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Traffic Accident Duration Modelling: A Computational Review

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Abstract-Rapid growth of population, urbanization, and the need for mobility in recent decades, are the key factors which have resulted in a tremendous expansion of road traffic in terms of volume, intensity, and complexity. Negative repercussions for these is a proportional increase in the number of road accidents involving injury, trauma and fatality. Apart from the growth in the number of vehicles on road, which, unfortunately, is always on the rise, the motivating part is the development of research and computing/statistical techniques which can be applied in this area. In this paper we review different approaches used for estimating the probable distributions of incident duration and the most common methods employed for such a purpose.

Index Terms- Road accidents; accident management; incident duration modelling.

1. INTRODUCTION

Road accident is a universal catastrophe with interminably floating trend. It can be universally accepted that this area needs progressive probe into various aspects with one final aim, which is, reduction of its occurrence and at least reduction in severity of its occurrence. Research on this area has been ongoing and is on a continuous rise since decades, as literature review helps us to understand. Slowly and steadily, several techniques, which can be mathematical, statistical or computing, have been identified and been experimented upon by researchers all over the world. Since region, environmental factors and a country's economic development (which has direct impact on condition and standard of roads), play a very important role in studies being conducted on occurrence of road accidents, it is beneficial to apply similar techniques to different regions [1].

Road accidents are normally categorized in two ways, first, as a single vehicle colliding with static object or objects, secondly as an accident involving several vehicles in which two or more vehicles may collide with each other or with surrounding objects. Before analyzing any aspect of a road accident, it is basic to understand and list the factors contributing as causes for the same.

1.1 *Driver behaviour*

One of the major causes attributing to road accidents. It can further be explored by classifying into sub categories.

1.1.1. *Carelessness*

A primary reason is carelessness on the part of the driver. Carelessness in following traffic rules, and traffic rules violation, for example, usage of mobile while driving, attributes to majority of road accidents. Driving without proper vision (without glasses) is another cause and carelessness shown by some drivers.

1.1.2. *Lack of proper experience*

Unqualified drivers, driving illegally without license or with license obtained by improper means will have no acquaintance of traffic rules and road signs. They are very likely to make mistakes and create accident scenarios due to sheer ignorance.

1.1.3. *Driving under mental stress*

Drinking and driving, where the driver drives under the influence of alcohol, is a traffic offense which is another important cause leading to road accidents. In these cases, alcohol affects human brain and reduces a person's reflexes substantially. More adverse psychological states of mind can be, driving under pressure which can be due to personal reasons like financial or family issues. A report states that utmost drivers had high percentages of blood alcohol ranging from 3.00-3.83/100 ml, which is far above the accepted level of 2.43/100ml. This is sufficient to make motor accidents likely to happen.

1.1.4. *Impatience*

Lack of patience while driving is an important factor leading to road accidents. This happens because of anxiety, leading to an urge to race and break traffic rules, in a hurry to reach the required destination. Sufferers in these cases are sometimes innocent pedestrians and other vehicles on road on similar track.

1.2. *Negligence by administration and transport authorities*

Absence of sincerity on the part of state authorities to look into proper road planning, road maintenance and traffic signal maintenance can be another important factor attributing to road accidents. Lack of seriousness and negligence while dealing with accident cases is another cause of fatalities due to accidents, in which police and hospital authorities have a major role to play.

1.3. *Environmental factors*

Extreme weather conditions make driving on roads difficult as well as dangerous. For example, there is a constant fear of tyres bursting due to excessive heat on roads while driving in severe summer conditions in the middle eastern countries.

2. ACCIDENT MANAGEMENT

In response to the severe consequences of accidents, a lot of attention has been focused on improving the effectiveness of accident management. Accident management can be defined as applying available resources to reducing the impacts of accident and its duration. It can be manifest in any initiative or programme in the fields of legislation, operation or technology, which aims to reduce the harmful impacts of accidents.

Accordingly, the total incident duration can be divided into several phases or interval times. The Highway Capacity Manual breaks down the total accident management duration into the following four phases:

2.1 ***Detection time***: the time between the incident occurrence and incident reporting time.

2.2 ***Response time:*** the time between incident reporting time and the arrival time of the first responder at the scene.

2.3 ***Clearance time:*** the time between the arrival of the first responder at the scene and the moment when the incident has been cleared from the highway.

2.4 ***Recovery time:*** the time taken for traffic flow to return to normal after the incident has been cleared.

Accident management process consists of the following seven phases:

1- Detection: The process by which a traffic incident becomes known to the transport agency or other responsible agencies. Several tools can be utilised to detect incidents, such as mobile phones, traffic patrol, CCTV systems, emergency telephone systems and traffic reporting services.

2- Verification: The key requirement of the verification stage is to collect further information about the incident, starting by confirming an incident occurrence. Other information, like the location and other relevant details, is important with regard to determining the proper initial response. Incident verification can be conducted by means of various methods, such as using CCTV systems or dispatching police patrols to the scene.

3- Motorist Information: This activity is necessary in order to inform motorists about the incident-related information or any route diversion. Disseminating information can be carried out by highway advisory radio, internet, variable message signs or other media services. However, this information has the potential to cause a harmful impact on the traffic if it is inaccurate or not updated.

4- Response: After confirming incident occurrence and obtaining incident details, the response process will be initiated. The appropriate personnel and equipment will be dispatched to the incident scene with an effective communication link between the responders and the activation of motorist information.

5- Site Management: The focus of this activity is to manage the available resources at the incident scene in order to maintain the safety of responders, incident victims and other motorists. Many functions occur during this phase, such as maintaining good co- ordination with incident responders, conducting incident assessment and assisting with injuries.

6- Traffic Management: This involves the utilization of traffic control measures around the incident scene to reduce the impact of the incident on traffic flow and to ensure the safety of responders. A possible way of performing this phase is by controlling roadway space, either by managing road lanes or creating a traffic diversion around the scene.

7- Clearance: This is the final phase of TIM, aiming to restore normal traffic flow by removing any obstacles such as vehicles, debris or wreckage before reopening the roadway to traffic. The length of this process depends upon using the appropriate equipment and technologies which should be made available on the scene, based on an accurate scene assessment carried out in the site management stage.

3. MODELLING OF ACCIDENT DURATION

3.1 *Probabilistic Distributions of Incident Duration*

This approach aims to investigate the probability distribution of incident duration by viewing this duration as a random variable. The key idea of this approach is to give the traffic operator an idea about the mean and variance of incident duration which might be useful for the purpose of predicting incident duration. Researchers claimed that each accident could include several stages, including: "1) detection, 2) initial response, 3) injury attention (if required), 4) emergency vehicle response (if required), 5) accident investigation, 6) debris removal, 7) clean-up, and 8) recovery". In addition, they assumed that the length of each stage has a direct impact on the length of the subsequent stage. Based on this assumption, they theorized that the distribution of total incident duration could be fitted to log-normal.

Nam and Mannering[3] analysed a two-year dataset of highway incidents in Washington State, USA. They broke down total incident duration into three interval times, including detection (reporting) time, response time, and clearance time. Both detection and response times' datasets were found to fit in a Weibull distribution. However, clearance time data fitted in a log-logistic distribution. Similarly, Wang et al.[4]found that the dataset of vehicle breakdown duration on the M4, UK, corresponded to a Weibull distribution.

3.2 *Linear Regression Models*

Linear regression is another approach used to predict incident duration. The key aspect of this method is to include several binary variables that represent incident characteristics to model their effects on accident duration (dependent variable) by fitting a linear equation[5].

Peeta et al.[6] applied a linear regression model to predict incident clearance time for incidents in Borman Expressway in North Indiana, USA. The model results demonstrated that the significant variables that affect incident clearance time are number of vehicles involved, severity of the incident, ramp, night time, temperature, rain and snow.

3.3 *Nonparametric Regression Method*

Nonparametric regression is a common technique employed for the purpose of predicting traffic flow. The main idea of this method is to utilize past experience to make a current decision for a similar experience. It is based on the data which explain the relationship between dependent and independent variables. The advantage of this method is that no specific assumption is required to explain the relationship between the dependent and independent variables[7].

Smith and Smith[7] conducted another study to forecast the clearance time of freeway accidents in Virginia. They used three different forecasting models: stochastic, nonparametric regression and classification tree. After developing these methods, none of the developed models produced an accurate prediction. This was interpreted as a function of poor data quality and model selection. Thus, it is apparent that this approach could be improved and may be developed to obtain an accurate result in further studies in the future.

3.4 *Decision Tree and Classification Tree*

This method is a nonparametric model designed to find out patterns in a certain dataset without any assumption regarding the underlying probabilistic distribution. It works through a repeated process of splitting the dataset into subgroups until termination, based on the significant explanatory variables. Also, it should be stressed that this method consists of a series of decision variables and the outcome represents the average incident duration of a specified dataset[7].

Knibble et al.[8] applied a classification tree to forecast incident clearance time in Utrecht (the Netherlands). A dataset of 1853 incidents with independent variables of incident type, vehicle type and casualties was used to construct this model. They found that only 1 out of 3 incidents were accurately predicted. This low level of accuracy can be attributed to their use of a low detailed dataset.

Kim et al.[9] redesigned CART and developed a Rule-Based Tree Model (RBTM) for the purposes of identifying the significant variables that influence incident duration and to predict incident duration for highway incidents in Maryland, USA. The results showed that several factors affect incident duration, including spatial variable, out of peak period, lane closure and wet pavement. Also, RBTM was found to have an advantage over CART for the given conditions.

3.5 *Bayesian Networks (BNs)*

The Bayesian Network (BN) approach has been used as a classification tree for many tasks, including document classification[10] and dialogue act recognition [11]. BNs are simply graphs where stochastic variables are used for nodes and the dependencies between these variables are represented by arcs. The BN method has three advantages that give this approach merit over other classification methods such as decision tree: bi-directional induction, incorporation of missing variables and probabilistic inference. Ozbay and Noyan [12] applied this approach to estimate incident clearance time in Virginia, USA. Their aim was to support decision makers (e.g. traffic operators and traffic engineers) in making real-time decisions. The assessment of the BN results for incident clearance time showed that this method was able to present the stochastic nature of incidents.

3.6 *Discrete Choice Models*

Discrete choice models are statistical measures that enable a choice to be made from a fixed set of alternatives. To achieve this, all of the possible alternatives need to be included in the set and the choice should be from the alternative set, only one alternative can be chosen and the set should have finite.

Lin et al.[13] developed an integrated approach of the discrete choice model and the rule-based model to predict incident duration in Maryland. Based on the needs of control centre operators, they divided the incident duration sample into several interval times with 5 minutes increment. Then they applied an order profit model to calibrate the model. The results showed that a discrete choice model was reliable for incidents with a duration of less than 60 minutes. To enhance the effectiveness of this approach, a rule-based model was developed to estimate incidents with a duration of more than 60 minutes.

3.7 *Fuzzy Logic (FL)*

Fuzzy Logic (FL) is a multi-valued logic that maps an input data into a scalar crisp output by allowing for intermediate values. The basic concepts of FL are linguistic variable, fuzzy if-then rule and calculus of fuzzy rules. In order to develop an FL system, four components are required: input, process structure and output flow concept, as well as sufficient expert knowledge.

Wang et al.[14] used this method to model vehicle breakdown duration in the UK. In this study, the authors aimed to analyze the available characteristics of vehicle breakdown incidents and developed two models using FL and Artificial Neural Networks (ANN). For this purpose, a dataset of 213 breakdown vehicle incidents, which occurred on the M4 motorway from May 2000 to April 2001, were obtained from the Road Network Master Database (RNMD). This dataset has many variables such as time of day, vehicle type, location and reporting mechanism. After collecting these records, a test of incident duration distribution (Kologorov-Smirnov) was carried out and the results demonstrated that the incident duration fitted into a Weibull distribution. Following a distribution test, two models were developed using FL and ANN. Based on the results of statistical parameters such as root mean square error and R^2, it concluded that ANN outperforms FL.

3.8 *Artificial Neural Network (ANN)*

An Artificial Neural Network (ANN) model is a relatively a new method that can be used to analyse the effects of independent variables on the dependent variable. ANN has been widely applied to issues in the field of transportation. Some of these applications include pavement maintenance, driver behaviour, traffic control and traffic forecasting. These methods are based on collecting data from different sources and computing them using an internal "transfer function". Some of the early studies applied this method for incident duration analysis and were focused on incident detection analysis [15]. Also, as mentioned in the previous section, this method was used to model vehicle breakdown duration in the UK, showing good results compared with FL.

Wei and Lee [16] developed two ANN models to forecast car accident duration in Taiwan. The first model was based on real-time data at the time of incident notification. In the second model, a series of updates were made to the preliminary forecasting in the first model, using incident data. Six experiments were conducted for the two models to study the relationship between the actual duration of car accidents and the predicted duration. All results showed the existence of a linear relationship between the actual duration and the predicted duration. Also, the correlation coefficient was found to be over 0.72. Furthermore, the accuracy of these models was tested by many criteria, including mean absolute percentage error, mean absolute error and root mean square error. The mean absolute percentage error was found to be less than 40% at each forecasting point in the second model. As a result of this, researchers concluded that these models are appropriate to forecast incident duration and are viable in Intelligent Transportation Systems.

4. CONCLUSION

Traffic accidents are the cause of a great deal of harmful impacts on safety and traffic. To mitigate these impacts, accident management has played a crucial role for several agencies worldwide. It aims to reduce incident duration and minimise incident impacts through applying different kinds of programmes or initiatives. In this paper we study and analyse several approaches that have been applied to model traffic accident durations. An investigation of the data used to study incident duration shows that several variables have been used to examine factors affecting incident duration. Among these factors are incident type, location, number of lanes affected, weather condition, incident time and number of vehicles involved. It is widely recognized that incident duration could fit at any distribution, and the assumption that assumes log-normal distribution can be rejected. Also, it should be stressed that poor data quality was a common problem in previous studies. Finally, it is worth mentioning that conducting comparisons of previous work is extremely difficult, because almost every study has applied a different method, used a different dataset, had different aims and used different data collection methods.

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