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On the transferability of traffic conflict-based safety assessment methods: A case of crash frequency-by-severity prediction models

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1. Introduction

Traffic conflict techniques for road safety assessments have become popular in recent years. Several studies have demonstrated accurate and reliable estimation of both total crash frequency and crash frequency-by-severity levels from prevalent traffic conflict indicators using extreme value theory (Zheng et al., 2019a, Zheng et al., 2019b, Arun et al., 2021a). However, the traffic conflict-based methods lag behind crash-based safety assessment methods in the transferability of models, which refers to applying the crash prediction models developed for a set of sites to a new external site. While several studies (Sawalha and Sayed, 2006, Shew et al., 2013) provide methods for transferring crash prediction models among sites, typically located in separate jurisdictions, the transferability of traffic conflict-based crash prediction models is unknown.

Traffic conflict-based crash prediction models are typically developed for a given set of study sites. However, the complexity of extreme value model estimation increases rapidly with data dimensionality (Arun et al., 2021b, Fu and Sayed, 2021), which can potentially limit the appeal of the more accurate multivariate extreme value models. Thus, this paper specifically investigates whether the multivariate model for estimating crash frequency-by-severity levels developed for signalised intersections in Brisbane in a previous study (Arun et al., 2021a) are transferable to other similar signalised intersections.

2. Method

2.1. Crash frequency-by-severity prediction model

Recently, Arun et al. (2021a) used a bivariate extreme value modelling approach to estimate crash frequency-by-severity levels. They used Time-to-Collision (TTC) and Modified Time-to-Collision (MTTC) as crash risk indicators and Delta-V (Δv) as crash severity indicator to estimate the frequencies of severe (Maximum Abbreviated Injury Scale ≥3; MAIS3+) and non-severe rear-end crashes at two signalised intersections in Brisbane, Queensland. Δv is defined as the expected post-collision change in a vehicle's velocity, which is assumed to have inelastically collided with another vehicle with the current velocity. The negated MTTC and Δv bivariate logistic was the best performing model in their study; hence, the same is tested for transferability in this study. The exact model specification is reproduced in Table 1 below.

Table 1: Crash frequency-by-severity prediction model from Arun et al. (2021a) (Logistic Negated MTTC and Δv Model)

	Parameter	Values
Marginals	$\hat{\sigma}_1$(SE)	0.141 (0.008)
	$\hat{\xi}_1$(SE)	-0.078 (0.043)
	u_1	-0.51
	ME1	821
	$\hat{\sigma}_2$(SE)	1.811 (0.098)
	$\hat{\xi}_2$(SE)	0.061 (0.043)
	u_2	11.16
	ME2	637
Dependence	φ	0.999 (2x10-6)
	JE	72
Estimated N_{total}		5.073
Estimated N_{severe}		0.417
Estimated $N_{non-severe}$		4.656

Legend:
$N_{total}, N_{severe}, and\ N_{non-severe}$: Number of the annual total, severe, and non-severe crashes, respectively
$(\boldsymbol{\hat{\sigma}_1}, \boldsymbol{\hat{\xi}_1}, \boldsymbol{u_1})$ $\boldsymbol{and}$ $(\boldsymbol{\hat{\sigma}_2}, \boldsymbol{\hat{\xi}_2}, \boldsymbol{u_2})$ are the scale, shape, and location parameters for negated MTTC and Δv margins, respectively
ME1 and ME2: Marginal Exceedances of negated MTTC and Δv margins, respectively; JE: Joint Exceedances; SE: Standard Error; 95% CI: Confidence Interval at 95% level of significance

2.2. Transferability of models

Transferability of conflict-based models involves estimating crash frequency at target intersections from the developed models using two approaches, namely, a) application-based approach and b) estimation-based approach (Essa et al., 2019). In the first approach, the uncalibrated model from Arun et al. (2021a) was directly applied to the conflicts observed at the target intersections. The underlying principle for this approach derives from the fundamental property of extreme value models wherein the number of conflict threshold exceedances is directly proportional to the number of expected crashes. Accordingly, expected crash frequency was estimated from Equation (1):

$$N_{crashes,target} = \frac{N_{crashes,model}}{N_{exceedances,model}} \times N_{exceedances,target} \quad (1),$$

where, $N_{crashes,target}$ is the number of predicted crashes (whether total, severe, or non-severe) at the target intersection, $N_{exceedances,target}$ is the number of exceedances of the conflict indicator thresholds given in Table 1, and $N_{crashes,model}$ and $N_{exceedances,model}$ are the corresponding model values. For estimating total crashes at a target intersection, the marginal exceedances of MTTC (ME1), the crash frequency indicator, were used as $N_{exceedances,model}$. $N_{exceedances,target}$ then was the number of MTTC values in the target dataset exceeding MTTC threshold ($\boldsymbol{u_1}$). For severe crashes, the joint exceedances (JE) and the number of MTTC and Δv values in the target dataset over their respective thresholds ($\boldsymbol{u_1}$ and $\boldsymbol{u_2}$) were used.

In the second approach, specific model parameters were calibrated to increase the accuracy of crash estimates. Since the target intersections were located within the same jurisdiction as the modelled intersections, only the conflict threshold parameter of the peak-over-threshold models was calibrated using the target dataset while retaining the scale and shape parameters. Calibration here refers to adjusting the threshold parameter so that the estimated crashes from the extreme value models were within the 95% Poisson confidence interval of observed crashes. The annual frequency of total and severe crashes were estimated using the relationships derived by Arun et al. (2021a) given in Equation (2) and Equation (3):

$$N_{T,total} = \frac{T}{\tau} \times \Pr(-MTTC \geq 0) = \frac{T}{\tau} \times [1 - F_{MTTC}(0)] \quad (2)$$

$$N_{T,severe} = \frac{T}{\tau} \times \Pr(-MTTC \geq 0 \wedge \Delta v \geq 16) = \frac{T}{\tau} \times [1 - F(0,16)] \quad (3)$$

where, $N_{T,total}$ and $N_{T,severe}$ are the number of total and severe crashes, respectively; τ is the conflict observation period (in hours); T is the desired crash estimation period, which in this study is equal to 1 year (=365×24 hours). The crash thresholds for the MTTC and Δv indicators, namely, 0 s and 16 m/s, respectively, were adopted from Arun et al. (2021a).

Both the approaches were validated using the method proposed by Songchitruksa and Tarko (2006), wherein crash estimates are deemed accurate if they lie within the Poisson confidence intervals constructed over the observed crashes. The two approaches were compared among themselves based on mean absolute deviations from the observed crashes.

3. Data

The study data included traffic conflicts collected in November 2019 at two intersections in Southeast Queensland (Table 2). This study defined traffic conflicts as any traffic interaction between two vehicles with a Time-to-Collision (TTC) value of less than or equal to 3.0 s based on previous studies (Zheng and Sayed, 2019, Arun et al., 2021a). The two target intersections were selected such that they were geometrically and operationally similar (four-legged signalised intersections) to the modelled sites. Moreover, to test the applicability of the uncalibrated model, the target intersections were selected from the same broad jurisdiction area (Southeast Queensland) as the modelled sites. Given that the models only considered rear-end conflicts, this study extracted and analysed the same type of conflicts. The details of the data collection and extraction methods are given in Arun et al. (2021a).

The Modified Time-to-Collision (MTTC) and Δv values were calculated for the rear-end traffic conflicts observed at the study sites using the standard formulae. The five-year (2015-2019) rear-end crash data for the sites were obtained from the Department of Transport and Main Roads, Queensland Government. No severe (MAIS3+) crashes were observed at the study intersections.

Table 2: Intersection-wise descriptive statistics of crash and conflict data

Intersection name	No. of total rear-end crashes (2015-19)	No. of severe rear-end crashes (2015-19)	Conflict indicator (units)	Mean	Median	Std. dev.
Stafford Rd – Appleby Rd – Shand St (SA) Intersection	6	0	MTTC (s)	1.01	0.88	0.53
			Δv (m/s)	6.31	6.17	3.16
Gold Coast Hwy – Hope Island Rd (GH) Intersection	12	0	MTTC (s)	0.85	0.86	0.23
			Δv (m/s)	5.33	5.01	2.13

4. Results and discussions

The annual total and severe crash frequencies were estimated using both the aforementioned approaches, and the results are given in Table 3. The application-based approach (with uncalibrated models) provided accurate estimates for the Gold Coast intersection. The estimated total and severe crashes were both within their respective observed 95% Poisson confidence intervals. However, the total number of crashes at the Stafford intersection was outside the 95% confidence interval, indicating that the application-based approach was unsuitable for this intersection. Thus, the model thresholds were calibrated using the usual extreme value theory approach of investigating the threshold stability, mean residual life, and spectral measure plots (Arun et al., 2021a). Subsequently, the total and severe annual crash frequencies were estimated per Eq. (2) and (3) and compared with the observed crash frequencies. The calibration approach led to a distinctive performance improvement for the Stafford intersection for both total and severe crash predictions, as the new estimates were within the observed confidence interval and the mean absolute deviations were lesser than in the previous case. Some marginal improvement was also seen in the overall accuracy of the Gold Coast intersection total crash estimates after calibration; however, the mean absolute deviation of severe crashes for this intersection increased, indicating that the overall benefit of calibration was less in case of this intersection.

Table 3: Estimation results for annual total and severe crashes using both approaches

Intersection	Category	Parameters	Values
		Application-based approach	
Stafford Rd – Appleby Rd – Shand St (SA) Intersection	Total Crashes	$N_{exceedances}$	442
		$N_{crashes,estimated}$	2.731
		$N_{crashes,observed}$ $(95\%\ CI)$	1.2 (0.44 – 2.612)
		Mean absolute deviation	1.531
	Severe Crashes (MAIS3+)	$N_{exceedances}$	26
		$N_{crashes,estimated}$	0.151
		$N_{crashes,observed}$ $(95\%\ CI)$	0.0 (0.0 – 0.738)
		Mean absolute deviation	0.151
Gold Coast Hwy – Hope Island Rd (GH) Intersection	Total Crashes	$N_{exceedances}$	462
		$N_{crashes,estimated}$	2.855
		$N_{crashes,observed}$ $(95\%\ CI)$	2.4 (1.24 – 4.192)
		Mean absolute deviation	0.455
	Severe Crashes (MAIS3+)	$N_{exceedances}$	6
		$N_{crashes,estimated}$	0.035
		$N_{crashes,observed}$ $(95\%\ CI)$	0.0 (0.0 – 0.738)
		Mean absolute deviation	0.035
		Estimation-based approach	
Stafford Rd – Appleby Rd – Shand St (SA) Intersection	Calibrated Thresholds	$u_{negatedMTTC}$	-0.63
		$u_{\Delta V}$	11.16
	Total Crashes	$N_{crashes,estimated}$	1.46
		$N_{crashes,observed}$ $(95\%\ CI)$	1.2 (0.44 – 2.612)
		Mean absolute deviation	0.26
	Severe Crashes (MAIS3+)	$N_{crashes,estimated}$	0.121
		$N_{crashes,observed}$ $(95\%\ CI)$	0.0 (0.0 – 0.738)

Intersection	Category	Parameters	Values
		Mean absolute deviation	0.121
Gold Coast Hwy – Hope Island Rd (GH) Intersection	Calibrated Thresholds	$u_{negatedMTTC}$	-0.6
		$u_{\Delta V}$	10.5
	Total Crashes	$N_{crashes,estimated}$	2.017
		$N_{crashes,observed}$ $(95\%\ CI)$	2.4 (1.24 – 4.192)
		Mean absolute deviation	0.383
	Severe Crashes (MAIS3+)	$N_{crashes,estimated}$	0.125
		$N_{crashes,observed}$ $(95\%\ CI)$	0.0 (0.0 – 0.738)
		Mean absolute deviation	0.125

5. Conclusions

This study examined two methods for transferring peak-over-threshold extreme value models from modelled sites to similar external sites. The study results show that the application-based approach with uncalibrated models might not be reliable. Calibrating the relevant model parameters can help increase the accuracy of the crash estimations from conflict-based extreme value models. Simply calibrating the threshold parameter can yield good results for transferring models within the same or nearby jurisdictions with similar traffic and driving patterns. In other cases, the calibration of scale and shape parameters may also be required.

7. References

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