Accident Analysis and Prevention 42 (2010) 282–289

Contents lists available at ScienceDirect

Accident Analysis and Prevention

journal homepage: www.elsevier.com/locate/aap

Development of an accident duration prediction model on the Korean Freeway Systems

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ARTICLE INFO

Article history:
Received 28 April 2009
Received in revised form 19 July 2009
Accepted 5 August 2009

Keywords:
Freeway accident
Accident duration
Duration prediction
Temporal transferability
Hazard-based duration models
Accelerated failure time (AFT) metric model

ABSTRACT

Since duration prediction is one of the most important steps in an accident management process, there have been several approaches developed for modeling accident duration. This paper presents a model for the purpose of accident duration prediction based on accurately recorded and large accident dataset from the Korean Freeway Systems. To develop the duration prediction model, this study utilizes the log-logistic accelerated failure time (AFT) metric model and a 2-year accident duration dataset from 2006 to 2007. Specifically, the 2006 dataset is utilized to develop the prediction model and then, the 2007 dataset was employed to test the temporal transferability of the 2006 model. Although the duration prediction model has limitations such as large prediction error due to the individual differences of the accident treatment teams in terms of clearing similar accidents, the results from the 2006 model yielded a reasonable prediction based on the mean absolute percentage error (MAPE) scale. Additionally, the results of the statistical test for temporal transferability indicated that the estimated parameters in the duration prediction model are stable over time. Thus, this temporal stability suggests that the model may have potential to be used as a basis for making rational diversion and dispatching decisions in the event of an accident. Ultimately, such information will beneficially help in mitigating traffic congestion due to accidents.

1. Introduction

A freeway incident is defined as any non-recurrent event that causes a temporary reduction in the roadway capacity due to various effects such as traffic accidents, disabled vehicles, severe weather, road construction, etc. However, the Oak Ridge National Laboratory (Chin et al., 2004) reported that freeway accidents were responsible for over 55% of delay caused by non-recurrent events that occurred on the USA freeways. Another study by Skabardonis et al. (2003) argued that freeway accidents accounted for 72% of non-recurrent traffic congestion. Thus, various studies have been undertaken to develop mitigation measures that minimizes non-recurrent congestion due to freeway accidents. A typical example of such efforts is the development of various types of accident management systems that are predominantly focused on clearing traffic accidents quickly and thus, minimizing the congestion effects on traffic flow.

Clearing an accident quickly requires efficient managerial support to make some effective decisions regarding the resources needed to dispatch the crew and clear the accident scene in a timely manner. This can often be achieved with the help of freeway operators through among others, a clear understanding of the factors affecting accident duration and appropriate use of the predicted accident duration information. In addition, any information that is predicted regarding accident duration is vital to the mitigation of congestion caused by a traffic accident because such information alerts motorists of the necessity to re-route or re-schedule their trips. Therefore, accident duration prediction constitutes one of the most important steps in the accident management process.

Based on the foregoing, the objective of this paper is to develop a duration prediction model for the purpose of accident duration prediction on the Korean Freeway Systems with reasonable accuracy and temporal stability. To accomplish this objective, accident dataset for the year 2006 collected from the Korean Freeway Systems was used to estimate and formulate a duration prediction model. Dataset from the same freeway system for the year 2007 was then used to test the temporal transferability of the model that was developed based on the 2006 dataset.

In terms of layout, this paper begins with a discussion of the definition of accident duration and a literature review. This is then followed by a discussion of the hazard-based duration models. The

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doi:10.1016/j.aap.2009.08.005

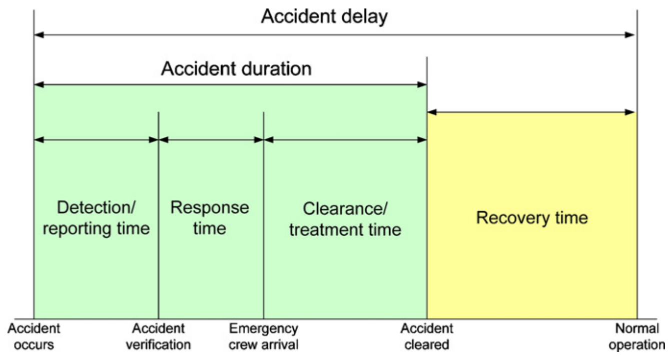


Fig. 1. Components of accident duration.

subsequent section provides the description of the dataset used in the study. Section six provides the model formulation/development including model estimation, the model parameter interpretation, evaluation of the model prediction accuracy, and test of temporal transferability. The paper then concludes with a summary of findings and recommendations.

2. Accident duration

Accident duration can be defined as the time difference between accident occurrences and when the response vehicles depart the accident scene (Garib et al., 1997; Nam and Mannering, 2000; Smith and Smith, 2001). According to the Highway Capacity Manual (TRB, 1994), the accident components can be divided into four phases: (1) accident detection/reporting time (time between accident occurrence and the accident detection or reporting), (2) response time (time between the accident detection and the arrival of the accident treatment team at the scene), (3) clearance time (time between treatment team's arrival at the scene and accident clearance), and (4) recovery time (time between accident clearance and the resumption of normal traffic flow without any upstream congestion caused by the accident).

As seen in Fig. 1, accident duration includes just the first three phases (detection/reporting time, response time, and clearance/treatment time). This means that the duration time relies on the accident detection/reporting time, the accessibility of the accident response/treatment team to the accident scene, and the treatment time for the accident. Thus, in total, duration is related to six primary factors: (1) detection, (2) accident time reflecting traffic patterns, (3) accident characteristics such as accident type, number of vehicles involved, accident location, and type of vehicles involved, (4) environmental conditions for accessing the accident location and clearing the accident parties and any associated debris, (5) geometric characteristics for accessing the accident location, and (6) execution capability of the accident treatment team. However, due to the difficultness of evaluating the execution capability of the accident treatment team, only the first five factors were used as the major or primary candidate independent variables in the duration model formulated in this study.

3. Literature review

There have been several approaches developed for modeling the time duration caused by freeway traffic incidents (vehicle accidents and disablements). These approaches can be classified into three types: (1) descriptive statistics, (2) analytical modeling, and (3) heuristic methods. Most of the previous studies were still at the level of using descriptive statistics for the data from time lap cameras (Juge et al., 1974), closed-circuit television (CCTV) (De Rose, 1964) and the police logs (Goolsby et al., 1971). However, the development of advanced technologies on data collection and data management led to the collection of high quality accident data with numerous information types as well as the ability to manage that data more efficiently. Additionally, such data is nowadays readily accessible from interactive databases. Consequently, analytical models using multivariate analysis such as regression methods (Golob et al., 1987; Giuliano, 1989; Garib et al., 1997), truncated regression methods (Khattak et al., 1995), survival analyses (Jones et al., 1991; Nam and Mannering, 2000; Stathopoulos and Karlaftis, 2002), and heuristic methods by knowledge based expert systems (Ozbay and Kachroo, 1999; Smith and Smith, 2001) have been developed and are in use today.

As suggested by Nam and Mannering (2000) and Stathopoulos and Karlaftis (2002), however, hazard-based duration models have an advantage in that they allow the explicit study of duration effects of accidents. Thus, in this study, hazard-based duration models, in particular the accelerated failure time (AFT) metric, were utilized to model the accident duration.

4. Hazard-based duration models

4.1. Hazard-based duration models applied to transportation field

Hazard-based duration models are the analysis methods used to describe the analysis of data in the form of time from a well-defined time origin until the occurrence of some particular event of an end-point (Collett, 2003). Such modeling is a common topic in many areas including biomedical, engineering, and social sciences. In the transportation field, hazard-based duration models have been applied to study a number of time-related issues. These include the time between individuals' traffic accidents (Jovanis and Chang, 1989; Mannering, 1993), the time between incident occurrence and its clearance (Jones et al., 1991; Nam and Mannering, 2000; Stathopoulos and Karlaftis, 2002), the time between trips (Mannering and Hamed, 1990; Hamed and Mannering, 1993; Ettema et al., 1995; Bhat, 1996a,b; Niemeier and Morita, 1996; Wang, 1996; Kitamura et al., 1997; Kharoufeh and Goulias, 2002; Bhat et al., 2004), and the time between households' vehicle purchases (Mannering and Winston, 1991; Gilbert, 1992; De Jong, 1996; Yamamoto and Kitamura, 2000).

In studying accident duration, the interesting variable is the length of time between an accident occurrence and its clearance. In addition, duration modeling is related to the likelihood that the duration will end in the next short time period $t+\Delta t$ given that it has lasted time t. Due to the fact that such a time variable is connected with a conditional probability, hazard-based duration modeling has an advantage in that it allows the explicit study of the relationship between accident duration and the explanatory variables (Jones et al., 1991; Nam and Mannering, 2000).

4.2. Mathematical expressions

The duration of a specific accident in hazard-based duration modeling is a realization of a continuous random variable T, with a cumulative distribution function, $F(t)$, which is called the failure function. This function of a random variable T is given by:

$$F(t) = \int_0^t f(u)\,du = Pr(T < t), \quad 0 < t < \infty \tag{1}$$

which specifies the probability that a random time variable T is less than some time value t. For all points that $F(t)$ is differentiable, a probability density function $f(t)$ is defined as:

$$f(t) = \frac{\partial F(t)}{\partial t} = \lim_{\Delta t \to 0} \frac{P(t \le T < t + \Delta t)}{\Delta t} \tag{2}$$

which gives the instantaneous probability that an accident's duration will end in the infinitesimally small interval $[t, t+\Delta t]$. Another basic function in hazard-based duration modeling is the survivor function, $S(t)$, which gives the probability that a duration lasts until time t, and is expressed as follows:

$$S(t) = 1 - F(t) = Pr(T \geq t) \quad (3)$$

Having mathematically defined the survivor function and the density of times that accident durations, the relationship between failure times and the survivor function is captured through the hazard function. The hazard function is basically an indicator of the instantaneous rate of change of the duration-ending probability at time t, conditioned on the fact that the accident duration lasted to time t, and this function is expressed as:

$$h(t) = \frac{f(t)}{S(t)} = \lim_{\Delta t \to 0} \frac{Pr(t \leq T \leq t + \Delta t | T \geq t)}{\Delta t} \quad (4)$$

In accident duration analysis, $h(t)$ is roughly interpreted as the rate at which the accident duration will end at time t, given that they have lasted for t minutes.

In accounting for the influence of explanatory variables using hazard-based duration models, there are two alternative forms: the proportional hazard (PH) metric and the accelerated failure (or life) time (AFT) metric model (Washington et al., 2003). Both modeling alternatives have the potential to provide valuable insights into the study of accident durations. However, the AFT metric model was selected for use in this study. More detailed statistical presentations of hazard-based duration models can be found in Hensher and Mannering (1994), Kalbfleisch and Prentice (2002), and Collett (2003).

5. Dataset description

Two different datasets were used to accomplish this study's two primary objectives (namely model development and temporal transferability testing). The first dataset includes 2369 accident data drawn from the Korea Highway Corporation (KHC) on 24 major freeways in Korea during the year 2006. This dataset was used to develop the prediction model for the accident duration prediction. The second dataset is composed of 2500 accident data collected from the same facility (KHC) during the year 2007. This second dataset was used to test the temporal transferability of the developed model (based on the 2006 dataset).

From the datasets, only the basic information that could be directly and easily reported by accident reporters in the event of an accident was utilized in the development of the model. Such basic information regarding the accident dataset from the KHC includes: (1) accident time; (2) accident characteristics such as accident type, vehicle type involved, severity such as the number of vehicles involved, fatality, and number of the injured, and accident location; (3) environmental conditions such as weather, road surface type, work zone, and vehicles parked in the shoulders or not; and (4) accident information source in terms of the reporter type. To consider the relationship between accident occurrence time and accident duration, the patterns with respect to time of the day, day of the week, and season were used as a candidate variable in the parametric duration modeling. Additionally, the time patterns also act as a proxy for the traffic volumes, vehicle mix, and possibly driver attitudes and familiarity (Karlaftis et al., 1999). In the study, the variable with respect to time of day was defined as four periods in terms of the traffic patterns in Korea: (1) night: 20:01–07:00, (2) AM peak: 07:01–09:00, (3) midday: 09:01–16:30, and (4) PM peak: 16:31–20:00.

The days of a week was divided into eight variables in order to separate holidays from weekdays. Additionally, the seasonal variable was classified into four categories based on the four seasons defined by the Korea Meteorological Administration; (1) Winter: November 29–March 08, (2) Spring: March 09–June 02, (3) Summer: June 03–September 18, and (4) Fall: September 19–November 28. Other variables were similarly classified as either a categorical or a continuous variable as follows:

Accident type: This variable includes *vehicle-to-facility due to vehicle's breakdown or careless driving, vehicle-to-vehicle, vehicle-to-person*[1]*, and vehicle's fire*. Accident type may generally affect the way and equipment of the removal work on the accident parties. Such accident types in turn affect the accident duration.

Accident location: This represents a location in terms of freeway segment types such as *main line, ramp, tunnel, bridge, tollgate, rest area, etc.* This variable may influence the time to dispatch an accident treatment team, for instance, depending on the location of an emergency service station, either outside or in the vicinity of a tollgate. This is primarily due to the fact that the freeways in Korea are all toll roads. Furthermore, this variable also influences the travel time to the accident scene, i.e., the further the location of an accident scene from a nearest emergency center, the longer the travel time and vice versa.

Involved vehicle type: Since accidents caused by larger vehicles may require a longer treatment time, it is often important to analyze the relationship between accident duration and the vehicle types that are involved. The accident dataset from the KHC included 11 types of vehicles: *sedan, SUV (Sports Utility Vehicle), mini-van, mid-size van (or mid-size bus), bus, small-size truck, mid-size truck, large-size truck, truck with trailer, and specially equipped vehicle such as oversize loaded truck and tow truck with towing a car*.

Accident severity: This includes *the number of fatality, the number of the injured, and the number of vehicles involved.* The variables with respect to the number of the injured and the number of vehicles involved were considered as continuous variables because duration often trended upward with an increase in the value of the corresponding variable. However, the number of the fatality variable was considered as a dichotomous variable (i.e., fatality case and the others) due to the sample size problem.

Road surface condition: This variable was considered due to the fact that it may affect the dispatching time as well as the treatment work, particularly if the road has poor surface ride characteristics. This variable comprises *dry, wet, snowy, and icy* conditions.

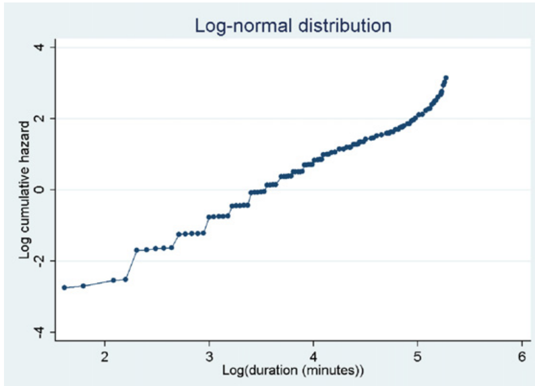
Presence of stopped vehicle on the shoulder: Under congested situations, the freeway emergency team usually uses the shoulders rather than the main line. Thus, it is generally assumed that accidents with vehicle stopped on the shoulders contribute to longer duration.

Work zone: If an accident occurs in an area of the work zone, the accident duration may be longer due among others to construction equipment and other construction-related barriers, which often tends to create a temporary loss of capacity.

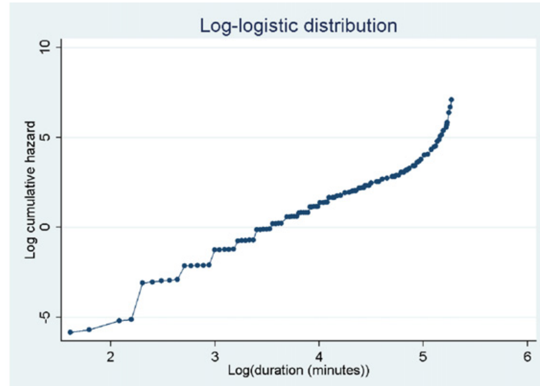
Reporter type: Freeway accident information in Korea is usually reported by independent freeway drivers. Otherwise, it is typically collected by the *FSP (Freeway Service Patrol), TISP (Traffic Information Service Provider), and FIC (Freeway Information Center*[2]*)*, based on a CCTV system established on the freeways. This variable acts as a proxy for the accident detection and reporting time as well as response time; see Fig. 1.

[1] Although the freeways in Korea are only for the vehicle, there exist some pedestrians in rural areas due to rare traffic volume.

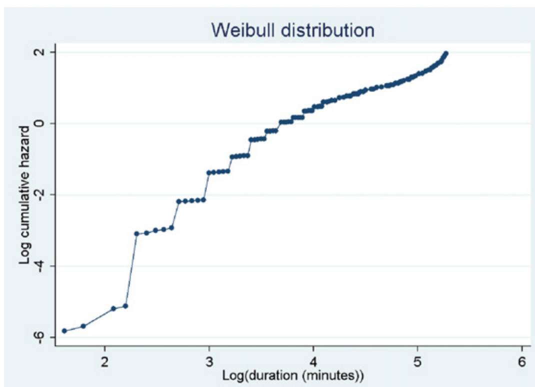
[2] There is a freeway information center in Korea to monitor freeway traffic conditions and to provide such information to users. Such an incident occurrence is manually observed and interpreted by monitoring personnel based on the CCTV monitors in the center, that are linked to the CCTV systems on the freeways.



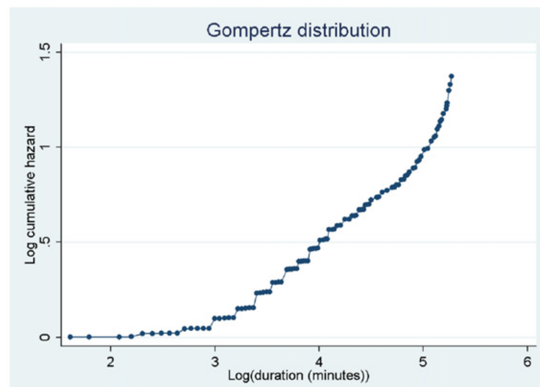
(a) Log-normal distribution



(b) Log-logistic distribution



(c) Weibull distribution



(d) Gompertz distribution

Fig. 2. Graphs on log cumulative hazard.

6. Model formulation/development

For the purpose of prediction, the fully parametric model is more informative than the semi-parametric model or Cox model (Hensher and Mannering, 1994; Hensher and Button, 2000; Kalbfleisch and Prentice, 2002; Collett, 2003). However, prior to fitting a parametric model, a distributional form for the hazard function must be specified. A common method of assessing whether a particular distribution for the duration time data is plausible is to compare the hazard function for the data with that of a chosen model.[3] When plotting the graph of that relationship, the selected distribution is reasonable if it is linear (Collett, 2003; Lawless, 2003; Lee and Wang, 2003).

As shown in Fig. 2, two distributions with respect to the log-normal and log-logistic distributions appear to be linear. Consequently, these distributions were employed to analyze the accident duration in this study. Additionally, this result is consistent with previous studies; the log-normal distribution suggested by Golob et al. (1987) and Giuliano (1989) and the log-logistic distribution suggested by Jones et al. (1991), Nam and Mannering (2000), and Stathopoulos and Karlaftis (2002).

6.1. Estimation of accident duration models

Although the log-normal and log-logistic models were fitted to the accident duration data on the Korean freeways, the log-logistic model was selected for the final analyses and duration prediction. This selection was based on the results of Akaike's Information Criterion (Akaike, 1974): 3860.55 for the log-logistic model and 3863.16 for the log-normal model. Additionally, the log-logistic model has an advantage over the log-normal model in that it is a simpler and easier to use mathematical expression for the hazard and survivor functions.

An overall goodness-of-fit for the model was assessed using the Cox–Snell residuals (Cox and Snell, 1968). The Cox–Snell residuals are essentially the estimated values of the cumulative hazard function for the jth observation at the corresponding event time t_j. It is frequently used as a means to check whether the data support a particular parametric form of the hazard function. As shown in Fig. 3, the plotted points fall closer to the reference line. Therefore, it can be concluded that the log-logistic AFT model provides a reasonable fit of the accident duration data.

6.2. Interpretation of the estimated models

The functional form of the hazard function for the log-logistic model is expressed as:

$$h(t) = \frac{\psi^{1/\gamma} t^{(1/\gamma - 1)}}{\gamma[1 + (\psi t)^{1/\gamma}]} \tag{5}$$

where $\psi \equiv \exp(-\boldsymbol{\beta}'\mathbf{X})$ for vectors of variables $\mathbf{X}$ and parameters $\boldsymbol{\beta}$, and γ is the shape parameter. The log-logistic hazard function is interpreted by using the shape parameter. That is, if $\gamma < 1$, the hazard increases with duration and then declines. On the other hand, when $\gamma \geq 1$, the hazard will monotonically decrease with duration.

From the results of the estimated model in Table 1, the point estimate of the shape parameter γ is less than one (i.e., $\gamma = 0.305$). This

[3] For the detailed description for checking if a parametric distribution fits the observed data, see Chapters 8 to 9 of the text book by Lee and Wang (2003).

Table 1
Log-logistic AFT model on 2006 data.

Variable	Estimated coefficient	Standard error	Wald statistics
Number of vehicles involved: 1,2,3,4,5+	0.086	0.015	5.57
Number injured: 0,1,2,3,4+	0.085	0.015	5.54
Fatality (1 if existed, 0 otherwise)	0.408	0.040	10.14
Involved vehicle type (1 if bus, 0 otherwise)	0.349	0.078	4.44
Involved vehicle type (1 if mid-size truck, 0 otherwise)	0.373	0.035	10.69
Involved vehicle type (1 if large-size truck, 0 otherwise)	0.559	0.044	12.73
Involved vehicle type (1 if truck with trailer, 0 otherwise)	0.670	0.050	13.50
Involved vehicle type (1 if specially equipped vehicle, 0 otherwise)	0.463	0.089	5.21
Accident type (1 if vehicle's fire, 0 otherwise)	0.368	0.073	5.02
Accident location (1 if toll gate, 0 otherwise)	−0.431	0.045	−9.50
Reporter type (1 if freeway service patrol, 0 otherwise)	−0.186	0.029	−6.46
Accident time (1 if night, 0 otherwise)	0.084	0.023	3.70
Constant	3.269	0.026	125.02
γ (shape parameter)	0.305	0.005	
Initial log-likelihood		−3608.672	
Log-likelihood at convergence		−1916.275	
Number of accidents		2369	

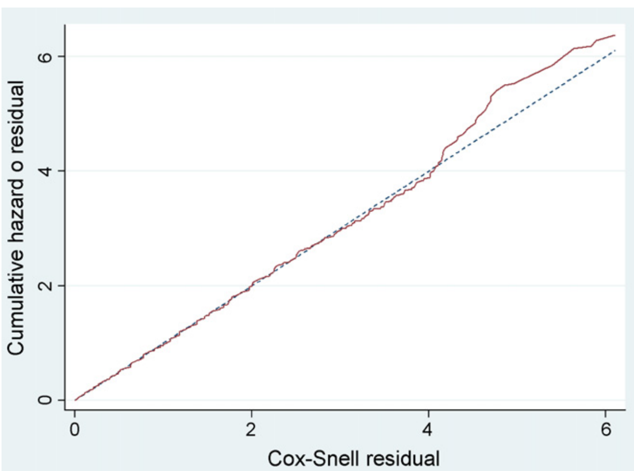


Fig. 3. Graph on cumulative hazard of Cox–Snell residuals.

means that the hazard increases to the inflection point and then decrease as shown in Fig. 4. The inflection point of the estimated model was calculated as 45.94 min; that is the hazard is increasing until 45.94 min and then decreases towards zero thereafter. This implies that accident duration times longer than 45.94 min are likely to end soon.A log-logistic AFT model is generally interpreted

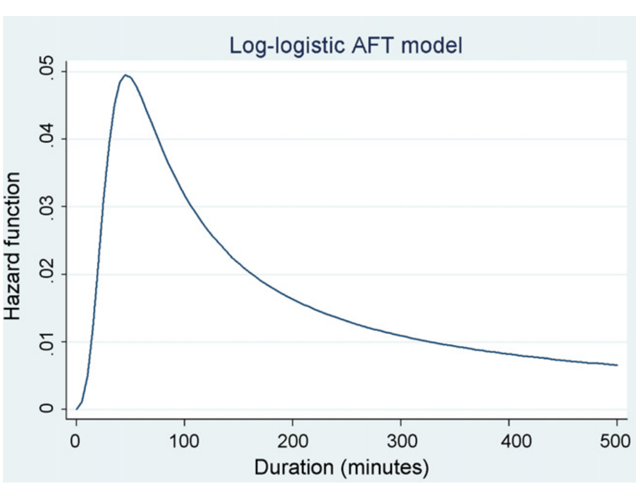


Fig. 4. Hazard function of log-logistic AFT model for accident duration.

by using the exponential coefficients, meaning that the exponential coefficients provide estimates of the multiplicative effect on time (i.e., duration in this case). For the example in Table 1, the exponential coefficient value of the variable with respect to the number of vehicles involved, as a positive coefficient in the 2006 model, is 1.094; determined as exp(0.090). This result is interpreted as that the duration is 9.4% longer as the number of vehicles involved is increased by one. Conversely, the exponential coefficient value of the variable with respect to accidents reported by FSP (negative coefficient) is 0.837, which is interpreted as that the duration for accidents reported by FSP is about 16.3% shorter than for the accidents reported by other sources. Table 2 shows the percentage change in duration due to one unit change (change from zero to one in the case of the indicator variable) of each variable for the model in Table 1.From the percentage changes in Table 2, most of the results were consistent with the theoretical expectation as described in the variable description part of this paper. As expected, the variables with respect to accident severity resulted in longer duration. Particularly, as the number of the injured and the involved vehicles increased, duration increased. A similar response trend is also observed for the accidents with fatality, i.e., the duration is equally longer. However, the sensitivity for the number of the injured is similar to that for the number of the vehicles involved (i.e., about 9%), but fatality (at 50%) is much more sensitive than the other two severity variables.

Additionally, accidents caused by bigger or heavy vehicles such as buses, mid-size trucks, large-size trucks, trucks with trailers and specially equipped vehicles have longer duration. However, the duration of accidents associated with specially equipped vehicles was less than the duration of accidents involving large-sized

Table 2
Percentage change in accident duration for the 2006 estimated model.

Variable	Percentage change (%)
Number of vehicles involved: 1,2,3,4,5+	9.0
Number injured: 0,1,2,3,4+	8.8
Fatality (1 if existed, 0 otherwise)	50.4
Involved vehicle type (1 if bus, 0 otherwise)	41.7
Involved vehicle type (1 if mid-size truck, 0 otherwise)	45.2
Involved vehicle type (1 if large-size truck, 0 otherwise)	75.0
Involved vehicle type (1 if truck with trailer, 0 otherwise)	95.4
Involved vehicle type (1 if specially equipped vehicle, 0 otherwise)	58.9
Accident type (1 if fire, 0 otherwise)	44.4
Accident location (1 if toll gate, 0 otherwise)	−35.0
Reporter type (1 if freeway service patrol, 0 otherwise)	−17.0
Accident time (1 if night, 0 otherwise)	8.7

trucks or trucks with trailers. This is probably attributed to the amendment of the Korean Road Act (Article 54 of December 31, 2005) that restricted the operation of specially equipped vehicles on the Korean freeways. Among others, this provisional amendment (Article 54) was tailored at minimizing accidents through tight enforcement of traffic safety and road maintenance regulations.

As for the accident type, accidents caused by vehicle's fire were found to be associated with longer duration. For containing the fire quickly as well as reducing accident duration, the Korean Road Traffic Act is needed to be amended so that all vehicles should be equipped with small portable fire extinguishers.

As would be expected, accidents that occurred in the vicinity of a tollgate lead to less duration. This is attributed to the readily availability of the emergency service vehicles (i.e., towing vehicles). In Korea, all the freeways are operated with a toll system and the towing services are operated by commercial companies (rather than public or government organizations). As such, the towing vehicles are typically stationed within the vicinity of a tollgate; thus reducing the arrival time for the accidents occurring near tollgates. Lastly, accidents reported by the FSP also exhibited shorter duration. Since FSP crews can directly control the accident scene as soon as they observe it, as well as being well connected with the emergency and accident management agencies, this result seems to be reasonably obvious. Another expected result is attributed to the covariate with respect to the accident occurrence time. Typically, accidents that occurred during the night period are not only compounded by poor environment on the accident dispatch and treatment due to narrow visual range at night, but also information scarcity due to fewer Reporters.

6.3. Evaluation of the model accuracy

Since the results of the prediction model are almost never exactly accurate, the evaluation of its accuracy is required. The mean absolute percentage error (MAPE) is a summary measure widely used for evaluating the accuracy of prediction results, and it is expressed as follows:

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{A_i - P_i}{A_i}\right| \tag{6}$$

where A_i is the actual value for the ith observation and P_i is the predicted value for the ith observation. The lower the MAPE value, the more accurate the prediction model is. Listed in Table 3 is a scale rating for evaluating the accuracy of a model based on the MAPE method, as developed by Lewis (1982). In this study, the MAPE value for the duration model in Table 1 was calculated as 47%, meaning that the prediction with the developed model has a reasonably acceptable accuracy.Another measure of effectiveness is related to a certain tolerance of the prediction error. As used by Smith and Smith (2001), it is useful to know the percentage of predictions that are within a certain tolerance of their actual duration times. Six tolerance values were used: 5, 10, 15, 20, 30, and 50 min. The model results for the measure of effectiveness are listed in Table 4. Sixty-one percent (1441 accidents out of 2369) have been predicted with less than 15 min of the prediction error.

Table 3
Scale of evaluation of prediction accuracy.

MAPE	Assessment
Less than 10%	Highly accurate prediction
11% to 20%	Good prediction
21% to 50%	Reasonable prediction
51% or more	Inaccurate prediction

Table 4
Summary of evaluation of the prediction accuracy.

Performance measure	Value
≤10 min	1068 accidents (45%)
≤15 min	1441 accidents (61%)
≤20 min	1732 accidents (73%)
≤30 min	2021 accidents (85%)
≤50 min	2200 accidents (93%)
Mean prediction error	18.0 min

For the accident management system process, this is an acceptable result because these predictions serve as aids and basis for making rational and timely diversion and dispatching decisions.Although the estimated model has great promising potential for the accident duration prediction on the Korean Freeway Systems, there are still some outliers with a large prediction error. As commented by Ozbay and Kachroo (1999), such a problem is largely due to the individual differences of accident treatment teams in clearing similar accidents, and it is one of the limitations of a duration prediction model.

6.4. Temporal transferability

Accident duration patterns change over time due to the change of various external factors such as management programs at the operational level, educational programs for drivers, and new technologies for roads and vehicles. Although the formulated model presented herein showed reasonableness as a prediction model with a MAPE value of 47%, its transferability with respect to time should be tested for future prediction purposes. Temporal transferability ensures that predictions made with the model have some validity in that the estimated parameters are stable over time (Washington et al., 2003).

To validate the temporal transferability, a likelihood ratio test was performed as follows:

$$-2[LL(\beta_{ba}) - LL(\beta_a)] \tag{7}$$

where $LL(\beta_{ba})$ is the restricted initial log-likelihood using the coefficients of the model estimated from time period b and $LL(\beta_a)$ is the maximum log-likelihood at convergence of the model using the data of time period a. This test statistic is χ^2 distributed with the degrees of freedom equal to the number of coefficients.

Additionally, the transferability of parameters between two time periods was tested using the following expression:

$$-2[LL(\beta_T) - LL(\beta_a) - LL(\beta_b)] \tag{8}$$

where $LL(\beta_T)$ is the log-likelihood at convergence of the model estimated with the data from both time periods, $LL(\beta_a)$ and $LL(\beta_b)$ are the log-likelihoods at convergence of the models using time period a and b, respectively. Similarly, this test statistic is χ^2 distributed with the degrees of freedom equal to the number of coefficients. Such χ^2 statistics provide the probability that the models have different parameters (Washington et al., 2003) (Table 5).

In this study, the 2006 and 2007 accident dataset were used to test the temporal transferability of the model. Table 6 summarizes the results of the likelihood ratio tests based on Eqs. (6) and (7). Since, all of the associated *p-values* are greater than 0.99, the hypothesis of temporal stability cannot be rejected at 99% confidence level. Thus, these test results indicate that the estimated parameters in the duration model are stable over time.

Temporal stability for accident duration models has been tested in some previous studies including Nam and Mannering (2000), which found that instability was present in all of their models. They attributed this instability largely to the evolving incident management programs in their study area. Due to the lack of multi-year data, many previous studies of accident duration modeling did not

Table 5
Log-logistic AFT models on 2007 data and 2006–2007 data.

Variable	2007 data			2006–2007 data		
	Estimated coefficient	Standard error	Wald statistics	Estimated coefficient	Standard error	Wald statistics
Number of vehicles involved: 1,2,3,4,5+	0.081	0.014	5.96	0.083	0.010	5.96
Number injured: 0,1,2,3,4+	0.090	0.014	6.27	0.088	0.010	6.27
Fatality (1 if existed, 0 otherwise)	0.378	0.035	10.75	0.391	0.026	10.75
Involved vehicle type (1 if bus, 0 otherwise)	0.320	0.080	3.98	0.333	0.056	3.98
Involved vehicle type (1 if mid-size truck, 0 otherwise)	0.378	0.034	11.13	0.376	0.024	11.13
Involved vehicle type (1 if large-size truck, 0 otherwise)	0.523	0.042	12.40	0.541	0.030	12.40
Involved vehicle type (1 if truck with trailer, 0 otherwise)	0.683	0.044	15.55	0.678	0.033	15.55
Involved vehicle type (1 if specially equipped vehicle, 0 otherwise)	0.489	0.104	4.69	0.473	0.068	4.69
Accident type (1 if vehicle's fire, 0 otherwise)	0.368	0.072	5.08	0.369	0.051	5.08
Accident location (1 if toll gate, 0 otherwise)	−0.396	0.046	−8.51	−0.414	0.032	−8.51
Reporter type (1 if freeway service patrol, 0 otherwise)	−0.186	0.030	−6.13	−0.186	0.021	−6.13
Accident time (1 if night, 0 otherwise)	0.079	0.021	3.67	0.081	0.016	3.67
Constant	3.272	0.024	136.49	3.271	0.018	136.49
γ (shape parameter)	0.302	0.005		0.304	0.004	
Initial log-likelihood		−3801.975			−7410.647	
Log-likelihood at convergence		−2015.568			−3932.682	
Number of accidents		2500			4869	

Table 6
Results of temporal transferability tests.

Issues	χ^2	Degree of freedom	p-Value
2006 data with 2007 coefficients	3.240	12	0.994
2007 data with 2006 coefficients	3.562	12	0.990
2006 and 2007 data with 2006 and 2007 coefficients	1.679	12	1.000

conduct formal tests of temporal stability. In the current study, from a statistical perspective, the estimated parameters in the duration prediction model presented in this paper appear to be stable over time; needless to say that the model transferability and stability was only tested over a one-year's dataset.

7. Conclusions and recommendations

This paper presented a model for the purpose of accident duration prediction based on accurately recorded and large accident datasets from the Korean Freeway Systems. To develop the duration prediction model, this study utilized the log-logistic accelerated failure time (AFT) metric model based on the 2-year accident datasets from 2006 to 2007. In the study, the 2006 dataset was utilized to develop the prediction model and then, the 2007 dataset was employed to test the temporal transferability of the formulated 2006 model. The estimated duration model based on the year 2006 was validated for the prediction accuracy with acceptable reasonableness. Although, the duration prediction model has some limitations such as large prediction error due to the individual differences of accident treatment teams in clearing similar accidents, the computed MAPE value was 47%, which represents a reasonable prediction based on the adapted MAPE scale.

Additionally, a likelihood ratio test based on a 2-year dataset (i.e., the years 2007 and 2006) was performed to validate the temporal transferability of the developed model. Plausible results were obtained. Since the associated *p-values* in all the models were greater than 0.99, the hypothesis of temporal stability cannot be rejected at 99% confidence level, meaning that the estimated parameters in the duration model are stable over time. Although based only on a 1-year's dataset (i.e., 2007), the results showed that the developed duration model could be reasonably used for accident duration prediction purposes. As noted above, temporal transferability of the developed model was accomplished only on the basis of the year 2007. Consequently, it still remains to validate the transferability and stability of the model in the succeeding years such as 2008, 2009. Thus, future studies should be directed towards this task.

Overall, such a model as developed in this study can be directly used for the prediction of accident duration on freeways as soon as the base accident information is reported. Then, the predicted information from such a model can be utilized as an aid and basis for making rational and timely diversion and dispatching decisions. Ultimately, such information will beneficially help in mitigating traffic congestion due to accidents.

Disclaimer

The contents of this paper reflect the views of the author who is responsible for the facts and accuracy of the data presented herein and do not necessarily reflect the official views or policies of any agency or institute. This paper does not constitute a standard, specification, nor is it intended for design, construction, bidding, or permit purposes. Trade names were used solely for information and not for product endorsement.

Acknowledgements

The author would like to convey his gratitude and appreciation to Lubinda F. Walubita (Dr.) of the Texas Transportation Institute (TTI – Texas A&M University System, TX, USA) for his invaluable editorial and technical comments on the paper. The author wishes to thank the anonymous reviewers for their comments and suggestions, which helped to improve the quality of the paper.

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