identified through investigation. However, the important issue is to separate the impact of non-recurrent congestion and recurrent congestion in the case of incident analysis. Hence, the primary interest in this study is the delay due to traffic incidents resulting from crashes, hazards and stationary vehicles. As indicated in the 'Highway Capacity Manual', Traffic Incident Delay (TID) is defined as the additional travel time experienced as a result of an incident, compared to the no incident condition (TRB, 2010).

To identify a TID, the first step is to define the normal traffic condition which can be considered as the recurrent profiles using Recurrent Speed Profile (RSP) and Recurrent Flow Profile (RFP). Then, TID can be calculated based on the difference between RSP and Daily Speed Profile (DSP).

The method is applied to a segment of freeway including *n* set of sequential links indexed *g=1,…, n* in which each link is identified based on the locations where loop detectors are available. It is assumed that estimated speeds and flows are representative of the speed and flow for the corresponding link. Days in the study period are represented by *d=1,…,P*.

As it was found in previous studies (Park, Messer and Urbanik Ii, 1998; Tavassoli Hojati et al., 2011; Chung, 2012), traffic behaviour is different for non-recurrent congestion under different weather conditions and temporal effects. In addition, weekdays (from Monday through Friday) and weekends (Saturday and Sunday), public holidays and school holidays have different traffic pattern and incident characteristics. Therefore, it is considered essential to analyse them separately. Hence, only the weekday data which are not school holiday or public holiday are examined here. These are called normal days in this study. Furthermore, time intervals in normal days in which the weather was rainy is excluded from the analysis. However, the method can be applied to other temporal conditions and adverse weather situations.

In addition, traffic data are aggregated into 5-min intervals at each link to obtain stable traffic data (Kwon, Mauch and Varaiya, 2006; Taehyung et al., 2007; Chung and Recker, 2012). As a result, each day is divided into 288 time intervals indexed *t=1,…,288*. Furthermore, $v_{g,d,t}$ is the speed at link *g*, time interval *t* on day *d* in kilometres per hour (km/h). Therefore, for each time interval *t* on each link *g* for all days in the study period, an array of speeds can be constructed, as long as data is available. and symbolized by $V_{g,t}$. Similar procedures can be employed to figure out the same concepts for flow and indexed by $f_{g,d,t}$, $F_{g,t}$.

To obtain RSP for each link *g* and each day of the week, Quantum-Frequency Algorithm (QFA) is applied (Venkatanarayana, Smith and Demetsky, 2008). Since this method does not require a priori pattern information or fine-tuning, the method is fast, robust and easy to implement. In addition, this method is considered an unbiased and a robust measure of high-frequency tendency. As a result, it is not biased by outliers unlike the historic average. In QFA, the probability density function (PDF) of the $V_{g,t}$ is determined. Then, the high frequency speed is identified by mode (point of maximum likelihood) searching in $V_{g,t}$ and is considered as the normal speed ($NS_{g,t}$). Since speed is averaged over 5-min intervals, this could cause variation of speed. As a result, there is a potential risk of overestimating or underestimating the speed profile. The moving average technique is employed to minimize the effect of this variation and to smooth the speed profile. For example, the moving average of three sequential speeds can be calculated as:

$$MNS_{g,t} = (NS_{g,t-1} + NS_{g,t} + NS_{g,t+1})/3 \tag{1}$$

where

$NS_{g,t}$ = the moving average of three sequential speeds;

$NS_{g,t-1}$ = the normal speed at one time-interval before t;

$NS_{g,t}$ = the normal speed at one time-interval at t;

$NS_{g,t+1}$ = the normal speed at one time-interval after t;

Subsequently, RSP_g for the entire time-intervals is obtained by considering together $MNS_{g,t}$ for each link. Considering the negative impact of non-recurrent congestion on speed, the comparison between RSP_g *and* DSP_g is capable of highlighting the impact of non-recurrent congestion events on each link. As indicated before, different RSP_g sets based on weekdays are required according to weekdays of DSP_g.

The next step is to identify non-recurrent congestion which is called an "event" in this study. The impacts of events including the amount of speed drop and its duration are considered as the criteria to recognize events. In this regards, an allowable percentage drop in speed is set according to the posted speed. Increased reduction in speed can be considered as an evidence of an event. In addition, continuation of speed drop in at least three successive time-intervals is the other criterion. Speed drop is calculated by the following equation:

$$drop_{g,t} = \left(1 - \frac{DSP_{g,t}}{RSP_{g,t}}\right) \times 100 \qquad (2)$$

where

$drop_{g,t}$ = percentage of speed drop on link g and time-interval t;

$DSP_{g,t}$ = speed on link g and time-interval t;

$RSP_{g,t}$ = recurrent speed on link g and time-interval t;

After finding the profile of the speed drop, the following expression is used to identify the non-recurrent events. The threshold value shown in this equation represents the allowable drop in speed. It is assumed that for links with posted speed of 100 km/h, 80 km/h and 70 km/h the allowable drops are 0.20, 0.25 and 0.30, respectively.

$$\exists \bar{t} \in t \,\middle|\, drop_{g,\bar{t}} \wedge drop_{g,\bar{t}+1} \wedge drop_{g,\bar{t}+2} \geq \text{threshold} \qquad (3)$$

where

$\bar{t}$ = time interval belonging to event duration;

threshold = allowable percentage drop in speed (20% for links with posted speed 100, 25% for 90 km/h and 30% for link with posted speed 80 and 70 km/h, respectively).

Once the event is identified, the next step is to find its start and end times, as well as its duration, and delay. In this regard, start time of the event ($\bar{t}_s$) is pinpointed by searching time backward from $\bar{t}$ to reach $drop_{g,\bar{t}}$ to about zero. Similarly, end time of the event ($\bar{t}_e$) is recognized by searching forward to find no drop in speed. Once all events in a day are identified, events with overlap are aggregated to one event and $\bar{t}_s$, $\bar{t}_e$ are adjusted accordingly. Event duration is calculated using equation 4. Data aggregation over 5-min intervals is required to convert duration to minutes.

$$DU_i = (\bar{t}_e - \bar{t}_s) \times 5 \qquad (4)$$

where DU_i is the duration of the event *i.*

Furthermore, the average extra travel time due to an event for each time interval can be calculated from the following equation:

$$\hat{T}^{i}_{g,d,\bar{t}} = -1 \times \min[l_g.(\frac{1}{RSP_{g,d,\bar{t}}} - \frac{1}{DSP_{g,d,\bar{t}}}), 0] \quad (5)$$

where $\hat{T}^{i}_{g,d,\bar{t}}$ is extra travel time due to an event *i* on link *g*, day *d* in each time interval $\bar{t} \in \{\bar{t}_s, ..., \bar{t}_e\}$ in hour (Hr), l_g is the link length in kilometre (km).

As a result, during an event duration DU_i for each event *i* on each link *g*, there would be a set of extra travel time $\hat{T}^{i}_{g,d,\bar{t}}$ for $\bar{t} \in \{\bar{t}_s, ..., \bar{t}_e\}$ which is shown by ETT_i. The probability density function of estimated ETT_i can be evaluated. The delay caused by an event *i* is then estimated on the upper tail of the distribution with an assumption of a 10% chance of being exceeded in ETT_i.

As mentioned by Hegyi, De Schutter and Hellendoorn (2005), the shock wave caused by congestion is dissolved within the freeway stretch and does propagate upstream and will impede the upstream speed. In this manner, once an event is identified in a link the propagation of the event is tracked upstream over the freeway until there is no identified event in upstream links as time passes. Therefore, a set of events are identified in successive links as a result of spatiotemporal effects of an event and indexed by *J.* This includes *j* affected links from 1 to *j* corresponding to link numbers.

The events and their impacts are identified by using traffic measures. However, the contributory factors of these events are not known. Using the details of incidents including location and time, the identified events and incidents can be matched to find the causes and details of matched events. However, due to the fact that the incident details are registered manually and are not necessarily reported accurately, the location and time of incidents may not be matched with the events location and time. Therefore, location and time of the un-matched incidents needs to be traced by searching for an event in the links in upstream or downstream of the specified incident location, as well as 60 minutes before and after the specified incident time.

Figure 1 illustrates schematically the speed reduction of an event. DSP has little fluctuation around RSP except in three time periods. The first period starts before 9:00 am until after 10:00 am and is identified as an event by satisfying equation 3. Conversely, the next two periods are not recognised as a major non-recurrent congestion and are not considered as an event. The method identifies start time $(\bar{t}_s)$ and end time $(\bar{t}_e)$ of the event and consequently event duration (DU_i) is calculated. Additionally, the result of matching incident database with events indicates the event *(i)* is matched with a reported incident which is assigned to *J*.

Therefore, traffic incident delay (TID) can be calculated by the following equation:

$$TID_m = \sum_{\forall i \in J} ETT_i \quad (6)$$

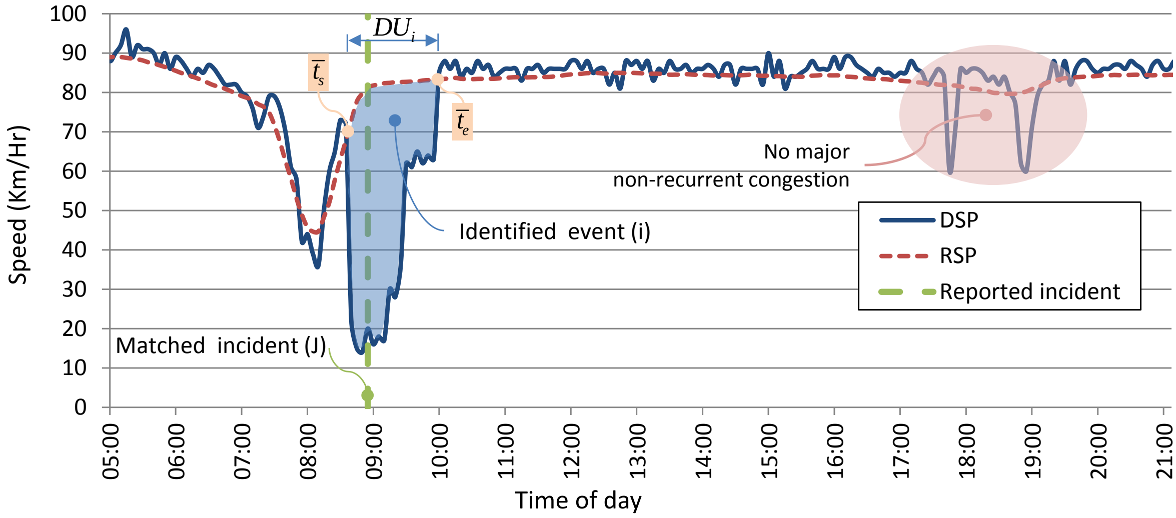
where

TID_m = delay caused by traffic incident (Hr);

M = incident number;

ETT_i = extra travel time caused by traffic incident on each link (Hr);

Figure 1- schematic event identification in a typical day



4. A case-study: Data Description

Traffic incidents are caused by complex interactions between factors. Due to the lack of comprehensive traffic incident data, a number of sources of data can be utilized to cover different important attributes related to traffic incident. A logical framework analysis (Logframe) as described in a later study by Tavassoli Hojati et al. (2012) was used to establish a comprehensive incident database for this study by combining different sources.

Incident data were obtained from the Queensland Department of Transport and Main Roads' STREAMS Incident Management System (SIMS) for South East Queensland (SEQ) urban road networks for a one-year period to November 2010. SIMS is an incident management system which is used throughout Queensland to capture incident traffic events which cause an impact on traffic flow on the road network. Weather data were received from Bureau of Meteorology stations around SEQ. Traffic data were received from Public Traffic Data Service (PTDS) which supplies traffic data including speed and flow from available loop detectors around South East Queensland network for a period of eighteen months to January 2011, (i.e. *P=562)*.

All incident events cause temporary capacity reductions. Some events occur unexpectedly such as vehicle-based incidents (e.g. crashes, stationary vehicles), other objects or obstructions on the road (e.g. debris), or extreme weather events (e.g. flood). There are also events that might not be expected by all road users, but which are planned and are publicly notified (e.g. roadworks and sports/cultural activities).The scope of this study is limited to unexpected non-recurrent congestion and only unplanned incidents have been considered in the analysis.

Figure 2 shows the density of incidents on the freeways network in SEQ. Incident density was concentrated around the Brisbane CBD areas, with the highest density along the Pacific Motorway south of the CBD. The density gradually diminished to the medium level, but rose again at the Pacific Motorway-Gateway Motorway interchange. Therefore, a section of the Pacific Motorway from CBD to Gateway Motorway on both directions is selected as a case study of congestion-related effects of freeway incidents in this research. Figure 3 illustrates the case study area which is highlighted in pink.

Figure 2: Heat map-density of all freeway incidents in SEQ

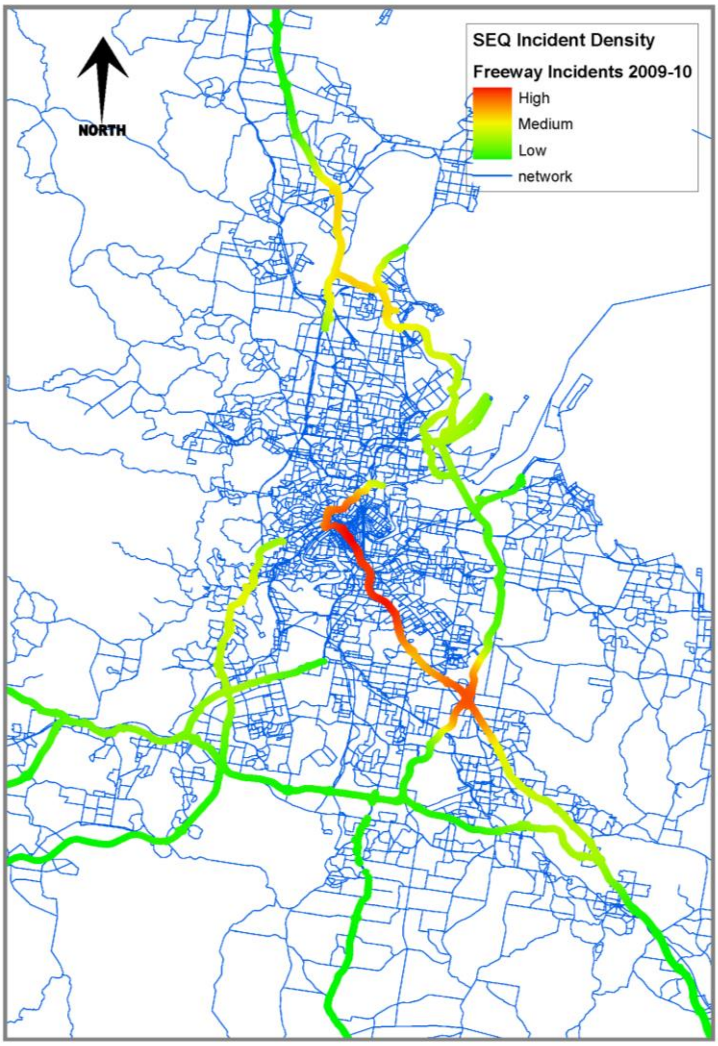
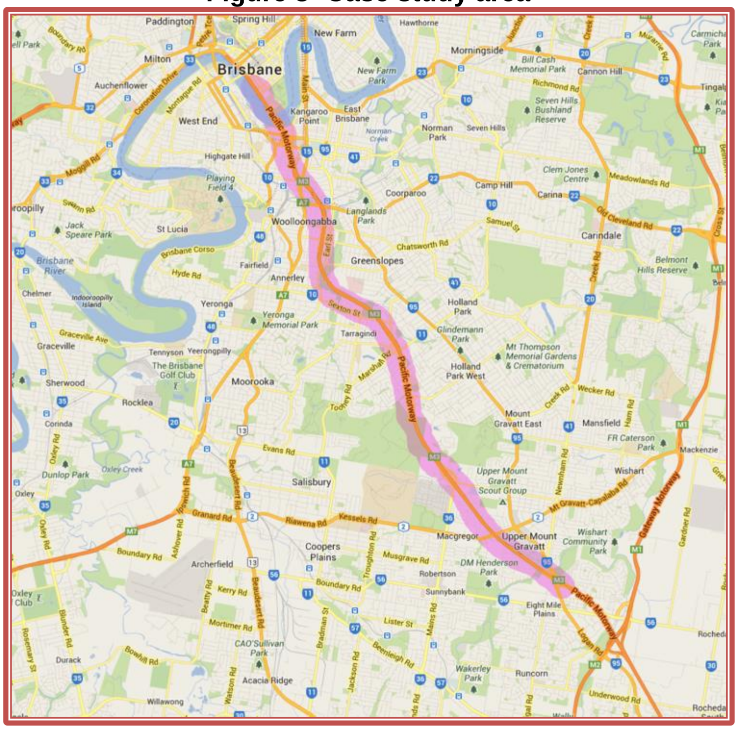


Figure 3- Case study area



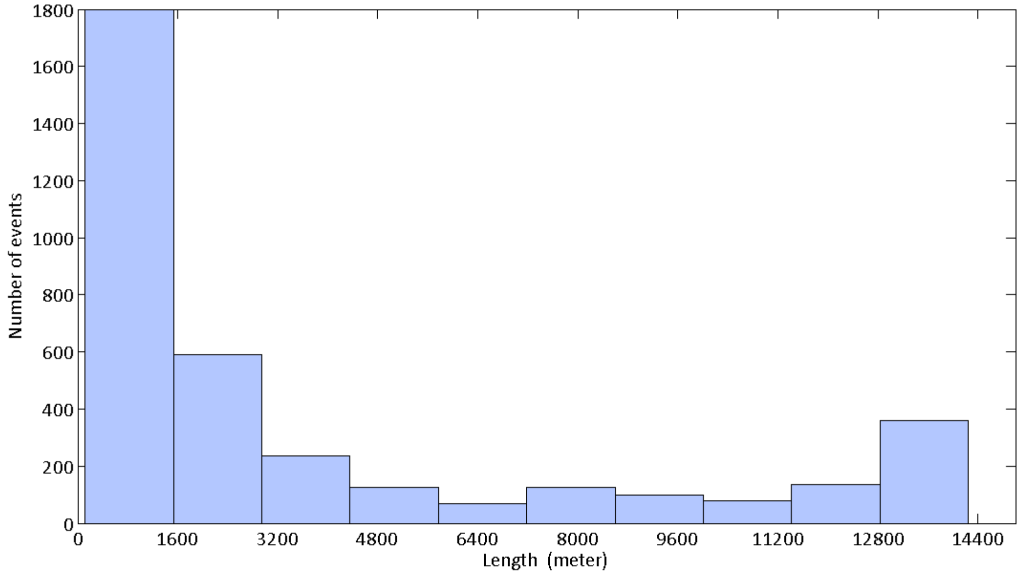
The length of the case study segment is 14.2 kilometre. Based on the location of inductive loop detectors, the case study is divided into seventeen (n_i=17) and fifteen (n_o=15) links in inbound and outbound, respectively. The length of the links are between 0.3 to 2.5 kilometre with range of 2 to 4 lanes and posted speed 70 to 100 km/h. Due to ILDs maintenance, two inbound links and one outbound links were not functioning during the study period. Considering just normal days and availability of traffic data due to the prevalence of equipment malfunctions of ILDs, each link has a range between 38 to 48 samples for each day of the week during the study period.

5. Data Analysis

The method is applied to the case study area which is described in the previous section. MATLAB codes have been developed in order to accomplish the methodology. As a result, 21382 non-recurrent congestions are recognized in the links during the study period. The results indicate that road works took place in the case study area in both directions in the same period. According to the nature of work zones, this type of incident is not considered as an unplanned incident and not considered in the study. Therefore, time intervals between 9:00 PM to 5:00 AM are excluded from the analysis.

The results indicate that 3621 events are identified in which 1974 events relate to inbound and 1647 events happened in the other direction. In addition, 2585 events were started in the case study area. Furthermore, 87 and 134 events were extended from the downstream to the upstream of the case study area and, therefore, affected the whole study area. Figure 4 illustrates the length of study area segment affected by each event. As it shows, most of the events have a length of less than 1.6 km. However, around 200 events caused delay in more than 90% of the segment length.

Figure 4- histogram of length of the segment affected by each event



The results of analysis indicate that days of the week follow different travel time patterns on peak periods. However, the same pattern can be seen for off peak periods as shows in figure 5 for inbound weekdays travel time in afternoon peak. Hence, different RSPs are calculated according to day of the week. This makes the analysis more accurate and sensitive.

Figure 6 displays the free-flow travel time and average recurrent travel time for both inbound and outbound in the case study area. Under free-flow condition, travellers can pass over the segment in around 9 minutes. In addition, travel time on inbound has two peaks in the morning and afternoon and rises time of journey up to 49%. Whereas, out bound has only one peak in the afternoon in which travel time increases about 38%. The results are in-line with the expected traffic behaviour.

As mentioned in the previous section for considering incidents, the scope of this research is limited to unplanned incidents. Therefore, incident types including crash, fault, flood, hazard, and stationary vehicles are only considered. Considering incidents on normal days and no rain condition, 2451 incidents data sets are extracted for the case study area for a one-year period from SIMS. The highest incident type is 'stationary vehicle' with approximately 75% followed by 'hazards' and 'crashes' with around 12% and 10%, respectively. The remaining 3% is due to 'flood' and 'alert' incidents and was excluded from analysis. Therefore, 2380 incidents are examined in this study.

Figure 5- Afternoon peak travel time on different days of the week

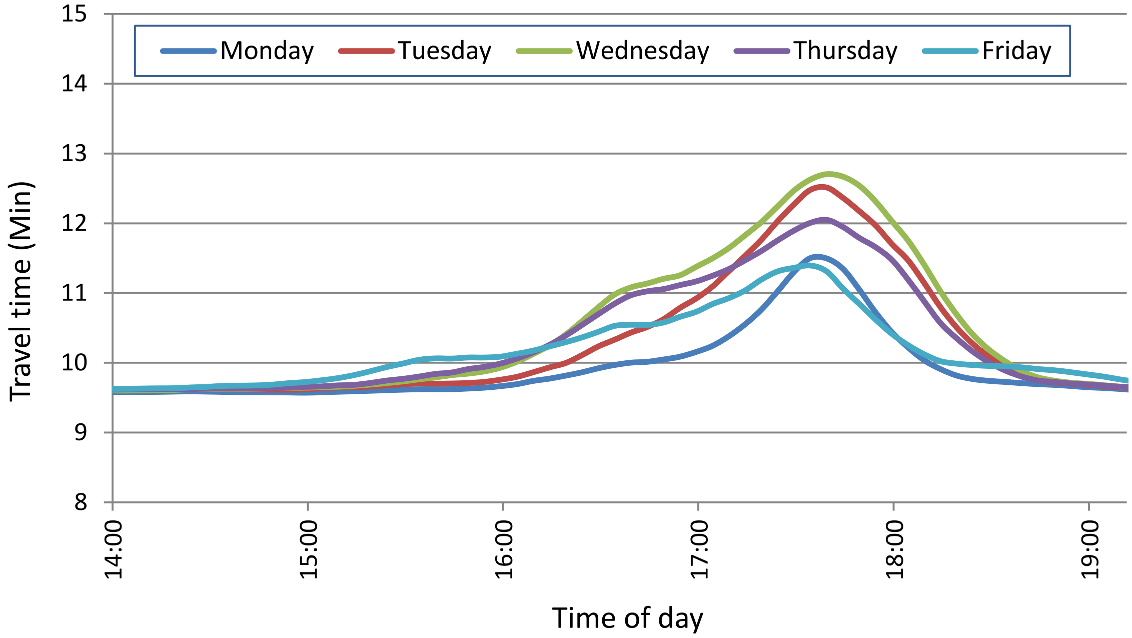
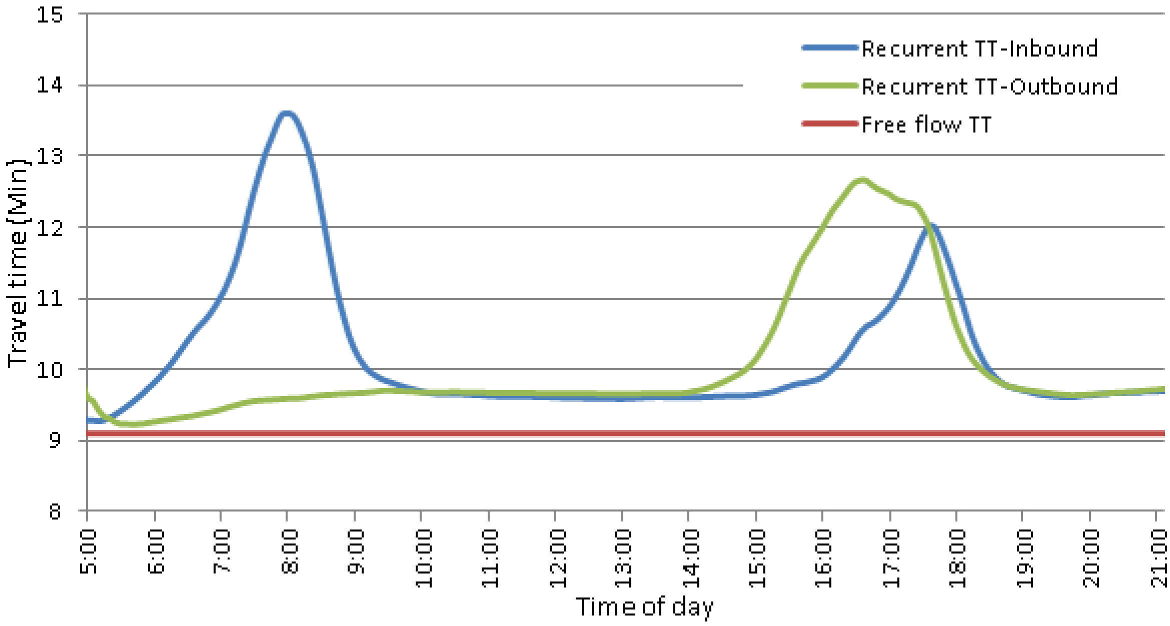


Figure 6- free-flow and recurrent trave time in the case study area



Analyses of the data reveal that 237 incidents are matched with the events. As indicated in the table, many of incidents have little or no impact on traffic movement on the network. This is due to the fact that the incident database is prepared for the purpose of traffic incident management and some incidents require attention although there is no impact on traffic. For matched incidents more information from events' attributes including duration and delay are available. Table 1 illustrates statistics of freeway incident duration for the three major types of incidents on weekdays.

Table 1: Freeway incident duration by incident type on weekdays: summary statistics

Incident type	Number of incidents	Mean*	Median*	SD*	Min*	Max*	COV**	Skewness	Kurtosis
Crash	99	140.3	135	72	25	380	51	0.7	0.3
Hazard	49	114	115	57	30	250	50	0.3	-0.7
Stationary vehicle	89	109	80	69	20	305	63	1.1	0.2

* In minutes ** Coefficient of variation

It can be seen from Table 1 that "crash" is the highest incident type on freeways, which accounts for approximately 42% of the 237 total incidents. "Stationary vehicle" and "hazard" incidents represent 38% and 20% of total incidents, respectively. All incident types have positive Skewness which indicates that the bulk of the durations lie to the left of the mean value. Kurtosis measures show that all incident types tend to have a flat top near to the mean. According to the coefficient of variation measures, incident duration has relatively more variability in "stationary vehicle" incidents than in "hazard" and "crash" incidents.

A variety of probability distribution types, namely, normal, lognormal, exponential, Weibull, gamma, logistic, and log-logistic, were employed in order to test the best model for each category of incident duration frequency distribution. Generally, these distributions are often considered for situations in which a skewed distribution for a non-negative random variable is needed (Washington, Karlaftis and Mannering, 2011). The Anderson-Darling (AD) statistic was selected to check the goodness-of-fit (GoF) and compare the fit of several distributions to select which one was the best or had the closest fit to the data. In this regard, the better the distribution fits the data, the smaller this measure would be. The null hypothesis for the A-D test is "the data follow a specified distribution". Minitab is used for curve fitting and hypothesis testing.The fitted distributions and related probability plot of incident durations are shown in Figure 7, and the related statistics for the selected distribution for each incident type are shown in Table 2.

The results indicated that freeway incident durations for crash and hazards during weekdays conform to a Weibull distribution. For stationary vehicles incidents, 3-Parameter Lognormal distribution is the best fitting distribution compared with the alternatives. All the *p* values are greater than .05 therefore at 95% confidence level all of the distributions could pass this criterion.

Traffic incident delay is calculated in the final stage of the method. Table 3 shows descriptive statistics of freeway traffic incident delay for the three major types of incidents on weekdays on the study area.

Table 2: Results of distribution analysis and goodness of fit test for different types of freeway incident on weekdays

Incident type	Distribution name	Distribution parameters	Goodness of Fit Test*	
			Anderson-Darling	*p*
Crash	Weibull	2.076 158.8	0.27	>0.25
Hazard	Weibull	2.147 129.4	0.377	>0.25
Stationary Vehicle	3-Parameter Lognormal	4.398 0.678 7.843	0.734	0.396

* GoF test statistics at 95% confidence level

Figure 7: Freeway incident duration distributions and probability plot for different types of incidents on weekdays

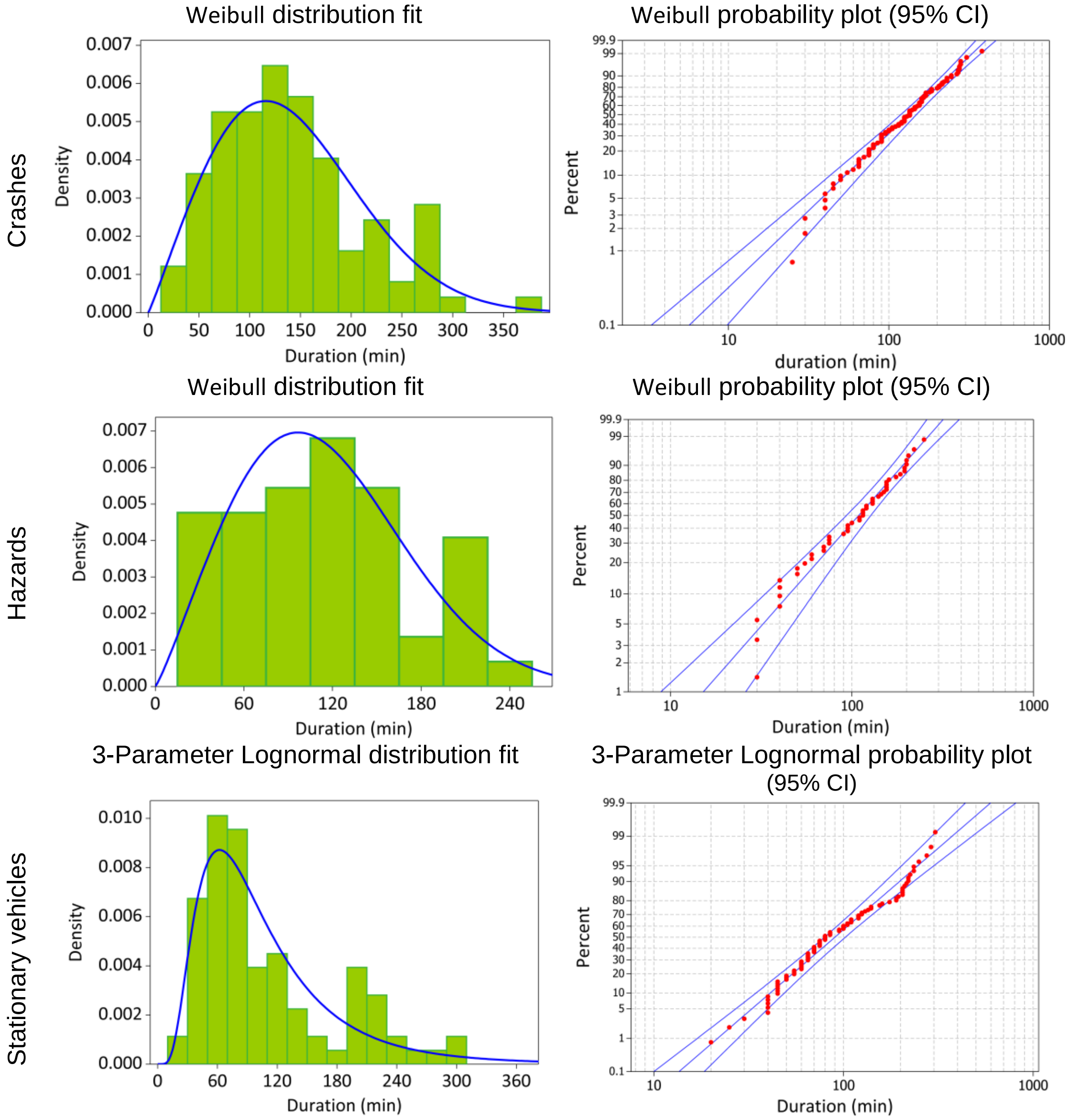


Table 3: Freeway incident delay by incident type on weekdays on the study area (%90 level of confidence): summary statistics

Incident type	Number of incidents	Mean*	Median*	SD*	Min*	Max*	COV**	Skewness	Kurtosis
Crash	99	10.5	9.1	6.7	1.1	31	64	1	0.76
Hazard	49	2.9	2.1	2.6	1	16	90	3.4	14
Stationary vehicle	89	5.7	3.3	5.4	1	30.5	95	1.73	3.97

* In minutes ** Coefficient of variation

It can be seen from Table 3 that crash type has, on average, the highest delay on freeways which is approximately more than twice of free-flow travel time. The average delay of "Stationary vehicle" and "hazard" incidents represent 63% and 32% of free-flow travel time, respectively. All incident types have positive Skewness which indicates that the bulk of the delays lie to the left of the mean value. Kurtosis measures show that "hazard" and "stationary vehicle" tend to have a flat top near to the mean compared to the other types which tend to have a distinct high near to the peak. According to the coefficient of variation measures, delay has relatively more variability in "crash" incidents than in "hazard" and "stationary vehicle" incidents.

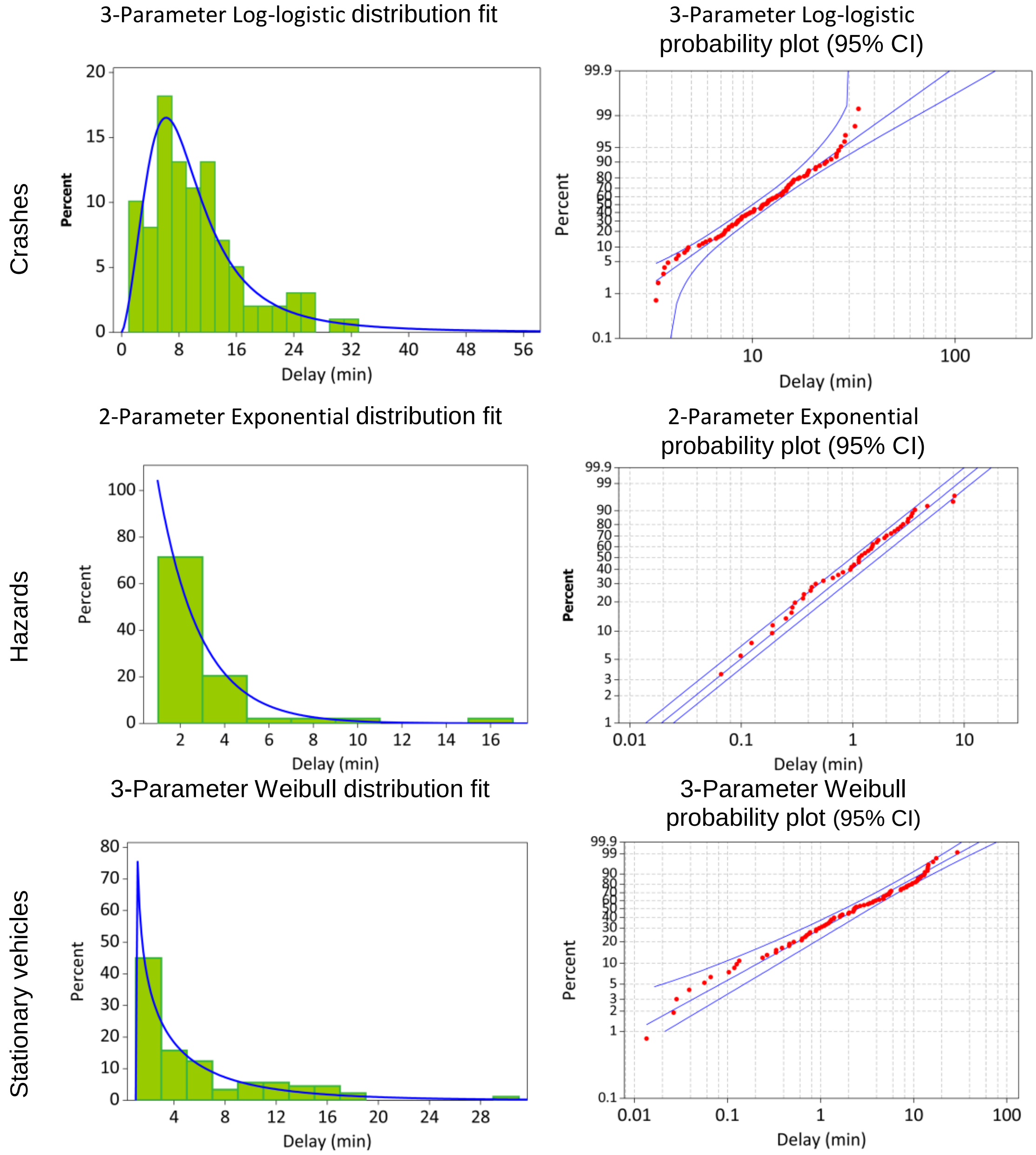
The fitted distributions and related probability plot of traffic incident delay are shown in Figure 8, and the related statistics for the selected distribution for each incident type are shown in Table 4. The results indicated that TID on each incident type follow different patterns which show each type of incident has its own characteristics. While TID of crash type follows 3-Parameter Log-logistic distribution, hazard type conforms to a 2-Parameter Exponential distribution. For stationary vehicles incidents, 3-Parameter Weibull distribution is the best fitting distribution compared with the alternatives. All the *p* values are greater than .05 therefore at 95% confidence level all of the distributions could pass this criterion. The probability plot figures represent the good prediction range if the red data points follow the specified line with in the range. As can be observed from figure 8, in crash type, relatively low and high delays are not located in the line. So, this model is not capable of predicting an accurate range.

Table 4: Results of distribution analysis and goodness of fit test for different types of freeway traffic incident delay on weekdays

Incident type	Distribution name	Distribution parameters	Goodness of Fit Test*	
			Anderson-Darling	*p*
Crash	3-Parameter Log-logistic	2.42 0.307 -2.221	0.138	0.138
Hazard	2-Parameter Exponential	1.912 0.966	0.62	>0.25
Stationary Vehicle	3-Parameter Weibull	0.765 4.054 0.993	0.465	0.28

* GoF test statistics at 95% confidence level

Figure 8: Freeway traffic incident delay distributions and probability plot for different types of incidents on weekdays



6. Conclusions and future research

This paper establishes an innovative method for quantifying the impact of traffic incident, namely: duration and delay on freeways based on conjunction of ILDs and reported incidents data. The method implements historical data to establish recurrent speed profile and identifies non-recurrent congestions based on their negative impact on speed. The proposed method uses only the location and the time of incident as well as traffic data from ILDs which are commonly available around the road network of cities. Therefore, this method is capable to be implemented in any freeway network in order to identify the impact of traffic incidents. It should be noted that, this study has a limitation due to the traffic incident data coverage which is limited to the reported incidents to the SIMS database which does not include all incidents.

In this study, an overview of the pattern and duration of three major types of incidents, namely, crash, hazard and stationary vehicle, on the SEQ network of freeways during weekdays for a one year period up to November 2010 has been presented. A total number of 237 incidents were identified in which traffic data have been affected. The inflection points of incident duration for crashes, hazards and stationary vehicles are 116, 97 and 60 minutes, respectively. This indicates, on average, the impact of crash type takes longer to be recovered to normal conditions. Also, the findings of this study revealed that the variance in incident duration within each incident type was fairly large. In addition, 3-Parameter Lognormal distribution was inferred to be appropriate for stationary vehicle and Weibull distribution for hazard and crash incidents on freeways. The substantial discrepancies among these patterns are due to the fact that a variety of contributory variables of a stochastic nature are included and are not all under the control of the responsible agencies. Therefore, any of those variables can have a crucial role in affecting the resulting incident duration.

The results clearly indicate that the durations and delays of each type of incident are uniquely different, and require different types of responses to clear them from a road and have differential impact on cumulative clearance times and hence delay.

Further research needs to be conducted to investigate the influence of numerous factors associated with incidents of various types on their duration. Consequently, incident delay and travel time reliability models can be established. Results would provide valuable information for the purpose of traffic incident management strategies and policy evaluation. In addition, such models can be used to quantify the effects of incidents on travel time reliability.

Finally, further research needs to be conducted to quantify the impact of other non-recurrent congestions such as work zones and inclement weather using the same method.

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