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Modelling Road Accident Injuries and Fatalities in Suratthani Province of Thailand Using Conway-Maxwell-Poisson Regression

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Abstract

In 2013, Thailand recorded the highest number of casualties in road traffic accidents among ASEAN countries and ranked second in the world, as reported in the 2015 World Health Organization survey (36.2 deaths per 100,000 population). Road safety has become a critical problem in the country, especially in provincial areas. Suratthani province has been one of the top ten provinces facing road traffic accidents for many years, with the largest number of accidents in the southern region. In this study, we investigated factors associated with injury and fatality counts per accident using the Conway-Maxwell-Poisson regression model based on data collected of 2,887 accidents in 2015. The six covariates considered were road type, road surface, road section, weather condition, light condition, and accident month. The results showed that the distribution of injury and fatality count data was underdispersed, which is rare. Road type, light condition, and accident month were statistically significant factors associated with count response. The mean injury and death count were 2.87 times higher for national highways than for rural roads when other variables were held constant. Driving at night, such numbers were reduced by a factor of 0.49 with streetlights, compared to those without streetlights. Our findings also showed that, for September as a reference month, human injuries and deaths on the road reduced for January, February, March, and August. These findings could be useful for establishing preventive measures at the road level in this province, and the method can be applied to wider regions.

Keywords: road crash fatalities, fatal accident, nonfatal accident, count model, underdispersion.

1. Introduction

In 2015, the United Nations Development Programme announced a sustainable development goal (SDG) target 3.6 was aimed at halving the number of global deaths and injuries from road traffic accidents (RTAs) by the 2020 (UN 2016). In the same year, a report from the WHO on road safety showed 1.25 million deaths, globally, due to road accidents (WHO 2015). It is a primary cause of deaths worldwide among people aged 15-29 years old. RTAs have become the top 10 causes of death. It moved from the ninth in 2000 to the seventh in 2019 (WHO 2020).

The WHO report in 2015 also reported Thailand as the second unsafe country in the world for driving on roads and the first in ASEAN, with 36.2 deaths per 100,000 population (WHO 2015). This problem has been exacerbated by inadequate public transport systems and the failure of road safety campaigns, causing economic and family losses for those dead and injured in accidents. Suratthani province has been one of the top ten provinces facing RTAs for many years and has the largest number of accidents in the southern region of Thailand. Suratthani province ranked first in 2009-2010 and second in 2011-2013 (Royal Thai Police 2013) in RTAs. In 2021, the province ranked first in the number of road accidents (Injury Data Collaboration Center 2018).

Accident frequencies at road sites are probably the most common crash count variables and their factors have been identified using various count regression models. Poisson regression is a traditional method for analyzing crash data. Nevertheless, in many cases, applying Poisson regression yields unsatisfactory results owing to overdispersion (Hilbe 2014). Negative binomial (NB) regression has been adopted in several studies to overcome this problem. Poch and Mannering (1996) applied the NB model to analyze traffic accidents at urban intersections in Bellevue. Patummasut et al. (2019) examined trends in motorcycle-related head injuries in Thailand. Elvik et al. (2019) studied the number of injury accidents on road bridges in Norway. Recently, Khattak et al. (2021) estimated the safety performance functions based on crash severity for signalized and unsignalized intersections. Various studies, including Lord et al. (2008), Liu et al. (2018), and Das (2022), have reported a relationship between crashes and contributing factors. The results of these studies indicate that the road and environmental conditions are factors associated with road safety.

Despite rare cases, crash data have sometimes exhibited characteristics of underdispersion, and the Conway-Maxwell-Poisson (CMP) regression is an alternative method of Poisson regression. The advantage of CMP regression is that it can handle both overdispersion and underdispersion count data (Lord et al. 2008). CMP regression has been used in many fields of study, such as the prediction of purchase timing and quantity decisions (Boatwright et al. 2003), and an analysis of internet search engine visits (Telang et al. 2004). For overdispersed crash data, Lord et al. (2008) evaluated an application of the CMP-generalized linear model (GLM) to analyze motor vehicle crashes and compared the results with those of the NB model. The results showed that CMP-GLM performed as well as the NB model. Later, Lord et al. (2010) tested the performance of the CMP-GLM for analyzing crash data exhibiting underdispersion. The results showed that the CMP-GLM provided better statistical performance than the gamma probability and traditional Poisson regression models. Lerdsuwansri et al. (2022) applied CMP regression to injury counts from RTAs and concluded that motor vehicle injuries were associated with road, environmental conditions, and month of the year.

There has been limited research in Thailand on modelling injury and death counts from RTAs. This study aimed at identifying road and environmental factors that affect injuries and fatalities in RTAs in the Suratthani province of Thailand, using the CMP regression model. Suratthani province was chosen as a case study owing to the availability of a very large number of RTAs.

2. Methods

2.1. Conway-Maxwell-Poisson regression model

The Poisson distribution is a probability distribution used to show how many times an event is likely to occur over a specified period (Hilbe 2014). Therefore, if Y is a discrete random variable that has a Poisson distribution with mean (λ), then the probability mass function of Y can be expressed as Equation (1):

$$P(Y=y)=\frac{e^{-\lambda}\lambda^{y}}{y!},\quad y=0,1,2,... \tag{1}$$

where $E(Y)=Var(Y)=\lambda$. The Poisson distribution has a rigid assumption that the mean must be equal to the variance, which is not feasible in real life.

The CMP distribution is a generalization of the Poisson distribution (Conway and Maxwell 1962). The CMP probability mass function proposed by Sellers and Shmueli (2010) is given by Equation (2).

$$P(Y=y)=\frac{\lambda^{y}}{(y!)^{\nu}Z(\lambda,\nu)},\quad y=0,1,2,... \tag{2}$$

where $Z(\lambda,\nu)=\sum_{s=0}^{\infty}\frac{\lambda^{s}}{(s!)^{\nu}}$ is a normalizing constant, $\nu\geq 0$ is a dispersion parameter; $\nu=1$ denotes equidispersion via the Poisson distribution, while $\nu<1$ and $\nu>1$ denote overdispersion and underdispersion, respectively. The CMP distribution is represented as an exponential family (Sellers et al. 2011), and the moments of the form can be expressed in Equation (3).

$$E\left(Y^{r+1}\right)=\begin{cases}\lambda\left[E\left(Y+1\right)\right]^{1-\nu} & r=0\\ \lambda\frac{\partial}{\partial\lambda}E\left(Y^{r}\right)+E\left(Y\right)E\left(Y^{r}\right) & r>0.\end{cases} \tag{3}$$

The expected value and variance are approximated using Equations (4) and (5), respectively.

$$E(Y)=\lambda\frac{\partial\log Z(\lambda,\nu)}{\partial\lambda}\approx\lambda^{1/\nu}-\frac{\nu-1}{2\nu}, \tag{4}$$

$$Var(Y)=\frac{\partial E(Y)}{\partial\log\lambda}\approx\frac{1}{\nu}\lambda^{1/\nu}. \tag{5}$$

More realistic models can be considered if we use covariates as regressors. Let Y_i represents the human injuries and fatalities at the i^{th} accident; λ_i is the mean of injury and fatality count at the i^{th} accident, $i=1,2,...,n.$ Here, we assumed that ν is a constant across all observations. Sellers and Shmueli (2010) showed the natural logarithm link function for CMP regression can be expressed by Equation (6).

$$\log E(Y_i)=\beta_0+\beta_1X_{i1}+\beta_2X_{i2}+...+\beta_pX_{ip}, \tag{6}$$

where β_k is the coefficient of the model predictor and X_k is the covariate, such as road type, road section, light condition, etc., where $k=1,2,...,p$ and p is the number of covariates. Because CMP is usually classified as an exponential family distribution, the maximum likelihood method is preferable for achieving an accurate estimation. Equation (7) shows the log-likelihood $(\log L)$ function for n observations.

$$\log L=\sum_{i=1}^{n}y_i\log\lambda_i-\nu\sum_{i=1}^{n}\log y_i!-\sum_{i=1}^{n}\log Z\left(\lambda_i,\nu\right). \tag{7}$$

For testing dispersion, we tested the null hypothesis of equidispersion in the Poisson distribution against the alternative of overdispersion or underdispersion phenomenon. The set of hypotheses, $H_0:\nu=1$ vs. $H_1:\nu\neq 1$, asks whether the use of Poisson regression is reasonable versus the alternative of fitting the CMP regression. The dispersion test statistic is shown in Equation (8):

$$\Lambda = -2\left[\log L(\hat{\beta}^{(0)}, \hat{\nu} = 1) - \log L(\hat{\beta}, \hat{\nu})\right], \tag{8}$$

where Λ is the likelihood ratio test (LRT), $\hat{\nu}$ is the dispersion estimate, a $\log L\left(\hat{\beta}^{(0)}, \hat{\nu} = 1\right)$ and $\log L\left(\hat{\beta}, \hat{\nu}\right)$ are the log-likelihood values associated with the Poisson and CMP maximum likelihood estimates, respectively. This test follows an approximate χ^2 distribution with one degree of freedom. This was a two-sided test.

Fitting CMP regression models to count data using the R package, COMPoissonReg is available in CRAN (Sellers et al. 2011). This package contains procedures for estimating CMP regression coefficients and standard errors under the constant dispersion assumption, as well as computing diagnostics and dispersion tests (Sellers et al. 2019).

2.2. Model Selection

2.2.1 Akaike information criterion

Akaike information criterion (AIC) is a measure of the goodness of fit of an estimated statistical model (Akaike 1974), and is defined in Equation (9):

$$\mathrm{AIC} = -2\log L + 2(p+1). \tag{9}$$

The model with the lowest AIC was considered the best among all available models.

2.2.2 Likelihood ratio test (LRT)

LRT was used to compare the two nested models. The null hypothesis was that a smaller model is the best model. This result is rejected when the test statistic is large. In other words, if the null hypothesis is rejected, then the larger model is a significant improvement over the smaller one (Darryl et al. 2017). The LRT statistic is the difference between the two likelihood functions and is expressed by Equation (10).

$$\mathrm{LRT} = -2\left[\log(L_s) - \log(L_g)\right]. \tag{10}$$

The simpler model (s) has fewer parameters than the general (g) model. The test statistic is distributed as a chi-squared random variable with degrees of freedom equal to the difference in the number of parameters between the two models.

3. Data

The number of RTAs including injuries and fatalities that occurred in the Suratthani province of Thailand in 2015 was obtained from the Department of Disaster Prevention and Mitigation (DDPM). The DDPM was established on the 3rd of October 2002 as an agency under the Ministry of the Interior to handle disaster management responsibilities. The DDPM has been set up to have a better and more effective mechanism to prevent disaster damage and loss, as well as to mitigate calamity due to man-made and natural disasters. In this study, we used data from 2015 because it was the most complete data and new information collected every month from accident statistics. Data before and after 2015 were available only for accidents that occurred during the festival periods, that is, the New Year Celebration (January and December) and Songkran Festival (April). A total of 2,887 RTAs in Suratthani province were recorded, and the frequencies of injury and death in each accident were analyzed as the response variable in the count regression model.

Table 1 lists the six covariate variables, levels of variables, and number of RTAs. The road types included national highways, rural roads, urban roads, and local streets. Local streets had the highest number of accidents, accounting for 49.36% of all the incidents. The road surface was dry and wet. Approximately 92% of all accidents occurred on dry road surfaces. The road sections were comprised of straight and curved roads and intersections. Driving on a straight road (80.26%) was riskier than driving on other roads. The weather conditions were sunny, rainy, and smoggy. The largest number of accidents were recorded on sunny days (89.23%). The light conditions were daylight, night with streetlights, and night without streetlight. Daylight had the highest number of accidents, accounting for 60.17%. The months of the accident were recorded from January to December. March had the highest number of accidents (12.57%), while September had the least number of accidents. When analyzing factors associated with injury and death counts, a baseline for each variable was chosen according to the lowest frequency to represent a safe condition when driving on roads. Then, other levels of a given covariate would be interpreted as riskier or safer conditions compared to the baseline.

4. Result

Table 2 lists the distributions of injury and fatality counts for 2,887 accidents. The observed injury and fatality data were counted from 1 to 10. The highest number of injuries and fatalities was one person per accident, which contributed 94.32%. In other words, for every road accident that occurred in Suratthani province, at least one person would be injured or dead. The mean of the empirical distribution of injury and fatality counts was 1.0759 and the variance was 0.1512. The variance-mean ratio was 0.1405, indicating underdispersed accident data. Evidently, the accident data did not follow the Poisson variance assumption. Both the AIC and LRT tests yielded the same conclusion for goodness of fit. Therefore, the CMP distribution performed better than the Poisson distribution.

Table 3 lists the parameter estimates of the CMP regression model for road-traffic injuries and fatalities. For ease of interpretation, the incidence rate ratio (IRR) and 95% confidence interval (CI) for each estimated coefficient were calculated. The AIC value was much lower than that obtained from the Poisson model, indicating an adequate model fitting. The results of this study were analyzed at a 5% statistical significance level. Three variables were statistically significant factors associated with count response. First, the coefficient for national highways was positive and its corresponding IRR was $(e^{1.0548})2.87.$ The 95% CI for this coefficient ranges from 0.36 to 1.75. Thus, the 95% CI for its corresponding IRR is between 1.43 and 5.75. The mean injury and death count were 1.43-5.75 times higher for national highways than rural roads when other variables were considered constant. Second, when driving at night with streetlights, such numbers were reduced by a factor of $(e^{-0.7143})0.49$ (95% CI: 0.33-0.73), compared to that without streetlights. The last factor was the month of the year. Our findings also showed that, for September as a reference month, human injuries and deaths on roads reduced for January, February, March, and August.

Table 1 Variables description and descriptive statistics of RTAs in Suratthani province, Thailand.

Variable description	Variable levels	RTAs (percentage)
Road Type	1: National Highway	518 (17.94)
	2: Rural Road	105 (3.64)
	3: Urban Road	839 (29.06)
	4: Local Street	1,425 (49.36)
Road Surface	1: Dry	2,662 (92.21)
	2: Wet	225 (7.79)
Road Section	1: Straight	2,317 (80.26)
	2: Curve	144 (4.99)
	3: Intersection	426 (14.75)
Weather Condition	1: Sunny	2,576 (89.23)
	2: Rainy	229 (7.93)
	3: Smoggy	82 (2.84)
Light Condition	1: Daylight	1,737 (60.17)
	2: Night with streetlight	555 (19.22)
	3: Night without streetlight	595 (20.61)
Accident Month	1: January	336 (11.64)
	2: February	332 (11.50)
	3: March	363 (12.57)
	4: April	275 (9.53)
	5: May	244 (8.45)
	6: June	284 (9.84)
	7: July	266 (9.21)
	8: August	179 (6.20)
	9: September	133 (4.61)
	10: October	204 (7.07)
	11: November	139 (4.81)
	12: December	132 (4.57)

Table 2 Distributions of injury and fatality counts for RTAs; empirical distribution, Poisson distribution (calculated from Equation 1), and CMP distribution (calculated from Equation 2)

Observed count	Empirical count	Poisson	CMP
0	0	958	52
1	2,723	1,059	2,565
2	134	570	269
3	20	204	1
4	4	55	
5	3	12	
6	1	2	
7	0		
8	1		
9	0		
10	1		
Total	2,887	2,887	2,887

Table 2 (Continued)

Observed count	Empirical count	Poisson	CMP
Mean	1.0759	1.0759	1.1080
Variance	0.1512	1.0759	0.1748
Dispersion parameter	-	-	8.8788
AIC	-	6,135.95	2,318.23
log-likelihood	-	–3,066.98	–1,157.12
#Parameters	-	1	2

Table 3 Results of the CMP regression model

Variables	$\hat{\beta}$ (SE)	IRR	95% Confidence Interval of IRR	
Road Type				
(Baseline: Rural Road)				
1: National Highway	1.0548 (0.3547)*	2.8714	1.4327	5.7547
3: Urban Road	–0.1037 (0.3533)	0.9015	0.4511	1.8018
4: Local Street	0.1380 (0.3479)	1.1480	0.5805	2.2702
Light Condition				
(Baseline: Night without streetlight)				
1: Daylight	–0.2317 (0.1436)	0.7932	0.5986	1.0510
2: Night with streetlight	–0.7143 (0.2068)*	0.4895	0.3264	0.7342
Accident Month				
(Baseline: September)				
1: January	–0.7340 (0.2924)*	0.4800	0.2706	0.8514
2: February	–0.8558 (0.3010)*	0.4249	0.2356	0.7666
3: March	–1.0274 (0.3030)*	0.3579	0.1976	0.6482
4: April	–0.4085 (0.2937)	0.6646	0.3738	1.1819
5: May	0.2269 (0.2867)	1.2547	0.7153	2.2008
6: June	–0.4429 (0.2995)	0.6422	0.3570	1.1550
7: July	–0.3616 (0.3028)	0.6966	0.3848	1.2610
8: August	–0.6591 (0.3306)*	0.5173	0.2706	0.9889
10: October	–0.3694 (0.3120)	0.6911	0.3750	1.2739
11: November	–0.4332 (0.3566)	0.6484	0.3223	1.3044
12: December	–0.6705 (0.3780)	0.5115	0.2438	1.0729
Poisson parameter	4.6639	-	-	-
Dispersion parameter	9.3663	-	-	-
AIC	2,240.07	-	-	-
log-likelihood	–1,102.04	-	-	-

* indicates statistical significance at the 5% level

5. Discussion

The current study examined the application of the CMP regression count model to handle underdispersed injury and fatality frequency data. Several variables (Table 1) were used to develop the counting model (Table 3). Statistical modelling revealed that only three explanatory variables had a significant relationship with the number of road traffic injuries and fatalities. The following section discusses the results.

In terms of road type, RTAs occurred frequently on national highways. The mean injury and death counts were higher for national highways than for rural roads. Similarly, Malin et al. (2019) summarized an effect of different types of roads on accidents related to injuries and deaths. They concluded that the relative accident risks were higher on motorways than on two-lane and multi-lane roads. A similar result by Sun et al. (2021) indicated that road types played an important role in RTAs. The higher the grade of the functional road, the fewer RTAs occur and fewer deaths are caused by RTAs. However, the conclusion of Yahaya et al. (2021) was different from our findings. They summarized that rural highways accounted for most RTA-related fatalities in Ghana.

Regarding light conditions, a statistically significant lower number of road traffic injuries and deaths were observed for driving at night with streetlights. A similar result was reported in Ghana regarding fatal injury crashes (Yahaya et al. 2021). The results showed that long-distance passenger vehicles are often scheduled to travel during the night without light, causing severe crashes. The findings showed that off-peak time and no streetlights during night were the influencing factors of fatal injury caused by severe crashes. Rab et al. (2018) summarized that fatal injury crashes occurring in darkness were most likely severe in the state of Illinois.

Our study in Suratthani province showed that fewer injuries and deaths occurred in January, February, March, and August than in September, the month with the lowest number of RTAs, as stated earlier. Karacasu et al. (2011) observed that there were more RTAs during the summer than in other months, and maximum accidents occurred in July and minimum in February. RTAs may occur at any time (month, day, or hour). These might be analyzed by occurrence time (season, weekend, weekday, and peak hour). Additionally, the day of the week appears to significantly affect the severity of accidents; during the working day, accidents were less severe than those during the weekend (Michalaki 2015).

The weather conditions and road surface did not affect the injuries and deaths on roads in Suratthani province. A similar result was reported in Turkey (Kadilar 2016) and Italy (Eboli et al. 2020), where weather conditions had statistically insignificant effects on accident severity. Sangare et al. (2021) determined the most significant variables in RTAs. They found that road surface variables (dry, wet, snow, ice, snow, and others) had a minor impact on accidents. However, different results have been reported in other studies. Malin et al. (2019) showed that the relative accident risk was over four times higher for slushy road conditions, and over two times higher for slippery and very slippery road conditions. According to Salli et al. (2008), the accident risk was more than four times higher for snowy or icy road surfaces than for bare road surfaces. For slushy road surfaces, the corresponding risk of fatal accidents is fivefold.

In our study, the road sections were not statistically significant. Other studies have reported different results. Hordofa et al. (2018) concluded that fatal accidents are more likely to occur on curved roads than straight roads. Chen et al. (2012) determined the severity of intersection crashes among vehicle occupants, pedestrians, and other vulnerable road users. Eboli et al. (2020) summarized that road-related factors mainly affect fatal injury (or minority) crashes.

In terms of model selection, the CMP regression model has the advantage of modelling both overdispersed and underdispersed data. However, it has relatively fewer applications in road safety research. The contribution of our study to the road accident literature is that it can accommodate underdispersed count data for the estimation accuracy of fatalities and injuries in traffic crashes. Other count models with the capability of handling overdispersed and underdispersed count data, such as generalized Poisson regression models and discrete Weibull regression models (Chaiprasithikul and Duangsaphon 2022a; 2022b), may be used in future studies. Alternatively, a zero-truncated regression model is an attractive choice for analyzing count data without zero counts. With data availability in the current study, when crashes occurred, there was at least one death or injury. Modelling such data with either Poisson or CMP regression may result in an estimation of zero counts. This could potentially indicate that when crashes occur, there would also be a case of property damage only. If the zero-truncated model is used, it may or may not provide guidance for practical applications. Exploitation of this model is left for future study.

6. Conclusions

The present study examined the count data of road accident injuries and fatalities in Suratthani province of Thailand in 2015 and identified the associated factors using the CMP regression model. The data used were characterized by underdispersion. This is rare in road safety analyses where overdispersion is common. Our findings showed that three factors that affected road traffic injuries and fatalities were road type, light conditions, and month of the year. The number of injuries and fatalities were higher for national highways than for rural roads. Driving at night was safer when streetlights were present than when they were absent. For September as a reference month, human injuries and deaths on the roads reduced for January, February, March, and August. Road safety managers should focus on these factors and enforce laws to improve the safety of vehicles, roads, and traffic systems. Data availability in 2015 may pose a limitation for the present study, but it narrows the scope of analysis to specific road and environmental factors. Other variables such as vehicle type, human factors (e.g., gender, age, driver's license), and time factors (e.g., season, day of week, time) can be analyzed in further studies to increase model accuracy.

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