Review of Incident Duration Prediction Methods

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Abstract: ***Traffic incidents cause a significant loss of life, economy, and productivity over injuries and fatalities, extended travel time and delay, and air pollution. Traffic incidents are one of the main causes of the Non-recurrent congestion which in turn can lead to secondary incidents. Predicting accurately incident duration plays an important role in reducing the influence of the Non-recurrent congestion on road capacity reduction and massive travel time loss. The objective of this paper is to give a thorough review of the studies and researches, mainly include the various phases of incident duration, data resources, and the different methods that are used in the duration time prediction and traffic incident duration influence factor analysis.***

Keywords: Incident Duration, Prediction, Machine Learning, Influence Factors

1. Introduction

On a daily basis, traffic incidents require active reaction and adaptability from operators and motorists. To produce accurate and timely travel advisory, basic information is the incident duration prediction, as defined by the period that extends from incident occurrence to the clearance of the road. During this period, the traffic operators need to execute a response strategy in an efficient way, which in turn depends on a variety of factors, some of these factors are measurable such as location or traffic conditions, number of lanes affected, while other factors are difficult to estimate such as capacity reduction, drivers attitude or probable for generating secondary accidents. Traffic operators also need to produce guidance information for drivers, this guidance must be consistently trustworthy and accurate.

To support an appropriate response, traffic management centers build workflows that collect the information, analyze it, and chose the right strategy for execution, with the use of updated information to govern traffic, disseminate information, and handle incident response resources [1].

When the traffic demand on the roadway exceeds its available capacity, Traffic congestion occurs. Such congestion can be divided into two types: recurrent and non-recurrent. Recurrent congestion is referred to the physical layout of the road, meaning that it is mainly caused by high traffic volume in finite roadway capacity, while non-recurrent traffic congestion is caused by random events on the road such as accidents, inclement weather, stalled vehicles, and work zones [2].

Traffic incidents such as vehicle crashes, debris, road maintenance, fire police, activities, etc. are still very prevalent, random, and dangerous. The occurrence of traffic incidents can lower road capacity because of lane closures that lead to traffic congestion and delays.

Traffic incidents are the main causes of non-recurrent congestion on urban arterial roads and urban expressways. Also, traffic congestion and travel delay can rise the occurrence likelihood of a secondary incident. Many cities around the world have constructed traffic management centers and deployed various traffic incident management systems to decrease traffic incidents and alleviate related congestion.

Two essential aspects of efficient traffic incident response are Traffic flow management and providing travelers with proper guidance during clearance periods. The prediction of incident duration has become the main focus of the researchers because giving an accurate prediction of traffic incident duration increase the performance of the response strategies, therefore researchers have proposed many effective methods for predicting traffic incident duration. With the use of different data, variables, and algorithms in these methods [3].

Even though a lot of methods have been suggested to predict the incident duration, however, there are deficiencies with the existing methods more or less. Firstly, some algorithms are difficult and take a lot of time to train.
Secondly, some methods are not easy to operate in a workable application.

Thirdly, the prediction accuracy of current methods is not satisfied, and need to be improved [4].

2. Related works

In this section, the state of the art in real-time incident duration prediction is reviewed. Details about these models are provided next. Table 1 summarizes several studies on predicting traffic incidents duration using various modeling techniques.

Khattak et al. (2016) investigated the Ordinary Least Squares

(OLS) regression model using a quantile regression method to predict the traffic incident duration. Road inventory data, traffic Incident data including incident duration and type of incident collected from Safety Service Patrol (SSP) of the Hampton Roads in Virginia during the period from 2013 to 2015were used to build and the developed models. Root mean square error (RMSE) was used to evaluate the developed models. Results showed that the RMSE for OLS is 82.29 min, while for the quantile regression with location-based prediction is 57.49 min [5].

Park, Haghani, and Zhang (2016) proposed a two-step method to develop an incident clearance duration estimation model based on Bayesian neural networks (BNN) and the TREPAN algorithm. Incident data including incident type, time of day, road, number of involved vehicles collected from Maryland State Highway Administration were used to develop the models. Incident data were split so that 80% of the data were used for training and 20% were used for validation. Backpropagation neural network (BPNN), classification and regression tree (CART), and support vector machine (SVM) methods were also used for further investigation of the performance of the developed model. The Mean absolute error for the BNN model was 0.6 [6].

Demiroluk and Ozbay (2014) developed the method of Bayesian networks (BNs) to predict incident duration. Three algorithms, Naïve Bayesian classifier, TAN, and K2, were used to build BN structures based on New Jersey incident data. The 10-fold cross-validation method and the Bayesian information criterion (BIC) statistic were used to evaluate the model's performance, and it showed that the BN with the Naïve Bayes algorithm is the best illustration for the data [7].

Ghosh, Savolainen, and Gates (2012) applied hazard-based duration models to estimate the incident clearance time. Six models were developed with different distributions for each model. Data were obtained from the side-fire microwaves in southeastern Michigan freeway with a total of 32,574 incidents during 2009. Data contained speed, sensor occupancy, and volumes by vehicle class as it collected for 5-minute intervals. It was found that the generalized F distribution outperformed the other distributions to estimate the time required to clear the incident [8].

Lin, Wang, and Sadek (2016) proposed a hybrid model based on the decision tree model M5P tree and the statistical model HBDM to estimate incident duration, which upgraded the M5P tree model to the M5P-HBDM model instead of the M5P tree with the linear regression model. Two datasets collected during two years with records of 602 accidents in Norfolk, Virginia were used to train and test the model as well as the M5P tree and the HBDM models. Mean absolute percentage error (MAPE) used to assess the three models, and it showed that the proposed model better than the other two [9].

Li, Pereira, and Ben-Akiva (2014) investigated a Multinomial logistic model to predict the incident duration. The probability of the model was specified by three different distributions which are Generalized gamma, Weibull, and Log-logistic. Incident data were collected over approximately two years from Singaporean expressways with total records of 12,093 incidents which were used to train and test the model with 8062, 4031 respectively. The applied mixture model was compared with the Traditional accelerated failure time (AFT) model. Mean average percent error (MAPE) showed that the proposed model gives more accurate duration prediction, the results also showed that the mixture model is more suitable for incident duration prediction with more than 15 min according to the Root mean square error (RMSE) and MAPE evaluation [10].

Hojati et al. (2014) proposed two hazard-based models, log-logistic accelerated failure time (AFT) and Weibull accelerated failure time (AFT) to predict the incident duration. Data from Southeast Queensland, Australia with 29 variables include information about incident specifics, features of measured traffic, infrastructure, and temporal effects were used to build the models.

Table 1: Summary for Related Works

Author	*Method*	*Factors*	*Duration of Study*	*Number of Incidents*	*Error Measures*	*Training and Testing Dataset*
Khattak et al. 2016 [5]	Regression Model	Incident type, roadway data, Time of day	2013-2015	85,000	RMSE=57.49 min	Not Reported
Park, Haghani, and Zhang 2016 [6]	Bayesian neural networks	Incident type, lane blockage, time of day, roadway type, number of involved vehicles, heavy vehicles, pavement condition, weather	2010 - 2011	13,987	MAE = 0.18 to 0.29 for the developed models	Training and Testing dataset were split into ratio 4:1
Demiroluk and Ozbay 2014 [7]	Bayesian networks	Time of day, Weather conditions, Duration of incident (min)	2011	4,172	MAE= 0.134 RMSE= 0.267	Cross-Validation Method with 10-fold
Ghosh, Savolainen and Gates 2012 [8]	Hazard-based	Speed, Traffic volume, Occupancy	2009	32,574	The generalized F distribution was shown to provide the best fit to the incident clearance time data	Not Reported
Lin,Wang and Sadek 2016 [9]	Combined M5P tree and HBDM	Weather conditions, Location code, Blocked	2005 -2006	Not Reported	for the I-64testing dataset, MAPE = 36.20%, For I-190 testing dataset,	Training dataset =

Author	*Method*	*Factors*	*Duration of Study*	*Number of Incidents*	*Error Measures*	*Training and Testing Dataset*
		lane			MAPE = 31.87%.	80.0% Testing dataset = 20.0%
Li et al. 2015 [10]	Hazard-based competing risks mixture	Traffic conditions, incident characteristics	January 2010 - December 2011	12,093	RMSE= 26.61 min MARE = 94.7%	Training dataset = 66.7% Testing dataset =33.3%
Hojati et al. 2014 [11]	Hazard-based	Incident details, characteristics of measured traffic, infrastructure, and temporal effects.	2010 - 2011	430	The model estimation results show that a Weibull AFT model with gamma heterogeneity provided the best fit for incidents caused by crashes, while a log-logistic AFT model with random parameters provided the best fit for incidents caused by hazards vehicles.	Not reported
Hojati et al. 2013 [12]	Parametric accelerated failure time (AFT)	Characteristics of the incidents, location, time of day, traffic characteristics of the incident	November 2009 - November 2010	3251	Weibull models with random parameters were most suitable for two types of incidents on freeways involving crashes and hazards. In addition, a Weibull model with gamma heterogeneity provided the best fit for stationary vehicle incidents.	Not reported
Wu, Chen, and Zheng 2011 [13]	Support Vector Regression (SVR)	Incident type, Vehicle type, Number of vehicles, Time of incident	May 1, 2005 - September 13, 2005	1853	Mean Absolute Error= 12.9034(Breakdown), 13.206(Lost-load), 12.2582(Accident).	Training dataset = 80.0% Testing dataset = 20.0%
Zou et al. 2018 [14]	Copula-based approach	Incident Type, Time of Day, Weather, Peak Hours (6:00–9:00, 15:00–18:00)	January 1 st - December 31 st in 2009	2584	MARE = 0.61	Training dataset = 58.0% Testing dataset = 42.0%
Wei and Lee 2007 [15]	adaptive Artificial Neural Network-based models	Incident characteristics, traffic data, time relationship, space relationship, geometry characteristics.	November 2004 - April 2005	24	MAE= 409.7, MAPE= 30.3, RMSE= 467.3	Training dataset = 75.0% Testing dataset = 25.0%
Ma et al. 2017 [16]	Gradient Boosting Decision Trees	Incident type, time of day, weather, hourly traffic volume	2012	1366	MARE = 16.44% (clearance time <15 min) MAPE = 33.13% (clearance time ≥15min)	Cross-Validation Method with 3-fold
Cong et al. 2018 [17]	Bayesian networks	Incident information, incident consequences, rescue resources	2008 – 2010	1,174	Area Under Curve= 0.905	Training dataset = 70.0% Testing dataset = 30.0%
Garib et al. 1997 [18]	Regression Model	Weather condition, time of day, number of lanes affected, number of vehicles involved	Not Reported	205	R^2 = 81 %	Not Reported
Hamad et al. 2018 [19]	Random Forests (RF)	Not Reported	January 1st, 2004 - December 31st, 2013	146,573	MAE = 14.97 min	Not Reported

The developed models indicate that the Weibull AFT model with gamma heterogeneity is more suitable for crash incidents, where the log-logistic AFT model with random parameters gives a better estimation for hazard and parked vehicle incidents [11].

Hojati et al. (2013) investigated different models of the Parametric accelerated failure time (AFT) which are log-logistic, lognormal, and Weibull—with fixed and random parameters, also a Weibull model with gamma heterogeneity. The models were applied on one year collected data from South East Queensland Australian freeway network with a total of 3251 incidents considering three types of incidents, crashes, hazards, and stationary vehicles on weekdays, with

28 variables investigated. The results showed that Weibull models with random parameters were more applicable for crashes and hazard incidents, while the stationary vehicle incidents were better dealt by the Weibull model with gamma heterogeneity [12].

Wu, Chen, and Zheng (2011) proposed a Support Vector Regression (SVR) model for the estimation of incident duration on a dataset from the Netherlands with 1853 instances involving 3 types of incidents which are break down incident, lost load incident and accident. It was found that the developed model gives more accurate incident duration prediction [13].

Zou et al. (2017) investigated two copula models, independent copula model, and Gumble copula model, to show the dependences of the response and clearance time for the incident. Data were collected over one year from freeway road sections in Seattle, Washington State with a total of 2584 records. Mean absolute percentage error (MAPE) and tolerances for the prediction error were used to compare and evaluate the models, and it was found that the copula-based multivariate approach gives a better performance [14].

Wei and Lee (2007) developed an adaptive procedure with two adaptive Artificial Neural Network-based models to subsequent prediction of total incident duration time. Mean absolute error (MAE), Mean absolute percentage error (MAPE) and Root mean square error (RMSE) were used for the models' evaluation, and particularly to compute the model's accuracy. It was found that this type of prediction from two models gives a better estimation [15].

Ma et al. (2017) investigated a gradient boosting decision trees (GBDTs) method to estimate the incident clearance time. Data were collected from Washington State over one year with records of 1366 incidents, considering weather conditions besides other data variables. The proposed model was compared with the back-propagation -neural network (BPNN), support vector machine (SVM), and random forest (RF). The mean absolute percent error (MAPE) used to assess the models, and it was found that the GBDT method exceeds the performance of the other three methods with clearance time less than or equal 15 min, also longer than 15 min [16].

3. Incident duration

Traffic incident is one of the main causes of non-recurrent congestion around the world, for both expressways and arterial networks [20]. Where these incidents affect the road capacity, increase the probability of a secondary crash, and generate negative economic and social impact [16].

Therefore, the prediction of incidents duration is very important to mitigate these effects, where an accurate estimation of traffic incident duration is necessary to effectively reroute traffic around the incident also for the traffic clearness [13].

Time between incident occurrence and roadway clearance is the definition of the incident duration. This duration can be divided into the following distinct time intervals:

- Reporting time: the time between incident occurrence and incident notification.
- Response time: the time between incident notification and rescuer arrival.
- Clearance time: the time between rescuer arrival and incident road clearance.

The duration of the incident can be estimated at each of the three points, incident occurrence, incident notification or rescuer arrival. Figure 1 illustrates the components of incident duration [15].

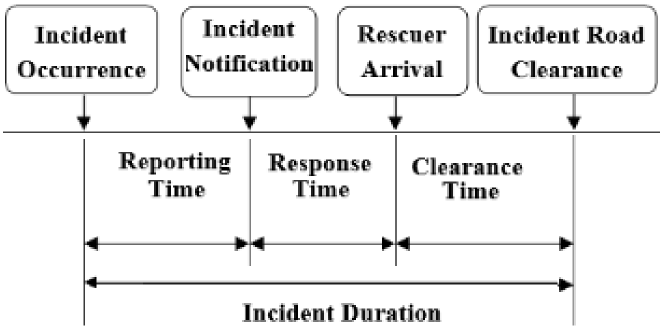

Figure 1: Components of Incident Duration

The time between incident clearance and being restored to the normal condition is defined as incident recovery time which could be added to the incident duration total time. In the entire incident management process, incident clearance is the most time-consuming phase, where double or even triple of the total incident duration can result from inefficient clearance of a severe incident [16].

4. Data Resources and Characteristics

Previous researchers used different datasets with numerous characteristics, such as various incident duration time phases, dataset sizes, and available data types, in their studies on traffic incident duration time prediction and analysis [21].

4.1 Data size

Traffic incident duration is determined by different factors, including some potential elements that cannot be observed. These elements make the traffic incident duration very heterogeneous by nature. Employing a larger data set is a possible approach to enhance the accuracy of analysis and prediction. The selected datasets in most studies consist of hundreds or thousands of incident logs, some of which are more than 30,000 records [8], [22]. While only a few studies use incident datasets with less than 100 records [15], [23].
In general, studies with small datasets are more precise, however estimation and prediction of traffic incident duration time profit more from a dataset with a large number of records. Larger datasets tend to be better and more comprehensively reflect the features of traffic incident duration.

4.2 Significant influencing factors

Previous studies have generally identified different factors that influence the incident duration time or clearance time, including incident characteristics, traffic flow conditions, temporal factors, roadway geometry, environmental conditions, operational factors, and some other factors, which are shown below:

- Incident characteristics: Incident severity, towing requirements, number of casualties, type of involved vehicles, incident type, number of lanes blocked and incident location.
- Environmental conditions: Rain, dry, snow, or wet.
- Temporal factors: Time of day, day of the week, season, the month of the year.
- Roadway geometry: Street, intersection, bottlenecks, horizontal/vertical alignment, road layout, roadway type.
- Traffic flow conditions: Flow, speed, occupancy, queue length.
- Operational factors: Lane closures, freeway courtesy service characteristics.
- Vehicle characteristics: Large trucks, trucks with trailers, compact trucks, taxis, special vehicles, number of vehicles involved.
- Others: Driver, special events, police response time, time that a police officer reaches the site, report mechanism, accident characteristics reported at accident notification.

5. Methodology

Over the past two decades, several studies have been initiated to investigate the feasibility of predicting the incident duration. Different approaches, ranging from statistical modeling methods to machine learning methods like neural networks, have been tested.

This paper present different methodologies to predict the traffic incident duration on highways. The methodology is usable on freeways, urban streets, and conventional highways. The methodology is sensitive to enhancements in facility surveillance and freeway service strategies.

Non-recurrent congestion is predicted in terms of annual vehicle hours of delay caused by incidents, weather, work zones, and so forth. The methodology uses incident probability trees, incident duration (sensitive to response times and surveillance), and estimates of remaining capacity during incidents to determine incident delay [24]. Since datasets used to build and validate the various models indicate different characteristics, a direct comparison of the results of these studies is quite difficult [25].

During the model building processing, the datasets should be split into two parts, the first part usually used to train the model with best selected hyperparameter, the second unseen part of the dataset will used to evaluate the developed model. Figure 2. below is the Methodology Block Diagram to construct and evaluate the prediction methods [34].

The most traffic incident prediction models can be classified into the following categories [20]:

- Regression models: including the truncated regression model, non-parametric regression model, ordinary least squares regression models, and partial least squares regression [5], [4].
- The stochastic model.
- Decision tree models [16], [26], [27].
- Artificial neural network models [15], [23].
- Genetic algorithm models [23].
- Hazard-based duration models [8], [10], [11], [12], [20], [28].
- The support vector machine [13], [29].
- Bayesian networks [6], [7], [17], [30], [31].
- Text analysis [1], [28].
- Hybrid models [9], [3], [32], [33].

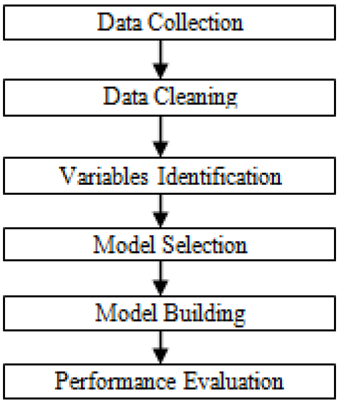

Figure 2: Methodology Block Diagram

The goal of developing incident duration models is to find the relationships between incident duration and affecting variables. Previous studies described similar sets of variables influencing incident duration, such as the incident type and severity, the geometric characteristics, the number and type of vehicles involved, the time of day and the emergency equipment.

Based on the previous studies, it can be noticed that any of the prediction method could has its strengths and weaknesses, thus, no certain method is expected to be the best method under any circumstances. If a complete incident duration prediction scope is to be covered, a combination of methods seems to be the best choice [25].

6. Conclusion

Traffic incidents are a major cause of delays, system unreliability, and inefficiency. To effectively support various traffic incident management strategies and applications, a proper method that can determine the significant factors for the traffic incident duration and prediction techniques must be applied to match various circumstances and data resources on time to predict traffic incident duration. This study reviews the research on traffic incident duration analysis and prediction. It also investigates the different data resources and characteristics, including data set size, significant influence factors, in addition to traffic incident time phases. Furthermore, it investigates the various techniques employed in traffic incident duration analysis and estimation. Machine learning techniques have been developed rapidly in the past few years, by that, providing new opportunities for traffic incident duration time analysis and prediction in many ways. Different traffic incidents are still the main reason for traffic congestion in urban road networks and highways between cities. So, exploring new methods to test and predict traffic incident duration more accurately is needed in the future to support the use of appropriate traffic operation strategies for traffic management under various traffic incident conditions.

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