Title

A Simple Time Sequential Procedure For Predicting Freeway Incident Duration

Authors
Khattak, Asad J.
Schofer, Joseph L.
Wang, Mu-han

Publication Date
1994

CALIFORNIA PATH PROGRAM
INSTITUTE OF TRANSPORTATION STUDIES
UNIVERSITY OF CALIFORNIA, BERKELEY

A Simple Time Sequential Procedure for Predicting Freeway Incident Duration

Asad J. Khattak
Joseph L. Schofer
Mu-Han Wang

California PATH Research Report
UCB-ITS-PRR-94-26

This work was performed as part of the California PATH Program of the University of California, in cooperation with the State of California Business, Transportation, and Housing Agency, Department of Transportation; and the United States Department of Transportation, Federal Highway Administration.

November 1994

ISSN 1055-1425

PATH Program
Institute of Transportation Studies
University of California at Berkeley

A SIMPLE TIME SEQUENTIAL PROCEDURE FOR PREDICTING FREEWAY INCIDENT DURATION

Asad J. Khattak

PATH Program, Institute of Transportation Studies
University of California at Berkeley
Berkeley, California

Joseph L. Schofer

Civil Engineering Department
Northwestern University
Evanston, Illinois

Mu-Han Wang

Civil Engineering Department
Purdue University
West Lafayette, Indiana

Submitted to:

California Department of Transportation

November 1994

Abstract

The objective of this study is to develop a methodology for incident duration prediction. First, we develop an understanding of factors that influence incident duration. Then, we use a series of truncated regression models to predict incident duration. The models account for the fact that incident information at a Traffic Operations Center is acquired over the life of the incident. The implications of this simple methodology for incident duration prediction are discussed.

Key Words: Advanced Transportation Management Systems, incident management, incident duration prediction, traffic operations, Chicago

Summary

The prediction of incident durations can facilitate incident management and support traveler decisions. This paper develops a procedure for predicting incident durations. First, the causal and non-causal factors which influence incident durations are conceptualized. These include *operational characteristics* such as response times and whether a heavy wrecker was used, *incident characteristics* such as injuries and number of vehicles involved and *environmental conditions* such as weather and visibility. Specific hypotheses are tested by developing truncated regression models of incident duration using data provided by the Illinois Department of Transportation (IDOT) on Chicago area freeways. The models show that incident durations are longer when the response times are higher, the incident information is not disseminated through the public media, there are severe injuries, trucks are involved in the incident, there is heavy loading in the truck, State property is damaged, and the weather is bad. The most important variables in incident duration prediction were incident characteristics and the consequent emergency response actions.

A time sequential methodology is developed to predict the incident durations as information about the incident is acquired in a Traffic Operations Center or TOC. Initially, after an incident is detected, information at a TOC is often acquired at a high rate, then information acquisition levels off and toward the end of an incident the acquired information may decay. Accordingly, the incident duration models grow in terms of their explanatory variables at first, then they are sustained during the middle stages and begin shrinking toward the end when information starts decaying. The estimated time sequential models remain statistically significant even after they have shrunk to a few remaining incidents. One purpose of this prediction methodology is to demonstrate the trade-off between early and accurate incident duration prediction. For the models to be operational, we suggest estimating similar models with more local data.

ACKNOWLEDGEMENT

Support for this study was provided by The Transportation Center at Northwestern University and the PATH Program, Institute of Transportation Studies, University of California at Berkeley. Data were furnished by J.H. Koziol of the Illinois Department of Transportation District One (Chicago area) Communication Center. An earlier version of the paper was submitted to TRB (presented at the 1994 Annual meeting) and the comments of two anonymous TRB reviewers are appreciated. This paper has been revised extensively since its submission to TRB. We greatly appreciate the comments of two anonymous IVHS Journal reviewers. Conclusions and interpretations are solely the responsibility of the authors, and do not necessarily reflect the views or policies of the Illinois Department of Transportation or the California Department of Transportation.

Table of Contents

List of Figures

List of Tables

1. INTRODUCTION

The continued growth in demand for automobile travel in urban areas increases the stress on the highway infrastructure. At the same time, resources available for expansion of the urban highway network are becoming increasingly limited, suggesting the importance of getting the most service out of the existing infrastructure. One way to do this is by responding quickly to manage and divert travelers away from incidents and related congestion. A major source of congestion is that induced by random incidents such as accidents, breakdowns, load spills, etc., which cause temporary and unexpected lane blockage, imposing delays. The Illinois Department of Transportation (IDOT) responds to over 100,000 incidents each year on the freeway system in the Chicago area. The flow restrictions resulting from these events may last only a few minutes, or they can affect travelers for hours, depending on the nature of the incident and efforts to clear it.

IDOT detects and verifies incidents with loop detectors, patrol vehicles, police and emergency operations, cellular phone calls, private traffic services, and by monitoring communications between CB radio users. After an incident is detected, patrol vehicles equipped with emergency gear are dispatched to provide assistance and clear the scene (McDermott 1980). Information regarding the incident may be disseminated through the Highway Advisory Radio (HAR) and Changeable Message Signs (CMSs) as well as through commercial radio and television stations.

Investigations of Advanced Transportation Management and Information Systems (ATMIS) have shown that such systems may have relatively larger transportation system benefits in incident conditions compared with recurring congestion (Al-Deek 1991). Therefore, any advanced information system should have the ability to detect incidents and predict incident and queue durations. Behavioral studies suggest that travelers have a strong interest in not merely "current" roadway performance information, which can be as much as fifteen minutes old when it is received, but in projective information, i.e., prediction of incident related traffic conditions ahead (Khattak 1991). Such predictions would give travelers a better basis for making diversion decisions, and at least they may adjust their expectations and reduce uncertainty.

The objective of this research is to develop a practical capability to predict incident duration, which may provide useful information for managing and improving incident response, as well as for informing travelers and supporting their diversion decisions. Data used in this effort came from historical records of a sample of freeway incidents in the Chicago metropolitan area, provided by the IDOT District One Communication Center.

2. LITERATURE

2.1 Incidents on Freeways

Table 1 presents a summary of selected studies that have examined the effect of various factors on incident duration (DeRose 1964; Goolsby 1971; Juge et al. 1974; Golob et al. 1987; Giuliano 1989; Jones et al. 1991). The average duration of incidents varies widely across studies, in part due to differences in incident types, locations, environments, and methodologies used for specific studies. Differences in durations may also be due to variation in the definition of incidents (Giuliano 1989).

Studies of the effect of incident characteristics on incident duration have found that longer incident durations were more likely if the incident involved injuries (Golob et al. 1987; Giuliano 1989; Jones et al. 1991), if there was an overturned vehicle (Golob et al. 1987), if greater number of lanes were blocked (Golob et al. 1987; Jones et al. 1991), if the incident occurred during the nighttime (Jones et al. 1991), if the facility was congested (Wilshire and Keese 1963) and if high-demand special events such as sporting events were occurring (Jones et al. 1991). There is some evidence in the literature to suggest seasonal variation in incident clearance times; specifically, it was found that incident durations varied by month of the year (Jones et al. 1991). Further, Jones et al. (199 1) found that peak-period incidents were cleared sooner than off-peak incidents, possibly due to Washington State Department of Transportation's policy of using tow trucks only during the peak period. The response times and other operational response variables were not used as explanatory variables due to their unavailability. Alcohol involvement was associated with shorter incident clearance times, possibly because of higher level of police response to such incidents (Jones et al. 1991). Overall, incident duration is influenced by contextual factors, incident characteristics, environmental conditions, locational and seasonal factors and driver attributes/condition.

2.2 Incident Management

Hall (1993) provides a good bibliography on incident management and addresses the issue of whether ATMIS and incident management can provide benefits. The main conclusion of the study is that incident management and ATMIS offer marginal benefits in terms of reducing delays experienced by travelers, especially during the peak period. Specifically, the elimination of incidents altogether will increase the "effective capacity," defined as the equivalent of expected capacity, over time by about 2-9% for a 1-5 mile recurrent bottleneck.

Ritchie and Prosser (1990) have developed a knowledge-based expert system to support the decisions of the Traffic Operations Center (TOC) personnel. It provided insights into the information acquisition process for our study. Specifically, the information acquisition and incident response process is broken down into incident detection, incident verification, identification and evaluation of alternative responses, implementation of selected responses and monitoring recovery.

2.3 Prediction of Travel Times

There has been virtually no work to our knowledge on short-term prediction of incident durations. Ben-Akiva et al. (1991) have identified the need for predictive information, and Ben-Akiva et al. (1992) have discussed initial methodologies for predicting traffic flows under mostly normal travel conditions. They assert that traffic flows can be analyzed based on (a) statistical techniques, (b) theoretical models that describe mechanics of flow, and (c) disaggregate models of individuals' route choice.

Recently, Cremer et al. (1993), Stephanedes and Kwon (1993), and Davis and Kang (1993) have presented frameworks for predicting traffic flows. Cremer et al. (1993) use a dynamic route guidance model to predict traffic flows and travel times on a simple network when capacity is reduced due to incidents, lane drops, or construction. However, incident duration is used as an input to the model. Our research complements these efforts by first exploring the process of incident occurrence and response, and then developing a method for estimation of incident durations.

Our literature search showed that studies of incident duration did not explicitly consider operational response characteristics--although it has long been realized that faster response times can reduce incident clearance times and improve freeway operation (Wilshire and Keese 1963). Further, the effect of disseminating incident information on clearance times has not been explored, and finally, there is virtually no work on predicting incident durations.

3 CONCEPTUAL STRUCTURE

3.1 Process of Incident Occurrence, Management, and Information Dissemination

When a major incident occurs on the Chicago area freeways, IDOT attempts to detect it through a multitude of information sources. After detection, the incident is "managed" both at the TOC and on the scene. The TOC staff dispatches the needed vehicles and equipment and contacts other agencies, such as the police and medical service, if needed. Further, the TOC personnel can disseminate incident information through the IDOT-operated information system (which includes HAR, CMSs, and a dedicated radio channel) as well as through commercial radio and television stations. The incident information is updated periodically. TOC personnel also maintain a log of the incoming information which is archived as incident reports, the source of data used in this study. Meanwhile, the on-site incident management team may redirect traffic, help with relocating vehicles, picking up debris, supplying needed fuel/minor repairs, etc. The police perform incident investigation and other law enforcement actions as needed. Other agencies such as the medical and fire-fighting services may also be involved in on-site incident management.

The process of incident occurrence and response is shown qualitatively on a queuing diagram in Figure 1. The arrival rate at the incident bottleneck exceeds the processing rate for the duration of the incident (Makigami et al. 1971; Al-Deek and Kanafani 199 1; Hall 1993). The delay experienced by motorists is represented by the area between cumulative arrival and departure curves. Note that the congestion may last significantly longer than the incident. The terms used in the figure are defined as follows:

Incident detection time is the time between the occurrence of the incident and detection of the incident. Response time is the lag between incident detection and the arrival of the first rescue vehicle; if the incident occurs within the sight of a patrol person, then both detection and response times may be negligibly small. Clearance time is the time between the start of the on-site rescue operation and the end of clean-up operation. This includes Emergency Medical Service response (if needed), incident investigation, and debris/spill removal. Incident duration is the time between occurrence of the incident and end of clean-up. Recovery time is the time between end of clean-up operation and the resumption of normal traffic conditions. The key point is that a reduction in incident duration reduces the total delay experienced by travelers. Further, predictive information about incident duration may help individuals in terms of anticipating delay and allow them to divert to alternate routes or otherwise change travel patterns before joining the queue. This would be indicated by a reduction in arrival rate at the incident bottleneck.

3.2 Causal and Non-causal Factors

The factors which influence incident durations include incident characteristics, environmental conditions, roadway/flow characteristics, locational factors and operational/response factors such as dissemination of incident information. For example, incident duration may be longer if the incident involves injuries, if the weather is adverse, if there is roadwork near the incident location, or if the response team takes longer to reach the incident scene. The existing flow conditions may be important because higher flow rates (e.g., due to peak periods and/or special events) may hamper the response to incidents. Further, operational factors such as implementation of special ramp metering and arterial signal optimization plans during incidents can reduce queues and possibly incident duration. Vehicle characteristics such as percentage of heavy trucks may influence incident durations, i.e., large trucks are more likely to interfere with incident clearance operations. Moreover, incident durations may be influenced by whether information regarding the incident is disseminated. This influence is likely to come through queue reduction, i.e., by encouraging mode and route diversion which reduces demand and facilitates on-site incident management. In addition, seasonal trends may exist, that is, incidents may be longer at certain times of the year due to a multitude of factors, e.g., tourist activity and economic activity.

Operational factors can be causal or non-causal. For example, shorter response time of emergency vehicle(s) may reduce incident duration; however, non-causal factors such as whether a heavy wrecker was used for clearing the incident may actually be associated with longer incident durations because they reflect the nature of the incidents, although they do not cause longer incidents.

Only some operational factors can be controlled by the incident management authorities. For example, it may be possible to reduce incident durations, by reducing response times, improving on-site incident management, or disseminating incident information. However, incident characteristics such as incident type, time of day, location, weather, etc., are obviously not subject to control.

Some factors may have both direct and indirect effects on incident durations. For example, adverse weather may increase the incident duration directly, and it may also increase response times. Furthermore, uni-directional causality may not exist among variables. For example, response times may depend on incident durations; that is, response teams may be quicker to respond to major incidents compared with minor ones. Clearly, the complexities of phenomena make it challenging to collect data and model incident duration accurately.

4. METHODOLOGY

The objectives of this research were addressed by developing a conceptual structure describing the relationship between incident duration and contributing factors. Data describing a sample of freeway incidents and responses to them were analyzed to test the effects of various factors on incident duration. Based on the factors that were found significant, a time sequential methodology for prediction of incident durations was developed which would support successively more informed and more accurate incident duration predictions as an incident progresses. This methodology accounts for the dynamic nature of the information acquisition process at a TOC. Finally, conclusions were drawn and implications of the findings for managing incidents, disseminating incident information and designing ATMIS were explored.

5. CONTEXT OF THE STUDY AND DATA DESCRIPTION

The Chicago area freeways form a radial network that is embedded with nearly 2000 loop detectors and is patrolled by IDOT emergency response vehicles. Other more specialized incident response equipment, including heavy wreckers, is stationed at an IDOT field office just off the Dan Ryan Expressway, about 3 miles south of the city center. IDOT provided us with a convenience sample of records of 109 larger incidents occurring in 1989 and 1990. Figure 2 shows the location of selected incidents in the sample data that occurred on six major Chicago area freeways. Statistical tests (chi-square) showed no statistically significant differences between expected and observed frequencies in terms of distance from the city center (5% level).

5.1 Data Collection

The IDOT incident records (Figure 3) provide information on the following factors:

- Incident characteristics that include incident type (e.g., accident, stall) incident description (extent, intensity, number and type of vehicles, number and severity of injuries, etc.), number of lanes affected, duration of lane closures. This information comes from on-scene reports communicated through the radio by trained emergency response personnel.
- Response characteristics that include emergency vehicle response times, number and type of emergency vehicles responding.
- Distribution of incident warning information.
- Environmental conditions such as weather.

Although the data are not "ideal," they are sufficiently detailed in terms of IDOT operational response and dissemination of incident information. These data are kept by the IDOT communication center in Schaumburg, which is responsible for managing the operation of Emergency Patrol Vehicles and directing incident clearance in the Chicago metropolitan area.

5.2 Overview

5.2.1 Incident Characteristics

Most incidents in this sample (73%) occurred on weekdays and 77% happened during the off-peak. A majority of them (73%) occurred when the weather was clear. Most incidents (76%) were accidents and 33% of the accidents were roll-overs. Almost 90% of the incidents involved more than one vehicle and 57% involved heavy vehicles, e.g., tractor trailer combinations. In 11% of the incidents, the load had to be removed from the vehicle in the clearance effort; 5% had non-solid loading, resulting in spills. (Information about hazardous material could not be obtained from the records, even though this may have influenced incident durations.) About 49% involved injuries, of which 68% were classified as severe. Close to 20% of the incidents resulted in damage to State property, e.g., roadside equipment.

5.2.2 *Response Operations*

The average response time of the first rescue vehicle was 7.5 minutes from the initial report. Some incidents were discovered by the patrol vehicles in which case the response times were zero. In 93% of the cases a second rescue vehicle responded by reaching the scene in an average of 14 minutes. About 45% of the incidents required a heavy wrecker which normally was dispatched from the IDOT Dan Ryan field office. Pavement sanding and salting were needed in 31% of the cases due to spills of fuel or bulk loads. Incident information was disseminated through HAR and CMSs in 60% of the cases.

5.2.3 *Incident Duration*

The true start time of an incident is not usually known. The durations in our data are *modified* incident durations, i.e., the incident duration less the detection time. Figure 4 shows the frequency distribution of modified incident durations in our data set. The mean is 71.6 minutes and the standard deviation is 41.6. This distribution is skewed, as opposed to approximately normal as with Jones et al. (1991), probably because our sample contains a disproportionate number of longer incidents. The exploration of relationships between incident duration and response time of the first and second rescue vehicles showed that shorter response times, particularly for the first rescue vehicle, are associated with smaller incident durations.

5.3 Data Representativeness

To determine the representativeness of this sample, it was compared with data from the Chicago Area Expressway Annual Report (1988), which documents all detected incidents on Chicago area freeways. A comparison of this sample with total incidents on the Chicago area freeways is shown in Table 2. It indicates no strong biases in terms of highway facility location, occurrence times and weather conditions, although our sample has fewer peak period incidents. This is probably because many peak period incidents are relatively small.

The comparison of incident durations with other studies reviewed earlier confirms that this sample is biased toward larger duration incidents. Further, most incidents in this sample are accidents, whereas we expected a higher frequency of non-accidents such as stalls. Therefore, we need to be careful in generalizing the results.

6. MODELING INCIDENT DURATION

Two statistical techniques were applied to estimate incident duration: the regression model because incident duration is a continuous variable; and survival models because incidents can be assumed to have an increasing or decreasing hazard functions (Jovanis and Chang 1987; Jones et al. 1991). The regression and survival model estimates were largely similar in terms of their statistical properties. Therefore, only the simpler and more intuitive regression model is reported.

The variables used in model development are as follows:

- Incident characteristics including incident type (accident, stall), vehicle type (light, heavy), number of vehicles involved, injuries and fatalities, and State property damage.
- Response and operational factors including the response times, number of rescue vehicles, whether a heavy wrecker was needed, if sanding/salting was done because of a spill/ice on the pavement and whether other agencies such as medical services and owners of the vehicles involved provided assistance.
- Environmental conditions such as weather and visibility.
- Locational characteristics such as the freeway where the incident occurred and distance from the city center.
- Seasonal factors such as month of the year.
- Flow conditions as reflected in time of day and day of the week variables.
- Motorist information captured through whether or not incident information was disseminated through HAR.

To test whether there are differences in detecting and managing incidents of different types, the sample was segmented by incident type (accident, stall, etc.). However, this did not produce significantly different parameter estimates.

We have used the truncated regression model for estimation because small values of incident duration are unobserved (Hausman and Wise 1977; Greene 1990). (Note that this technique is different from Tobit models (Greene 1990) where observations above or below a certain value are "piled up.") At the time this sample was taken, the traffic surveillance system in Chicago did not allow for observation of short duration incidents, i.e., incidents lasting a few minutes were likely to go undetected. The minimum incident duration in this data set was 13 minutes.

Assume that the relationship between incident durations, y, and independent variables x_1, x_2, ..., x_k is of the form:

$$y_i = \beta_1 x_{i1} + \beta_2 x_{i2} + \ldots + \beta_k x_{ik} + \varepsilon_i = \beta' \mathbf{x}_i + \varepsilon_i$$

Where i refers to the i th observation; the set of n observations can be denoted as:

$$\mathbf{Y} = \mathbf{X}\beta + \varepsilon \qquad (1)$$

Where:

$\mathbf{Y}$ = Vector of n dependent variable observations on incident duration,

$\mathbf{X}$ = Matrix of k independent variables and n observations,

β = Vector of k parameters,

ε = The error term with expected value zero and variance σ^2.

Therefore $\mathbf{Y}$ is distributed normally with mean $\mathbf{X}\beta$ and variance σ^2, that is, $\mathbf{Y} \sim N(\mathbf{X}\beta, \sigma^2)$.

Suppose the truncation point is τ_0; thus the observations,

$y_i = \beta' \mathbf{x}_i + \varepsilon_i \quad > \quad \tau_0$ are included in the data observed, and

$y_i = \beta' \mathbf{x}_i + \varepsilon_i \quad \leq \quad \tau_0$ are excluded.

Figure 5 illustrates truncation more clearly. We expect that higher response times will be associated with higher incident durations, and this relationship is represented by the solid line. However, due to the inability to record small incidents, truncation occurs at the horizontal line and the empty circles are eliminated from the data set. The resulting regression line, shown as dashed in the figure, will not estimate the effect of response times correctly. There is a correlation between the error term and the explanatory variables. The magnitude of the bias would depend on τ_0, β, σ^2 and $\mathbf{x}_i$. Estimation using ordinary least squares regression gives biased results that can be overcome through maximum likelihood procedures (Greene 1990). The density function is given by:

$$f(y_i) = [\,(1/\sigma)\,\phi((y_i - \beta'\mathbf{x}_i) / \sigma)\,] \,/\, [\,1 - \Phi\,((\tau_0 - \beta'\mathbf{x}_i) / \sigma)\,] \qquad (2)$$

The Log-Likelihood function is given by:

$$\ln L = -\,n/2\,(\ln(2\pi) + \ln(\sigma^2)) - 1/(2\,\sigma^2)\,\Sigma_i\,(y_i - \beta'\mathbf{x}_i)^2 - \Sigma_i \ln[\,1 - \Phi\,((\tau_0 - \beta'\mathbf{x}_i)/\,\sigma))\,] \qquad (3)$$

Where,

$\phi(.)$ is the standard normal probability density function,

$\Phi(.)$ is the standard normal cumulative density function.

The values of β and σ are maximized.

Table 3 shows the selected model based on our judgement and statistical significance. The truncation point was arbitrarily chosen to be 10 minutes, based on our judgement and the data set, assuming that smaller incidents go undetected. The variables have the expected signs. A positive sign means increasing incident duration are associated with an increase in explanatory variable value. The unexplained portion of the model can be attributed to factors such as differences in efficiency of the rescue team and differences in the efficiency of TOC dispatch personnel.

The model shows that policy-sensitive variables significantly influence incident durations. Specifically, incident durations increased when the response time of the first patrol vehicle was longer; however, the response time of the second rescue vehicle did not have a statistically significant effect. The magnitude of the response time parameter indicates that a one-minute reduction in response time of the first rescue vehicle may decrease the incident duration by slightly more than one-half minute. Considering that the average response time was 7.5 minutes and the average incident duration was 71.6 minutes, there may be some limited potential for reducing response times and with them incident durations.

Reporting the incident on HAR and CMSs was associated with shorter incident durations. This is quite surprising, since IDOT personnel tended to use HAR only for larger incidents. Disseminating incident information seems to reduce incident duration by more than 5 minutes. Considering the high cost of delay, this reduction in incident duration is significant. Based on a value of time of $8 per hour per vehicle and incident lasting 60 minutes with 75% capacity reduction, Garrison and Mannering (1990) suggest that each minute of incident duration costs $2200 in lost time to the motorists--not accounting for psychological costs such as increased driver frustration and anxiety. The finding that information influences system performance is also in conformity with the behavioral studies which showed that travelers were more likely to divert in response to delays if they received information through radio traffic reports compared with observing congestion (Khattak 1991). Informing travelers about incidents may allow them to change their normal travel patterns (e.g., they may take alternate routes), avoiding delays and reducing the time needed to clear the incident. This suggests that HAR, CMSs and other electronic media perform a useful function during incidents in terms of duration reduction. However, it does not necessarily follow that information dissemination results in a reduction of total system delay

(Arnott et al. 1991; Ben-Akiva et al. 1991).

Injuries, involvement of heavy vehicles, heavy loading and non-solid loading caused incident durations to be longer. Further, if the freeway facility was damaged and if the weather was adverse (fog, rain, snow, etc.), then incident durations were longer. Severe weather seems to add 17 minutes to incident duration. During adverse weather, incident frequency increases sharply, overloading the incident response system and resulting in longer response times; however, such incident effects were not captured directly in this model. When the incident involves a vehicle with non-solid loading, it adds 39 minutes. The non-causal operational variables show that incidents requiring sanding and salting took 21 minutes longer to clear, whereas when a heavy wrecker was used, the incidents were 13 minutes longer. Similarly, if the incident required response from other agencies (fire, ambulance, environmental management units, etc.), then the incident durations were longer.

7. A METHODOLOGY FOR PREDICTION: TIME SEQUENTIAL INCIDENT DURATION MODELS

At the TOC, information about the incident is acquired sequentially. A typical sequence is as follows. After detection of an incident, an emergency patrol vehicle is dispatched to the incident scene. Upon reaching the scene, the patrol person provides an eyewitness account of the incident, i.e., details about the severity, casualties, etc. After the initial assessment, the patrol person may request more assistance and may ask that other agencies be contacted. Thus, while an incident duration model that uses all of the variables from historical records is helpful for understanding factors contributing to duration, it has little or no operational value, since we can only apply it at a point in time when we already know the duration of the event. From a practical standpoint, we need an approach that will support earlier but probably less-accurate duration prediction with fewer variables, to be updated in a series of steps as new information arrives.

The proposed time sequential incident duration methodology is based on the sequential acquisition (and decay) of incident-related information at a TOC over the life of an incident. First, the methodology identifies stages based on availability of information while the incident lasts. During the initial stage, when an incident is first reported, often very little is known about its attributes and the actions needed to clear it. Typically, the only variables available or known at the TOC are incident location, time of day and weather. During subsequent stages, more information is acquired, and consequently better predictions can be made. Second, certain previously acquired information could become irrelevant to predicting the remaining incident duration. For example, as illustrated in Figure 1, if a heavy wrecker has completed its operation, then information about its operation may be irrelevant to predicting the remaining incident duration at a subsequent stage. Therefore, subsequent prediction stages may be characterized by the addition and/or deletion of explanatory variable(s).

There are several methods that can be used to model the process of incident duration prediction. A series of truncated regression models is appropriate for estimation at various stages of the incident process. Alternatively, one could estimate duration models, based on conditional probability. A set of regressors (covariates) can be used to predict the probability of an incident lasting x minutes, given that it has lasted y minutes (where $y < x$). We have chosen to report the truncated regression results because the parameter estimates are more meaningful. Also the regression models would appeal to the TOC personnel, because of their simpler structure and interpretation.

The Stage 0 model (when the incident information is first acquired in the TOC) is similar to Equation (1) except the explanatory variables are those available at the time:

$$\mathbf{Y} = \mathbf{X}\beta + \varepsilon \qquad (4)$$

Where:

$\mathbf{Y}$ = Vector of n dependent variable observations on incident duration,

$\mathbf{X}$ = Matrix of p_0 independent variables available at Stage 0 and n observations,

β = Vector of p_0 parameters at Stage 0,

ε = The error term with expected value zero and variance σ^2.

The truncation point τ_0 for Stage 0 was chosen to be 10 minutes as before. From a model estimation perspective, the β estimates may be biased due to the unavailability of complete information at the stage. The only instances when bias may not exist are when the unavailable variables are unrelated to the available variables, or if the β estimates of unavailable variables are all zero; that is, if the future information does not significantly predict incident durations. Ironically, the exclusion of unavailable variables may actually have an advantage: reduced multicollinearity problems. The bias due to unavailability of variables can be dealt with by including proxy variables.

At Stage 1, more information is acquired at the TOC during the time τ_1 while some detected incidents would cease to exist. The incidents that cease to exist can be treated as unobserved and the truncation point moved from τ_0 to $\tau_0 + \tau_1$ in Figure 5. Thus, incidents are dropped from successive models when they are cleared before the activation of that model; hence there will be successively smaller sample sizes (the new sample size will be n - ν_1, where ν_1 incidents have ceased to exist during the interval τ_1 and $\nu_1 \geq 0$). We estimate the Stage 1 model with the condition that observations:

$$y_i = \beta' \mathbf{x}_i + \varepsilon_i \quad > \quad \tau_0 + \tau_1 \text{ are included in the data, and}$$

$$y_i = \beta' \mathbf{x}_i + \varepsilon_i \quad \leq \quad \tau_0 + \tau_1 \text{ are excluded.}$$

The basic model presented in Equation (4) is retained with new definitions as follows:

$\mathbf{Y}$ = Vector of n - ν_1 (un-ceased) incident duration observations,

$\mathbf{X}$ = Matrix of p_1 independent variables available at Stage 1 and n - ν_1 observations; $p_1 = [(p_0 - d_1) + a_1]$, and a_1 denotes the freshly acquired information on new variables during time interval τ_1 (and the information is available for forecasting at the end of τ_1); d_1 denotes the decayed information that has become irrelevant to prediction during the time interval τ_1 (and should not be used for forecasting at the end of τ_1). Thus p_1 includes the original variables along with the newly acquired variables and excludes the decayed variables,

β = Vector of p_1 parameters at Stage 1,

ε = The error term.

The observation of TOC operations in Chicago indicates that information is often acquired in spurts (e.g., when a patrol person reaches the scene and starts describing incident details); however, it may not decay in spurts.

Certain conditions should be satisfied for the methodology to work:

$d_\varphi \in p_{\varphi-1}$ Only those pieces of information can decay which already exist (are included in the model), and φ is an index for stages,

$d_\varphi \notin a_\varphi$ The stages should each be set such that information acquired during an interval does not decay during the same interval.

For Stage w, the model is given by:

$y_i = \beta' \mathbf{x}_i + \varepsilon_i$ > $\tau_0 + \tau_1 + ... + \tau_w$ are included, and

$y_i = \beta' \mathbf{x}_i + \varepsilon_i \qquad \leq \qquad \tau_0 + \tau_1 + ... + \tau_w$ are excluded.

The new definitions for the model presented in equation 4 are:

Y = Vector of n - ν_w dependent variable observations on incident duration,

X = Matrix of p_w independent variables available at Stage w and n - ν_w observations; $p_w = [(p_{w-1} - d_w) + a_w]$, and p_{w-1} denotes the information on variables at Stage w - 1, a_w denotes the freshly acquired information during time interval τ_w; d_w denotes the decayed information that has become irrelevant to the prediction during the time interval τ_w,

β = Vector of p_w parameters at Stage w,

ε = The error term.

The equations can be estimated using the maximum likelihood procedure as indicated before. The estimation process terminates when there are too few incidents remaining in the sample to make meaningful forecasts. This methodology accounts for the information acquisition and decay process at a TOC. In using the methodology for prediction of a single incident, the prediction stages will end when the incident clears.

Initially in the incident occurrence process, the models would “grow” in terms of explanatory variables (rate of information acquisition at the TOC is greater than the rate of information decay); they may “sustain” themselves during the middle, and “shrink” toward the end (rate of information acquisition is less than the rate of information decay).

There are two criteria used to determine information decay. In selecting candidate variables for decay, theoretical justification and statistical significance of the variable should be considered. It is asserted that only information about operational factors may decay, while information about incident characteristics and environmental conditions will not. For example, if heavy wrecker operation (whenever required) is completed within a certain time period from the incident occurrence, then it becomes a candidate for removal in models that predict durations after that time. On the other hand, incident characteristics and environmental conditions are expected to be constant.

We developed a series of truncated incident duration models using statistically significant variables shown in Table 3, with each successive model changing the mix of explanatory variables. The intent is to provide the capability to make a series of increasingly accurate duration forecasts, with accuracy increasing as more information becomes available in a TOC.

We analyzed our sample of IDOT incident history records to determine the typical sequence in which data items became available for prediction. The average time from initial report at which each data item became available is shown in Table 4. Owing to the large variation in their time of availability, it was decided to calculate the probability that a particular variable will be available for inclusion in a model within a certain time (see Wang 1991 for details). The probabilities are computed based on the mean and variance of the time a variable becomes available by considering the normal probability distribution (although we did not conduct formal tests to determine the realism of the normality assumption on the data presented in Table 4). Based on the probabilities, satisfaction of the conditions elaborated previously and our judgement, it was decided to predict incident durations at the time of detection (truncated at 10 minutes) and in increments of 5 minutes after the incident is detected up to the time when information acquisition stabilizes.

Models estimated using variables available at specific intervals and their parameter estimates are presented in Table 5. The parameters seem to have the expected signs and reasonable magnitudes. The average for the dependent variables increases with each successive model because with the passage of time only the larger incidents remain in the data set. The goodness of fit improves due to two reasons: more information becomes available, and the sample size decreases. Model 1, representing the time of incident detection, uses only weather (always known), time of day, and location; the time and location variables capture the effects of other variables not yet available and are included to reduce the bias due to exclusion of unavailable variables. Further, they may also reflect the influence of road geometry, pavement conditions and flow characteristics. Although the weather and time of day variables are statistically significant, this model is poor because of the exclusion of some important variables. However, it is realistic in the variables included, and it reflects a reasonable model for an early prediction. As expected, the magnitude of the effect of weather parameter is relatively large in Model 1 compared with the rest of the models because it absorbs the effect of unavailable variables.

Note that starting with Model 6 the prediction time interval τ is increased from 5 to 10 minutes simply for concision. The time of day variable TIME1 becomes statistically insignificant at the 10% level in Model 2, but is kept in for demonstration purposes until it is dropped from Models 9 and 10. Information decay starts in Model 9 where the response time of the first rescue vehicle became insignificant and was dropped. Overall, the bulk of estimated parameters remain statistically significant when considering only larger incidents.

We have used the HAR/CMS variable in Model 5, however, it is likely to be shifted to earlier models after the time sequential methodology is implemented. This is because the TOC personnel will have enhanced capability to predict incident durations and the ability to implement their information dissemination decisions relatively sooner.

At any stage, the TOC personnel would be interested in disseminating information on the remaining time needed to clear the incident. (Khattak (199 1) found that Chicago area automobile commuters were strongly interested in knowing the time needed to clear an incident.) To predict the remaining incident duration, the same model parameters can be used, except the constant term should reflect the time elapsed since the beginning of the incident. For example, the remaining time after an incident has lasted for x minutes is predicted by simply changing the constant for a model to Estimated Constant - x. The models will be used in the following manner. When a particular incident is first reported, the TOC personnel will predict a single value for the incident duration using specific values for the explanatory variables in Model 1. They would disseminate the duration information to travelers through electronic media. Note that the TOC personnel may also disseminate information about the confidence intervals associated with the prediction. The prediction interval for a particular incident can be easily calculated and it will be greater than if we were predicting the mean incident duration for many incidents (Greene 1990). Upon the receipt of more information during the next (5 minute) interval, the TOC personnel will update their duration prediction using Model 2, except they will adjust the constant term from 12.57 to 12.57 - 5. This reflects that a certain time (5 minutes) has elapsed in the life of the incident. They would continue to update their predictions similarly for the subsequent models.

8. VALIDITY OF MODELS

The purpose behind estimation of time sequential models is to demonstrate the methodology rather than its use in traffic operations. The next logical step would be to test and validate the model. Larger and more representative samples would be needed before the models can become operational. However, such data are not available at this time. We considered splitting the data set into two to test validity; however, the idea was dropped owing to the small sample size. Another way to test model validity, without new data, is to assess the reasonableness and consistency of the results and interpretation. The estimation results are consistent with our expectations and with findings from earlier studies. For example, it was confirmed in this study that incident durations were longer if the incident involved injuries (Golob et al. 1987; Giuliano 1989; Jones et al. 1991). Moreover, the models are not "under-specified" in terms of operational response factors.

9. CONCLUSIONS

Investigation of factors influencing the duration of Chicago-area freeway incidents showed that the most important variables were incident characteristics and the consequent emergency response actions. Using data from reports of communications between incident management personnel in the field and TOC, a model of incident duration was estimated which showed the relative predictive power of each of these variables. Analysis of historical incident communications records showed, however, that the key variables in this model become available at various points in the life of an incident, with the total set of variables available only when the incident has cleared. Thus, such a model based on historical records is of little practical value for real-time incident duration prediction.

Construction of a practical incident duration model must recognize the sequential availability of data items. The temporal patterns of the arrival of data elements were explored for the Chicago data set, and the results were used to estimate a series of incident duration models. The concept underlying these models is that forecasts of incident duration made earlier in the life of an incident may be useful both for incident management and for informing motorists, even if those early estimates are of restricted accuracy because of the lack of availability of some explanatory variables.

Models were developed to include those variables typically available at the IDOT Communications Center at the time of the first report of an incident, and at subsequent intervals into the incident. We used a series of truncated regression models for estimation; however, we recognize that alternate models, based on conditional probabilities, can also be formulated. Each successive model can predict the remaining life of the incident, and, as expected, the goodness-of-fit improved as additional variables were introduced.

While available information may differ in other settings, this sequential approach to forecasting incident duration offers a framework for building other, more locally relevant models of incident duration that reflect the increasing availability of detailed incident information as the events proceed. This approach offers a reasonable balance between the values of *early* and *accurate* incident duration forecasts. Models of this type may be improved if field personnel can be trained to provide real-time reports of incident characteristics and progress toward incident clearance in a timely and systematic manner, so that data for exercising the duration forecasting models will be available as needed.

Future research efforts might productively focus on examining alternate models for prediction of remaining incident duration, and importantly establishing links between incident duration and queue duration both at the theoretical and empirical levels. Further, there is a need to explore how predictive information would impact traveler behavior and whether greater benefits can be obtained by disseminating predictive information.

REFERENCES

Al-Deek, H. 1991. *The role of advanced traveler information systems in incident management.* PhD Dissertation, UCB-ITS-DS-91-5. Institute of Transportation Studies, University of California at Berkeley.

Al-Deek, H., and A. Kanafani. 1991. *Incident management with advanced traveller information systems.* California PATH working paper UCB-ITS-PWP-91-5. Institute of Transportation Studies, University of California at Berkeley.

Arnott, R., A. de Palma, and R. Lindsey. 1991. Does providing information to drivers reduce traffic congestion? *Transportation Research* A, Vol. 25 A, No. 5, pp. 309-318.

Ben-Akiva, M., A. de Palma, and I. Kaysi. 1991. Dynamic network models and driver information systems. *Transportation Research* A, Vol. 25A, No. 5, pp. 251-266.

Ben-Akiva, M., E. Kroes, J. Ruiter, S. Smulders, J. Whittaker, and K. Lindveld. 1992. Real-time prediction of traffic congestion. Paper presented at *6th World Conference on Transport Research,* Lyon, France.

Cremer, M., F. Meissner, and S. Schrieber. 1993. On predictive control schemes in dynamic rerouting strategies. *Transportation and traffic flow theory,* C. Daganzo (ed). Elsevier Science Publishers, pp. 407-426.

Chicago area expressway annual report, Chicago Police Department, Chicago, 1988.

Davis, G., and J. Kang. 1993. Filtering and prediction on freeways using Markov models. *Proceedings of pacific rim conference.* American Society of Civil Engineers, Seattle, Washington, pp. 43-49.

DeRose, F. 1964. An analysis of random freeway traffic accidents and vehicle disabilities. *Highway Research Board,* HRR 59, Washington, D.C., pp. 53-65.

Garrison, D. and F. Mannering. 1990. Assessing the traffic impacts of freeway incident and driver information. *ITE Journal 60* (7), pp. 19-23.

Giuliano, G., 1989. Incident characteristics, frequency and duration on a high volume urban freeway. *Transportation Research* A, Vol. 23A, No. 5, pp. 387-396.

Golob, T., W. Recker, and J. Leonard. 1987. An analysis of the severity and incident duration of truck involved freeway incidents *Accident Analysis and Prevention,* Vol. 19, No. 5, pp. 375-395.

Goolsby, M. 1971. Influence of incident on freeway quality of service. *Highway Research Board,* HRR 349, Washington, D.C., pp. 4 1-46.

Greene, W. 1990. *Econometric analysis.* New York: Macmillan Publishing Company.

Hall, R. 1993. Non-recurrent congestion: How big is the problem? Are traveler information systems the solution? *Transportation Research* Vol. 1C, No. 1, pp. 89-103.

Hausman, J., and D. Wise. 1977. Social experimentation, truncated distributions, and efficient estimation. *Econometrica,* Vol. 45, No. 4, pp. 919-938.

Jones, B., L. Janssen, and F. Mannering. 1991. Analysis of the frequency and duration of freeway accidents in Seattle. *Accident Analysis and Prevention,* Vol. 23, No. 4, pp. 239-255.

Jovanis, P., and H. Chang. 1989. Disaggregate model of highway accident occurrence using survival theory. *Accident Analysis and Prevention,* Vol. 21, No. 5, pp. 445-458.

Juge, J., K. Kennedy, and T. Wang. 1974. *Early detection and rapid removal of disabled vehicles and other hazards from the freeway.* Final report to California Department of Transportation and California Highway Patrol.

Khattak, A. 1991. *Driver Response to Unexpected Travel Conditions: Effect of Information and other Factors.* PhD Dissertation, Department of Civil Engineering, Northwestern University, Evanston, Illinois.

McDermott, J. 1980. Freeway Surveillance and Control in Chicago Area. *Transportation Engineering Journal,* TE 3, pp. 333-348.

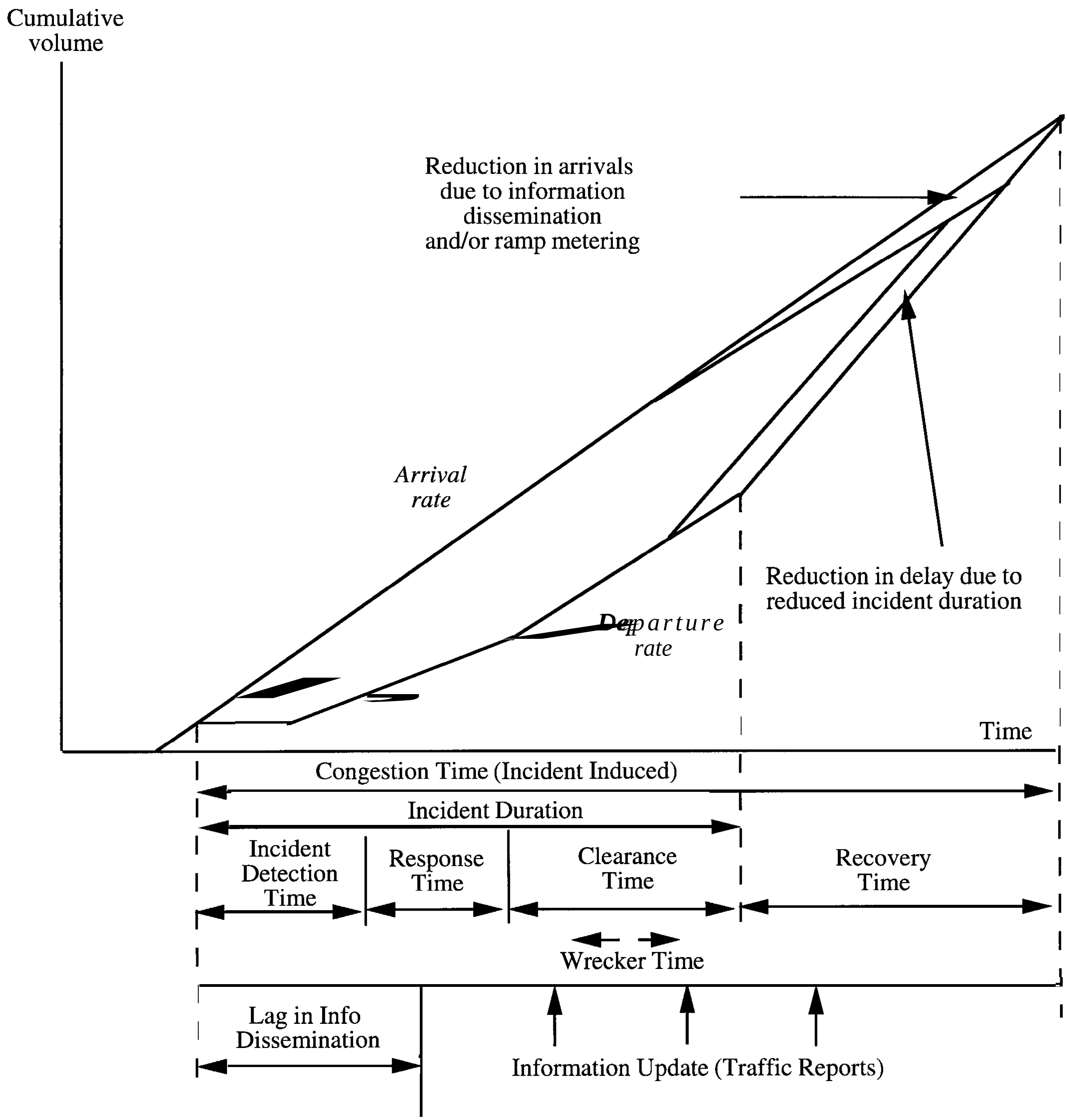
Makigami, Y., G. Newell., and R. Rothery. 1971. Three-dimensional representation of traffic flow.*Transportation Science,* ORSA, Vol. 5, No. 3, pp. 302-313.

Ritchie, S., and N. Prosser. 1990. Development of a prototype real-time expert system for managing non-recurring freeway congestion. *OECD Workshop on expert Systems in Transportation,* Vol. 1, Finland, pp. 129-153.

Stephanedes, Y., and E. Kwon. 1993. Adaptive Demand Diversion Prediction for Integrated Control of Freeway Corridors. *Transportation Research C,* Vol 1C, No. 1, pp. 23-42.

Wang, M. 1991. *Modeling freeway incident clearance times.* Unpublished MS Thesis. Civil Engineering Department, Northwestern University, Evanston, Illinois.

Wilshire, R. and C. Keese. 1963. *Effect of traffic Accidents on Freeway Operations,* Research report, Texas Transportation Institute, A & M College of Texas, College Station, Bulletin No. 22 E 21-63.



Note: Clearance Time includes EMS response, injury attention, accident investigation, debris removal and clean-up times.

Figure 1. The incident occurrence process.

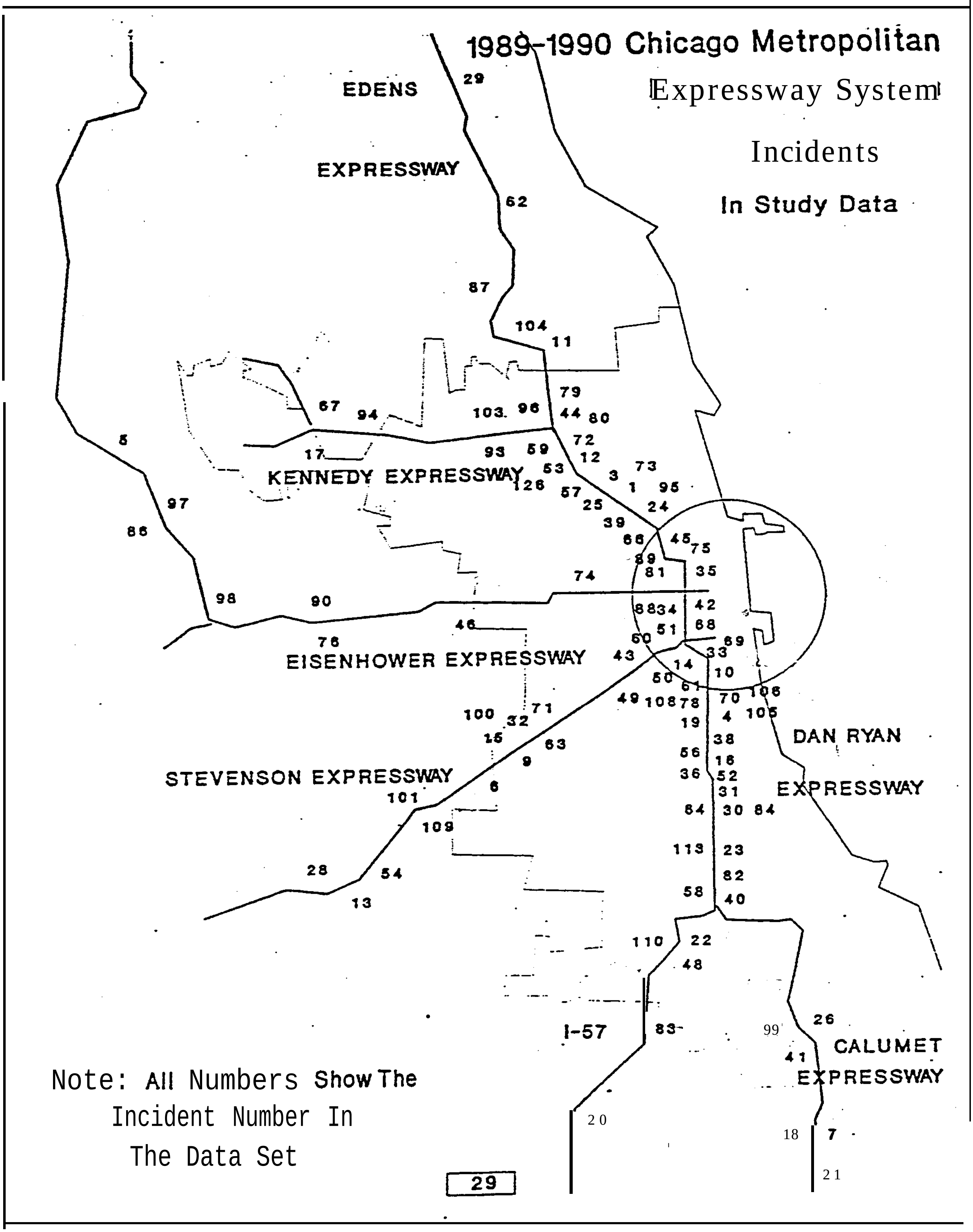


Figure 2. Location of incidents in sample data

TIME/DATE RECEIVED 3:26am (TIME:0), Wednesday (DATE:0)
SUBJECT: Rolled over semi (TYPE:2)

LOCATION: SB Calumet at 130 exit [on ramp]	LOAD/WEIGHT/TYPE OF TRUCK 54,000 lbs of diapers

FOR EACH ENTER TIME CR NA CRT: 3:45AM HAR: 3:44AM CMS:
SPRINGFIELD NOTIFICATION: [TIME] 4:36AM FAXED: [TIME] 7:30AM

DETAILS & NOTIFICATIONS

3:26am: Control was notified by Dist #4 that they have a rolled over semi on the exit ramp from SE Calumet to EB 130th. (NTRUCK: 1, DIR:0, LOC: 6, DIST: 16 miles)
3:27am: Control notified 912 [Cannatello]
3:27am: 954 [Martin] enroute
3:28am: 914 [Smaladino] enroute
3:30am: Control notified T. Smith at home
3:44AM: 934 [LAU] Standing by 3501 for 923, heavy wrecker. if needed-.
3:44am: 954 stated that the ramp is blocked with a semi weight of 50,000 lbs, the semi is mostly on the grass. (RESP: 18 MIN., LOAD: 1, NONCON: 0)
3:45am: Control did H.A.R (EAR: 1)
3:46am: TK did CRT
3:55am: 914 stated to have 923 & 958 enroute just in case. (WRECKER: 1, SECOND: 11 min.)
3:55am: 934 is now in 923, 964 [Bowen] enroute to 3501 for 951.
3:58am: 954 stated that the semi is loaded with 54,000 lbs of diapers,' (HEAVY: 1, NONCON: 0)
5:14am: Control asked 914 for an update, he'stated that they are uprising the semi with the air bags the semi trailer might be split open.
5:15am: Control Updated
5:26am: '914 stated that the semi is upright
5:51am: Ramp is open. HAR & CRT.
6:39am: Mr. Klafeta notified.
3 hours of lane blockage (CLEAR: 180 min.)

Note: The words within ( ) is the variable name and its identified value.

Figure 3. Sample of IDOT incident log

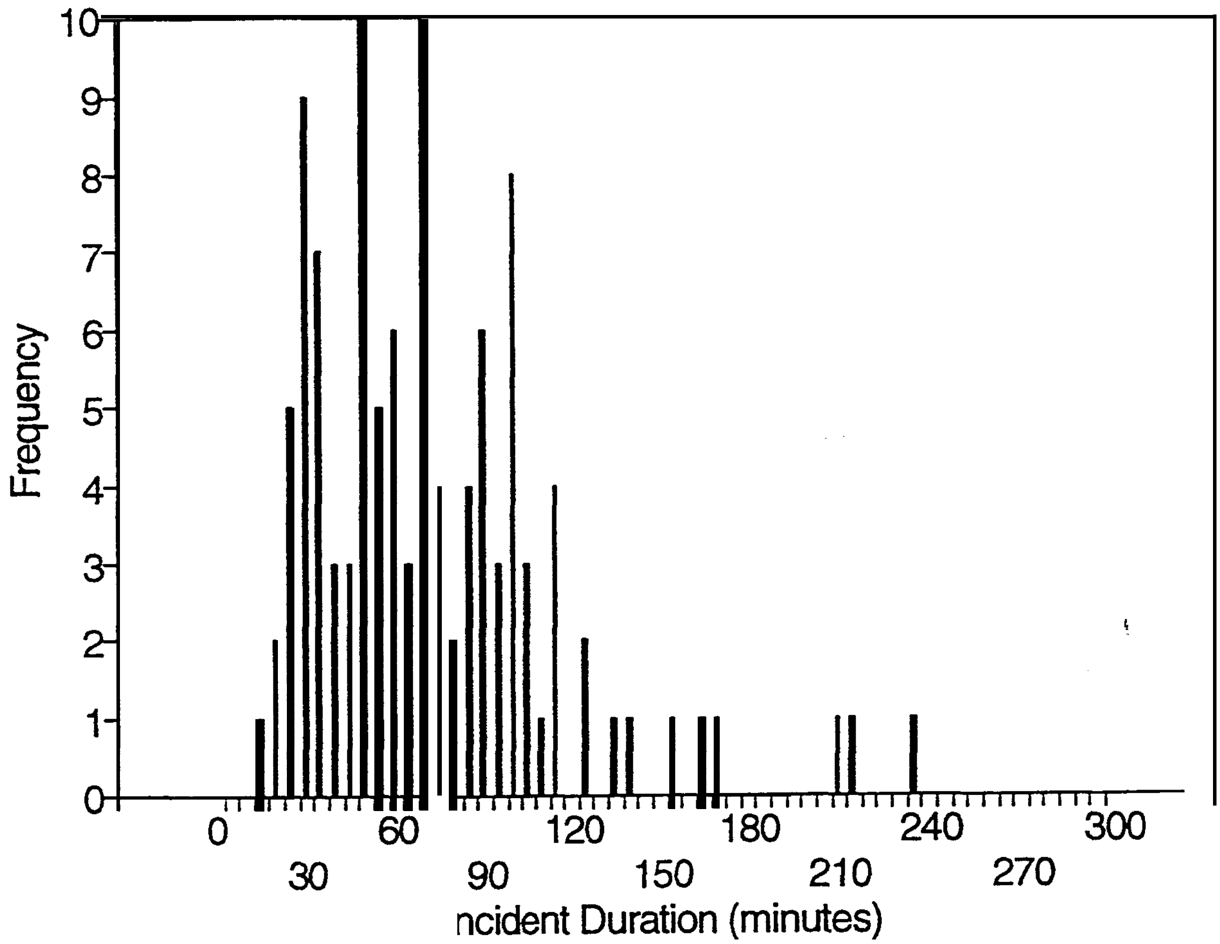


Figure 4. Distribution of incident duration

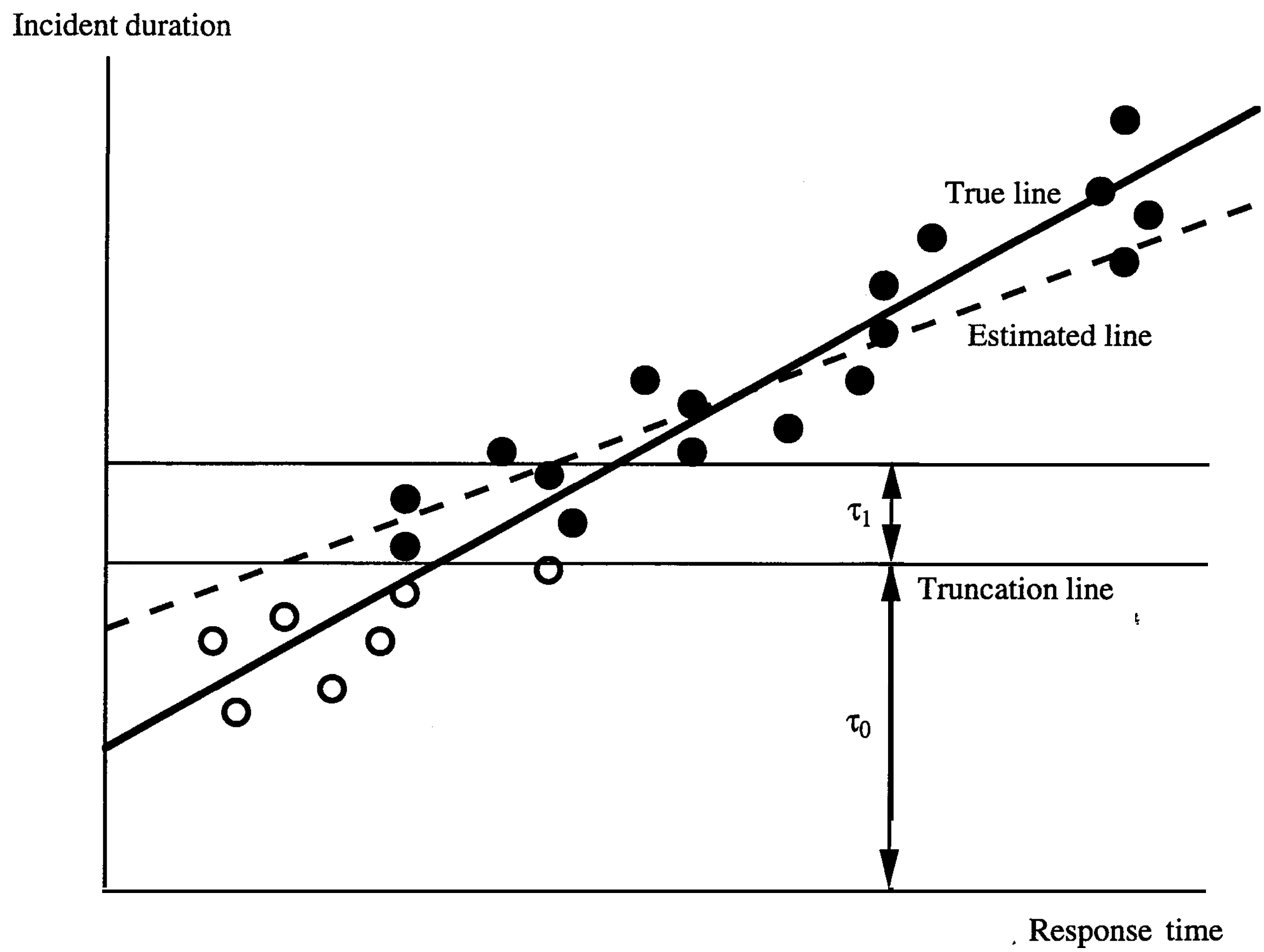


Figure 5. Illustration of bias due to unobserved incident durations (Modified from Hausman and Wise (1977))

Table 1. Summary of selected incident studies.

	DeRose (1964)	Goolsby (1971)	Juge et al. (1974)	Golob et al.* (1987)	Giuliano** (1989)	Jones et al. (1991)	This study (1992)
Average accident duration (min.)	6.14	45					
Average non-accident (stalls) duration (min.)	5.24	18					
Average duration of all incidents (min.)	?	?	42	40-144	37	50***	72
Sample size	927	?	196	332	270	2156	109
Study location	John Lodge F/way Detroit, MI	Gulf F/way Houston, TX	Los Angeles, CA	Southern CA	I-10 Los Angeles, CA	WA	Six F/ways Chicago, IL
Data collection method	CCTV/Observers	Police logs	Time lapse camera	Police logs	Police logs	State records	State records
Data collection period	1962-1963	1968-1969	1973-1974	1983-1984	1983-1984	1987-1989	1989-1990

*Truck accidents only
**Bad weather days screened out
***Estimated from graphical representation of data.
CCTV=Closed Circuit Television.

Table 2. Comparison of incidents in the 1989-1990 sample and the 1988 Chicago Area Expressway Annual Report.

	Sample % N=109	Total % N=20,496
Incident location--Freeway		
Edens	9.2	6.2
Kennedy	21.1	27.3
Eisenhower	17.4	23.9
Stevenson	15.6	10.2
Dan Ryan I	22.0	21.1
Dan Ryan II	6.4	3.7
Calumet	8.3	7.6
Distance from the Central Business District		
0-5 miles	43.1	48.7
5-15 miles	47.7	44.0
more than 15 miles	8.3	7.3
Day of the week		
Weekend	26.6	24.1
Weekday	73.4	75.9
Time of day		
Peak period	22.9	38.4
Off-peak	77.1	61.6
Weather conditions		
Clear	73.4	77.0
Not clear	26.6	23.0

Table 3. Incident duration truncated regression model (point of truncation = 10 minutes).

Variable	ß	(t-statistics)
Operational/Response Factors		
RESP1 (Response time of first rescue vehicle in minutes)	0.59	(3.89)
HARCMS (1 if incident information disseminated through HAR & CMS, 0 Otherwise)	-5.34	(-2.39)
WRECKER (1 if a heavy wrecker was used 0 Otherwise)	12.66	(4.97)
SANDSALT (1 if sanding/salting was done, 0 Otherwise)	21.24	(8.83)
OTHER (1 if other agencies responded, 0 Otherwise)	28.38	(10.44)
Incident Characteristics		
SEVINJ (1 if incident involved severe injuries/fatalities, 0 Otherwise)	28.14	(10.73)
NTRUCK (Number of trucks involved in the incident)	18.07	(8.92)
LOAD (1 if the loading in vehicle was heavy, 0 Otherwise)	35.43	(11.41)
NONSOLID (1 if the loading was non-solid, 0 Otherwise)	39.33	(7.83)
DAMAGE (1 if State property was damaged, 0 Otherwise)	38.03	(13.87)
Environmental Conditions		
WEATHER (1 if weather was adverse, 0 Otherwise)	17.3 19	(7.03)
CONSTANT	10.34	(3.74)
σ	9.85	(13.69)
Summary Statistics		
N	98	
L(ß)	-359.85	
L(MS)	-490.06	
ρ^2_{MS}	0.2657	

Note: $\rho^2_{MS}=1-[L(\beta)/L(MS)]$. L(MS) is the log-likelihood at market shares, estimated with the constant term and σ. The sample size is 98 instead of 109 due to the deletion of missing data.

Table 4. Descriptive statistics for times when significant variables become available.

Variable	Mean	Std. Dev.	Minimum	Maximum
Clearance time	71.60	41.64	13.0	232.0
Extreme weather condition	0.0	0.0	0.0	0.0
Number of heavy vehicles involved	6.93	8.21	0.0	44.0
Whether a heavy wrecker was needed	7.30	8.74	0.0	50.0
Whether the loading on vehicle was non-solid	7.45	7.22	0.0	38.0
Whether freeway facility was damaged	7.55	7.01	0.0	38.0
Whether there was heavy loading on vehicle	7.66	7.22	0.0	38.0
Response time of the first rescue vehicle	7.70	7.28	0.0	38.0
Whether there were severe injuries/fatalities	7.74	7.46	0.0	38.0
Whether other response agencies were needed	10.21	11.72	0.0	69.0
Whether sanding/salting was needed	12.02	14.74	0.0	78.0
HAR/CMS incident report disseminated to public	15.85	10.56	1.0	44.0

Table 5. Incident duration regression models for time sequential prediction.

Variable	Model 1 (Truncation=10 min.) ß (t-statistics)	Model 2 (Truncation=15 min ß (t-statistics)	Model 3 (Truncation=20 min.) ß (t-statistics)	Model 4 (Truncation=25 min.) ß (t-statistics)	Model 5 (Truncation=30 min. ß (t-statistics)
WEATHER	39.58 (2.96)	12.57 (1.51)	21.67 (4.43)	16.39 (4.64)	15.89 (6.44)
TIME1*	57.24 (2.69)	17.68 (1.22)	6.61 (0.68)	0.19 (0.03)	-8.65 (-1.64)
TIME2**	60.69 (2.63)	2.48 (0.16)	-8.70 (-0.94)	-2.83 (-0.42)	-9.97 (-2.22)
LOCATION***	12.13 (0.74)	-4.17 (-0.39)	-7.36 (-1.14)	-8.85 (-1.91)	-7.07 (-2.19)
DAMAGE		55.69 (6.33)	46.28 (8.91)	37.84 (9.36)	39.65 (14.76)
NONSOLID		76.25 (4.75)	53.57 (5.28)	41.59 (5.51)	47.80 (9.15)
RESP1		0.95 (2.03)	0.98 (3.38)	1.15 (5.44)	0.63 (4.10)
NTRUCK			17.77 (4.44)	20.25 (6.76)	15.09 (7.05)
SEVINJ			35.60 (6.63)	28.25 (7.16)	30.63 (10.87)
LOAD			37.76 (6.18)	34.14 (7.72)	37.99 (12.48)
WRECKER			24.26 (4.92)	19.45 (5.43)	13.48 (5.31)
OTHER				30.33 (7.92)	27.16 (10.33)
SANDSALT					23.39 (9.55)
HARCMS					-5.05 (-2.16)
CONSTANT	34.31 (2.85)	38.30 (5.47)	4.10 (0.66)	6.08 (1.33)	11.44 (3.48)
σ	47.98 (8.40)	31.83 (10.30)	18.29 (11.98)	13.24 (12.36)	9.05 (12.49)
Summary Statistics					
N	109	108	96	92	85
L(MS)	-546.50	-536.90	-472.09	-448.75	-412.59
$L(\beta)$	-536.36	-501.11	-400.43	-355.39	-301.35
ρ^2_{MS}	0.0185	0.0667	0.1518	0.2080	0.2696
Mean Dep. Var. (min)	71.06	71.59	73.29	75.54	79.42

*TIME1=1 if incident occurrence time is between 6:00 AM-8:00 AM, 0 Otherwise;
**TIME2=1 if incident occurrence time is between 10:00 PM-12:00 Midnight, 0 Otherwise;
***LOCATION=1 if incident occurred on Eisenhower Expressway, 0 Otherwise;

All other variables are defined in Table 4. Note that $\rho^2_{MS}=1-[L(\beta)/L(MS)]$. L(MS) is the log-likelihood at market shares, estimated with the constant term and σ.

Table 5. (continued) Incident duration regression models for time sequential prediction.

Variable	Model 6 (Truncation=40 min.) ß (t-statistics)	Model 7 (Truncation=50 min.) ß (t-statistics)	Model 8 (Truncation=60 min.) ß (t-statistics)	Model 9 (Truncation=70 min.) ß (t-statistics)	Model 10 (Truncation=80 min.) ß (t-statistics)
WEATHER	15.95 (6.34)	17.60 (6.53)	17.14 (6.59)	18.76 (6.18)	19.82 (5.93)
TIME1*	-7.63 (-1.31)	-6.24 (-1.11)	-7.54 (-1.52)	----------------	----------------
TIME2**	-10.74 (-2.42)	-12.64 (-2.89)	-6.56 (-1.49)	-7.63 (-1.68)	-8.69 (-1.81)
LOCATION***	-7.10 (-2.11)	-8.17 (-2.30)	-6.73 (-1.99)	-10.23 (-2.77)	-10.97 (-2.80)
DAMAGE	39.95 (14.68)	40.24 (14.10)	36.42 (13.55)	37.75 (13.09)	38.51 (12.62)
NONSOLID	48.57 (9.45)	48.68 (9.80)	50.86 (10.69)	51.31 (10.48)	54.17 (10.68)
RESP1	0.52 (3.27)	0.43 (2.58)	0.30 (1.87)	----------------	----------------
NTRUCK	13.99 (6.39)	12.51 (5.48)	13.87 (6.25)	10.03 (3.67)	7.22 (2.25)
SEVINJ	31.43 (10.48)	30.09 (9.27)	22.72 (6.95)	22.05 (5.44)	25.40 (5.85)
LOAD	37.53 (12.27)	37.14 (11.83)	31.97 (10.24)	30.99 (9.13)	33.18 (9.34)
WRECKER	14.13 (5.40)	12.02 (4.32)	10.27 (3.78)	10.60 (3.10)	8.82 (2.33)
OTHER	25.96 (9.69)	23.77 (8.51)	22.74 (9.02)	19.24 (6.86)	18.52 (6.20)
SANDSALT	24.84 (2.50)	24.59 (9.40)	25.10 (9.75)	26.19 (10.26)	27.88 (9.82)
HARCMS	-5.17 (-2.01)	-3.75 (-1.42)	-8.93 (-3.39)	-9.82 (-3.12)	-11.19 (-3.12)
CONSTANT	12.51 (3.47)	16.62 (4.15)	27.12 (5.97)	34.67 (6.56)	35.98 (6.10)
σ	8.78 (11.59)	8.33 (10.44)	7.12 (9.77)	7.22 (8.73)	7.05 (7.93)
Summary Statistics					
N	76	63	54	42	37
L(MS)	-362.78	-297.80	-250.63	-193.89	-165.28
L(β)	-267.03	-218.87	-176.97	-138.55	-119.53
ρ^2_{MS}	0.2639	0.2650	0.4162	0.2854	0.2768
Mean Dep. Var. (min)	84.67	92.44	98.39	107.38	111.80

*TIME1=1 if incident occurrence time is between 6:00 AM-8:00 AM, 0 Otherwise;
**TIME2=1 if incident occurrence time is between 10:00 PM-12:00 Midnight, 0 Otherwise;
***LOCATION=1 if incident occurred on Eisenhower Expressway, 0 Otherwise;

All other variables are defined in Table 4. Note that ρ^2_{MS}=1-[L(β)/L(MS)]. L(MS) is the log-likelihood at market shares, estimated with the constant term and σ.