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An analysis of traffic incidents on an Australian urban road network

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Abstract

Assessing and prioritising cost-effective strategies to mitigate the impact of traffic incidents on non-recurrent congestion on major roads are currently a major challenge for road network operations. There is a lack of relevant local research in this area. Several incident duration models developed from international research are not considered appropriate for Australian conditions due to different driver behaviour and traffic environment contexts. A comprehensive data mining research project was undertaken to analyse traffic incident data, obtained from the Queensland Department of Transport and Main Roads' STREAMS Incident Management System (SIMS) for a one year period ending in November 2010. Various factors that contributed to frequency, type, characteristics, duration and location of traffic incidents were examined and the findings are discussed in this paper. Results indicate that breakdown, multiple vehicle crash and debris were the major sources of incidents. Although incident frequency dropped sharply on weekends, the average incident duration was similar or longer than those of weekdays. Also, rainfall increased the incident duration in all categories. Furthermore, a variety of probability distribution functions were employed in order to test the best model for each category of incident duration frequency distribution. Log-normal distribution was inferred to be appropriate for crash and stationary vehicle incidents and gamma distribution for hazard incidents. Future research directions have been identified, particularly the estimation of the impact (cost) of traffic incidents, to assist in prioritising investment.

1. Introduction

Traffic congestion has steadily increased especially in urban networks as a result of population growth and density and increased motorisation. This has reduced transport mobility and consequently has resulted in millions of hours of vehicle delays, air pollution and fuel consumption that might 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, 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 et al., 2002). Systematic understanding of incident characteristics and patterns is essential to restore a road network to full capacity. Therefore, the collection and analysis of traffic incident data and its components is crucial. In addition, 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 et al., 2003). In addition, predicting incident components is vital for providing reliable traffic information and improving travel time reliability (Lyman et al., 2008).

This paper summarises the early findings of a study aimed at developing models to predict incident durations and frequencies 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 incident data analysis from different points of view along with categorising the data into homogenous patterns for data grouping analysis purposes. Then, incident duration frequency distributions 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 research literature demonstrates that various methodologies and techniques have been employed to examine incident data, which has included frequency and duration, mainly on freeways in the past few decades.

Most of the analytical techniques for modelling incident frequency found in the literature relate to crash frequency. The findings suggested that although both negative binomial and Poisson regression models are presented as appropriate techniques for exploring the frequency of crashes, the former models are more suitable. This is because the mean and the variance need to be equal in the Poisson regression models, however the variance of crash data is expected to be greater than the mean and the negative binomial does not comply with this limitation (Jones et al., 1991; Skabardonis et al., 1999; Carson et al., 2001; Chang, 2005).

The most representative approaches for incident duration models can be categorised into the following groups: 1) linear regression analysis (Valenti et al., 2010; Garib et al., 1997), 2) nonparametric regression method and classification tree model (Smith et al., 2001), 3) conditional probability analysis (Chung, 2010; Stathopoulos et al., 2002; Nam et al., 2000), 4) probabilistic distribution analysis (Giuliano, 1989; Golob et al., 1987), 5) time sequential method (Khattak et al., 1995), 6) discrete choice model (Lin et al., 2004), 7) Bayes classifier (Boyles et al., 2007), 8) fuzzy logic models (Kim et al., 2001), and 9) artificial neural networks (Wang et al., 2005).

Incident duration was found to follow log-normal distribution in many studies (Skabardonis et al., 1999; Golob et al., 1987; Giuliano, 1989), while other studies showed that the duration of incidents was characterised by a log-logistic distribution (Jones et al., 1991; Nam et al., 2000; Stathopoulos et al., 2002; Chung, 2010).

However, many of the research studies in the literature cannot be generalised to other cases due to the fact that: 1) the research is based on small sample size of up to several hundred incident records, 2) the incomplete or poor quality of the incident data weakens the accuracy of the developed models, or 3) even though there are a few proposed models with rather high efficiency, they still cannot be applied to other cases as the characteristics of the model factors are inconsistent with one another or the factor(s) data does not exist in other cases.

In addition, the results of previous research studies cannot be compared since 1) different variables have been used in different studies, 2) results might not be transferable across different locations, and 3) the data collection and reporting process are too different. In view of these study limitations, analysis of traffic incidents on Australian urban road networks needs to be undertaken to examine the factors arising from the literature as well as to identify other potential factors that might have a strong relationship with the duration of traffic incidents. In this study three types of incident will be considered, namely crash, hazard and stationary vehicle incidents.

3. Research framework and data description

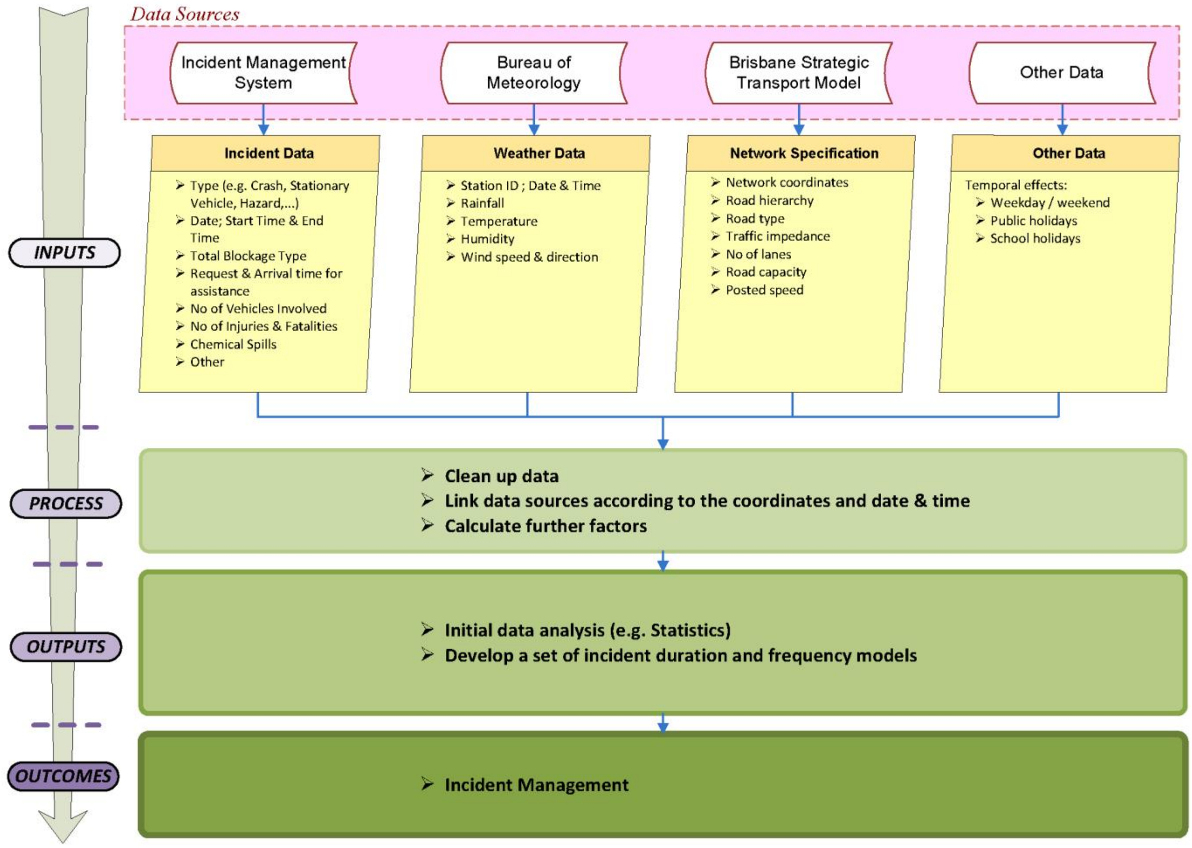
Availability of incident data is the most important factor in analysing the characteristics of traffic incidents. Then the examination of their impact on traffic flow is performed which provides reliable inputs for evaluation of various programs in traffic incident management (TIM). Often, due to the lack of a comprehensive database of incident data, accessing the local historical data has been a major challenge for researchers (Konduri et al., 2003).

To overcome this limitation, a logical framework analysis (Logframe) was designed in order to establish an analytical process for structuring and systematising the data collection and the analysis of this research. The Logframe has four main stages, namely: inputs, process, outputs, and outcomes. Figure 1 shows this framework and its components for this study. The first stage is “inputs” which have influential effects on the next stages and results. In this regard, all the factors that can affect the outcomes of the research need to be identified in this stage.

Incident data was obtained from the Queensland Department of Transport and Main Roads’ STREAMS Incident Management System (SIMS) for SEQ urban road networks for a one-year period up 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. These events can be classified as traffic Incidents, equipment faults or other events as shown in Figure 2 (Webster, 2010). The objective of this paper is limited to the non-recurrent congestion events so only unplanned incident data will be considered in the analysis. When an incident is notified to the Brisbane Metropolitan Transport Management Centre (BMTMC), various types of incident information are recorded in SIMS. The main factors are: priority, incident location, type, classification, start-time and end-time, request and arrival time of assistance. Priority indicates the level of importance and severity of an incident in three levels: high, medium and low. Incident type describes the type of incident which has occurred, such as crash, fault, flood, hazard, roadworks, and stationary vehicles as shown in Figure 2.

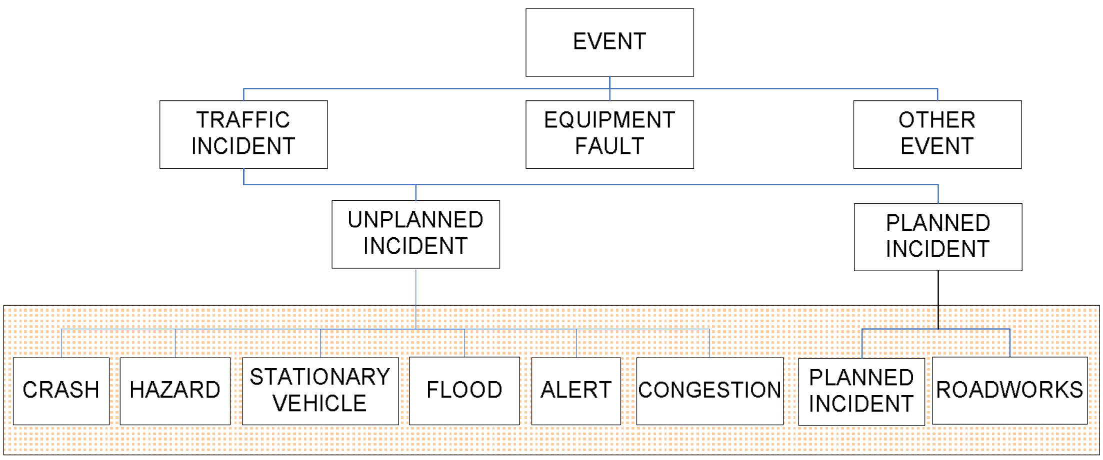
All incident events cause temporary capacity reductions. Some events occur unexpectedly such as vehicle-based incidents (e.g. crashes, stationary vehicles), other objects or obstructions on the road (e.g. debris), or extreme weather events (e.g. flood). There are also events that might not be expected by all road users, but which are planned events and are publicly notified (e.g. roadworks and sports/cultural activities). The scope of this study is limited to the non-recurrent congestion so only unplanned incidents will be considered in the analysis. In addition, since a congestion-type incident is defined as “a condition on networks that occurs as use increases, and is characterised by slower speeds, longer trip times, and increased queuing" (Webster, 2010) and directly relates to recurrent congestion, this type of incident is excluded from the analysis. A large number of stationary vehicle incidents relate to a "tow zone" where illegally parked vehicles are in clearways and this has limited, if any, impact on congestion, therefore, this classification was also omitted from the analysis.

Figure 1: Logical framework analysis for the research



Weather data were received from 10 Bureau of Meteorology stations around SEQ which included rainfall, temperature, humidity, wind speed and wind direction for the same period as the incident data. The road specifications data were captured from modelled traffic data in the Brisbane Strategic Transport Model (BSTM) including road hierarchy, road type, number of lanes, road capacity, and posted speed. Chung (2010) stated that temporal effects such as day and type of day – week day/ weekends, holiday, public holiday and school holiday needed to be incorporated in incident analysis.

Figure 2: SIMS Structure



(Source: Webster, 2010)

The next stage in the Logframe approach is “process”. In this stage, all the data which were collected or gathered from different sources needed to be processed prior to the analysis stage. The first task in this stage was cleaning the data. During this process, all the factors were evaluated and all out of range data excluded or fixed. Missing data were also fixed or excluded from the data sources. After cleaning the data from different sources, the next task was linking all the sources by referring to the coordinates, date and time of the incidents. A combination of geographic information systems (GIS) software and clustering analysis was applied in this study in order to investigate the impact and contribution of different factors on incidents. The next step was to calculate further factors from available variables; for example, incident duration or duration of rainfall for each incident.

The third stage in Logframe is “outputs”. In this stage, a general analysis is done to find the effect and the significance of each identified factor. Then, statistical analysis is conducted in order to establish the relationship between the incident duration (dependent/outcome variable) and the independent/predictor variables.

The final stage in Logframe is “outcomes”. Based on the results from the previous stage, final models are established for incident management and travel time reliability modelling. The results of this stage are useful for evaluating the impacts of different policies and scenarios in this research area.

4. Data Analysis

The incident data combined with data from other sources, described in the previous section, was investigated and analysed in order to provide an understanding of the characteristics of the historical incident data. The investigation process was separated into two distinct areas; namely: 1) incident frequency, and 2) incident duration, which are discussed below.

4.1. Incident frequency

Traffic Incidents are categorised by type in the SIMS database. As described in the previous section, the road hierarchy associated with each incident record was identified and matched with SIMS incident data for the analysis, which are provided in Table 1.

Table 1: Number of incidents of different type according to the road hierarchy

Incident type	Road hierarchy			Total incidents
	Freeway	Arterial	Local	
Alert	7		2	9
Crash	1246	2694	680	4620
Flood	4	26	9	39
Hazard	1964	1910	453	4327
Stationary Vehicle	2212	2073	358	4643
Total	**5433**	**6703**	**1502**	**13638**

It can be seen from Table 1 that ‘stationary vehicle’ and ‘crash’ are the two highest incident types, which account for approximately 34% and 33.9% respectively of the 13,638 incident records examined. This is followed by ‘hazard’ at 31.7% and the remaining 0.4% is due to ‘flood’ and ‘alert’ incidents. Only the three major incident types, that is, crash, hazard and stationary vehicle, were analysed further in this study. Figure 3 depicts the number of incidents by incident type. For the crash type, “multiple vehicle” was the most frequent incident and mostly occurred on arterial roads. There was a fairly low number of heavy vehicle (HVRU) crashes, however as far as their impacts on congestion are concerned, this sort of crash incident has a very significant contribution. As for the stationary vehicle incidents, “breakdown” scored the most frequent number of incidents compared with other classifications within the same group, which accounted for nearly 82% of all incidents in this category. For the hazard type, “debris” on the freeways was the most dominant classification which accounted for approximately 39% of all hazard incidents. The analysis shows that nearly 40% of incidents occurred on freeways, 49% on arterial roads and only 11% on local roads for the studied data period. The reason for low incident frequency on local roads might be due to the fact that these sorts of incidents were not reported or not registered based on their low importance. Furthermore, typical speed and traffic volume on local roads are considerably lower than that of the freeways and arterial roads.

Figure 3: Number of incidents for different classification of incident types

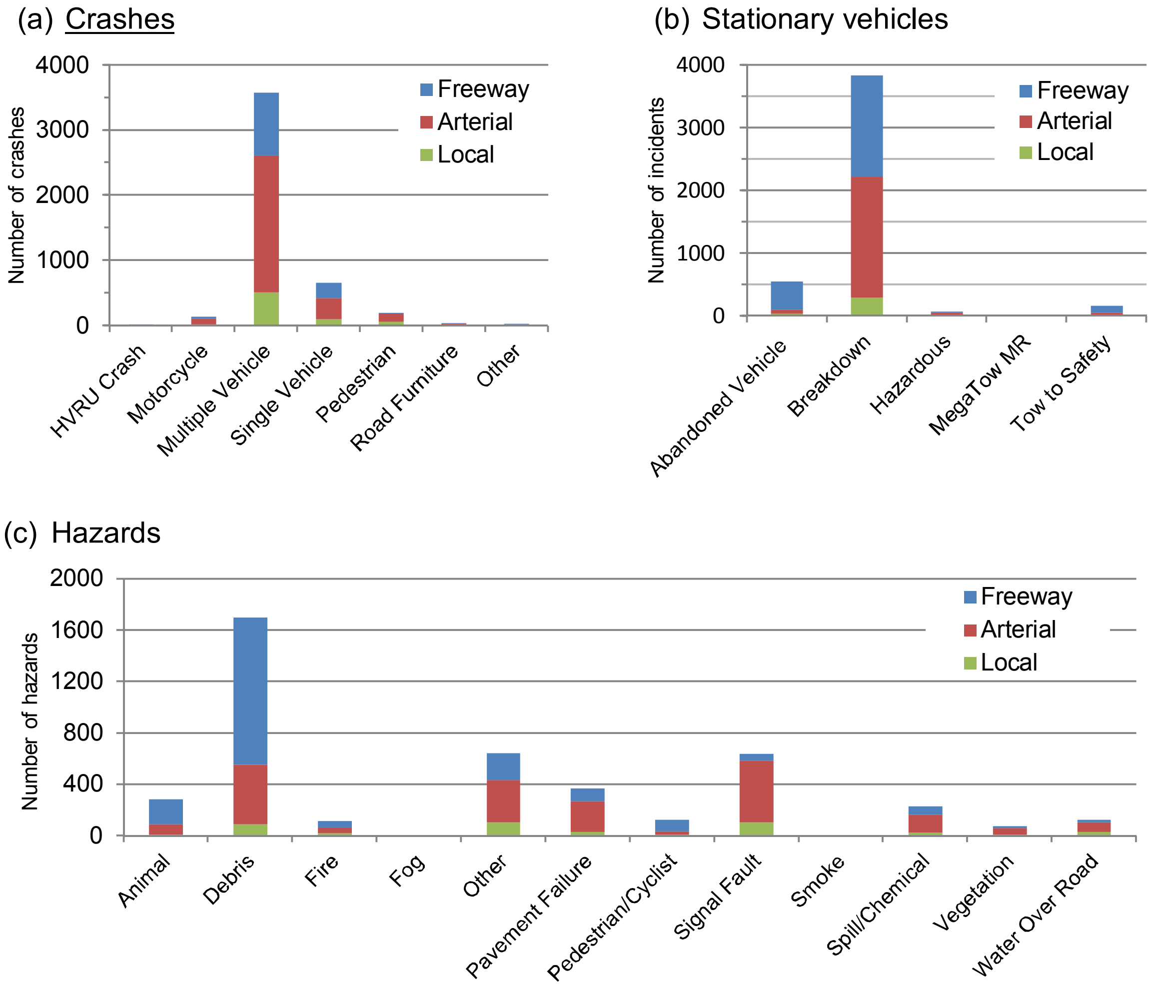
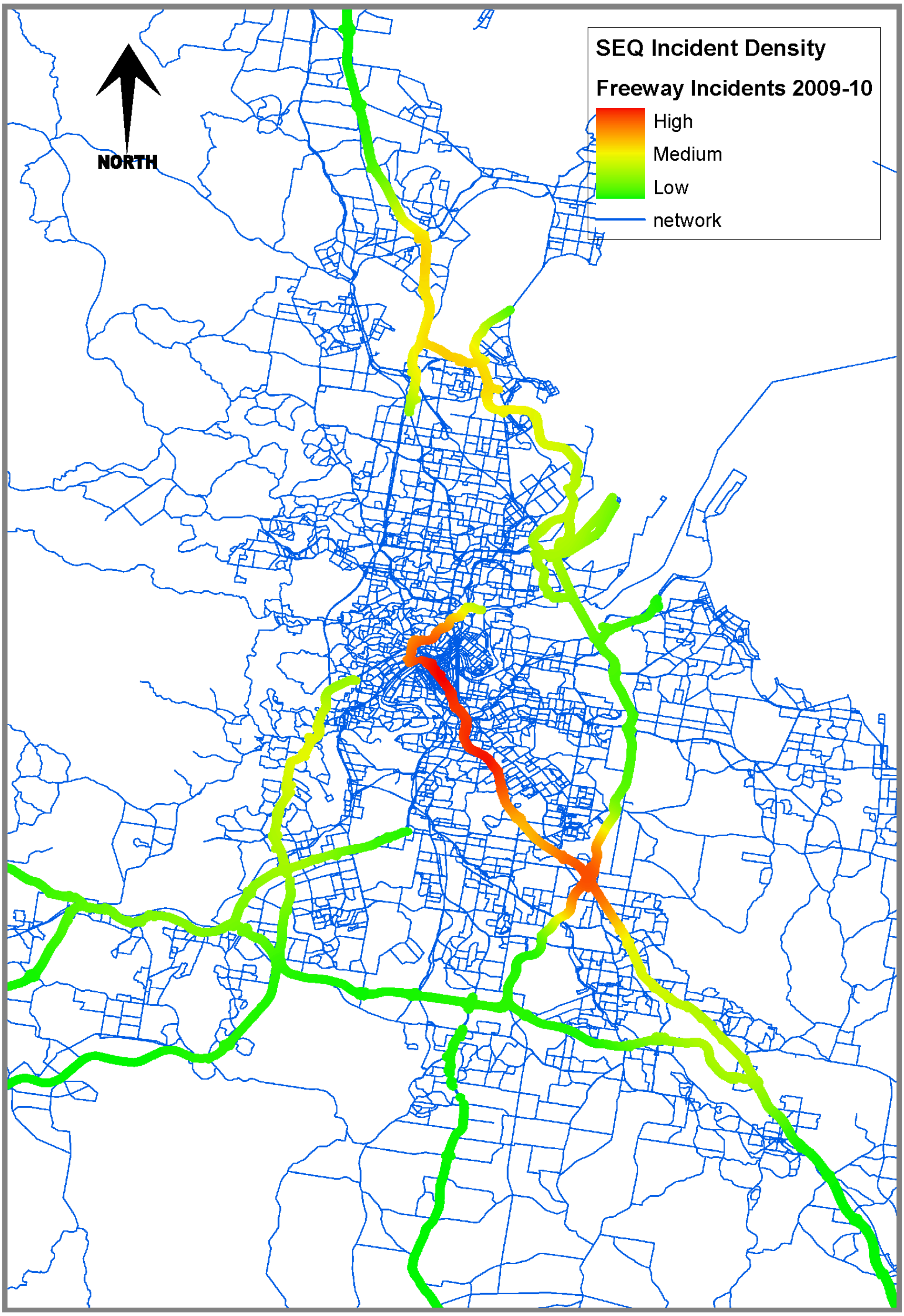


Figure 4 shows the density of incidents on the freeways network in SEQ. Incident density was concentrated around the Brisbane CBD areas, with the highest density along the Pacific Motorway south of the CBD. The density gradually diminished to the medium level, but rose again at the Pacific Motorway-Gateway Motorway interchange. Incident density then gradually reduced after the interchange and became medium to low density after passing the Pacific Motorway-Logan Motorway interchange. The Gateway Motorway has experienced medium incident density around the Bruce Highway area.

Figures 5 to 7 show the variability of the incidents for the months of the year, days of the week, and time of day by road hierarchy, respectively. The graphs in Figure 5 show that the frequency of traffic incidents fluctuated by month on both freeways and arterial roads.

The number of incidents increased gradually from January until it reached a maximum in March, and then dropped slightly in April. From then onwards, the number of incidents for all three road hierarchies was quite consistent until October and November when the number of incidents increased slightly and then dropped to the overall average level in December. However, the trend for local roads was flat with around 100 incidents per month.

Figure 4: Heat map-density of all freeway incidents in SEQ



It can be seen from Figure 6 that the difference in the frequency of incidents changed slightly from Monday to Friday but dramatically plunged on the weekend for all the road hierarchies considered.

Figure 7 illustrates the rate of incident occurrence throughout a typical day. Interestingly, the trend of incident occurrence was similar to the traffic flow pattern during a typical day. In addition, the vast majority of all incidents occurred when the road network experienced extremely high traffic volume (near or exceeding the roadway capacity). This trend implies that traffic flow parameters appear to have a strong correlation with incident occurrence and thus suggests further investigation. The number of incidents on freeways and arterials peaked during the morning peak hours of 7:00 and 9:00 and during the afternoon peak hours of 15:00 and 16:00. More incidents occurred in the afternoon peak hours and most incidents occurred on the arterial roads.

Figure 5: Incidents by months of year and road hierarchy

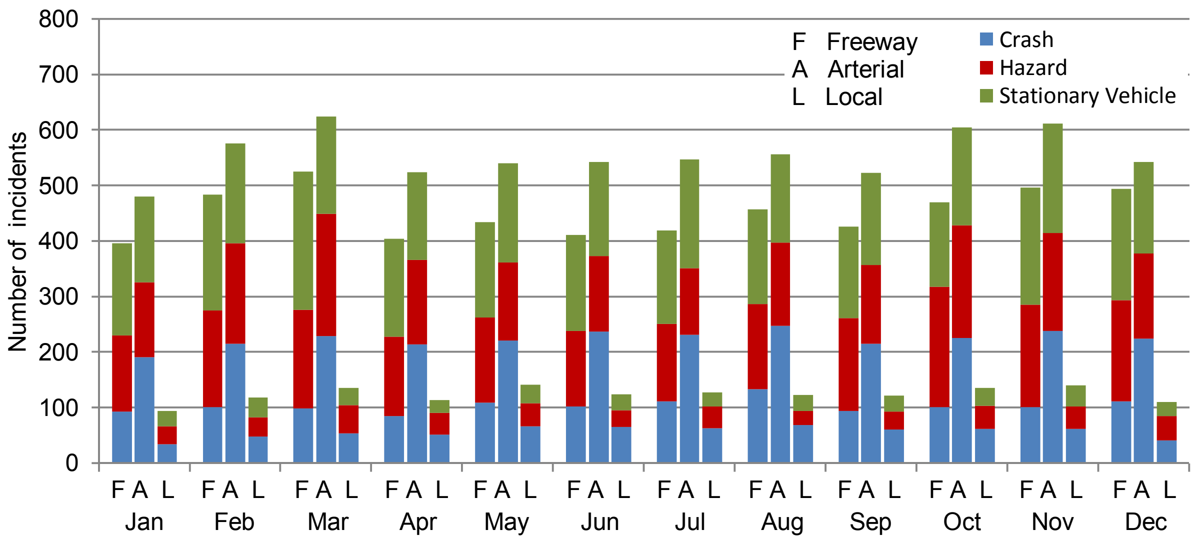


Figure 6: Incidents by day of week and road hierarchy

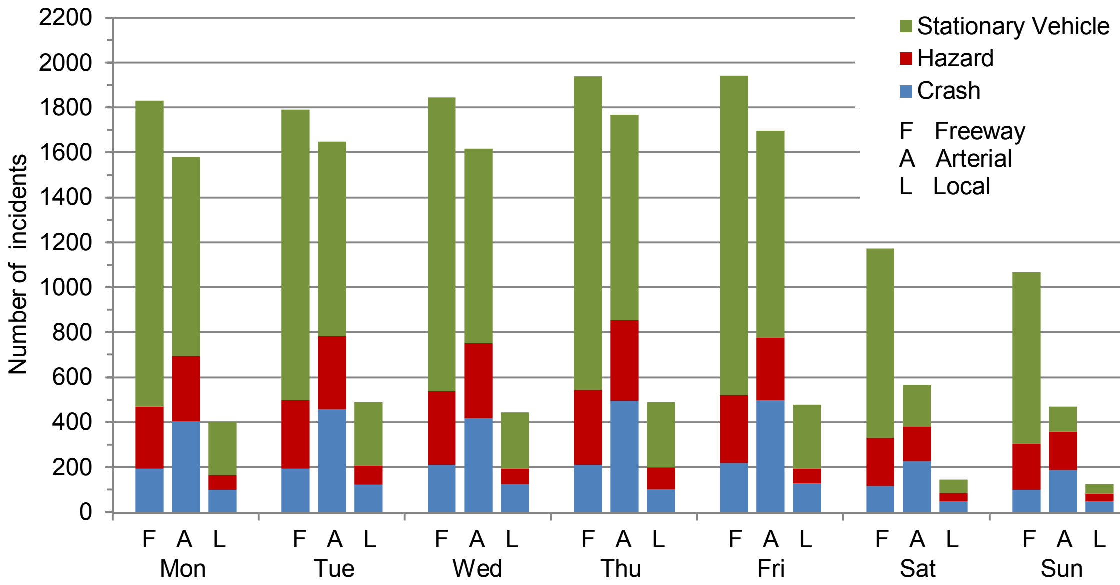
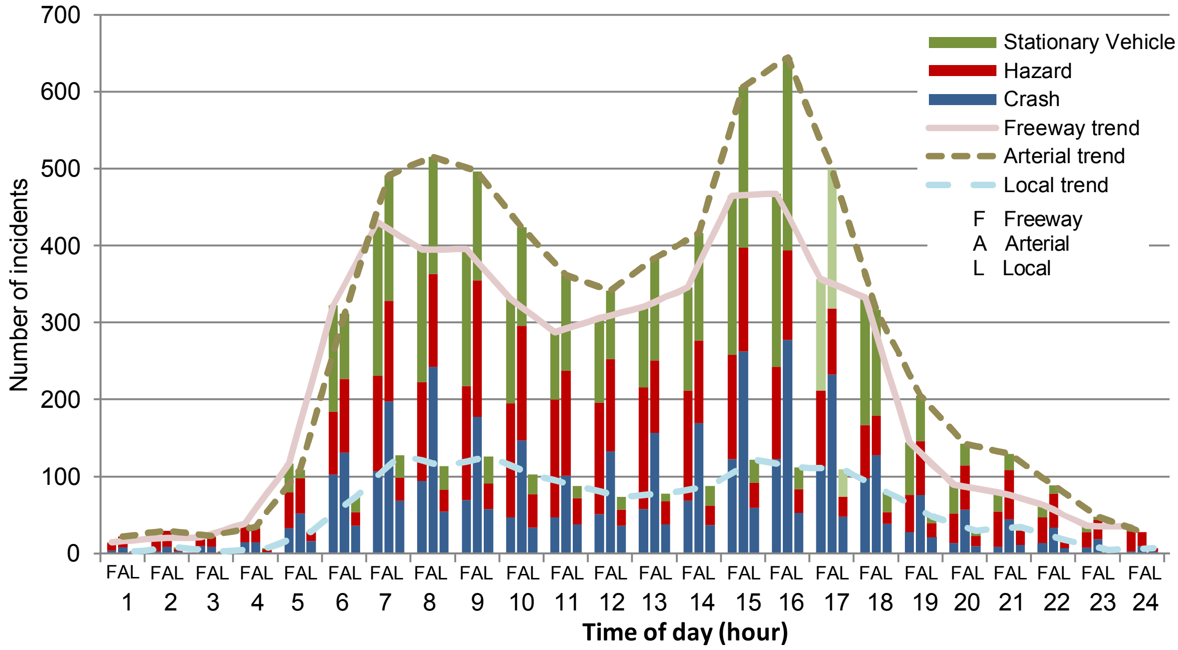


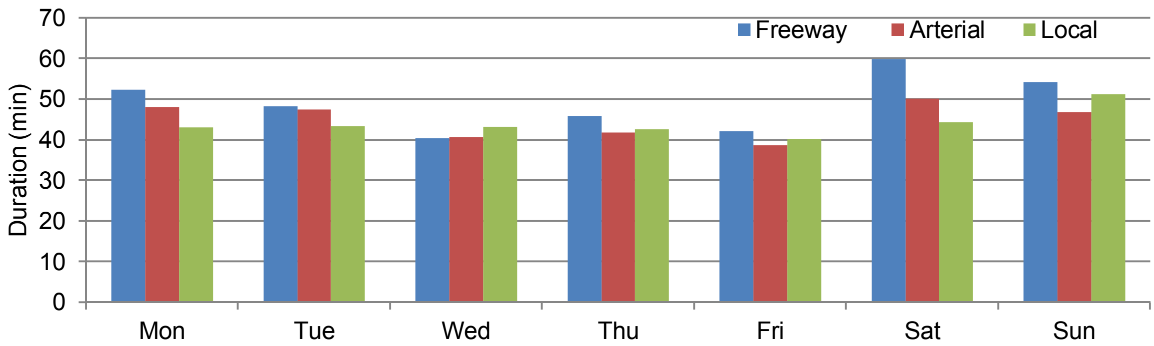
Figure 7: Incidents by time of day and road hierarchy



4.2. Incident duration

The duration of incidents is a major factor affecting non-recurring congestion. In general, the total incident duration is calculated from the time the incident is detected until the time it is cleared. For all recorded incidents, the average duration was 1 h 25 min, while for freeway incidents it was 1 h 33 min. In addition, the minimum average duration for the crash type was 45 min, followed by stationary vehicle and hazard types with 78 min and 136 min, respectively. Figure 8 shows the average duration for crash incidents by days of the week and different road hierarchies. It can be seen that the average incident duration was longer on weekends compared to weekdays. In addition, the average incident duration was slightly higher on Monday compared to other weekdays.

Figure 8: Crash duration by day of week and different road hierarchy



The average duration by time of day is shown in Figure 9 for crash incidents and road hierarchy. The minimum incident duration in the morning peak was 45 min while that of the afternoon peak was 36 min. Also it can be seen that the average incident duration dramatically increased during the night, although the number of incidents was lower than that of the day time.

Table 2 shows the incident frequency, the average and the 95 percentile of incident duration in rain and no-rain conditions. The average duration of incidents increased in rainy conditions in all categories. However, rain had more effect on hazard incidents for all road types.

Figure 9: Crash duration by time of day and different road hierarchy

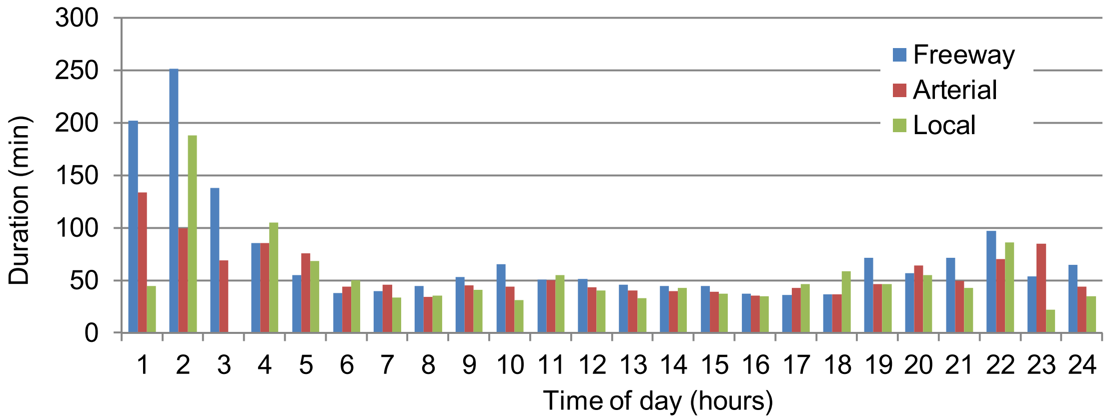


Table 2: Comparison of the effects of rain on the number and duration of incidents*

Incident type		Road Type					
		Freeway		Arterial		Local	
		Rain	No Rain	Rain	No Rain	Rain	No Rain
crash	NI	104	736	192	1681	51	435
	AD	47	40	45	41	43	43
	95^{th}D	124	95	105	95	172	123
	Diff%	30.5%		10.5%		40.0%	
Hazard	NI	105	1125	151	1128	36	259
	AD	125	94	228	154	233	153
	95^{th}D	540	368	885	565	1102	502
	Diff%	46.9%		56.5%		119.7%	
Stationary vehicle	NI	141	1348	140	1388	22	239
	AD	71	59	35	33	42	44
	95^{th}D	315	265	105	95	221	145
	Diff%	18.9%		10.5%		52.4%	

* NI: Number of incidents, AD: Average incident duration (minute) ,95^{th}D: 95 percentile of incident duration, Diff%: percentage difference between 95^{th}D in Rain and No rain

Histograms of incident duration frequency distributions for different road types and incident types on weekdays are shown in Figure 10. The Freedman–Diaconis rule (Freedman et al., 1981) was used to select the size of the bins of the histogram. Then the least square optimisation was performed to find the probability distribution functions of best-fit to the data. As shown in the figure, the distribution is skewed to left which implies positive skewness of the data.

A variety of distributional alternatives, namely, the log-normal, the Gamma, and the Weibull distributions 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 et al., 2009). The fitted distributions are also shown in Figure 10, and the related statistics are shown in Table 3. Also the plotted data and the results indicate that incident durations for crash type and stationary vehicle type in all road hierarchies conform to a log-normal distribution rather than the other distribution alternatives. For hazard incidents, gamma distribution seems to be the best fitting distribution compared with the other two distribution alternatives. However, more models need to be tested for this type of incident on freeways, since there was a big difference between the standard deviation of the data and the gamma model for these incidents.

Figure 10: Incident duration distributions for different types of incident on weekdays *

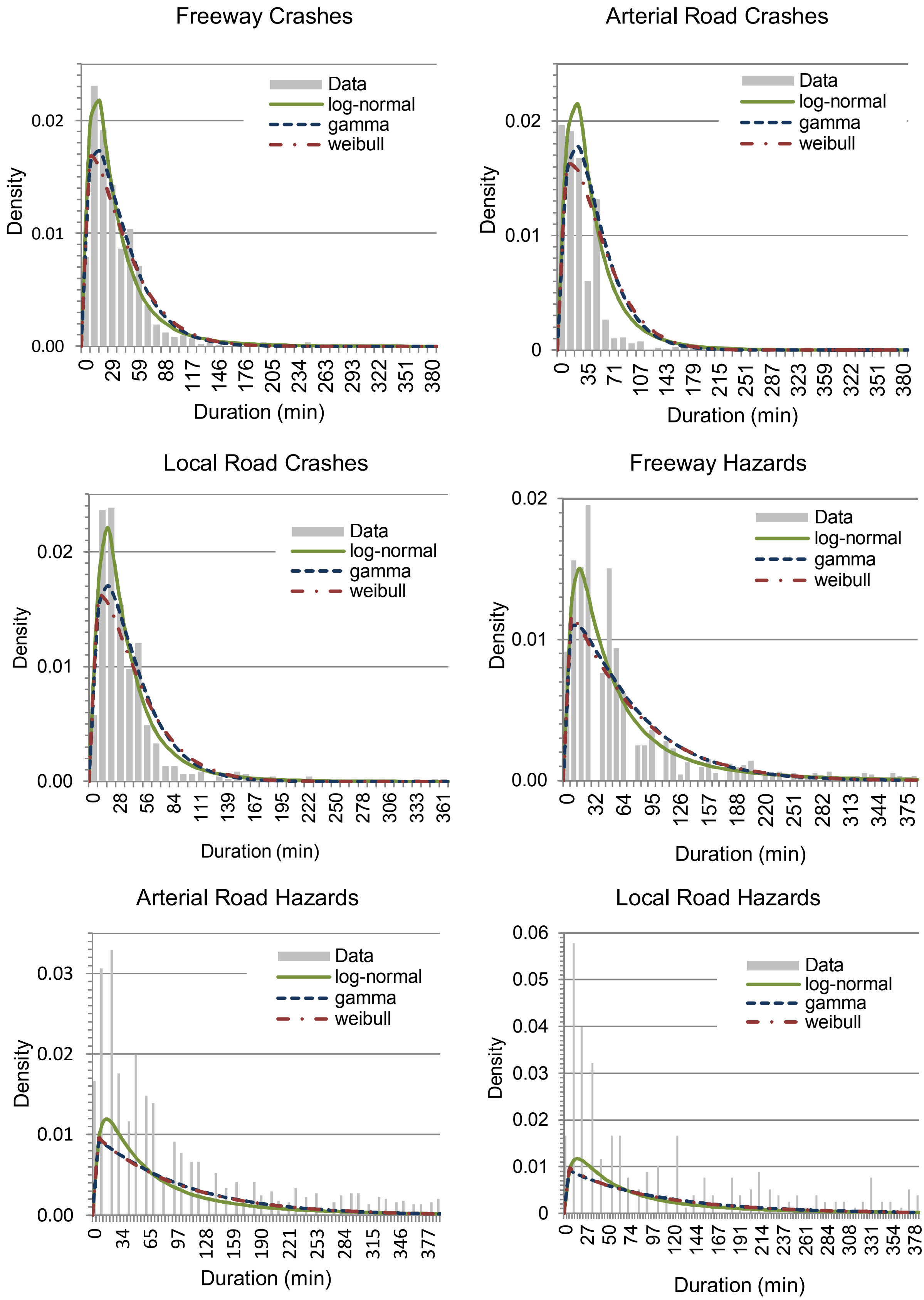
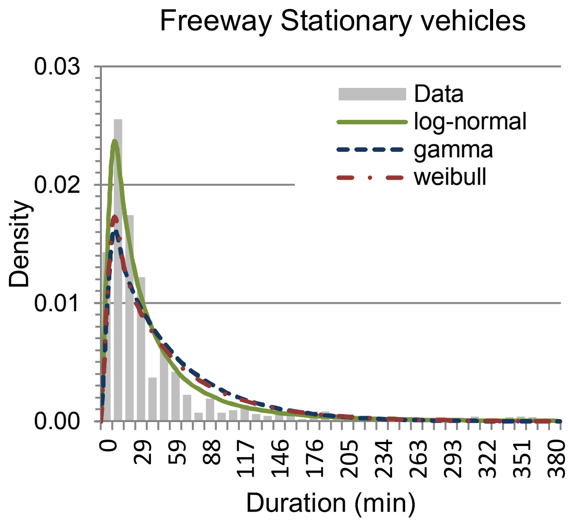
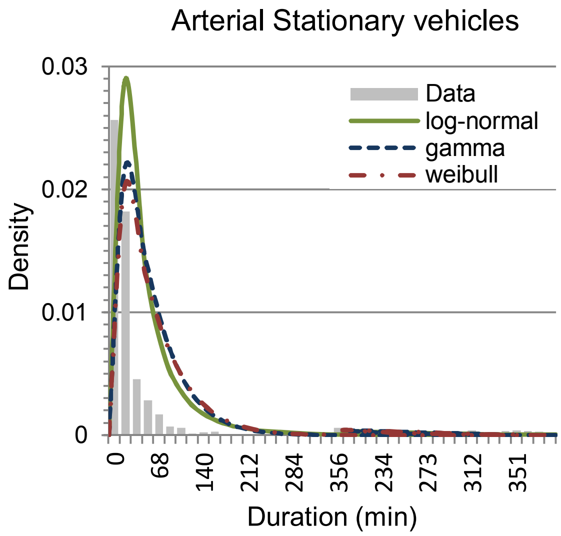
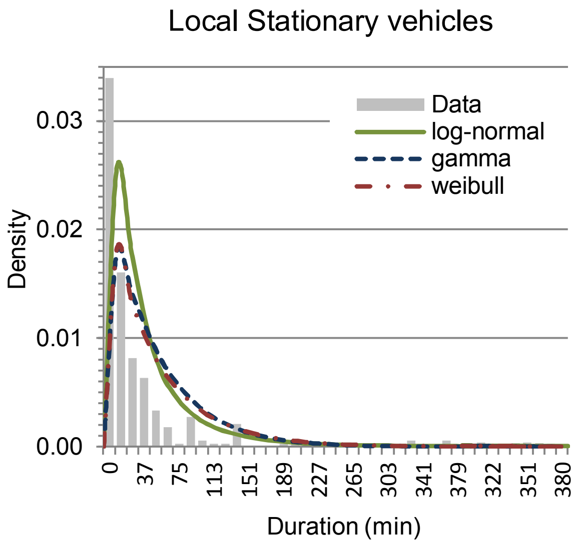


Figure 10 (continued): Incident duration distributions for different types of incidents on weekdays *







(a) Crash

Table 3: Observed and fitted statistical parameters for incident duration (min)

Incident type		Freeway Obs. data	Freeway log-normal	Freeway gamma	Freeway weibull	Arterial Obs. data	Arterial log-normal	Arterial gamma	Arterial weibull	Local Obs. data	Local log-normal	Local gamma	Local weibull
Crash	$\overline{X}$	41.3	41.6	41.3	41.6	40.8	40.8	40.8	41.2	42.5	42.1	42.5	42.9
	SD	41.1	40.8	31.9	34.1	37.7	35.2	29.2	31.7	42.8	38.6	32.2	35.0
Hazard	$\overline{X}$	69.3	71.7	69.3	69.5	96.9	106.2	96.9	96.9	104.3	114.8	104.3	104.2
	SD	73.5	93.1	62.5	65.1	98.4	171.2	94.8	96.7	105.9	197.7	105.6	108.0
Stationary vehicle	$\overline{X}$	52.9	51.3	52.9	52.4	32.8	32.2	32.8	33.1	42.5	40.2	42.5	42.4
	SD	71.8	76.6	54.5	58.3	36.0	32.6	26.9	29.1	58.2	48.5	40.1	43.5

$\overline{X}$: Mean, SD: Standard Deviation, Obs: observed

5. Summary

Based on the proposed framework, additional factors were fused with the incident data obtained from SIMS. Then, the contributing factors to traffic incidents, that is, frequency, type, characteristics, duration and the location of traffic incidents were examined. The major findings are summarised as follows:

- A total number of 13,590 incidents were recorded, giving an average frequency of 13 crash, 12 hazard, and 13 stationary vehicle incidents per day. The related incident durations were 45, 136 and 78 minutes, respectively.
- Breakdown (28%), multiple vehicle crash (26%) and debris (13%) were found to be the major sources of incidents in this research.
- The highest density of freeway incidents in SEQ occurred along the Pacific Motorway, between the CBD and the Gateway Motorway interchange.
- The highest monthly number of incidents was in March (9.5% of all incidents), and the lowest was in January (7.2% of all incidents).
- Incident frequency dropped sharply on the weekends, but the average incident duration was about the same or greater than that of the weekdays.
- Overall, the highest occurrence of incidents occurred between 16:00 and 17:00 hours.
- Rainfall appeared to have a positive relationship with the incident duration; however, further research needs to be conducted in order to quantify the extent of rain impact on incident duration.
- Log-normal distribution was found to be appropriate for crash and stationary vehicle incidents while gamma distribution was appropriate for hazard incidents.

6. Conclusions and future research

This paper uses logical framework analysis in order to establish an innovative approach in dealing with comprehensive incident data mining and analysis. This paper has shown that a number of variables have considerable effects on incident duration and frequency. The consequences of undertaking an analysis without access to such a range of variables can be very problematic, since the results would be biased and consequently may lead to erroneous outcomes. In this regard, professional GIS software needs to be employed with a high level of expertise in order to verify the quality of data from different sources, clean up the data, and eventually undertake data fusion and consolidation. Using this method provides more opportunities to generate useful outputs, that is, visual representation which is more effective in conveying the results, particularly to the decision-makers. In this study, an overview of the frequency, pattern and duration of three major types of incidents, namely, crash, hazard and stationary vehicle, on the SEQ network of freeways, arterial roads and local roads for a one year period up to November 2010 are presented. The results showed that incident duration and frequency varied across the types of incident, road hierarchy, and time of day, day of the week and even the month of the year. In addition, the findings of this study reveal that the variance in terms of frequency and duration within each category was fairly large.

Further research will have to be conducted in order to thoroughly scrutinise the incident types and allocate appropriate weights to each type, according to its respective incident duration and the prevailing traffic conditions. The density could be investigated based on an appropriate scale of the difference in incident-type weights and the results can then be used to compute the distribution of incident density in corresponding to the effects of each incident type for the studied network. The results would be useful for evaluating the quality of data and monitoring the change in incident characteristics over time. Consequently, incident response resources can be allocated more effectively. In addition, ultimately the impacts of traffic incidents on the road networks can be quantified for future incident mitigation investment.

Furthermore, it is recommended that the effects of traffic flow parameters on traffic incident duration be investigated. Consequently, statistical models can be developed to estimate incident frequencies and durations for each category based on Australian conditions. Results would provide valuable information for the purpose of traffic incident management strategies and policy evaluation. In addition, by having such models, the effects of incidents on travel time reliability can be quantified.

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