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Development of Crash Prediction Models for Uncontrolled Intersections

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ABSTRACT

Statistical or crash prediction models have frequently been used in highway safety studies. A crash prediction model is a mathematical formula describing the relation between the safety level of existing roads and variables that explain this level. They can be used in identifying major contributing factors or establish relationship between crashes and explanatory variables, such as traffic flows, speed parameters, and highway geometric variables. This study involves the development of crash prediction models for uncontrolled intersections of the urban regions of Calicut district.Different modelling techniques like linear regression and generalised linear models were used for the study.The number of crashes was considered as the dependent variable and the traffic volume, speed and geometric data were taken as the independent variables. Four legged intersections were considered for the study. Models were developed at the intersection level and at the approach level. These models can predict the safety of various uncontrolled intersections .Suitable improvements in the geometric characteristics of the intersection can be done by identifying the factors which cause the crashes.

Keywords

Crash Prediction Models (CPM); Intersections; Uncontrolled; Approach speed; Geometric data

1. INTRODUCTION

Each year more than 1.2 million people die due to road crashes around the World (W.H.O. 2004). The “Study on Global Burden of Disease” undertaken by the World Health Organization (W.H.O.), Harvard University, and World Bank, showed that road traffic accident were the world’s ninth biggest cause of death during 1990, the study forecast that, by the year 2020 road accident would move up to third place in the table of major causes of death and disability.

According to documented statistics, intersections are among the most hazardous locations on roadway systems. Many studies (Kumara and Chin, 2004,Kennedy and Sexton, 2009), have extensively analysed safety of signalized intersections. Uncontrolled intersections are those intersections with stop control, yield control or no traffic control. These intersections can be differentiated from the signalized ones in their operational functions that take place without the presence of a traffic signal. So it is important to model the safety at uncontrolled intersections.

The dependent variable in a crash prediction model is the number of crashes, while the independent variables are traffic flow, speed and geometric characteristics. Through accident prediction models, researchers have identified correlation between crash risk and many different explanatory factors, such as traffic volume, roadway geometries, temporal effects, driver characteristics etc. Several approaches have been developed to identify these relationships including linear regression models, poisson regression models, negative binomial regression models and zero inflated poisson models.Objectives of the present study is to identify the various factors that affect the safety of uncontrolled intersections, identify the suitable modelling technique for safety prediction according to thecollected data and develop crash prediction models for uncontrolled intersections.

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2. LITERATURE REVIEW

Many research works has been carried out across the nation and the world in the area of road safety using various techniques. Bauer and Harwood (2000) developed statistical models to account the relationship between traffic accidents and highway geometric elements for at-grade intersections. The regression models were found to explain between 16 and 39 percent of the variability in the accident data. However, most of that variability was explained by the traffic volume variables considered. Geometric design variables accounted for only a small additional portion of the variability.

Salifu (2003) provided an improved method for safety appraisal in Ghana through the development and application of suitable accident prediction models for unsignalised urban junctions. In this study, negative binomial models were used for developments of models for three legged and four legged intersections. The results showed that the best models obtained were based exclusively on traffic exposure functions and it explained 50 per cent more of the systematic variation in crashes at unsignalized intersections.Aine Kusumawati et al (2010) in their paper describes the application of Empirical Bayesian (EB) approach for identifying and ranking hazardous signalized junctions in Singapore. Crash prediction models for four-legged and three legged signalized junctions were developed using Negative Binomial (NB) regression model. The models were thus used in estimating safety of the intersections.

3.THEORETICAL FRAMEWORK

Various forms of mathematical models can be used for crash prediction. Some of them have been listed below.

3.1 Multiple Linear Regression

Multiple linear regression is a statistical methodology describing relationships between a continuous outcome and a set of explanatory variables (Kutner et al, 2005).The model form is as follows:

$Y_i=a_0+a_1X_1+a_2X_2+....+a_nX_n$ (1)

Y_i is the accident frequency for the intersection/approach, i,X_1, X_2etc. are the explanatory variables and a_0, $a_1$are the regression coefficients.

3.2 Poisson Regression

Poisson distribution possess the most desirable statistical properties in describing vehicle accident events, but limitation of the model is that the variance of the accident data is constrained to be equal to the mean. Poisson regression models are estimated by specifying the poisson parameter μ_i as a function of explanatory variables.

$\mu_i= E \times \exp({}_jX_{ij})$ (2)

E = Traffic exposure for road segment I; X_{ij}= Vector of independent variables for roadway segment i; ${}_j$= Vector of coefficient for the independent variables.

3.3 Negative Binomial Regression

By relaxing the condition of mean equal to variance, the negative binomial regression models have more desirable properties than Poisson models to describe the relationship between accident occurrence and road characteristics (Chin and Quddus, 2003).

The general form of the model is as follows:

$\mu_i= E \times \exp({}_jX_{ij}+\varepsilon_i)$ (3)

Where, $\exp(\varepsilon_i)$ is a gamma-distributed error term with mean 1 and variance α^2.

3.4Zero Inflated Models

When there is a zero accident record over a period of time, it may indicate either that the intersection is nearly safe, or that the zero record is a chance occurrence that crashes are not reported.As a result, there has been considerable interest in recent years in regression models based on zero-inflated distributions. To handle count data with excess zeros, the zero-inflated negative binomial or poisson models are employed (Kumara and Chin, 2003).

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4. DATA COLLECTION AND EXPLORATION

4.1 Data Collection

The urban region of Calicut district was selected as the study area.Data was collected from 24 four legged uncontrolled intersections. Datarequired includesthe trafficdata, accidentdata, approach speed data and geometric data of the selected intersections.

Accident data during the period 2007-2013 was collected from the city traffic police station. Accident types include fatal injury, grievousinjury, minor injury and property damage. From the accident data collected, intersection related crashes were sorted out. Crashes occurred at each leg of the intersection was recorded separately.

Traffic data required include traffic volume data and approach speed data. Traffic volume was collected by using both video graphic technique and manual method. Three hour classified volume count was conducted during 9.00 am to 12.00 pm for each intersection. Entering and exiting volume count for each approach leg was done separately.Three hour traffic volume count was converted to Average Daily Traffic (ADT) using suitable conversion factors.

Approach speed of the intersection was found out using spot speed method. A twenty meter stretch was selected for the spot speed study on each of the major leg and time required for a vehicle to cover that twenty meter stretch was noted. Speed was noted for all the vehicles separately. Speed data was analysed and average speed, 95th percentile speed and 85th percentile speed were found out.

The geometric data was collected for all the intersections. The various geometric data collected include approach width, entrywidth, mediandetails, shoulder details, sidewalk details, pedestrian crossing details, speed reduction measures, bus stop details etc. Geometric data was entered and appropriate ratings were given wherever necessary.

4.2Preliminary analysis

Theseverity wise distributionof crashes given in figure 1, shows that most of the crashes are of grevious injury type and fatal crashes are less. The plot of number of crashes and traffic volume given in figure 2 indicates the scatter of points without any specific trend.The entry width of cross road is showing a negative correlation with the number of crashes as shown in figure 3.

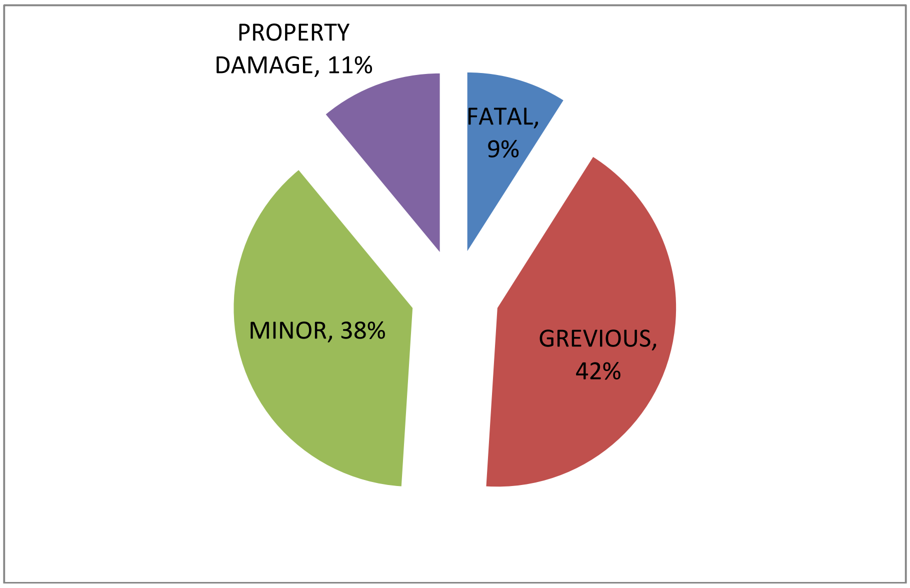

Fig 1. Severity wise distribution of crashes

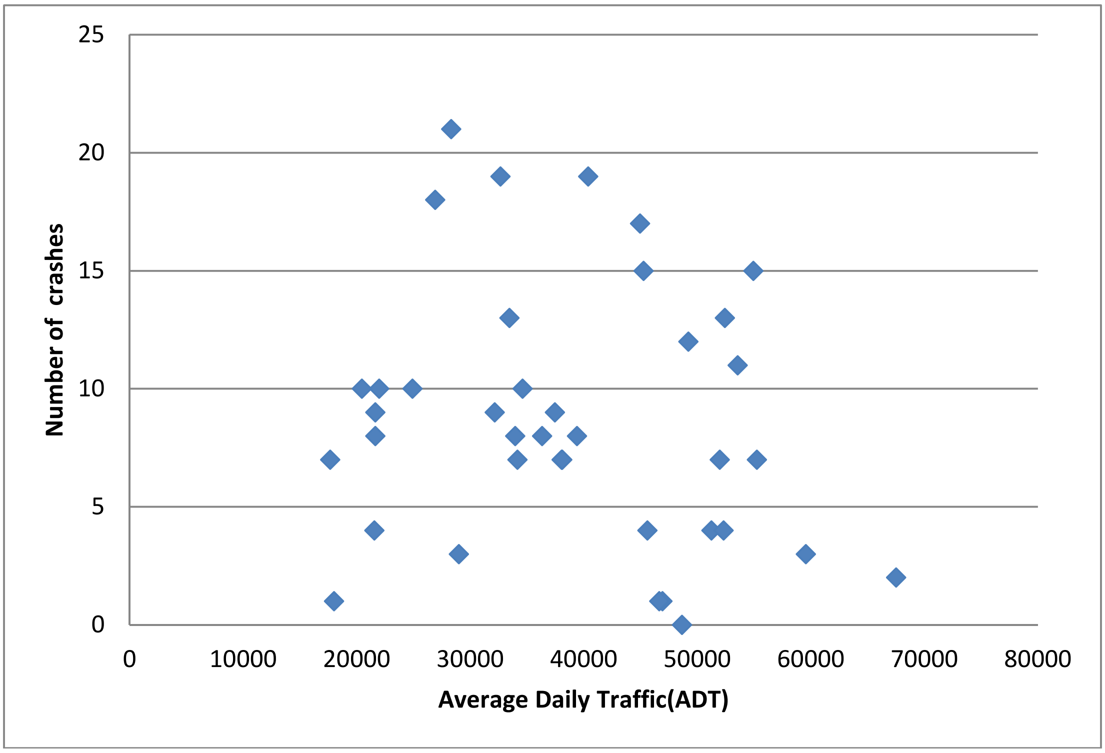

Fig 2. Number of crashes Vs Average Daily Traffic (ADT)

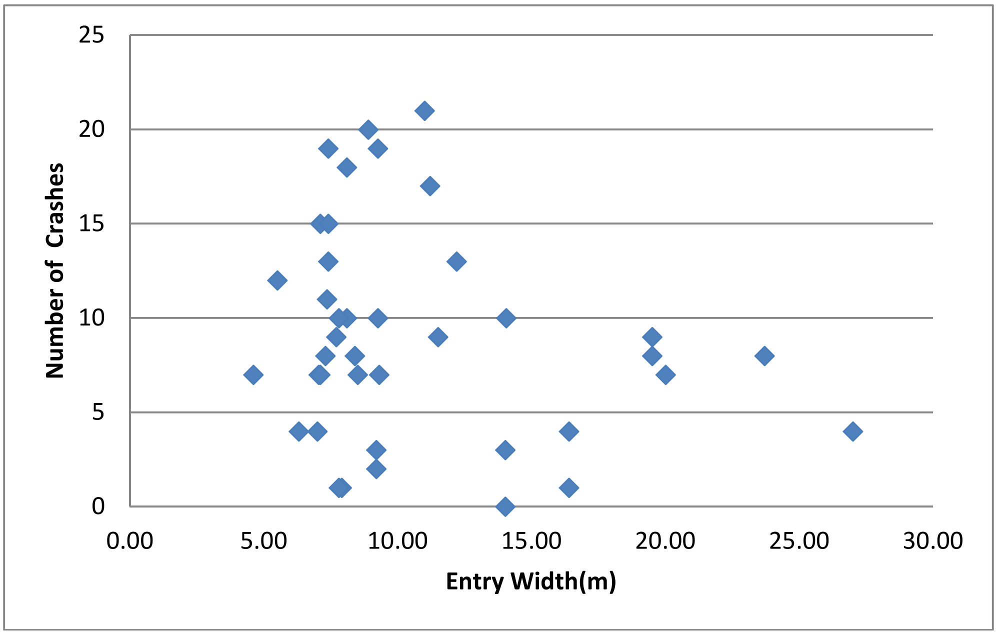

Fig 3.Number of crashes Vs Entry width

Correlation analysis was done to identify the candidate variables and table 1 shows the variables identified for model development.

Table 1.Variables used in model development

Variable	Description
ACC pd/year	Property damage per year
ACC ftl/year	Fatal crashes per year
ACCmi/year	Minor injury per year
ACCgr/year	Grevious injury per year
ACC total/year	Total crashes per year
ADT Ent.	Entering ADT (PCU)
ADT Ext.	Exiting ADT (PCU)
ADT Ttl.	Total ADT (PCU)
Ln(Ent.ADT/app)	Logarithm of Entering ADT per approach width
Ln(Ext.ADT/app)	Logarithm of Exiting ADT per approach width
Ln(Ttl ADT/app)	Logarithm of Total ADT per approach width
Ent ADT /app	Entering ADT per approach width
Ext ADT /app	Exiting ADT per approach width
Ttl ADT /app	Total ADT per approach width
ENTADTSH	Share of entering ADT as of total ADT
EXTADTSH	Share of exiting ADT as of total ADT
ADTMJSH	Share of Major road ADT as of total ADT
ADTMISH	Share of Minor road ADT as of total ADT
MNBMN	Major ADT/Minor ADT
MNXMJ	Product of Major road and minor road ADT
FMI	Minor road ADT(PCU)
FMJ	Major road ADT(PCU)
ENMI	Entry width of minor road(m)
TWMI	Type of way of minor road(oneway-1/twoway-2)
CTMI	Carriageway type of minor road(single-1,dual-2)
Ln(MNXMJ)	Logarithm of product of minor road and major road ADT
App.W	Approach width(m)
EW	Entry width (m)
TR	Turn Restriction(all-1,straight-2,right-3,left-4,nil-5)
AS	Approach Speed(k.p.h)
98^{th}	Ninety eighth percentile speed(k.p.h)
LGHT	Street lighting(centrally placed-1,along the sides-2,both-3,absent-4)
SHW	Average Shoulder width(m)
SPDR	Speed reduction measures(hump-1,rumblestrips-2,nil-0)
BST	Bus stop details(nil-1,farside-2,mouthside-3,nearside-4)
EL	Edge line marking(present-1,absent-0)
NL	Number of lanes
CHN	Channelization(present-0,absent-1)
FC	Functional class(arterial-1,subarterial-2,minor collector-3)
CT	Carriageway type(single-1,dual-2)
CWL	Central White Line(present-1,absent-0)
UPSD	Upstream distance to nearest signalised intersection(km)

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5.MODEL DEVELOPMENT

Regression analysis is the one which is widely used for model development. Different models were tried including linear, negative binomial, poisson models and zero inflated models. Both intersection level models and approach level models were developed. In approach level models, separate models were developed for minor and major roads for different type of crashes. The best fit models and their statistics are given in table 2.

The best fit models were having minimum RMSE (root mean square error) value. The variables in the models are significant at 95% confidence interval.

In the case of major roads, increase in approach speed and number of lanes increases the probability of crashes and increase in entry width decreases the accident probability. Approach width is also having a positive correlation with number of crashes in the case of major roads.

In the case of minor roads, themajor factors influencing the accident occurrence are found to be approach width, channelization, speed reduction measures and traffic volume. The presence of bus stop increases the number of property damages in the case of minor roads. Linear models are found to be best fit for minor roads of four legged intersections.

In the intersection level models the traffic volume is coming to be the most significant variable. Other variables which are influencing are the approach speed and upstream distance to nearest signalised intersection.

Table 2.Models for four legged intersections

Approach level models				
Major roads				
Accident Type	**Type of model**	**Model form**	**R^2/ McFadden pseudo R squared**	**RMSE**
Fatal	Linear model	$A\quad /y = 0.581 - (7.31 * 10^{-5})[E\quad .A\quad /a\quad] + (5.23 * 10\text{^} - 5)[T\quad .A\quad /a\quad] + 0.006[A\quad] + 0.079[A\quad .W] + 0.355[N\quad] + 0.138[C\quad] - 0.055[S\quad]$	0.5770	0.2420
Grievous	Poisson model	$A\quad /y = e\text{^}[-0.593[F\quad] - (6.92 * 10^{-5})[E\quad .A\quad] + 0.708[N\quad]]$	0.1037	0.9370
Minor	Poisson model	$A\quad /y = e\text{^}[5.949[E\quad] + (1.52 * 10^{-5})[E\quad .A\quad] - (4.68 * 10^{-5})[E\quad .A\quad] + [0.054[A\quad] - 0.110[E\quad] + 0.251[A\quad .W]]$	0.1116	0.9490
Property Damage	Linear model	$A\quad /y = -0.301 + (6.322 * 10^{-5})[E\quad .A\quad /A\quad] + 0.277[A\quad .W] + 1.146[N\quad] + 0.074[L\quad] - 0.139[S\quad]$	0.3370	0.2960
Minor roads				
Fatal	Poisson model	$A\quad /y = e\text{^}[-0.812[A\quad .W] + 2.825[C\quad]]$	0.3601	0.3010
Grievous	Linear model	$A\quad /y = 1.339 - 0.217[F\quad] + 13.167[E\quad] + 14.031[L\quad (E\quad .A\quad /a\quad)] - 0.416[N\quad] + 0.314[T\quad] + 0.374[C\quad] + 0.217[S\quad] - 14.109[L\quad (T\quad .A\quad /a\quad)]$	0.2930	1.0610

Minor	Linear model	$A\ /y = 4.724 - 0.492[C\ ] - 0.908[E\ ] - 0.136[A\ .W] + 1.099[C.\ ] - 0.249[L\ ] - 0.302[E\ ] - 0.438[S.\ ] - 1.910[L\ (E\ .A\ /a\ )] + 2.052[L\ (E\ .A\ /a\ )]$	0.4080	1.3570
Property damage	Linear model	$A\ /y = 0.180 + 6.2 * 10\text{^}5[A\ E\ .] - 0.059[A\ .W] + 0.045[B\ ] - 0.107[C\ ] - 0.113[S.\ ]$	0.3290	0.4120
Intersection level models				
Fatal	Linear model	$A\ /y = 4.616 - 0.952[L\ (E\ .A\ /a\ )] + 0.001[98^{th}]$	0.3980	0.5740
Grievous	Poisson model	$A\ /y = e\text{^}[(1.53 * 10^{-5})[A\ .] + 0.951[A\ + [0.290[U\ ] + 0.023[A\ ]]$	0.2178	1.790
Minor	Poisson model	$A\ /y = e\text{^}[0.014[M\ ] + 0.034[A\ ] + [0.236[U\ ]]$	0.2346	2.2790
Property damage	Linear model	$A\ /y = 46.303 + 0.355[U\ ] - 1.457[M\ ] + 0.001[A\ .] + 12.345[L\ (A\ /a\ )] + 0.148[A\ ]$	0.9040	4.7620

6. CONCLUSIONS

The models developed show that not only the traffic exposure, but also the various geometric characteristics of the intersections are influencing the number of crashes. The major geometric factors that are influencing the accident occurrence of four legged intersections are approach width, shoulderwidth, presence of bus stops, speed reduction measures etc. In the case of intersection level models, traffic exposure is found to be the most influencing variable. Poisson models and linear models seem to explain most of the variations in accident rates as their RMSE values are found to be less.

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