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Crash costs involving articulated trucks and multi-combination vehicles

Hamish Murray[1], Paula Macias[2], Alexander Paz[2]

[1] School of Mathematical Sciences, Faculty of Science, Queensland University of Technology, Brisbane, Australia

[2] School of Civil & Environmental Engineering, Faculty of Engineering, Queensland University of Technology, Brisbane, Australia

Email for correspondence (presenting author): paula.macias@hdr.qut.edu.au

Abstract

This study presents a comprehensive statistical analysis of expected crash costs per 1,000 Tonne-Kilometres of Payload for Articulated Trucks (ARTs) and Multi-Combination Vehicles (MCVs) across diverse road types. The study explores the suitability of different models, focusing on the hurdle lognormal model due to its compatibility with the dataset's characteristics. The research sheds light on the relationship between road types, vehicle types, Annual Average Daily Traffic (AADT) and its logistic transformations and crash costs, providing insights that can inform decision-making and road safety strategies.

1. Introduction

Heavy vehicles (HV) play a pivotal role in the growing freight industry, which is highly important for the economic performance of any nation, but due to their size and weight can lead to significant crashes. Besides the loss of lives, injuries, and traffic disturbances, HV crashes have a substantial economic impact. Analyzing crash costs not only highlights the financial impact on society but also informs policymakers and planners.

This study analyses the relationship between AADT and crash cost per 1,000 Tonne-Kilometres travelled. The original crash dataset contained 5,845 road segments. Of these, 2,914 are at least partially gazetted for MCVs, with 95% fully gazetted for MCVs. The only filtering removes all sections that are not gazetted for MCVs (approximately 50%).

Employing a hurdle lognormal model, this study examines the crash cost per thousand tonne-kilometres of payload in relation to AADT or relevant transformations. It encompasses diverse road types and facilitates comparisons of diverse expectations for heavy vehicle crash costs. In the quest for an appropriate model, negative binomial and quartile mixed models were also explored. Ultimately, the hurdle lognormal model emerged as the most fitting choice, given the continuous nature of the dependent variable and the dataset's abundance of zero values. Notably, the inclusion of a weighting mechanism that accords greater consideration to fully MCV-gazetted road segments, longer segments, and specific timeframes significantly shaped the modelling process.

This study investigated various specifications and transformations to ascertain the optimal approach for modelling crash cost per thousand tonne-kilometres of payload using AADT. The model outputs generally align with expectations, revealing that increased AADT correlates with higher anticipated crash costs. However, this relationship's nuances vary by road and vehicle type. While the logarithm of roadway AADT may not exhibit the strongest relationship, it proves apt for the required analysis. Notably, the analysis zeros in on comparing crash cost outcomes between segments with different types of vehicles and road infrastructure at identical AADT levels.

This research explores a unique combination of vehicle and road types with a dataset much more populated with zeroes than in the current literature. As such, different challenges were faced in gaining insights from this data. Potential applications for limiting the use of certain vehicles on roads with particularly high expected crash cost has not been performed before.

2. Methodology

2.1 Identify suitable regression models

Poisson and negative binomial are the most used models to predict count data applied to the number of crash occurrences on road segments over time. Modelling crash cost rather than count data accounts for the differences in severity among crashes. Three model types have been used for crash cost: quantile mixed modelling, hurdle modelling and negative binomial.

The negative binomial modelling method is often employed due to its suitability for overdispersed count data, but it may not align well with the discrete assumptions of the method. On the other hand, quantile mixed modelling has found limited application, primarily in assessing crash barrier costs on a single road type (two-lane highway, where barrier costs may be an appropriate measure while being less appropriate on other road types).

The hurdle model presents itself as an appealing choice due to its distinct treatment of zero occurrences and positive counts (Ma et al., 2016). This approach is particularly apt for this study, given that the response variable exhibits two differing states, each with its unique statistical characteristics. The central feature of the hurdle model is its recognition of the excessive frequency of zero occurrences, by maintaining separate parameters for both zero occurrences and counts, accommodating a variety of distributions for the positive count component.

For the hurdle approach, the zero-probability distribution is given as a logistic model, as it provides the best specification for determining the probability of binary outcomes – either a crash has or has not occurred on the given road segment. In this context, the "hurdle" signifies the probability that the given event is zero. To address the positive-value distribution, lognormal, gamma and normal can be tested. The positive-value distribution provides an expected value when a crash event occurs. By integrating both aspects of the model, an overall expected crash cost is derived. The implementation of the hurdle lognormal equation was carried out using the R package brms for Bayesian methods (Bürkner, 2017; Bürkner, 2021).

2.2 Methods to obtain statistically significant and logical results

Observations reveal diverse trends across road types. Rural single-carriageways exhibit the highest crash costs, while motorways and rural dual-carriageways show lower maximum costs.

The estimation of models for ART and MCVs considered three alternative variables or transformations including the AADT of either articulated trucks or MCVs, with these alternatives being vehicle AADT, log vehicle AADT and log of the product of roadway AADT multiplied by vehicle AADT.

2.3 Validation

Models are validated using approximate leave-one-out cross-validation with the loo R package, which evaluates based on PSIS. Model estimate reliability is calculated using the summary Pareto k diagnostics. Metrics for model fit include WAIC and epod, suitable for Bayesian models (Gelman et al., 2014). Model fit accuracy is compared by analysing the significance of best fits, and testing if differences between models are statistically significant. This is done by dividing the *elpd* (theoretical expected pointwise predictive density) difference of the best and reference models by the standard error difference and comparing it to a z-score. This is an approximate measure which provides an indication of the relative strength of different models (Vehtari et al., 2017).

3. Results and discussion

3.1 Prediction

To find the expected crash cost, first find the probability of a crash:

$$\text{P(Crash)} = 1 - P(\text{No Crash}) \quad (1)$$

and:

$$E(\text{Crash Cost}|\text{Crash}) = e^{\mu+(\sigma^2)/2} \quad (2)$$

then:

$$E(\text{Crash Cost}) = P(\text{Crash}) \cdot E(\text{Crash Cost}|\text{Crash}) \quad (3)$$

The two components of the model are the hurdle and μ terms. To find the expected crash cost, the general equation is:

$$E(\text{Crash Cost}) = (1 - h_u) \times e^{\mu+(\sigma^2)/2} \quad (4)$$

In this case, the h_u and μ terms are related to the AADT independent variable:

$$h_u = \frac{1}{1+e^{-(\alpha x+\beta)}} \quad (5)$$

$$\mu = (\delta x + \varepsilon) \quad (6)$$

where x is the independent variable. The h_u term involves a probability transformation to ensure its value remains between 0 and 1. The μ term does not have this constraint but is involved in a log transformation.

3.2 Results of roadway models

Table 1 summarises all coefficients of the best-fit models. These results may be used to show the relative size of effects (where the dependent and independent variables are the same but cannot be directly interpreted. Interpretation of these results requires the use of the equations above.

Table 1: Coefficient for all models

Roadway	Vehicle Type	AADT Variable	h_u Int (β)	h_u AADT (α)	Int (ε)	μ AADT (δ)	Sigma (σ)
Motorways	ART	Log AADT	15.34	-1.55	7.08	-0.46	0.92
	MCVs	Log AADT	27.70	-2.53	5.45	-0.37	0.73
Rural Single	ART	Log AADT	5.08	-0.64	2.76	-0.08	1.28
	MCVs	Log AADT	4.70	-0.59	0.43	0.13	1.36
Rural Dual	ART	Log AADT	9.24	-0.89	21.29	-1.91	0.74
	MCVs	Log AADT	7.60	-0.70	-15.39	1.59	1.28
Urban Single	ART	Log AADT	7.49	-0.59	8.86	-0.55	1.06
	MCVs	Log AADT	6.15	-0.38	3.37	0.03	1.80
Urban Dual	ART	Log AADT	5.09	-0.39	8.19	-0.50	1.24
	MCVs	Log AADT	3.83	-0.15	7.54	-0.48	1.09

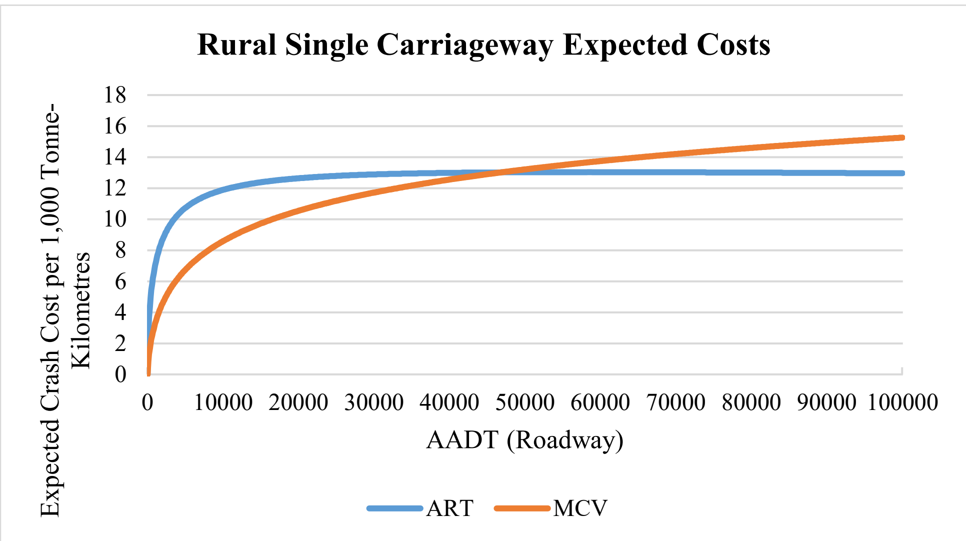
* Note: Log AADT = Log(Roadway AADT)

The relationship between the probability of no crash and the expected crash cost per 1,000 tonne-kilometres of payload with roadway AADT was analysed for each road type.

On motorways, the MCV expected crash cost rates are consistently below the ART amount at the same roadway AADT. Differences in expected crash cost ratios are experienced for rural dual carriageways, MCVs show increases in expected crash costs with increasing log AADT, meanwhile, the expected crash cost ratios for articulated trucks are downward sloping.

For both MCVs and ART in rural single-carriageways, the expected crash cost increases similarly above 50 thousand AADT (corresponding to approximately 5 log AADT). The ART expected crash cost is above that for an MCV at the same vehicle AADT, but the gap between these values narrows significantly as roadway AADT increases. At higher values of roadway AADT, the change in ART expected crash cost is flattening out, while the MCV value is continuing to increase as shown in figure 1.

Figure 1: Relationship between AADT and TCC/1000TKM Payload for Rural Single Carriageway



Overall, many roadway/vehicle type combinations show strong relationships between roadway AADT and expected crash cost per 1,000TKM payload, while other combinations of roadway AADT and vehicle type show limited relationships, where the data available is highly varied.

4. Conclusion and future directions

The results presented demonstrate the relationship between roadway AADT and crash costs for Articulated vehicles and MCVs across roadway types. This relationship is varied, which reflects the potential impacts of roadway traffic on crash costs for different vehicle types on various roadway types.

Further research is recommended to explore other analysis methods. Current results indicate some relationships between AADT transformations and crash cost estimates. While the insights presented by this study examine the likely effects of AADT on expected crash costs, there may be other contributing factors that could be considered including:

- Relative intensity of traffic in various locations and how the timing of the crash relates to AADT.
- Whether vehicle type AADT is a better predictive indicator.
- Variables unrelated to traffic but potentially relevant to the likelihood and severity of crashes that contribute to crash costs, including environmental factors such as road conditions and lighting.

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