# Evaluating Safety of Urban Arterial Roads of Medium Sized Indian City

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**Abstract:** This paper estimates the safety performance of urban arterial mid-block of medium sized Indian city based on fatal crashes as a function of traffic level and road network features. The fatal crashes on arterial mid-blocks are analyzed separately from junction crashes. The accident prediction models developed are based on 126 fatal crashes occurred in 6 years (2005-2010) in Vadodara, India on 263 mid-block arterial road segments. The crash locations obtained from police first information reports have been plotted on a GIS base. The explanatory variables used in the study are segment length, level of traffic, number of unsignalized junctions on the segment, and presence of median. The mid-blocks with heavy traffic have highest traffic crash risk, which reduces up to 20% on low level traffic road segments. Crash risk reduces as number of junctions increase and segments with medians have higher risk compared to segments without medians.

**Keywords:** Fatal crashes, Road safety, Crash prediction model, Medium size city, India

## 1. INTRODUCTION

This paper presents fatal crash prediction model for medium sized city of India. The traffic patterns in these cities are different compared to mega cities of India as well as cities of developed countries. The case study city, Vadodara has population of 1.67 million and spread in about 158 square kilometer. The motorized two-wheeler (M2W) contributes the highest modal share and it represents all motorized two-wheelers including motorcycles, scooters, and mopeds in this study. The auto-rickshaw (three wheeled taxi) is a very popular and accepted para-transit mode. Speed limits are not strictly observed/enforced in the city. Road side parking is a common practice.
The modal share observed in one day travel diary (Prajapati, 2012) is given in Table 1.

Table 1. Modal share of one day trip

| Mode | Percent modal share |
|---|---|
| Bus | 11.8 |
| Car | 6.6 |
| Auto-rickshaw (Para-transit) | 13.5 |
| Motorized two-wheeler (M2W) | 46.7 |
| Bicycle | 10 |
| Walk | 11.4 |

Urban infrastructure improvement implemented to improve the transportation system focus on the speed of motorized vehicles and address problems like their congestion and ignores the safety and convenience of bicyclists and pedestrians. The present situation of inadequate and poor mass transit, increased use of para-transit & personalized transport and decline in walking and bicycle trips, leads to congestion, energy wastage, crashes as well as air pollution. The proportion of road users killed is shown in Figure 1 based on three age groups minor (up to 18), young (18-60), and elder (above 60).

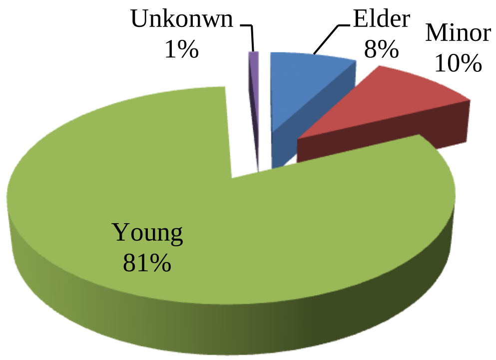


Figure 1. Proportion of road users killed in fatal crashes

More than 80% victims were from "young" age group shows that the travel exposure increases the risk, because young people travel more than minor and elder age group people.

Table 2. Victim versus impacting vehicle in fatal road crashes

| Victims | Impacting Vehicle/Object | | | | | | | Total |
|---|---|---|---|---|---|---|---|---|
| | Truck | Bus | Car | Auto-rickshaw | M2W | Other | Single-vehicle | |
| Bicycle | 5.1 | 1.9 | 2.2 | 0.7 | 1.3 | 0.9 | 0.0 | 12.2 |
| Pedestrian | 7.9 | 3.1 | 4.2 | 0.6 | 4.2 | 12.0 | 0.0 | 32.1 |
| Truck | 3.2 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 3.7 | 7.0 |
| Bus | 0.3 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 0.1 | 0.6 |
| Car | 1.5 | 0.6 | 0.9 | 0.0 | 0.0 | 0.3 | 0.7 | 4.0 |
| Auto-rickshaw | 0.9 | 0.4 | 0.3 | 0.6 | 0.0 | 0.1 | 0.9 | 3.2 |
| M2W | 16.7 | 3.8 | 3.8 | 0.6 | 4.0 | 3.7 | 7.6 | 40.1 |
| Other | 0.1 | 0.0 | 0.1 | 0.0 | 0.0 | 0.6 | 0.0 | 0.9 |
| Total | 35.7 | 10.1 | 11.6 | 2.5 | 9.5 | 17.6 | 13.0 | 100.0 |

- The biggest victim of fatal crashes is motorized two-wheeler (M2W) users and this group approached beyond 40% of total fatality. More than 40% M2W users were killed by truck alone.
- The second most dangerous category of fatal crashes for M2W users is single-vehicle crashes. Almost 19% out of total M2W users killed were killed in single-vehicle crash; normally occurred due to slipped or collide with divider as per police records.
- As seen in the figure, 32% pedestrians were killed and stand on second highest number as victim type in urban fatalities.

- Other vehicles in the table include unknown vehicles and bicycle, cycle-rickshaw, and tractor. Unknown vehicles were killed 35% pedestrians of total pedestrian fatalities, while truck in 25% cases.
- The third major victim of urban crash fatalities is bicyclists. 42% bicycle users were killed by trucks. Other two most dangerous impacting vehicles for bicyclists are car and bus with 18% and 16% involvement respectively.
- Surprisingly, 7% victims in fatal crashes were truck users, some of them were travelling as passengers along with goods. 52% victims were killed in single-vehicle crash, while 46% were killed in crash with another truck only.

More than 84% fatalities involved pedestrian, bicycle users and M2W. Thus, vulnerable road users were at the highest risk in fatal road crashes in the city.

Predictive models to assess safety in terms of number of fatal crashes has been used in determining expected number of crashes (fatal) at various road infrastructures like signalized/ unsignalized intersections, roundabouts and mid blocks. These models are useful for possible safety treatment as well as in the evaluation of such treatments.

Most of the research carried out for accident prediction models are based on electronic data, while this study is based on the data, which was collected by personal visits at all the police stations of the city in the form of First Investigation Reports (FIRs). All fatal road crashes are recorded in the police stations. The minor and major injury crashes were not reported in many road crash cases. Therefore this study is carried out using only fatal crashes of the Vadodara city. The locations of accident spots were derived from the FIR reports.

## 2. PREVIOUS RESEARCH

Sawalha and Sayed (2001) used generalized linear modeling approach to develop accident prediction model for estimating the safety potential of urban arterials in cities of Vancouver and Richmond, Canada based on 3 year accident data and 392 road segments. It was concluded that significant factor for accident occurrences were section length, traffic volume, unsignalzed intersection density, driveway density, pedestrian walkway density, number of traffic lanes, type of median, and type of land use.

Hadayeghi *et al.* (2003) have developed macro-level negative binomial regression models based on 1 year accident data from Toronto with 1 day travel diary for accident prediction as a function of socioeconomic and demographic, traffic demand, and network data variables.

Greibe (2003) has developed accident prediction models using generalized linear modeling techniques for urban roads based on data from 1036 junctions and 142 km road (314 links) in urban areas. He has developed separate models for all crashes, injury crashes, and certain types of crashes (based on type of collision, involving pedestrians, etc.)

Hauer *et al.* (2004) have developed statistical model to predict crashes for urban four-lane undivided road segments based on negative multinomial distribution for parameter estimation using four year accident data and involved 196.34 kilometer of road. The study has explained various models for on-the-road as well as off-the-road injury and property damage crashes. The major findings of the study shows strong influence of annual average daily traffic, number of commercial driveways and speed limit while weak influence of vertical alignment and lane or shoulder width on the accident frequency. It was also noted that on four-lane urban roads, horizontal curves of moderate degree may be safer than tangent road section.

Montella (2005) has explained safety reviews and quantified safety gains where he has developed model using generalized linear modeling techniques based on negative binomial distribution error structure and was assessed in 406 km roads. The main variables included in the model were length of the segments and average annual daily traffic. The model fit was tested by scaled deviance and Pearson $\chi^2$.

El-Basyouny and Sayed (2006) have compared traditional negative binomial and modified negative binomial regression techniques and it make use of accident data, volume and geometric data corresponding to 392 arterial segments in British Columbia, Canada.

Caliendo *et al.* (2007) have developed crash prediction models for four-lane median divided Italian motorway on the basis of 5 year accident data based on Poisson, Negative Binomial and Negative Multinomial regression models. Model parameters were estimated by the Maximum Likelihood Method, and Generalized Likelihood Ration Test was applied to detect the significant variables; length, curvature, annual average daily traffic, sight distance, side friction coefficient, longitudinal slope, and presence of junctions.

Ma *et al.* (2010) conducted a study to investigate the risk factors associated to sever crash occurrences on arterial roads (including junctions) through generalized estimating equations with negative binomial link function in Beijing using 4 year crash data and included 123. Km of road segments to estimate models.

It is evident from the previous studies that separate accident prediction models for arterial roads are required from road junctions and they are function of traffic volume and road network characteristics like segment length, unsignalized junction on the road segment, number of road-lanes, presence of median. The generalized linear modeling approach with negative binomial error structure is widely used to develop crash prediction models; some researchers were also used negative multinomial and generalized estimating equations approach in their study. The fatal crash records have been collected through several visits of all police stations of the city, subsequently coded, and then get digitized all crash locations on GIS road network for the further analysis. No such research on medium sized urban city has been conducted in Indian context.

## 3. DATA DESCRIPTION

A 6 year (2005-2010) fatal crashes data were collected in the form of FIRs from police department of the Vadodara city. The data is digitized in three categories; accident details, vehicle details, and victim details. Through careful examination of crash reports and by using Google Maps, fatal crashes on mid-blocks of arterial roads were segregated. The arterial road network has been developed using Google Map and ArcGIS software.

Total 643 fatal crashes occurred on 263 arterial mid-blocks within the urban limits of the city during the study period of 6 year (2005-2010); 360 (56%) on arterial roads, 239 (37%) on highways and 44 (7%) on streets. About 35% fatal crashes occurred on mid-blocks out of total crashes on arterial roads.

The entire 218.6 km of urban arterial roads were divided into 263 links; between two successive arterial road intersections. One road segment has number of street intersections and they are unsignalized intersections. The road links vary significantly in their length from 86 meter to 4.11 km. Proportion of arterial road segment length for median is:

1. Total segment length having median (154 links) is 90.78 km and

2. Total segment length without median (104 links) is 127.82 km.

Speed limits are not observed/enforced in the city. Road side parking is common practice.

No systematic traffic volume data recorded in the city by any local authority and this is common for many medium sized Indian cities. The city road network of arterial roads consists of 263 segments and it has been digitized during the study as it is not readily available. It was not feasible for the author to conduct observational traffic survey over all these segments. In the absence of reliable traffic volume data, the traffic levels were used for 263 links and they are represented as heavy traffic, medium traffic, and low traffic. The heavy traffic level is considered as the base in the modeling. The traffic level assigned to each link by 15 years of living and academic research experience of one of the author and several discussions with the personnel of local bodies of the city. It was also observed that most of the road segments with heavy traffic are with median and consist of more lanes compared to segments with lower traffic.

1. Low traffic – 86 links
2. Medium traffic – 74 links
3. Heavy traffic – 103 links

The road segments were having intersections ranging from zero to maximum 34 street intersections of all types. They are categorized in 4 groups as given below in Table 3 for the modeling analysis and accommodated in the model with 3 dummy explanatory parameters, category number 4 is considered as base.

Table 3. Junction Density Coding Used in SPSS

| Junction density code used | Number of junctions per kilometer | Number of links |
|---|---|---|
| 1 | ≥14 | 34 (12.9%) |
| 2 | 10 to 13 | 39 (14.8%) |
| 3 | 5 to 9 | 110 (41.8%) |
| 4 | 0 or 4 | 80 (30.4%) |

## 4. MODEL DEVELOPMENT

The number of crashes observed on the road segment per year is non-negative integer value, that is, count data. Count data are properly modeled by Poisson and negative binomial regression models.

Road crashes are rare and random events, and therefore the count of crashes on an entity in short time period can fluctuate considerably. This property of crash data, along with fact that counts are non-negative integer and discrete, makes conventional linear regression with normally distribute error structure inappropriate for modeling of crash data. Instead, Poisson and negative binomial (NB) regression have been used. One requirement of the Poisson distribution is that the mean of the count process equals its variance. The data are said to be under-dispersed (mean > variance) and over-dispersed (mean < variance), and parameter vector is biased if corrective measures are not taken. This problem can be resolved with the use of a negative binomial (NB) model. In previous research, crash data were found to display overdispersion. The expected number of crashes per year is given by Washington *et al.* (2003)

$$\lambda_i = \mathrm{EXP}(\beta X_i + \varepsilon_i) \tag{1}$$

where The $X_i$ is a vector of explanatory variable and β is a vector of estimable parameters and EXP($\varepsilon_i$) is a gamma-distributed error term with mean 1 and variance $\alpha^2$. The addition of this term allows the variance to differ from the mean as below:

$$VAR[y_i] = E[y_i][1 + \alpha E[y_i]] = E[y_i] + \alpha E[y_i]^2 \tag{2}$$

The Poisson regression model is regarded as a limiting model of the negative binomial regression model as α approaches zero, which means that the selection between these two models is dependent on the value of α. The parameter α is often referred to as over-dispersion parameter.

The negative binomial distribution has the form:

$$P(y_i) = \frac{\Gamma\left((1/\propto)+y_i\right)}{\Gamma(1/\propto)\lambda_i}\left[\frac{1/\propto}{1/\propto+\lambda_i}\right]^{1/\propto} f\left[\frac{\lambda_i}{(1/\propto)+\lambda_i}\right]^{y_i} \tag{3}$$

where Γ(.) is a gamma function. This results in the likelihood function:

$$L(\lambda_i) = \prod_i \frac{\Gamma\left((1/\propto)+y_i\right)}{\Gamma(1/\propto)\lambda_i}\left[\frac{1/\propto}{1/\propto+\lambda_i}\right]^{1/\propto} f\left[\frac{\lambda_i}{(1/\propto)+\lambda_i}\right]^{y_i} \tag{4}$$

When the data is over-dispersed, the estimated variance term is larger than under a true Poisson process.

The dispersion parameter is calculated as per approached used by (Sawalha *et al.*, 2001).

$$\alpha = \frac{Pearson\,\chi^2}{n-p} \tag{5}$$

where n = number of observations; p = number of model parameters; and Pearson Chi-Square $\chi^2$ is defined as

$$Pearson\,\chi^2 = \sum_{i=1}^{n} \frac{[y_i - E(\lambda_i)]^2}{VAR\,(y_i)} \tag{6}$$

where $y_i$ = observed number of fatal crashes on segment I; $E(\lambda_i)$ = predicted number of fatal crashes for segment I as obtained from the crash prediction model; VAR($y_i$) is the variance of the observed number of fatal crashes. For the data used in this study, the value of α comes to 1.5, which is greater than 1 and therefore data cannot be explained by Poisson distribution, and a negative binomial regression model is fitted to the data.

The statistical software SPSS was used to estimate the model's parameters. Three models were developed using negative binomial regression for the arterial road segments; First model was formulated using only traffic level as explanatory variable, which is represented by three levels; low traffic, medium traffic, and heavy traffic. The results are shown in the Table 3. The second model was developed using traffic, as previous model along with road segment length, and junction density on the segment. The summary of this model is given in Table 4, which shows all variables are significant in 95% confidence interval. The junction density represents the number of unsignalized street junctions on the arterial road segment. The last model explains the influence of traffic level, segment length, junction density and presence of median on fatal crashes on arterial mid-blocks. Table 5 summarizes the parameter estimates and their associated statistics under negative binomial regression technique. The arterial roads with heavy traffic have wider carriage ways and median. The variable median indicates the presence or absence of median on road segment.

### 4.1 Goodness-of-fit

The Pearson chi-square is one of the commonly adopted measures of goodness-of-fit for generalized linear regression of count data (Hadayeghi *et al.* (2003), Cafiso, *et. al*. (2010), El-Basyouny and Sayed (2006), Montella (2005)). For model to be accepted, the calculated Pearson chi-square must be less than critical value of chi-square distribution value that is based on model’s degree of freedom and a level of significance.

The goodness-of-fit statistics is also measured by Scaled Deviance – The scaled deviance (Sawalha and Sayed (2001)) is the likelihood ratio test statistic measuring twice the difference between log likelihoods of studied model and the full or saturated model. The greater the scaled deviance, the poorer the fit (Agresti (2002)).

## 5. RESULTS

SPSS was used for parameter estimations using log link and maximum likelihood estimates in negative binomial distribution using 6 year data in this study. The following models were developed using road network characteristics like segment length, intersection density, presence of median and traffic characteristics is represented by traffic level. All the models were developed using negative binomial error structure as data is over-dispersed. Tables 4, 5, 6, and 7 contain the negative binomial regression coefficients for each of the predicted variables along with their standard errors, Wald chi-square values, p-values for 95% confidence intervals. The model form to predict per year fatal crashes is given after every table (Table 4-7) that showing parameter estimation. The model intercept has been modified to predict per year crash as model has used 6 year crash data. This effect in exponential form is given by adding (ln(1/6)) -1.79176 in every model intercept.

Table 4. Results of Model1 with Traffic Level Only

| Negative Binomial Model | | | | | | |
|---|---|---|---|---|---|---|
| Parameter | Estimate | DF | Standard Error | Wald $\chi^2$ | Significance | Exp(B) |
| Intercept | -0.216 | 1 | 0.1871 | 1.332 | 0.248 | 0.806 |
| Traffic Level | | | | | | |
| Low Traffic=1 | -1.754 | 1 | 0.3819 | 21.088 | 0.000 | 0.173 |
| Medium Traffic=2 | -0.654 | 1 | 0.3150 | 4.314 | 0.038 | 0.520 |
| Heavy Traffic=3 | 0 | 1 | | | | 1 |
| **Goodness of fit** | | | | | | |
| Number of Observations (n) | 263 | | | | | |
| Number of Parameters (p) | 3 | | | | | |
| Degree of Freedom (n-p-1) | 259 | | | | | |
| Scaled Deviance | 167.438 | | | | | |
| Pearson Chi-Square | 250.096 | | | | | |
| The critical Chi-Square | 297.5383 | | | | | |

Model form: fatal crashes on arterial mid-block per 6 years = exp[ intercept + b1(traffic) ] and fatal crashes per year = exp [-2.00776 + b1(traffic) ]

Table 5. Results of Model2 with Traffic Level, Length, Junction Density

| Negative Binomial Model | | | | | | |
|---|---|---|---|---|---|---|
| Parameter | Estimate | DF | Standard Error | Wald $\chi^2$ | Significance | Exp(B) |
| Intercept | -0.465 | 1 | 0.1748 | 7.069 | 0.008 | 0.628 |
| Traffic Level | | | | | | |
| Low Traffic=1 | -1.556 | 1 | 0.3171 | 24.066 | 0.000 | 0.211 |
| Medium Traffic=2 | -0.437 | 1 | 0.2204 | 3.923 | 0.048 | 0.646 |
| Heavy Traffic=3 | 0 | 1 | | | | 1 |
| Junction Density | | | | | | |
| 1 | -0.863 | 1 | 0.3846 | 5.030 | 0.025 | 0.422 |
| 2 | -1.408 | 1 | 0.3614 | 15.171 | 0.000 | 0.245 |
| 3 | -0.731 | 1 | 0.2138 | 11.675 | 0.001 | 0.482 |
| 4 | 0 | | | | | 1 |
| Segment Length | 0.641 | 1 | 0.0855 | 56.158 | 0.000 | 1.897 |
| Goodness of fit | | | | | | |
| Number of Observations (n) | 263 | | | | | |
| Number of Parameters (p) | 8 | | | | | |
| Degree of Freedom (n-p-1) | 254 | | | | | |
| Scaled Deviance | 257.450 | | | | | |
| Pearson Chi-Square | 390.702 | | | | | |
| The critical Chi-Square | 292.1749 | | | | | |

Model form is fatal crashes on arterial mid-block per 6 years = exp[ intercept + b1(traffic) + b2(junction density) + (b3 x length) ]
and crashes per year = exp [-2.25676 + b1(traffic) + b2(junction density) + (b3 x length) ]

Table 6. Results of Model3 with Traffic Level, Length, Junction Density, and Median

| Negative Binomial Model | | | | | | |
|---|---|---|---|---|---|---|
| Parameter | Estimate | DF | Standard Error | Wald $\chi^2$ | Significance | Exp(B) |
| Intercept | -0.620 | 1 | 0.2606 | 5.671 | 0.017 | 0.538 |
| Traffic Level | | | | | | |
| Low Traffic=1 | -1.622 | 1 | 0.3881 | 17.472 | 0.000 | 0.197 |
| Medium Traffic=2 | -0.526 | 1 | 0.2944 | 3.189 | 0.074 | 0.591 |
| Heavy Traffic=3 | 0 | 1 | | | | 1 |
| Junction Density | | | | | | |
| 1 | -0.828 | 1 | 0.4606 | 3.232 | 0.072 | 0.437 |
| 2 | -1.386 | 1 | 0.4144 | 11.196 | 0.001 | 0.250 |
| 3 | -0.645 | 1 | 0.2921 | 4.876 | 0.027 | 0.525 |
| 4 | 0 | | | | | 1 |
| Median | | | | | | |
| 0 | -0.057 | 1 | 0.2708 | 0.045 | 0.833 | 0.944 |
| 1 | 0 | | | | | 1 |
| Segment Length | 0.817 | 1 | 0.1698 | 23.127 | 0.000 | 2.263 |
| Goodness of fit | | | | | | |
| Number of Observations (n) | 263 | | | | | |
| Number of Parameters (p) | 10 | | | | | |
| Degree of Freedom (n-p-1) | 252 | | | | | |
| Scaled Deviance | 170.673 | | | | | |
| Pearson Chi-Square | 282.919 | | | | | |
| The critical Chi-Square | 290.0285 | | | | | |

Model form is fatal crashes on arterial mid-block per 6 years = exp[ intercept + b1(traffic) + b2(junction density) + (b3 x length) + b4(median) ]
and crashes per year = exp [-2.41176 + b1(traffic) + b2(junction density) + (b3 x length) + b4(median) ]

Table 7. Results of Model4 with Traffic Level and Junction Density

| Negative Binomial Model | | | | | | |
|---|---|---|---|---|---|---|
| Parameter | Estimate | DF | Standard Error | Wald $\chi^2$ | Significance | Exp(B) |
| Intercept | 0.200 | 1 | 0.2221 | 0.809 | 0.369 | 1.221 |
| Traffic Level | | | | | | |
| Low Traffic=1 | -1.576 | 1 | 0.3849 | 16.763 | 0.000 | 0.207 |
| Medium Traffic=2 | -0.546 | 1 | 0.3152 | 2.998 | 0.083 | 0.579 |
| Heavy Traffic=3 | 0 | 1 | | | | 1 |
| Junction Density | | | | | | |
| 1 | -0.987 | 1 | 0.4938 | 3.991 | 0.046 | 0.373 |
| 2 | -1.430 | 1 | 0.4734 | 9.122 | 0.003 | 0.239 |
| 3 | -0.652 | 1 | 0.3069 | 4.518 | 0.034 | 0.521 |
| 4 | 0 | | | | | 1 |
| Goodness of fit | | | | | | |
| Number of Observations (n) | 263 | | | | | |
| Number of Parameters (p) | 7 | | | | | |
| Degree of Freedom (n-p-1) | 255 | | | | | |
| Scaled Deviance | 168.869 | | | | | |
| Pearson Chi-Square | 257.980 | | | | | |
| The critical Chi-Square | 296.3207 | | | | | |

Model form is fatal crashes on arterial mid-block per 6 years = exp[intercept + b1(traffic) + b2(junction density)]
and crashes per year = exp [-1.59176 + b1(traffic) + b2(junction density) ]

## 6. DISCUSSIONS

Pearson chi-square and scaled deviance values can be used to rank the models according to best data fit. Model 2 is not acceptable as calculated Pearson chi-square is not less than critical chi-square value as well as scaled deviance is also highest. Model 3 with independent variables as traffic level, segment length, junction density, and presence of median is the best with lowest scaled deviance.

### 6.1 Impact of Traffic Level

The traffic level appeared as almost significant variable in all models. The negative sign of intercept of dummy variables of traffic level indicates reduced risk of fatal crashes on mid-blocks with medium and low traffic compared to high level of traffic. The exp(B) column values from Table 4 to 6 indicate that the medium traffic level has reduced crash associated risk up to 50% to 60% and mid-blocks with low traffic have quite lower risk up to 20%

compared to heavy traffic. Caliendo *et al.*, (2007) showed in their study the increase of crashes with increase of traffic. The arterial roads with higher level of traffic in the city have more road-lanes and wider carriage ways. The results revealed that there is more risk on the roads with more lanes. It was confirmed (Ma et al. (2010)) that arterials with heavier traffic volume and more road lanes tended to have more severe crashes. Greibe (2003) showed in his study reduced rate of crashes with increase in number of lanes and increase in road width.

### 6.2 Impact of Junction Density

Looking at the sign of intercept of junction density parameter, with respect to base junction density (up to 4 intersections per km on the mid-block), the risk is decreasing as the number of junctions increasing on the mid-block. The Exp(B) column shows the proportion in the reduction of crash risk.

Ma *et al*. (2010) derived from his study that number of side accesses was found to be a significant factor that increasing severe crash occurrences on the road segments, which is conforming other studies. Caliendo *et al.* (2007) concluded that presence of junction increases total and severe crashes as per annual average daily traffic. The study conducted by Sawalha and Sayed (2001) using 3 years crash data for Canada has shown positive association between risk and unsignalized intersection density on mid-block, while this study revealed negative association between crash occurrence and junction in the mid-block. Greibe (2003) has revealed in his study increase in crashes with increase in number of minor side roads per km

In the context of medium sized Indian city, the effect of unsignalized junctions in mid-block is different. More number of junctions results in reduction in the speed of traffic of arterial road segments and subsequently reduction in fatal crashes also.

### 6.3 Impact of Road Segment Length

There are 263 road segments of arterial roads analyzed in this study having road length varying from 86 meters to 4.11 km, with mean 0.85 km. The positive sign of its intercept confirms the increase in risk with every kilometer of travel, which also conforms to the findings of Caliendo *et al.* (2007), Sawalha and Sayed (2001), Hadayeghi *et al*.(2003), and Ma *et al.* (2010), which also matches along intuition. The Exp(B) explain the 2% increase in the accidental risk for every 1 kilometer additional exposure.

### 6.4 Impact of Median

The presence of median proved insignificant parameter. The study of Sawalha and Sayed (2001) estimated 10% crash reduction by conversion from an undivided arterial to one with a raised curb median. Sites with lower posted speed limits (Ma et al. (2010)) and those with medians generally were associated with fewer severe crashes, which contradict with observations of this study. Greibe (2003) derived crash rate of 0.47 per million vehicle km on road segments with median while that of without median is 0.69. Roads with medians in our case are wider road segments compared to roads without medians, resulting in higher speeds. Therefore we get higher crash risk on roads with medians.

## 7. CONCLUSION

This paper has combined data from police first information (FIR) reports with other data base to develop a fatal crash prediction model for urban arterial. It was found that number of fatal crashes increases as the traffic level and length of road segment increases and decreases as the number of junction per kilometer increases on the road segment. These findings have important bearing on the design of urban arterial roads. In the absence of facilities for pedestrians and bicyclists, arterial roads with wider carriageway and higher number of lanes increase the risk of fatal crash for pedestrians and bicyclists. Presence of medians may result in higher speeds of motorized vehicles and in the absence of facilities for pedestrians and bicyclists the crash risk increases. The impact of other geometric design parameters should be evaluated to improve the road safety. Again it is difficult to work in the absence of electronic database in the country like India.

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