Improve Safety Performance of Un-Signalized Intersections in Oman

Siham G. Farag

***Abstract*—**The main objective of this paper is to provide a new methodology for road safety assessment in Oman through the development of suitable accident prediction models. GLM technique with Poisson or NBR using SAS package was carried out to develop these models. The paper utilized the accidents data of 31 un-signalized T-intersections during three years. Five goodness-of-fit measures were used to assess the overall quality of the developed models. Two types of models were developed separately; the flow-based models including only traffic exposure functions, and the full models containing both exposure functions and other significant geometry and traffic variables.

The results show that, traffic exposure functions produced much better fit to the accident data. The most effective geometric variables were major-road mean speed, minor-road 85th percentile speed, major-road lane width, distance to the nearest junction, and right-turn curb radius.

The developed models can be used for intersection treatment or upgrading and specify the appropriate design parameters of T-intersections.

Finally, the models presented in this thesis reflect the intersection conditions in Oman and could represent the typical conditions in several countries in the middle east area, especially gulf countries.

***Keywords*—**Accidents Prediction Models (APMs), Generalized Linear Model (GLM), T-intersections, Oman.

I. Introduction

THE development of transportation system is considered as one of the hallmarks for the development of a country's civilization. However, this development is accompanied by several problems like air pollution, noise, congestion, traffic accidents, etc. that affect our daily life.

Traffic accidents represent a worldwide major problem. Over 1.2 million people die each year on the world's roads, and between 20 and 50 million suffer non-fatal injuries [1]. Without increasing the efforts and new initiatives, road traffic fatalities are predicted to rise to the fifth leading cause of death by 2030, resulting in an estimated 2.4 million fatalities per year. Furthermore, traffic deaths are predicted to increase by 83% in low income and middle income countries**.**

Oman has seen a remarkable development during the past four decades through the rapid economic growth, modernization, and the infrastructure development. This has reflected on the increase of automobile usage and the car ownership. According to the Global Road Safety Report 2013, Oman had registered 30.4 deaths per 100,000 people in 2010. Oman registered as the highest death rate from road accidents in the GCC and third highest in the Eastern Mediterranean region [2].

Accidents are very complex events as these are combination of highway geometry factors, human factors, vehicle, and environmental and pavement conditions. Highway geometry is considered one of the most important factors affecting the efficiency and safety of a highway system. At least one geometric factor is responsible for 60% of the total accidents [3]. Although, road intersections constitute a small part of the overall highway system, they are defined as the most hazardous locations. They represent the points of conflict in the road network because of the different types of movements (crossing, merging, and diverging) and a combination of different road users [4]. In the USA the accidents at intersection represent about 43% of the total accidents [5]. Approximately 55% of the collision accidents occurred at intersections in Canada [6]. In Oman the preliminary data analysis of the case study shows that accidents at intersections represent 47 % of total accidents and 53% of injuries [7]. Un-signalized intersections with priority controls as T-intersection are usually not self-enforcing. Therefore, the potential for inter-vehicular conflicts and accidents at such intersections is usually very high [4].

The main objective of this paper is to develop a suitable accident prediction models for accident frequency and severity for un-signalized intersections (T-intersections). These models relate geometric and traffic flow variables to accident frequency at road intersections. Based on these models, it should be possible to determine which variables are the best indicators of road intersection safety in Oman. In addition, it might be possible to identify and treat any deficiency on a road intersection and this may improve its safety performance.

II. Literature Review

The safety performance studies have been developed using one of the followings approaches: the average from historical accident data, expert judgments made by experienced engineers, before-and-after studies, black spot studies, and statistical models [7].

The statistical models provide quantitative relationships between accidents and various characteristics. The two statistical methods that have been used to develop accident prediction models are conventional linear regression modeling and generalized linear regression modeling [8].

The conventional linear regression techniques were used in developing the early accident predictive models. However several researchers [9]-[11] have proved the inappropriateness of linear regression for modeling traffic accidents. The

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accepted convention in modeling safety relationship now is Generalized Linear Modeling (GLM), applying Poisson or Negative Binomial Distributions (NBD). Examples of previous studies on accident prediction models for intersections are discussed in the following sections.

Reference [12] used the accident prediction models to study 91 un-signalized intersections in Ghana. He used the GLIM software package to build separate models for X and T intersections using 3 years of accidents data along with other traffic and geometric data. He found that the accident potential of T-junctions that had YIELD or no control was adjudged to be much lower than that of similar sites with STOP control. The most influential traffic exposure function for X- unction accidents was the sum of the crossing flow products (CFPD), whilst the cross product of minor and major road traffic inflows (XPDF) influenced accidents at T-junctions most.

Reference [13] examined traffic accidents injury severity for 2,043 un-signalized intersections. They explored three approaches, the accepted one dealt with only the severe versus non-severe crash levels using binary probit. They found that the important factors that affecting the traffic volume on the major approach, and the number of through lanes on the minor. The geometric factors, the upstream and downstream distance to the nearest signalized intersection, left and right shoulder width, number of left turn movements on the minor approach, and number of right and left turn lanes on the major approach. As for driver factors, young and very young at-fault drivers were associated with the least fatal probability compared to other age groups.

Reference [14] developed a Road Accident Prediction Model Based on System Dynamics Approach in for Chennai city. The road accident prediction model was developed using factors of human behaviors, vehicle factors and road factors. The system dynamics road accident prediction model was developed using STELLA software. They established simple practicable simulation road accident models that can predict the expected number of accidents from 2010 to 2020. The predicted number of accident in 2010 was 5255 and accident for the year 2020 will be 21612.

Also, [15] introduced a developed machine learning technique, multivariate adaptive regression splines (MARS) to predict vehicles' angle accidents at un- signalized intersections in Florida. They estimated two models for angle accidents frequency at 3- and 4-legged un-signalized intersections. They examined treating accidents frequency as a continuous response variable for fitting a MARS model by considering the natural logarithm of the crash frequency. They found that the most effective factors are traffic volume on the major road, the upstream distance to the nearest signalized intersection, the distance between successive un-signalized intersections, median type on the major approach, percentage of trucks on the major approach, size of the intersection and the geographic location within the state.

In the fact of that Oman has a highest rate of road accident, yet very limited researches have been carried out. It seems that there are no comprehensive previous studies about accident prediction models in Oman due to lack of appropriate data. Improving road safety in Oman is a pressing national concern; therefore, this study participates with national efforts in road safety engineering assessment and accident analysis.

III. Data Collection

The intersections used in this study were obtained from Dhofar Governorate; Sultanate of Oman. A sample of un-signalized intersections (T-intersections) was chosen for two main reasons. The first is that these types of intersections constitute the major component of intersections in Dhofar road network [16]. The second is that, based on accident statistics, T-intersection exhibited the highest proportions of accidents at intersections in Dhofar region, 57.2% [7]. Selection of study intersections was determined while taking into considerations; the availability of accident, traffic volume, and geometry data, there is no geometric changes in the selected sites during the period of study, and almost all T intersections are with 90 degrees. Fig 1 shows the map of study area and types of selected intersections.

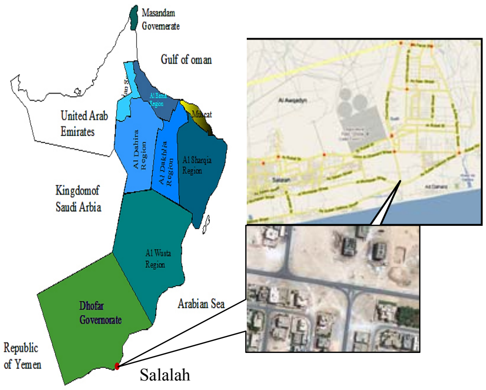

Fig. 1 A map of study area and types of selected intersections

A. Accident Data

About 223 accidents for three years (2007 to 2010) were obtained from the Royal Oman Police (ROP). The reporting system of road accidents is based on Accident Report Form (ARF) which is manual recording. Although the quality of data provided by ROP, it wasn’t suitable for such study. The main challenge in this study is to prepare the data in appropriate method that suitable for this study. Therefore, a database has been designed to manage the data collection process and facilitates the retrieval of the required records from the database according to predefined criteria [7]. The accident frequencies were calculated for total accidents, and then divided to the severity of accidents and number of vehicles-involved accidents. Severity accidents were subdivided according to injury accidents and property damage only (PDO) accidents. The number of vehicles-involved accidents was divided to single vehicle accidents and collision accidents. The collision accidents were subdivided to rear-end, right angle, sideswipe, and head-on accidents. Table I summarizes the statistics of T - intersection accidents.

TABLE I
T - INTERSECTION ACCIDENTS STATISTICS

Symbol	Accident Type	Max	Min	Average	SD
ACC	Total Accidents	34	0	7.2	7.93
IA	Injury Accidents	15	0	2.7	3.31
PDO	Property Damage Only Accidents	19	0	4.48	5.03
SA	Single Accidents	7	0	1.25	1.79
RA	Right-Angle Accidents	8	0	1.52	1.99
REA	Rear-End Accidents	8	0	1.32	2.07
SWA	Sideswipe Accidents	9	0	1.87	2.26
HA	Head-On Accidents	6	0	1.23	1.64

B. Geometric Characteristics Data

The geometric characteristics data were obtained as digital maps from Dhofar Municipality [16]. The selected T-intersections were classified to six types according to presence and absence of channelization on minor road acceleration lane on major road, deceleration lane on major road. Table II summarizes the statistics of T - intersection accidents.

TABLE II
SUMMARY STATISTICS OF T - INTERSECTION FEATURES

Symbol	Name	Max	Min	Average	SD
DTNJ	Distance to Nearest Junction in meter	486.0	14.0	153.68	110.5
MAJW	Major Road Width in meter	12.00	2.50	4.50	1.83
MINW	Minor Road Width in meter	6.00	2.50	3.50	0.59
RR	Right Curb Radius in meter	54.00	5.80	21.57	9.70
RL	Left Curb Radius in meter	179.50	0.00	26.90	29.59
ISW	Island Width in meter	35	1.2	6.42	8.52
ISL	Island Length in meter	145	9	41.7	53.74
Categorized Geometric Variable					
EMIS	Existence of Minor Road Island	exist = 15		not exist = 16	
EML	Existence of acceleration lane on major road	exist = 14		not exist = 17	
ERL	Existence of deceleration lane on major road	exist = 12		not exist = 19	

C. Traffic Flow Characteristics Data

Traffic volumes and speeds data were obtained from Salalah road network traffic movement study [16]. The traffic volumes in the study were converted to Annual Average Daily Traffic (AADT) using appropriate growth factors between 0.33% and 6.11% as mentioned in that study. The required traffic volume data are major and minor road T-intersections have six types of turning movements' traffic volumes, as shown in Fig 2.

Table III presents the description of traffic flow functions used in the modeling stage.

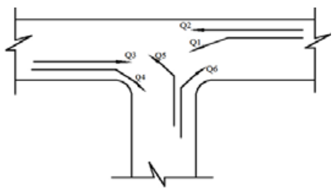

Fig. 2 Traffic flow streams at T-intersections

TABLE III
THE DESCRIPTION OF TRAFFIC FLOW FUNCTIONS

Traffic flow	Description	Equation
MAJF	Major Road inflow	MAJF = Q1 + Q2 + Q3 + Q4
MINF	Minor Road inflow	MINF = Q5 + Q6
TINF	Total inflow	TINF = Q1 + Q2 + Q3 + Q4 + Q5 + Q6
XPDF	Cross product flow	XPDF = MAJF×MINF
MEFP	Merging flow products	MEFP = (Q1×Q4) + (Q3×Q6) + (Q2×Q5)
DIFP	Diverging flow products	DIFP = (Q1×Q2) + (Q3×Q4) + (Q5×Q6)
CFPD	Cross flow products	CFPD = (Q1×Q5) + (Q3×Q5) + (Q3×Q1)
ENCP	Encounter flow products	ENCP = MEFP + DIFP + CFPD
MRSH	Minor road share of traffic	MRSH = MINF/TINF
PMAL	Proportion of left turn major inflow	PMAL = Q1/MINF
PMIL	Proportion of left turn minor inflow	PMIL = Q5/MAJF

The total AADT for the major roads at the selected T-intersections varies between 1479 and 26700 vehicle/day (vpd) and for minor roads between 612 and 6595 vpd. The major road 85th percentile speed varies between 29.5 and 77.1km/h, and the minor road 85th percentile speed varies between 23.7 and 69km/h.

IV. METHODOLOGY

The objective for modeling accident is to find out quantitative relationships between accidents frequencies and road characteristics (traffic flow, geometric design, etc.).

Generalized Linear Model (GLM) technique with Poisson or Negative Binomial Regression (NBR) using SAS package was carried out to develop these models. Accident Prediction Models (APM) offers the most appropriate and recently almost exclusively mathematical tools for studying road safety. (GLM) can overcome the limitations associated with conventional linear regression modeling of traffic accidents.

The procedure modeling can be summarized as define the independent variables (intersections geometric, traffic and speed) and in dependent variables (accident groups); selecting the mathematical form; developing several models, testing the significant of the coefficients of the variables, and examining the multi-collinearity or correlation between explanatory variables.

A. Regression Analysis

The Poisson regression provides the most appropriate statistical properties for modeling the accidents (rare, discrete, non-negative events). The Poisson error structure assumes the mean and the variance are equal. However, it has been shown by [17], [18] that most accident data are likely to be over-dispersed (the variance is greater than the mean). This indicates that the negative binomial distribution is usually the more realistic assumption for the error structure. Reference [11] pointed out that a simple way to overcome the over-dispersion problem is to use negative binomial or compound Poisson regression models. The choice between Poisson and negative Binomial Regression can be decided using two approaches.

1) Assume the Poisson distribution then calculate the dispersion testes, Pearson's Chi-squared ratio, and/or scaled. If these values are significantly greater than one, then the data have over-dispersion. Hence, the best appropriate regression for modeling the data is Negative Binomial regression.
2) Start with a negative binomial model, and then check the significant of the estimated coefficient of over-dispersion parameter (α). If (α) is significantly different from zero, then the negative binomial model is the correct choice [19].

The general form used in this study is:

$$E(\mu)=kQ^{\beta_i} exp\left(\sum \beta_j X_{ij}\right) \quad (1)$$

where: E(μ) = the expected number of intersection accidents (3 years in this study); Q = general traffic flow function; k, βi *and* βj = the model parameters to be estimated; $Xi\,j$ = a vector of variables representing other traffic and road variables.

B. Model Evaluation

Three types of assessments were made.

1) Assessment of Individual Model Parameters by two types of tests; the first test is to ensure that the estimated parameter coefficients are statistically significant using Chi-squared statistic as presented in (2).

These were computed by SAS software package [20] using GENMODE procedure as follows:

$$x^2 = \left(\frac{\beta_i}{S.E_i}\right)^2 \quad (2)$$

where: "β" _"i" is the coefficient value; and s*,* Ei are the standard error of coefficient estimate.

The second test is to examine whether a parameter's contribution to the reduction in deviance is significant. This is used to assess the significance of adding one or more terms to a model. If the required level of significance is 5 % the drop in deviance following the addition of one parameter, should be at least 3.84 ($x^2$with 1.0 DF).

2) Assessment of Goodness-of-Fit Of Model by three methods:

The first: is the deviance value, which follows the (X^2) distribution for testing the goodness-of-fit [21]. It is expressed as in (3):

$$2(LL(\beta)\text{-}LL(0)) \quad (3)$$

where; $LL\ (\beta)$ = the log-likelihood of model at convergence; and $LL\ (0)$ = the log-likelihood of model with only the constant term (without any parameters).

The second: is the log-likelihood ratio index (ρ^2) [22], which is the indication of the additional variation in accident frequency caused by adding more parameters to the constant term only. The log -likelihood ratio index (ρ2) can be expressed in (4):

$$\rho^2=1\text{-}LL(\beta)/LL(0) \quad (4)$$

The third is the negative binomial over-dispersion parameter (α) [11] to determine how the variance of the data is explained in a relative sense. This can be expressed using (5):

$$R^2_\alpha=1\text{-}\frac{\alpha}{\alpha_{max}} \quad (5)$$

where: α = the estimated over-dispersion parameter for the chosen model; and α_{max}= the estimated over-dispersion parameter for the model with only the intercept term.

3) Selecting the best Model: AIC (Akiake's Information Critersion) is used to select which of two models or more best of fits [19]-[23]. The smaller the value of *AIC* is the better model. Equation (6) calculates the *AIC*:

$$AIC= -2xML+2xK \quad (6)$$

where; *ML* is the maximum log-likelihood of the model under consideration; *K* is the number of effective variables of the model without constant.

V. Model Results and Analysis

A total of 223 accidents were recorded for 31 T-intersections. Two types of models have been examined for each accident group. The first type is the flow-based models, including best single flow-based models and the best combined flow-based model (including more than one traffic flow variable) if existed. The second type is the full models that contain the best flow-based model variables along with other significant geometric and speed variables.

The accident frequencies were calculated for total accidents (ACC), and then divided to the severity of accidents and number of vehicles-involved accidents. Severity accidents were subdivided according to injury accidents (IA) and property damage only (PDO) accidents. The number of vehicles-involved accidents was divided to single vehicle accidents (SA) and collision accidents. The collision accidents were subdivided to rear-end accidents (REA), right angle accidents (RA), sideswipe accidents (SWA), and head-on accidents (HA). Table IV presents the best-fitting models for total accidents.

The best flow-based models are:

$$ACC=3.92\times10^{-4} ENCP^{0.5741} \quad (7)$$

$$ACC=8.5\times10^{-5} MAJF^{1.1346} e^{0.37MRSH} \quad (8)$$

The best full model is:

$$ACC=6.3\times10^{-7} MAJF^{1.5108} e^{\substack{0.0301MRSH\text{-}0.42DTNJ\text{-}0.2879MAJW+ \\ 0.275MIS+0.MINS+0.237MAJMS+0.0363RR}} \quad (9)$$

TABLE IV
THE BEST-FITTING MODELS FOR TOTAL ACCIDENTS

Parameter	Model Type	Null Model	Flow-Based Models		Full Model
			A	B	A
Intercept	Estimate	1.97	-8.018	-9.36	-14.2782
	Std error	0.19	2.05	2.4709	3.3698
	p-value	<0.0001	<0.0001	0.0002	<0.0001
Log ENCP	Estimate		0.5741		
	Std error		0.1187		
	p-value		<0.0001		
Log MAJF	Estimate			1.1346	1.5108
	Std error			0.2468	0.2916
	p-value			<0.0001	<0.0001
MRSH	Estimate			0.0375	0.0301
	Std error			0.0202	0.0172
	p-value			0.0638	0.0800
DTNJ	Estimate				-0.0042
	Std error				0.0019
	p-value				0.0274
MAJW	Estimate				-0.2879
	Std error				0.0986
	p-value				0.0035
MINS	Estimate				0.0275
	Std error				0.0143
	p-value				0.0544
MAJMS	Estimate				0.0237
	Std error				0.0127
	p-value				0.0616
RR	Estimate				0.0363
	Std error				0.0180
	p-value				0.0438
Over-dispersion (α)	Estimate	1.0136	0.4467	0.4781	0.2734
	Std error	0.3073	0.1742	0.1825	0.1242
Summary Statistics					
Number of Intersections (df)		31 (30)	31 (29)	31 (28)	31(24)
Scaled deviance (dispersion)		36.24(1.208)	37.37(1.29)	37.30(1.33)	36.48 (1.5)
$\chi 2$ (dispersion)		31.70(1.056)	32.24(1.11)	32.82(1.17)	30.01 (1.3)
$\chi 2$ Test value @ (0.05,df)		43.773	42.56	41.34	36.42
Log-likelihood at zero (LL(0))			-94.229		
Log-likelihood at convergence (LL(β))		-	-85.413	-86.073	-80.422
2(LL(β)-LL(0))		-	17.632	16.312	27.614
ρ^2=1-(LL(β)/LL(0))		-	0.094	0.087	0.147
AIC		-	172.826	176.146	174.844
R_α^2		-	0.559	0.528	0.730

For the flow-based models, the expected total accident frequency increased approximately as a function of the square root of the exposure function ENCP. The combined traffic flow-based model includes the major traffic flow MAJF with the minor road share of traffic MRSH. With increasing both of them, the total accidents increase. The effect of major flow on increasing the total accidents is higher than ENCP where the exponent value for this function is more than 1.0. For the two alternative flow-based models, the one based on the encounter flow products function (ENCP) was the most preferred, because it used one less degree of freedom and still produce higher proportion of systematic variation explained (55.9%) and smaller AIC.

For the full model, the factors used in this model are distance to nearest junction, width of major road lane, the minor road 85th percentile speed, the major mean speed, and the right curb radius. All the variables are significant at the 10% significance level. All signs of the coefficients of these variables express the expected direction of this relationship.

The negative coefficient of distance to nearest junction and the width of major road lane indicates that an increase in both of them decrease the total accidents. This may be because the number of conflict points at intersections decreases. The positive sign of the minor road 85th percentile speed, the major mean speed, and the right curb radius means that with increasing these variables the total accidents increase. The proportion of systematic variation in accident frequency explained by the full model was about 73%. Summary of the best flow-based models found in this study are presented in Table V.

TABLE V
THE BEST FLOW-BASED MODELS

Accidents	Full Model
ACC	$6.3 \times 10^{-7} MAJF^{1.5108} e^{\left(\begin{smallmatrix}0.0301MRSH-0..42DTNJ-0.2879MAJW+\\0.275MIS+0.MINS+0.237MAJMS+0.0363RR\end{smallmatrix}\right)}$
IA	$3.88 \times 10^{-8} MEFP^{0.8553} e^{\left(\begin{smallmatrix}-0.006DTNJ+0.0434MAJM-0.2943MAJW+\\0.052MINMS+0.3936RR\end{smallmatrix}\right)}$
PDO	$9.1 \times 10^{-5} XPDF^{0.6662} e^{(-0.1506MAJW)}$
SA	$4.01 \times 10^{-9} ENCP^{0.8448} e^{(0.0474MAJMS+0.043MINS)}$
RAA	$1.8 \times 10^{-8} XPDF^{0.8583} e^{(0.0197PMIL+0.0368MINS+.0406RR)}$
REA	$3.8 \times 10^{-11} MAJF^{2.7702} e^{(-0.4408MAJW)}$
SWA	$4.17 \times 10^{-5} DIFP^{0.7004} e^{(-0.1828MAJW)}$
HA	$8.8 \times 10^{-6} DIFP^{0.6723} e^{(0.0217MAJS-0.0421ISL)}$

VI. CONCLUSION AND RECOMMENDATION

Two types of models flow-based models and the full models were developed separately for different types of accidents. Three goodness-of-fit measures were mainly used to assess the overall quality of the developed models.

Overall the results showed that, the flow-based models for the various types of accident defined by the primary collision produced higher proportion explained than the corresponding models for single accidents or injury accidents.

The traffic exposure functions such as the sum of encounter flow products (ENCP), the cross products of flow (XPDF) and the merging flow products (MEFP) produced much better fit to the accident data for the T-intersection models.

Also, increasing the minor road share of traffic MRSH was most significant in increasing each of total, right angle and sideswipe accidents. However, increasing the proportion of left turn major inflow increases the head-on accidents. The increase of the proportion of left turn minor inflow leads to increase in the right angle and head-on accidents. The most significant geometric variables in the case of T-intersection accident models were distance to nearest junction, the major width, and the island length with negative signs. The major and the minor road 85th percentile speed, the major road mean speed, and the right curb radius with positive sign.

The procedures outlined in this study present an improved basis for appraising and quantifying of accident potential and its determining variables. The study could be useful in evaluate the accident implications of individual intersection features. Since the magnitude and direction of their impact on accident frequency has now been quantified, it can help in making a comparison of design/safety schemes before detailed design is done. To improve upon the methodology and continue its use into the future, some further work is recommended, as follows:

1) It is highly recommended to moderate the ROP data collection system.
2) Carry out a similar but more extensive study from all Omani regions involving a larger database, with improved quality and broader range of independent variables.
3) Review or validate the prediction models periodically, since they cannot be valid for all times.
4) Develop separate prediction models for other types of intersections as well as road links using comprehensive data, such as link sections on urban roads and trunk roads.

Analysis according to different accident groups for each type of intersection can show up the variables that affect each type of accidents. Different models for different types of accidents help decision makers to identify the sites with high risk to specific type of accidents and provide the suitable solutions

Finally, the models presented in this paper reflect the intersection conditions in Oman and could represent the typical conditions in several countries in the Middle East area, especially gulf countries.

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