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Creating resilient emergency plans by incorporating travel time reliability into the evacuation process

Susilawati[1], Michael A. P. Taylor[1], Sekhar V.C. Somenahalli[1]

Institute for Sustainable Systems and Technologies

Email for correspondence: susilawati.susilawati@postgrads.unisa.edu.au

Abstract

Transport networks are one of the lifeline systems that serve the community by providing essential mobility for personal travel and goods movement, as well as for access by emergency services. The performance of transport networks is threatened by the increased frequency and severity of floods, cyclones and bush fires as an effect of climate change, and therefore we need to adapt our networks and service provision to cope with new climate regimes and human settlement patterns. Given a definition of travel time reliability which assesses the probability of finishing a trip before a specified time (travel time threshold), we propose a travel time reliability metric for emergency and evacuation plans which considers demand and capacity uncertainties as well as other behaviour related factors that are of concern in evacuation planning.

This metric measure the additional travel time during the evacuation process based on one specific distribution, the Burr distribution that has been found to represent the distribution of variations in journey travel times. The three parameter version of the Burr distribution is a continuous distribution with two shape parameters and one scale parameter. It can be used to generate refined travel time reliability metrics that reflect the observed characteristics of positive skew and long upper tails in travel time variability. The new travel time metric can be used as a performance measure in emergency service and evacuation planning plans. We conclude that this metric can play a vital role as a decision support tool for more robust and reliable evacuation plan in order to plan and provide more resilient transport systems.

1. Introduction

The performance of many transport networks is threatened by an increasing frequency and severity of floods, cyclones and bush fires as a result of more extreme weather events due to climate change. The floods and cyclones might totally or partially close the roads or collapse the bridges, bush fires might block the access for emergency service to evacuate the community. These transport network disruptions reduce transport service provision which lead to some consequences not only to the community but also to the evacuation process and emergency services. For instances, short term and long term impacts of the transport network disruption might change the community trip planning by either change their route to alternative route or change their transport mode. At the worst case scenario during the evacuation process, the community could not evacuate from hazard area.

According to previous studies, these consequences can be measured in several ways. The road network vulnerability, which measures community loss as well as the emergency service reduction by quantifying the differences of the index values under normal conditions and during disruptions, is one alternative metrics. Additionally, transport networks reliability might also be used to assess the probabilities of reaching the destination by a desired time, or of completing the trip at all.

Travel time reliability, which measures the probability to finish the trip within a specified time under different circumstances has been known as the day to day transport network performance metric. The more reliable the travel times, the better the transport performance. For more than two decades there has been a growing interest in developing and refining the existing method and metrics of travel time reliability. However, it only a limited number of studies have incorporated the travel time reliability metrics in to the evacuation process.

Therefore this study seeks to incorporate travel time reliability metrics in the evacuation process by considering the demand and capacity uncertainty. It uses data from the Adelaide longitudinal travel time database developed by the authors. The study also suggests a new metric to model and predict travel time reliability and includes this new metric in models of the evacuation process. The paper concludes by indicating how transport planners can use travel time reliability in refining the current methods and plans for evacuation processes.

This paper is divided into five main sections:

- The literature review discusses the travel time reliability concept under the umbrella of transport network reliability and the recent development of the travel time reliability metrics. This section also reviews the current practice in the evacuation process concerning the role of transport modelling in the process and the drawbacks of previous models.
- Discussion outlines the opportunity to incorporate the travel time reliability metrics to the evacuation process.
- The Data section describes the process by which the journey to work travel time data was collected and how to measure reliability by using existing metrics. It also introduces the recent travel time reliability metric by utilising the properties of the Burr distribution based on analysis of Adelaide longitudinal travel time database.
- Results examines the variability of the travel time under four different conditions and also compares the existing travel time reliability metrics and the proposed metrics
- Conclusion

2. Literature Review

2.1 Travel Time Reliability

Different types of incidents, either short term (e.g. vehicle breakdowns) or long term (e.g. bridge collapse), or random (e.g. road crashes) or intentional (e.g. road works), can happen at any time and can adversely affect transport network performance. Long delays and queuing because of incidents can stretch travel times much longer than the travel time under normal conditions. Under the worst conditions where unexpected incidents occur, travellers may not be able to adjust their trip times. Consequently some journeys take longer than expected.

Travel time reliability is based on the concept of a travel time that meets travellers' expectations (Small, 1982). Travellers expect their travel times not to exceed a scheduled value, or an average travel time plus some acceptable additional time, and hence they can decide on a starting time for the journey. Thus in general, travel time reliability can be defined as the probability of finishing a trip within a specified time under different traffic conditions.

Travel time reliability has been measured by looking into either day to day or time of day travel time variability. The lower the variability of travel time the higher its reliability and the more stable and predictable the trip time (Bell and Iida, 2003). Thus the knowledge about the shape of the travel time distribution becomes necessary.

Research on fitting continuous distributions to observed travel time data began many decades ago. While initial belief was that the normal distribution was appropriate, Wardrop (1952) first suggested that travel times followed a skewed distribution. Later, Herman and Lam (1974) analysed urban arterial travel time data collected in Detroit in a longitudinal study of work trip journey times. They found significant skew in the observed times and proposed either the Gamma or lognormal distributions to represent travel time variability. Using continuous travel time data collected in Chicago, Polus (1979) found that the Gamma distribution was superior to normal or lognormal distributions. More recently, Al Deek and Emam (2006) have used the Weibull distribution to model travel time reliability.

Richardson and Taylor (1978) collected and analysed longitudinal travel time data in Melbourne. They assessed the correlations between travel times on each section of the study route, and developed relationships between the travel time variability and the level of congestion. They concluded that travel times on a link were independent of those on other links along the route, and that the observed travel time variability might be represented by a lognormal distribution. More recently, by using the eight years of continuous travel time data from the Adelaide database, Susilawati et al (2010) found that neither the Normal or Log Normal distributions could fit the observed travel time distributions. Through exhaustive goodness of fitting test, they summarized concluded that the three parameter Burr distribution could be used to represent the observed data.

However, given the notion that travel time reliability is about providing reliable travel time to commuters for on time arrival at their destinations, for simplicity the existing metrics tend to use the Normal distribution properties such as the standard deviation, variance, coefficient of variation and the 95th percentile travel time to measure the travel time reliability (Bates et al, 2001). The 95th percentile is the common metric propose as the travel time threshold. This percentile is notionally justified by the implication that it allows an employee one possibility to arrive late in the office over 20 working days. This outcome should not get her or him into trouble.

Some alternative travel time reliability metrics have also been proposed. FHWA (2006) introduced a buffer time (BT_t) to represent the additional time above the average travel time ($\bar{t}$) required for on-time arrival. The buffer time is the difference between the 95th percentile travel time (t_{95}) and the mean travel time:

$$BT_t = t_{95} - \bar{t}$$

FHWA (2006) also established a travel time reliability index (Planning Index, PI_t), which is the ratio of the 95th percentile travel time to the 'ideal' travel time, taken to be the free flow travel time (t_f):

$$PI_t = t_{95} / t_f$$

Additionally, van Lint and van Zuylen (2005) proposed the so-called skew-width methods. The skewness of the travel time λ^{skew} is defined as the ratio of difference of 90th percentile (t_{90}) and 50th percentile (t_{50}) travel time and the differences between 50th percentile and 10th percentile (t_{10}) travel time. The width of travel time λ^{var} is defined as the ratio of the differences of 90th percentile and 50th percentile travel time and the 50th percentile travel time. The equation of the skewness and the width travel time as follow;

$$\lambda^{skew} = \frac{t_{90} - t_{50}}{t_{90} - t_{10}}$$

$$\lambda^{\text{var}} = \frac{t_{90} - t_{50}}{t_{50}}$$

In the United Kingdom, Black and Chin (2007) developed a model of link and corridor travel time variability. This related the coefficient of variation of travel time variability (CV_t) to the congestion level in the study area:

$$CV_t = \alpha CI_t^{\beta}$$

where CI_t is a congestion index, defined as $CI_t = t / t_f$, and α and β are estimated parameters. They first considered travel time variability at the link level, and then used standardised link travel times to develop a corridor travel time reliability model:

$$CV_t = 0.16 CI_t^{1.02} D^{-0.39}$$

where D (km) is the route length and -0.39 is an estimated parameter (the elasticity of CV_t with respect to distance).

A similar model was developed by Richardson and Taylor (1978), who showed that under certain restrictive conditions the theoretical value of β would be 0.5.

Similarly, Eliasson (2006) developed a model for estimating the standard deviation (s) of individual travel times in terms of mean travel time, link length (L) and free flow travel time. This model is

$$s = \rho \lambda_{TOD} \lambda_{SPD} L^{\kappa} \bar{t}^{\gamma} \left(\frac{\bar{t}}{t_f} - 1 \right)^{\omega}$$

where λ_{TOD} and λ_{SPD} are dummy variables representing time of day and the speed limit, ρ is a constant, and κ, γ and ω are estimated parameters.

2.2 Proposed Travel Time Reliability Metrics

Through exhaustive goodness of fit testing, the Burr distribution has been shown to fit the empirical Adelaide travel time data (Susilawati et al, 2010). This distribution was developed by Burr (1942) for the expressive purpose of fitting a cumulative distribution function (cdf) to a diversity of frequency data forms. It allows a wide variety of shapes in its probability density function (pdf) (Zimmer et al, 1998), making it useful for fitting many types of data and for approximating many different distributions (e.g. lognormal, and normal).

In its basic form it has three parameters, c, k and α. The probability density function (pdf) $f(x\ c,k,\alpha)$ of the Burr distribution is

$$f(x,c,k,\alpha) = ck \left(\frac{x}{\alpha} \right)^{c-1} \left(1 + \left(\frac{x}{\alpha} \right)^{c} \right)^{-(k+1)}$$

where $x > 0$, $c > 0$, $k > 0$ and $\alpha > 0$. The cdf $F(x, c, k, \alpha)$ is given by

$$F(x,c,k,\alpha) = 1 - (1 + \left(\frac{x}{\alpha} \right)^{c})^{-k}$$

The Burr distribution thus has a flexible shape and is well behaved algebraically. A number of reliability engineering applications have utilised it to model the product life process (Abdel-Ghaly et al., 1997). The distribution has an algebraic tail that is useful in modelling less frequent failures (Soliman, 2005). As its cdf can be written in closed form, its percentiles are easily computed.

The rest of study uses the Normal and Burr distribution properties such as the standard deviation and the 95th percentile to assess travel time reliability.

2.3 Evacuation Process

There are numbers of studies that have been undertaken to investigate the process for evacuation planning. Generally, the aims of the current models are to estimate the time to evacuate the entire population of a region or city, to model the multimodal evacuation process during the anticipated traffic chaos, and sometimes to quantify the effects the traveller information systems during the evacuation process (Tu et al., 2010).

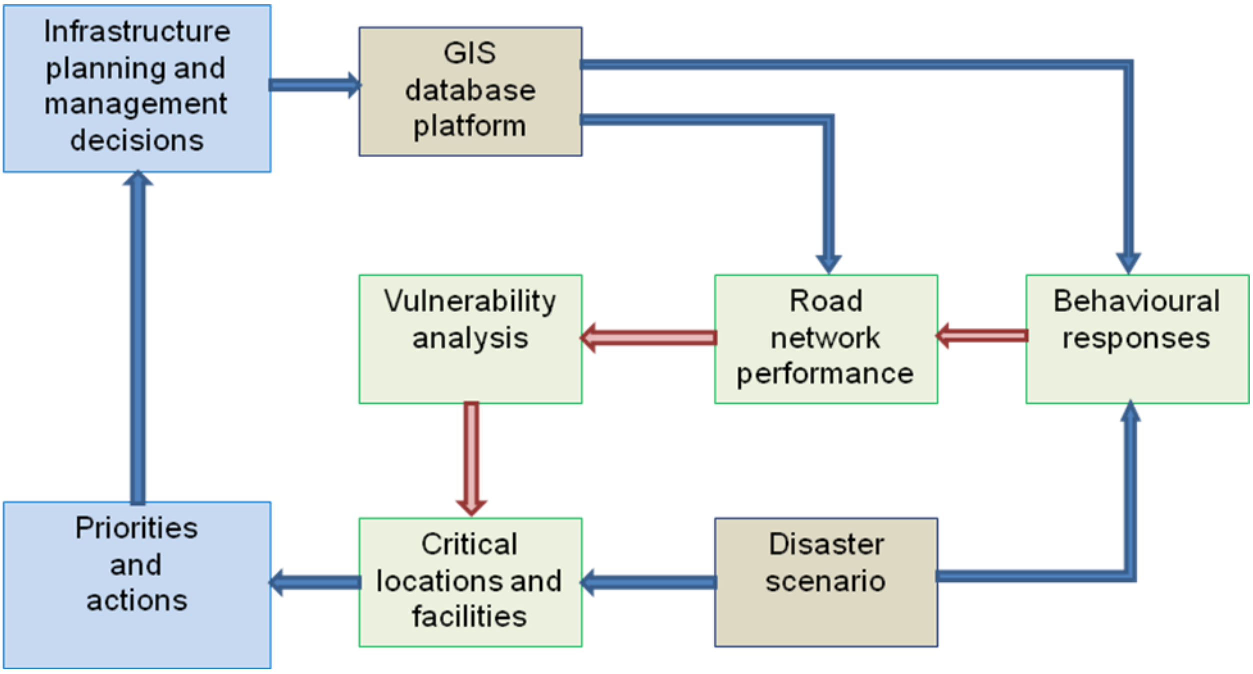
Evacuation process modelling and strategy become necessary in order to reduce the potentially severe impacts of an increased frequency of the natural disasters on the community (e.g. as a result of more extreme weather events due to climate change). It is a complex process that is built by not only the evacuation management process, behaviour response and the reliable information system but also includes complex and difficult transportation network modelling (Dow and Cutter, 1998, Drabek, 1999). It also depends on the scale and type of the natural disasters and hazard events (floods, bush fires, hurricanes, and tsunami); the bigger the hazard events, the bigger and more complex the evacuation strategies. Additionally, in relation to the type of hazard event, require evacuation process for a hurricane evacuation might be much different from that for other emergencies, such as floods, bush fires or tsunami.

In order to accommodate this complex systems, Geographic Information Systems (GIS) and micro level traffic modelling are some applications commonly adopted in the evacuation process decision tool (Pidd et al., 1996, Sheffi et al., 1982).

Figure 1 illustrates the elements of the evacuation process which was derived from Sohn (2006). It clearly demonstrates that major elements in the evacuation process decision support system are interrelated. The type and scale of the events will influence the infrastructure planning and management decision that will affect the type of spatial data needed. Road network performance and behaviour responses are two important elements in the GIS database platform that greatly affect the disaster scenario. Previous research indicates that road network performance during an evacuation may be greatly different to the normal day to day road network performance because of the different behaviour of the road users (Tu et a.l, 2010). One recent study in The Netherlands found that during the evacuation process, drivers tended to increase driving speeds limit and acceleration rates, and reduce the time headway and minimum gap distance (Tu et al., 2010). Additionally, there might be road network failures such as the bridge collapse or closure of one or more road lanes because of landslides or other disruptions during the evacuation process, which could eventually reduce the road network performance.

Road network vulnerability analysis can be conducted by considering these two components. Network vulnerability aims to identify vulnerable areas and critical infrastructure locations in the network, thereby informing the emergency service authorities about priorities and the development of action plans for the most critical locations and areas.

Figure 1 The elements of the evacuation process



At the micro level, generally, the evacuation phases can be divided into three phases namely:

1. The time an evacuee needs to recognise a dangerous situation;
2. The time an evacuee needs to decide which course of action to take; and
3. The time an evacuee needs to move toward the safety area (Hamacher and Tjandra, 2001).

The first two phases are greatly influenced by institutional arrangements and behavioural issues, so that most research on the evacuation process has focussed on the third phase, i.e. modelling. The third phase corresponds to transport modelling in order to get the best scenario and best route under demand and capacity uncertainty, and so move large numbers of people within a specified time. This transport modelling usually incorporates not only the technical and operational components but also should consider the behaviour response of the evacuees, including such mixed factors as panic, anxiety, bravery, altruism and fear during this process.

Micro and macro transport demand modellings can be used to model and simulate the evacuation process (Hamacher and Tjandra, 2001). Like any other transport demand model, evacuation process modelling requires a large amount of traffic data such as road network configuration, traffic volume, travel time, speed and delay. However, some of the literature suggests that the biggest drawback in modelling the evacuation process is the lack of actual the traffic data collected during the evacuation process (Litman, 2006). Kwon and Pitt (2005) acquired and used travel time data that was previously generated from micro simulation models running under different scenarios. Other studies simply use free flow travel time by assuming that traffic volumes never exceed road capacity. On the other hand, the New South Wales State Emergency Service uses a rural evacuation model which assumes that road capacity is half of that under normal conditions (ESM et al., 2009). Louisiana Department of Transportation observed traffic behaviour during the evacuation process for hurricane Ivan, which included collection of traffic volumes under evacuation conditions. They found that traffic volumes were not as high as expected, but were still similar to normal peak traffic volumes. While they could investigate traffic volumes on some highways in Louisiana, the study was unable to estimate travel times and speeds during the evacuation period (Wolshon and McArdle, 2009).

Despite the fact that the Louisiana model had been extensively developed over many years ago, there were still some drawbacks in it. In 2005, thousands of people failed to reach the designated safe areas before hurricane Katrina swept across New Orleans, and they were subsequently isolated for days without water, food or medical care. This is because they lacked access to the presumed transportation modes for evacuation (Litman, 2006).

A few months after hurricane Katrina, the same coast was swept by hurricane Rita. Even though the transport agency and the emergency authority were prepared to anticipate the worst conditions and had learnt from the previous event in order to minimise the number of victims, unfortunately the evacuation process again seemed to fail, this time when many evacuees were trapped on the highway due to fuel supply problems (Litman, 2006). Litman suggests that the biggest mistake during those evacuation strategies was the inability of the transport agency to estimate reliable transit times. On the other hand, during hurricane Rita, thousand of cars were stranded in queues on highways as the transport authority did not anticipate the volume of traffic. In summary, the failure of the hurricane Katrina and Rita evacuation plans was that the transport authority failed to predict and anticipate the increase in demand for transport during the evacuation and failed to include the behaviour in its planning for the evacuation process (Litman, 2006).

3. Discussion

From the review, there are some lines by which we can build a bridge between the transport network reliability in general and the travel time reliability in particular with the evacuation process planning and strategy. The largest concern in evacuation planning and strategy is how to ensure that the evacuation process can be successfully done during the time available under conditions of demand and capacity uncertainty. The recent evacuation models also face some drawbacks and limitations in terms of estimating the travel times applying during an evacuation, due to the lack of available data and the complex behavioral processes involved. The lack of traffic data that can actually represent the traffic characteristics during the evacuation time is also a problem.

In parallel with the travel time reliability definition that measures the probability to finish a trip within a specified time, having knowledge of the level of travel time reliability will be useful or evacuation planning and modeling. Based on these facts, we propose to apply the known travel time reliability metrics to the evacuation process by considering the rational additional travel time to the evacuation travel time. For instance, assume the average travel time to traverse the origin and destination under the normal traffic condition is 30 minutes. During an incident leading to closure of one lane on that route (i.e. that the road capacity is reduced) then the travel time could increase by (say) 10 minutes, therefore, the travel time needed to finish the trip is 40 minutes. Quantifying the day to day demand and capacity fluctuation, the transport authority can suggest to the traveler that the reliable travel time is the 95th percentile of travel time, which is 45 minutes. Having this information would allow the traveler to plan their trip duration for 45 minutes.

A similar assumption can also be applied for the evacuation travel time, based on the worst scenario, such as closure of more than one lane with some adjacent roads also closed. Then the travel time could be doubled or even tripled when compared to normal conditions. Then the transport authority could plan the evacuation time based on this assumption.

It is obviously easier to collect travel time data during normal conditions than during an evacuation process. However, the normal condition travel time data might not readily represent the evacuation process. Therefore we could assume that travel times observed during road incidents (such as road works and special events that require closure of some road sections could be used to represent traffic data under emergency conditions. In the next section, we discuss the Adelaide travel time reliability results under different traffic conditions and seek to use those results for the evacuation process.

4. Data

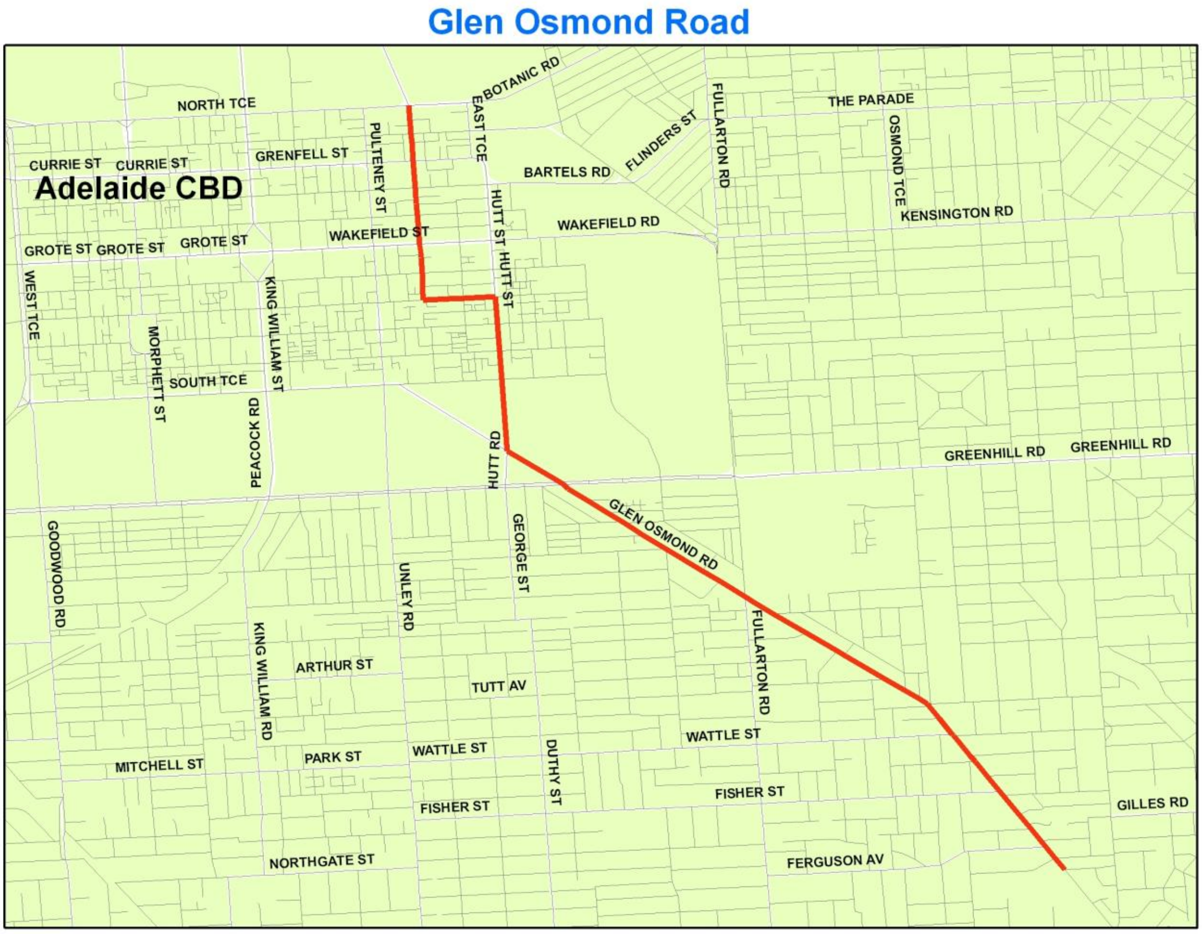
This study used a set of longitudinal travel time data from the Adelaide database. The data was collected by using GPS equipped vehicles making regular journey to work trips, each of which started at about the same time of day and with similar driving behaviour. The specific set of travel time data is the Glen Osmond Road (GOR) data set, including 16 successive links from the suburb of Glen Osmond to the Adelaide CBD. The lengths of links vary between 150 m to 600 m with speed limits of either 50km/h or 60km/h. Total route length is about 6 km and the total number of travel time observations is 178 days. The properties of the links in along the Glen Osmond road route are shown in Table 1 and illustrated in Figure 2.

Table 1 Glen Osmond's Link Properties

Link Name	Link no	Link Length (m)	Mean (s)	Standard Deviation (s)	Coefficient of Variation
GOR[a]:Queens Ln-Bevington Rd	1	1146	122.7	54.2	0.442
GOR: Bevington Rd - Fullarton Rd	2	1058	141.1	76.5	0.542
GOR: Fullarton Rd- Young St	3	458	38.5	21.2	0.552
GOR: Young St - Greenhill Rd	4	606	112.1	53.4	0.477
GOR: Greenhill Rd – Hutt Rd	5	331	33.0	21.1	0.640
Hutt Rd: GOR –South Tc	6	405	41.8	13.4	0.320
Hutt St: South Tc – Gilles St	7	165	23.2	13.5	0.583
Hutt St: Gilles St- Halifax St	8	150	16.5	7.3	0.446
Hutt St: Halifax St - Angas St	9	311	31.8	10.6	0.334
Angas St: Hutt St - Frome St	10	337	39.5	10.9	0.277
Frome St: Angas St - Wakefield St	11	165	45.7	26.4	0.578
Frome St: Wakefield St - Flinders St	12	165	26.7	17.2	0.644
Frome St: Flinders St – Pirie St	13	152	26.2	25.7	0.980
Frome St: Pirie St - Grenfell St	14	156	63.6	52.2	0.820
Frome St: Grenfell St - Rundle St	15	153	41.5	47.7	1.148
Frome St: Rundle St – North Tc	16	162	57.6	35.4	0.614

a. GOR = Glen Osmond Road

Figure 2 the Glen Osmond route on a map of the Adelaide metropolitan area.



Travel time variability was assessed from the day to day variations in travel time along the route in the morning peak. This particular data set was collected over 12 months starting in February 2007. There were four separate types of traffic condition identified along the route during the study period:

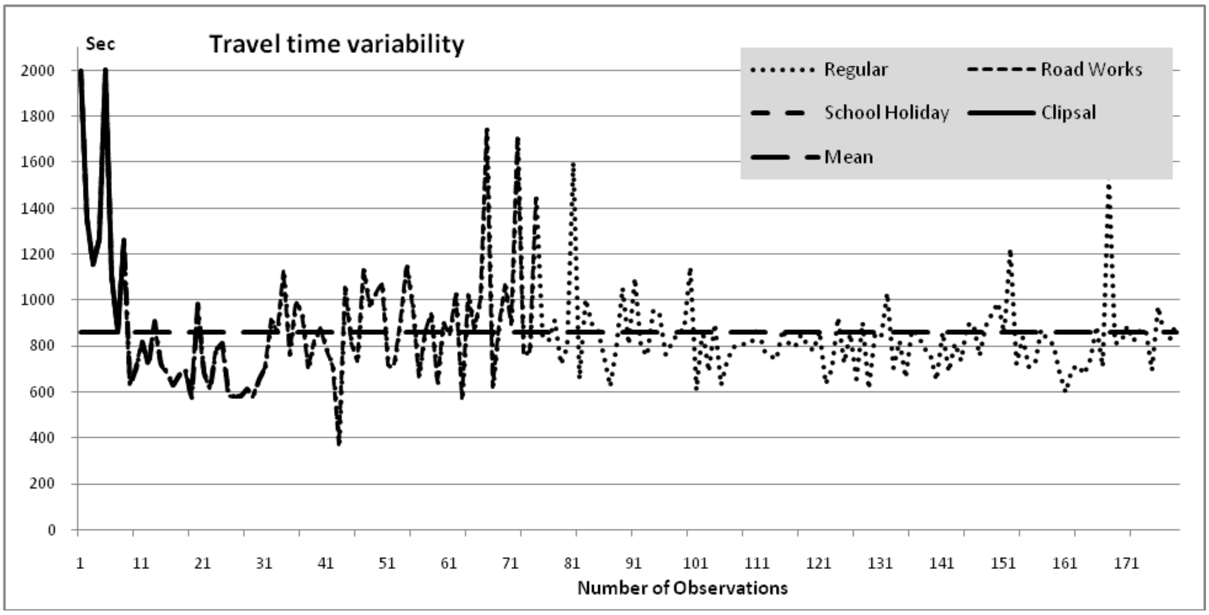
- Regular (normal) traffic conditions
- During the Clipsal 500 event – an annual motor sport event in the Adelaide CBD - where some links adjacent to the route are closed to traffic and the capacity of some other links is reduced;
- During an extended period of road works at the northern end of the route (October-December 2007) when lane closures were imposed on certain links, and the link capacity was therefore partially reduced
- During school holidays when there is less demand than the normal condition but capacity remains the same.

These four separate conditions provide indications of traffic conditions during demand and capacity uncertainty.

5. Results

The travel time data that have been used in this study is the total travel time needed to traverse the route, as the sums of the link travel time data. Figure 3 shows day to day travel time variability during the four conditions described above. There are clearly large fluctuations in the observed travel times. The first condition is during the Clipsal car race event when travel times are much higher than for other conditions. During this period travel time reaches 2000 seconds (30 minutes) which is double the average travel time. In contrast for some other cases where the travel time is very low, such as during the school holidays, the minimum observed travel time is about 650 seconds. Another peak can be also found during the road works period where the highest travel time reached 1700 seconds, although this is still lower than the Clipsal travel times.

Figure 3 Travel time variability for four different traffic conditions



For more detail of the Glen Osmond travel time properties, Figure 4 shows the box plot of the travel time data for each of the four conditions.

Figure 4 The Box Plots of travel time data for the four condition

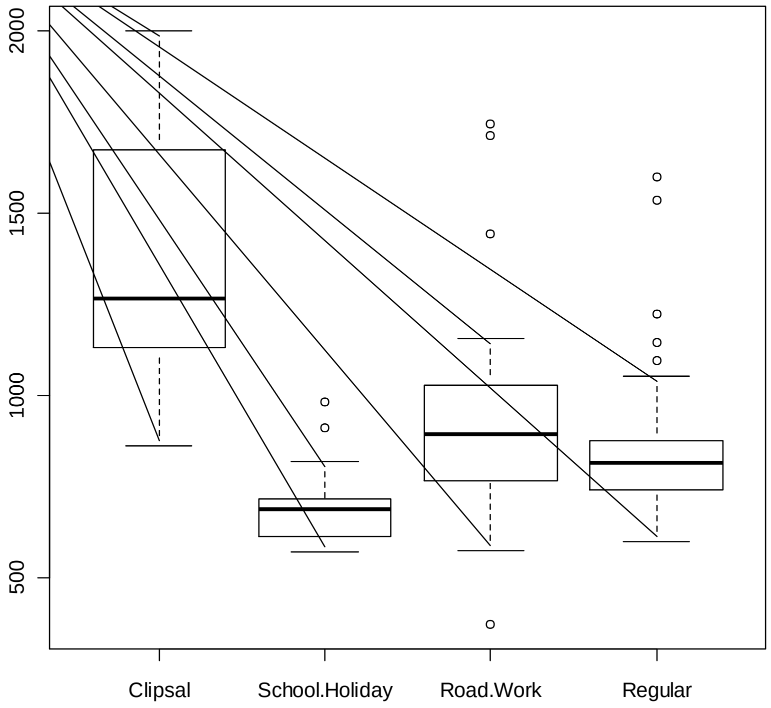
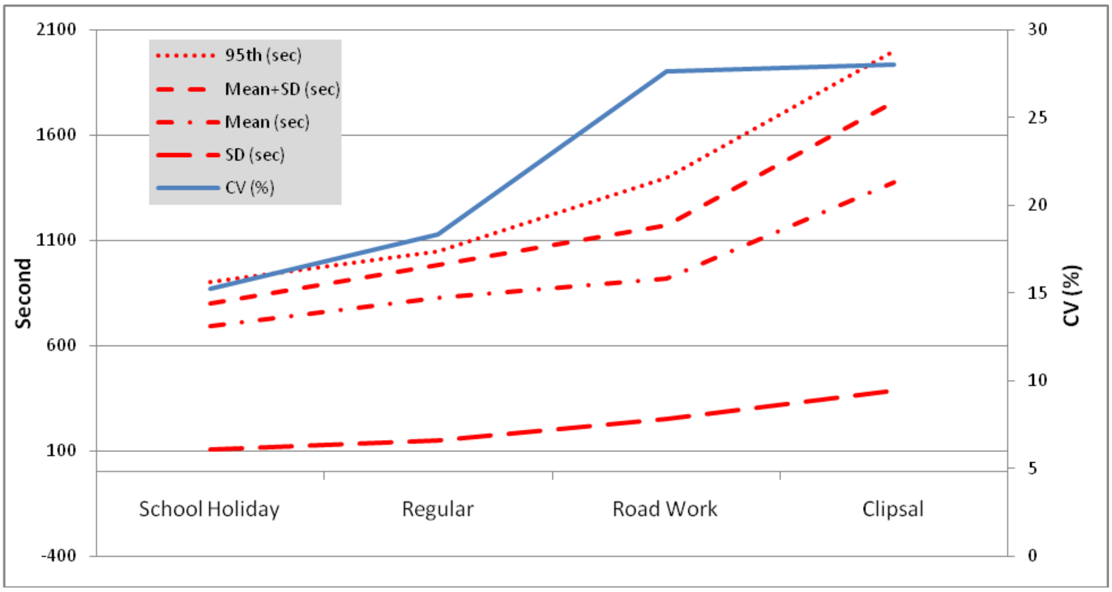


Figure 5 shows the travel time properties including the mean, standard deviation, coefficient of variation and the 95th percentile of travel time under the four different conditions.

Figure 5 95th Percentile, Mean, Standard deviation and the Coefficient of variation of travel time



The result is similar to that shown in Figure 4. The longest travel time is during the Clipsal period when there is a degree of traffic chaos and the traffic volumes along the route also exceeded those of the normal conditions because of the closure of adjacent roads. The shortest travel time occurred in the school holidays.

Figure 5 also shows that the difference in the standard deviations during the Clipsal period and the regular condition is more than 100 percent.

Figure 6 shows the buffer time and planning index of the Glen Osmond travel time data. The result is not much different from the previous findings, the highest planning index and the 95th percentile of travel time occurs during Clipsal and road works while the lowest is during the school holidays. Clipsal's planning index is three times of school holiday planning index, same goes to the 95th percentile of travel time.

Figure 6 95th Percentile and Planning Index for four conditions

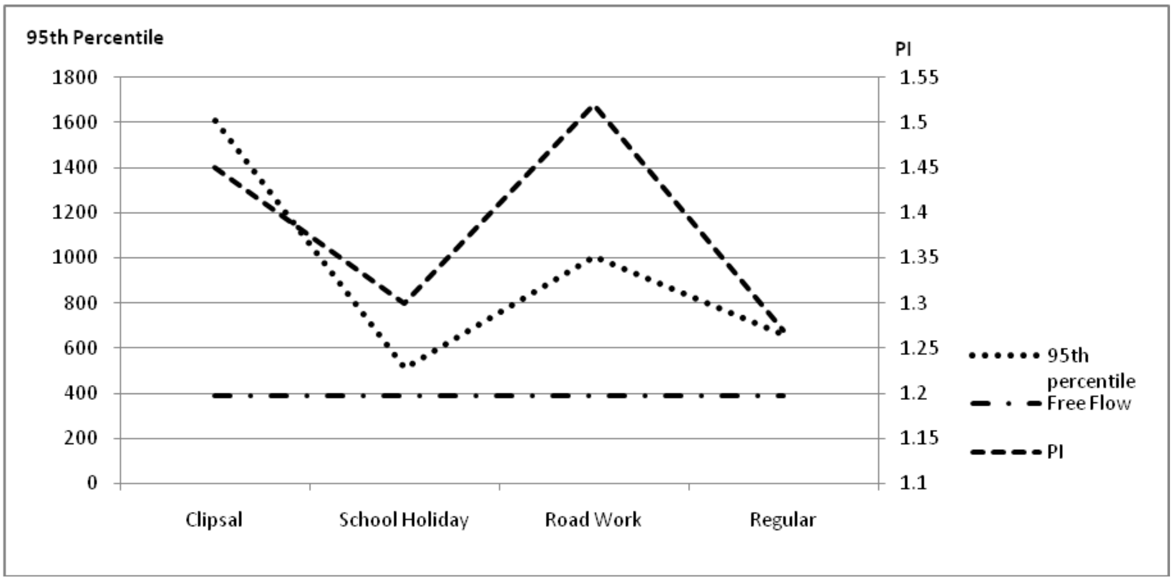


Figure 6 shows the 95th percentile and the planning index for the four conditions of the GOR travel time data. The highest 95th percentile and the planning index is for Clipsal data while the lowest 95th percentile is during the school holidays and the lowest planning index is during the regular condition. As previously noted, the planning index is the ratio between the 95th percentile travel time and the average travel time. Having a 1.52 planning index during the road work period means that in order to ensure to on time arrival at the destination, the reliable travel time needs to be 1.52 times the average travel time. The limitation of this metric is the traveller needs to know the average travel time first in order to know the time that they need to complete the trip. However, for the 95th percentile metric, when the traveller know the 95th percentile of the travel time, then they will easily plan their trip. These two examples are for the day to day trips, how about the evacution process? A similar assumption can be also made, whereby the transport agency can use either the planning index or the 95th percentile travel time during the incidents, by assuming that there will be a one in 20 chance that the evacuation time will be insufficient.

The summary from these findings is the 95th percentile be a more useful metric for the required travel time under an evacuation as it provides a sufficient additional travel time for the evacuee. Furthermore, by considering that the Clipsal condition is the worst condition, then the Clipsal condition might give a better view to the planner when facing the situation when some roads are closed because of an emergency. Thus they can simulate the evacuation process by considering that the travel time will be perhaps three times that of the regular condition.

The road work travel time might give some view about likely traffic conditions where one or more lanes on a link were closed. The effect was not as bad as during Clipsal, but it also had a large impact on the total travel time, which reached more than double the regular route travel time, even though the closure effect was quite local in nature.

The above data analysis was based on the assumption that normal distribution fits the travel time distribution. However, as the shape of the travel time distributions is positively skewed with long upper tails and this distribution does not seem to fit empirical travel time data sets particularly well, then use of the estimated 95th percentile travel time from the Normal distribution would not necessarily give the correct value for the travel time reliability.

The Burr distribution can be used as an alternative approach to estimate the travel time reliability given its superior ability to represent the observed data, and the results from this distribution then used to estimate the evacuation travel time requirement.

Using the maximum likelihood estimation, Table 2 summarise the result of the Kolmogorov Smirnov goodness of fit test and other properties of Burr and Normal distribution. Because of limited number of observations during road work and Clipsal, then we used total travel time data, without separated into four different conditions.

Table 2 The Kolmogorov Smirnov Goodness of fit test and other properties of Burr distribution

Properties	Distribution	
	Burr	Normal
Kolmogorov Smirnov Test		
Critical Value (0.05)	0.65581	1.1919E-5
P value	0.10179	0.10179
	Accepted	Rejected
c	11.96	-
K	0.5138	-
A	740.58	-
Mean	856.22	857.842
SD	221.72	232.92
Variance	49159.17	54249.76
50th Percentile	813.30	819
95th Percentile	1246.31	1261.5

The result shows that the Burr distribution significantly fit the travel time data while the Normal distribution does not fit. This table also shows statistically fitted values for the Burr distribution are similar to the values assumed for the normal distribution, except that there are differences in the percentiles,

6. Conclusion

The evacuation process is a complex process which is affected not only by institutional issues but also by the community behaviour. The basic method applied in evacuation planning is use of a decision support tool which integrates data on geographic, road network and other features into a single system and also incorporates transport modelling capability. From a transportation system point of view, the transport modelling of an evacuation process is different from the normal, although for purposes of simplicity the four step transport model has been commonly adopted. From some of the literature, the drawback of the existing model is the lack of empirical data (especially on travel times during emergency evacuations) and a lack of the methods to validate the model.

Travel time reliability is one branch of the big umbrella of transport network reliability. It measures the probability of the traveller finishing their trip within a designated time period. The commonly used method is to advise and inform the traveller about day to day transport activity. The application of travel time reliability information in the evacuation process is still limited.

Therefore this paper tried to incorporate this approach to provide for better evacuation plans and strategies by using existing travel time reliability metrics. It tested these metrics under four different traffic conditions in the Adelaide metropolitan area. By considering the demand and capacity fluctuation during the evacuation process, this paper might suggest that in order to model the evacuation process especially some methods related to the transport demand model, the use of the 95th percentile travel time might give better and more reliable trip times for the evacuation process. Providing information based on the 95th percentile travel time might provide a better indication of required time for evacuee to leave a disaster area. Additionally, the properties of Burr distribution can be also considered to offer refinement of the travel time reliability metric.

This study still has some limitation as this approach did not test the existing evacuation model. However, the findings should be useful in the evacuation modelling framework.

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