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Role of Multiagency Response and On-Scene Times in Large-Scale Traffic Incidents

Xiaobing Li, Asad J. Khattak, and Behram Wali

Traffic incidents, often known as nonrecurring events, impose enormous economic and social costs. Compared with short-duration incidents, large-scale incidents can substantially disrupt traffic flow by blocking lanes on highways for long periods. A careful examination of large-scale traffic incidents and associated factors can assist with actionable large-scale incident management strategies. For such an analysis, a unique and comprehensive 5-year incident database on East Tennessee roadways was assembled to conduct an in-depth investigation of large-scale incidents, especially focusing on operational responses, that is, response and on-scene times by various agencies. Incidents longer than 120 min and blocking at least one lane were considered large scale; the database contained 890 incidents, which was about 0.69% of all reported incidents. Rigorous fixed- and random-parameter, hazard-based duration models were estimated to account for the possibility of unobserved heterogeneity in large-scale incidents. The modeling results reveal significant heterogeneity in associations between operational responses and large-scale incident durations. A 30-min increase in response time for the first, second, and third (or more) highway response units translated to a 2.8%, 1.6%, and 4.2% increase in large-scale incident durations, respectively. In addition, longer response times for towing and highway patrol were significantly associated with longer incident durations. Given large-scale incidents, associated factors included vehicle fire, unscheduled roadwork, weekdays, afternoon peaks, and traffic volume. Notably, the associations were heterogeneous; that is, the direction could be positive in some cases and negative in others. Practical implications of the results for large-scale incident management are discussed.

In December 2011, a tractor trailer combination hauling potatoes crashed on U.S. Interstate 40 between Nashville and Knoxville, Tennessee, closing that Interstate for 12 h. This widely publicized occurrence prompted an aggressive initiative aimed at improving incident management and conducted jointly by the Tennessee Department of Transportation (Tennessee DOT) and Tennessee's Department of Safety and Homeland Security. Improving roadway availability through incident prevention, particularly large-scale incident management, is a Tennessee DOT priority. Incidents like the infamous potato spill not only delay motorists but also impose significant costs on motor carriers. Generally, traffic incidents are nonrecurring events imposing enormous costs on society with regard to productivity loss and delay. In 2015, the Urban Mobility Scorecard released by Texas Transportation Institute analyzed mobility data from 1982 to 2014 and termed the nation's congestion problem as "very large" (*1*). It revealed that traffic congestion in 2014 across 471 metropolitan regions of the United States wasted a significant amount of time and caused an annual travel delay of 6.9 billion hours and 3.1 billion wasted gallons of fuel, a total of $121 billion annual congestion costs nationally (*1*). Conservatively, traffic incidents account for approximately 25% of traffic congestion and are a leading cause of unexpected traffic congestion (*2*). Although short- to medium-duration incidents can affect traffic operations and mobility, large-scale incidents substantially disrupt traffic flow by blocking lanes for long periods of time (*3*). Specifically, a 10-min lane blockage can cause 40+ min of extra travel delay (*4*). Also, large-scale traffic incidents are more complex and require more response resources and close coordination between different agencies to clear the incident scene and restore normal traffic (*3*). Large-scale incidents may trigger special arterial signal coordination plans to deal with diverted traffic, detours, special resources for cleanup, and dissemination of dynamic information to the public. Despite the costs and adverse consequences of large-scale incidents, in-depth analysis of such incidents and identification of key associated factors have received limited attention in the literature.

From the perspective of incident duration modeling, a broad spectrum of studies has focused on analyzing traffic incidents—specifically incident durations—to identify key factors associated with incidents for better incident management strategies (*5–8*). From a methodological standpoint, incident durations and associated factors have been modeled successfully using a diverse set of rigorous statistical tools such as truncated and quantile regression (*9, 10*), hazard-based duration models (*6, 11*), Bayesian network tools (*12–14*), artificial neural networks (*15, 16*), text analysis and competing risk models (*17, 18*), and recently finite mixture models (*19*), among others. Several correlates such as accident and injury involvement, lane closure, number of vehicles, temporal and spatial factors, heavy-truck involvement, and adverse weather were found positively associated with longer incident durations (*6, 10, 13, 14*). A paper by Zhang et al. contains a summary of findings from different studies (*3*). However, the aforementioned studies did not explicitly focus on identifying key correlates that may be associated with the duration of large-scale incidents, which are different from other traffic incidents in that they typically require multiagency coordination for multiple injuries or a spill of hazardous materials. A thorough understanding of the important correlates is needed to devise strategies for responding to such incidents effectively.

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Although there is considerable literature on the general analysis of incidents, few studies have explicitly focused on analyzing large-scale incidents. Zhang et al. conducted an in-depth spatial–temporal and statistical analysis of large-scale incidents on urban freeways in Hampton Roads, Virginia (*3*). The incidents were found to be 16 times (on average 216 min) longer than non-large-scale incidents (16 min). The average incident duration was found to be 163 min by Nam and Mannering (*6*). Furthermore, Zhang et al. identified locations prone to large-scale incidents and found that large-scale incidents typically occur during morning and evening peaks (*3*). Empirically, large-scale incidents showed a significant positive association with work zones, presence of curvature, and occurrence of secondary incidents (*3*). Similar results were obtained from the analysis of cascading incident events on urban freeways (*20*).

Previous studies have provided actionable strategies for large-scale incident management, but they did not focus on multiagency operational responses, specifically response and on-scene times that are likely to be associated with the longer durations of large-scale events. From a methodological perspective, fixed associations between large-scale incident duration and associated factors were assumed in most studies. These assumptions are restrictive given the presence of several unobserved factors in incident databases and in light of the new methods that have emerged to deal with heterogeneity. Recent studies have identified the importance of addressing unobserved heterogeneity and the implications for general incident duration analysis (*11, 18*).

RESEARCH OBJECTIVE AND CONTRIBUTION

The current study conducted an in-depth analysis of large-scale incidents. The main objectives were to

- Identify large-scale traffic incidents by using appropriate criteria and create a comprehensive database that can allow in-depth investigation of such crashes;
- Conceptualize and quantify the associations between large-scale incident durations and multiagency operational responses, especially their response and on-scene times; and
- Investigate unobserved heterogeneity in large-scale incident duration analysis by developing random-parameter, hazard-based duration models.

Such an analysis is important given the disproportionately high costs of large-scale incidents. A careful examination of large-scale incident durations and associated factors can assist in developing actionable improvement strategies for large-scale incident management. The analysis is also original and timely in the sense that a unique database was assembled that allowed exhaustive investigation of large-scale incidents and their association with multiagency operational responses. Tennessee DOT has an incident database that contains information about incident duration, incident type, duration of lane blocking, response time, and incident location. However, several new variables were coded manually from detailed incident reports for large-scale incidents that include response and on-scene times for multiple agencies: service patrols; incident response units; police, fire, emergency, and towing; and variables such as number of vehicles involved and use of highway advisory radio (HAR) and dynamic message signs (DMSs). Unobserved heterogeneity, explored in this study, is often present in incident duration data. The current study contributed methodologically by estimating rigorous fixed- and random-parameter, hazard-based duration models. To the best of the authors' knowledge, such random-parameter models have not been applied in incident duration modeling.

METHODOLOGY

Data Source

Data analyzed in this study were obtained from the Tennessee DOT Region 1 Traffic Management Center. A web-based archiving tool called LOCATE/IM was used to access the incident database. The management center maintains the database through Tennessee SmartWay and the Tennessee DOT HELP program. The data contain traffic incident summaries and detailed operational reports. Summary data were collected from September 29, 2010, to December 31, 2015, and cover 26 counties with 17 routes (7 freeways and 10 major highways). A total of 129,088 incident records were obtained.

Data Assembly and Selection of Large-Scale Incidents

Large-scale incidents were identified by using the obtained data. Past methodology, the *Manual on Uniform Traffic Control Devices,* Tennessee traffic incident management goals (removing incidents within 90 min), and mean durations in this database all contribute to the identification as large scale of incidents lasting more than 120 min and having at least one lane blocked. A total of 890 of 129,088 incidents—approximately 0.69%—were selected from all incidents. Their locations are displayed in Figure 1, which indicates that most of them occurred near urban areas.

Substantial effort went into creating a comprehensive database for the selected large-scale incidents. The data were collected and enhanced by creating new variables from incident operations reports, as well as plotting incidents in Google Earth to obtain spatial information such as number of lanes. Tennessee crash reports were also used to obtain data such as annual average daily traffic (AADT).

Figure 2 shows the general structure of the incident management process over time (*a*) and the data obtained (*b*). With a focus on the multiagency operational response during large-scale incidents, detailed incident reports were reviewed to extract relevant temporal operational data such as response times and on-scene times for each agency [the highway incident response unit (HIRU), police, emergency medical services, and so on]. Incident reports maintained by Tennessee DOT contain detailed information about response and on-scene times for different agencies, but the data are not readily available for statistical analysis.

To capture the operational characteristics of each agency—such as the Highway Safety Patrol (HSP), administered by the Tennessee Department of Safety and Homeland Security; HIRUs, administered by Tennessee DOT; local police and fire departments; and others—detailed incident reports were downloaded from the Tennessee DOT database and used for coding new variables. These variables, such as HIRU response, number of vehicles involved, percentage of lane blockage, secondary incident occurrence, and hazardous material incidents, were either directly obtained from the database or indirectly calculated from detailed incident reports, Google Earth, and Tennessee crash reports. Newly coded variables were integrated with existing incident variables, and a unique database was created. Potential relationships between incident duration and multiagency response variables can be causal or noncausal. For example, the shorter response time of ambulances may be associated with the reduced duration of an incident, whereas use of a towing service may be associated with longer-duration incidents. However, this association does not mean that the use of a towing service caused the incident to be longer. It may be that towing services were likely

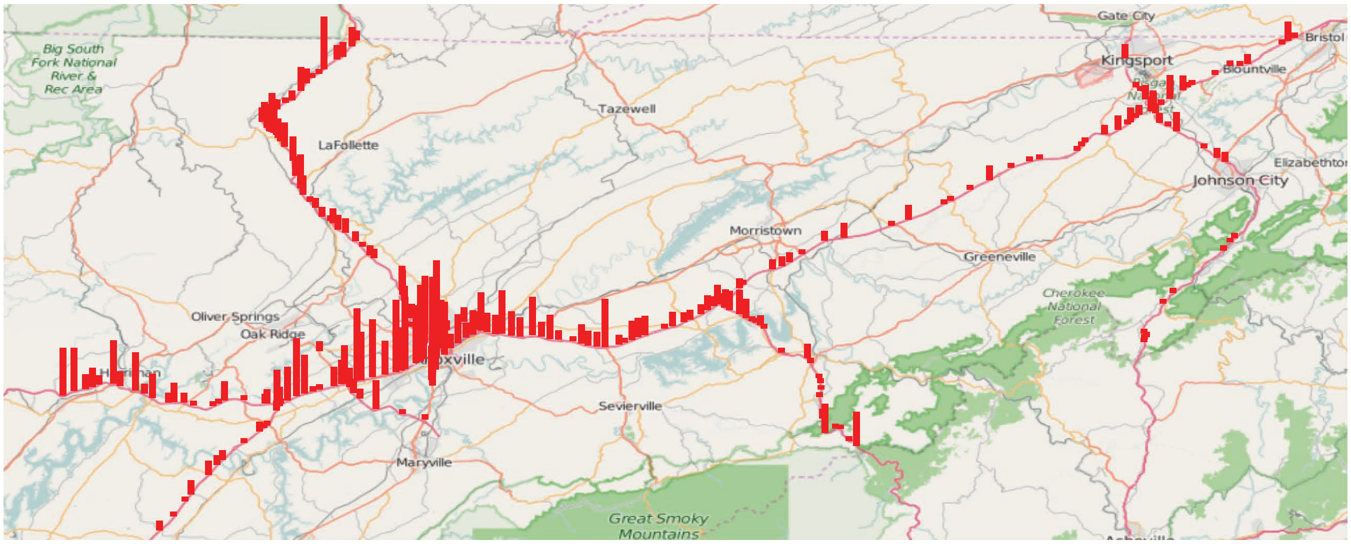

FIGURE 1 Spatial distribution of large-scale incidents within Tennessee DOT Region 1.

to be used for longer-duration accidents. These relationships were investigated further in the study.

Bidirectional relationships may exist between incident duration and response time as opposed to the unidirectional relationships assumed in this study. Specifically, response times of various agencies were assumed as correlates of incident duration, but it is also possible that incident managers may respond more promptly to longer-duration incidents. This response time may show up as a negative correlation between response times and incident durations, indicating that potentially longer incident durations can be a predictor of an agency's response time. This simultaneity issue was recognized. However, capturing simultaneity through modeling was not done because of a large number of

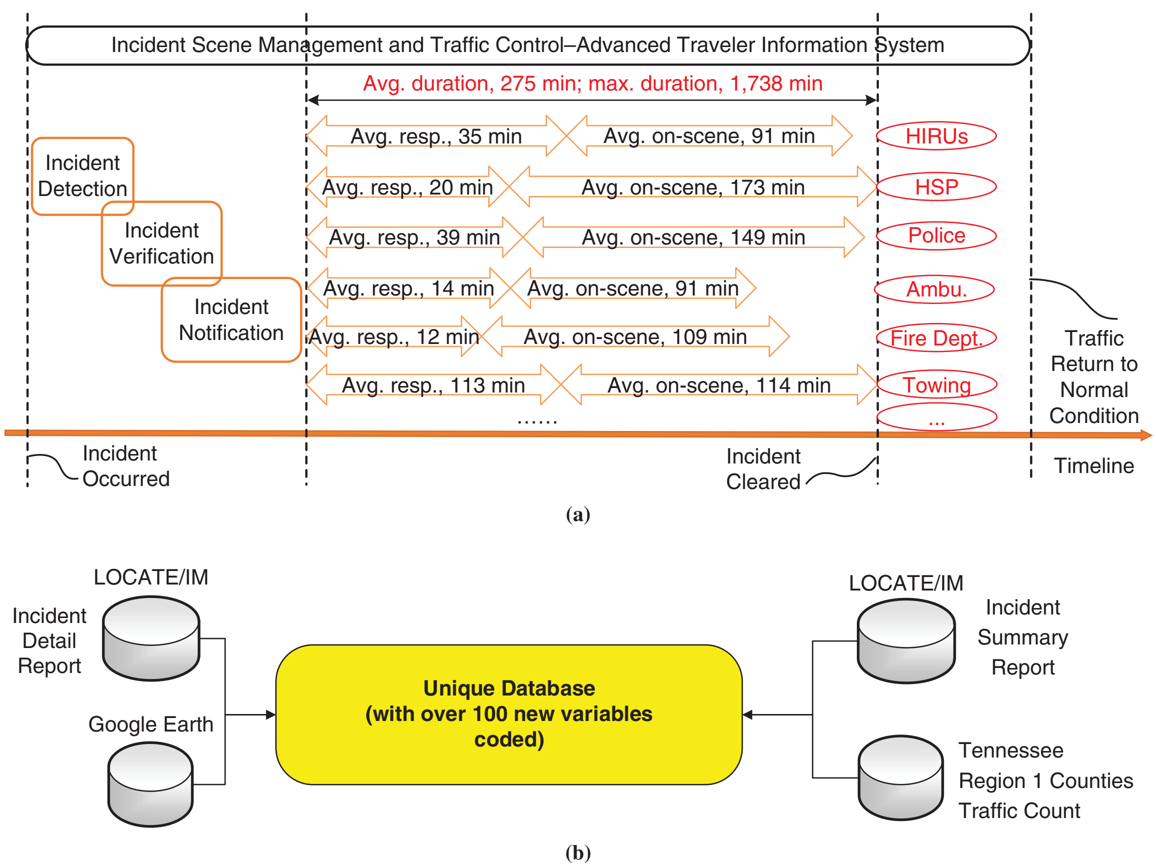

FIGURE 2 Critical traffic incident management components and framework of data integration source (resp. = response; HIRU = highway incident response unit; HSP = highway safety patrol; ambu. = ambulance; dept. = department).

missing values for response times of different agencies. For example, the response time of the first HIRU was available for only 44.2% of the sampled large-scale incidents (Table 1). In addition, the modeling would be complicated by the presence of several response times, given that multiple agencies are often involved. Nevertheless, it will be valuable to investigate the bidirectional relationships between incident duration and response time by using a simultaneous multiequation modeling framework.

Incident Duration Modeling

The hazard-based modeling approach is adopted in this study on the basis of theoretical and empirical criteria. First, numerous researchers have used this technique for modeling durations (*6, 21*). Second, incident durations are time dependent, for which this approach is particularly suitable. Third, the hazard-based approach facilitates interpretation of duration data by using a dynamic sequence of conditional probabilities. The hazard-based modeling approach is described as follows.

T is a nonnegative random continuous variable representing duration of an incident. The hazard at time t on the continuous time scale is denoted $h(t)$, and it is defined as the instantaneous probability that the incident duration will end in an infinitesimally small time Δt after time t, given that the incident duration has already lasted until time t. This concept is referred to as "duration dependence." The precise mathematical definition for $h(t)$ with regard to probability is

$$h(t) = \frac{\lim_{\Delta t \to 0^+} \Pr\left(t \le T < t + \Delta t | T > t\right)}{\Delta t} \tag{1}$$

This mathematical form makes it possible to relate the hazard to the probability density function and the cumulative distribution

TABLE 1 Descriptive Statistics of Variables Associated with Large-Scale Incidents

Variable	Sample Size	Mean	SD	Min.	Max.	VIF
Incident duration (min)[a]	890	274.90	199.22	121	1,738	na
Incident type						
Multivehicle crash	890	0.316	0.465	0	1	1.246
Vehicle fire	890	0.079	0.271	0	1	1.109
Unscheduled roadwork	890	0.128	0.334	0	1	1.265
Temporal factor						
Afternoon peak	890	0.228	0.419	0	1	1.08
Weekday	890	0.794	0.404	0	1	1.048
Traffic volume: AADT (log form)	890	11.057	0.553	10.087	12.162	0.112
Operational response						
Response time of first HIRU	394	1.18	2.928	0.033	30.033	1.364
Response time of second HIRU	245	2.585	6.358	0.033	60.133	1.559
Average response time if three or more HIRUs responded	75	4.498	6.789	0.166	44.133	1.624
Response time of HSP	102	0.668	1.165	0.032	5.266	1.32
Response time for police	232	1.3011	8.874	0.033	132.8	6.405
Response time for ambulance	130	0.473	0.886	0.0333	5.7	1.283
Response time for towing company	229	3.761	9.389	0.033	132.8	7.237
Average on-scene time for HIRU	432	3.026	3.434	0.0333	27	1.607
On-scene time for HSP	95	5.775	6.007	0.1	36.033	2.138
On-scene time for police	226	4.951	5.17	0.033	49.3	1.893
On-scene time for ambulance	120	3.026	4.466	0.033	29.533	2.047
On-scene time for towing company	219	3.812	5.231	0.033	29.4	2.032
Indicators for missing values of response and on-scene times of different agencies						
Indicator variable for first HIRU	890	0.556	0.497	0	1	2.051
Indicator variable for second HIRU	890	0.723	0.447	0	1	2.095
Indicator variable for third or more HIRUs	890	0.915	0.277	0	1	1.85
Indicator variable for HIRU average on-scene time	890	0.514	0.5	0	1	1.32
Indicator variable for HSP	890	0.885	0.318	0	1	1.972
Indicator variable for police	890	0.739	0.439	0	1	2.538
Indicator variable for ambulance	890	0.853	0.353	0	1	2.209
Indicator variable for towing company	890	0.742	0.437	0	1	2.877
Other deployed resources						
Response time for hazardous material	14	2.233	2.301	0.0333	7.933	8.369
On-scene time for hazardous material	13	3.674	2.934	0.067	10.1	6.176
Number of HAR deployed	705	2.850	1.806	1	8	96.25
Average HAR deployment time	685	7.370	10.20	0.000	76.533	63.78
Number of DMSs deployed	751	2.500	2.024	1	26	1.938
Average DMSs deployment time	743	6.547	7.735	0.0000	108.13	96.02

NOTE: All response, on-scene times and deployment time are scaled in 30 minutes. VIF = variance inflation factor; na = not applicable.
[a]10th percentile is 132 minutes, 25th percentile is 152 minutes, 50th percentile is 203 minutes, 75th percentile is 321 minutes, and 90th percentile is 497 minutes.

function for T. Specifically, the probability that the incident does not elapse before time t is $F(t) = \Pr(T < t)$. The probability that the duration will terminate in an infinitesimally small time Δt after time t is $f(t) = dF(t)/dt$. So the survival function, which gives the probability that an incident has a duration greater than or equal to t, is $S(t) = \Pr(T \geq t) = 1 - F(t)$. Thus the hazard can be reformulated as

$$h(t) = \frac{F(t)}{S(t)} \tag{2}$$

If the hazard function slopes upward, $dh(t)/dt > 0$ at time t, the function will have positive duration dependence; this function means that the probability that the incident will end soon increases as the incident duration lasts. Otherwise, it is negative duration dependence. If $dh(t)/dt = 0$, the probability is independent of incident duration. Therefore, the shape (the underlying distribution of the hazard function) has important implications for duration dynamics, because an incorrect specification may result in severe biases when quantification of factor effects is attempted. Three distributions—log normal, log logistic, and Weibull—are employed to study extreme values that match the intention of large-scale incidents and to find the best fit using maximum likelihood for fixed parametric models. To explore the effect of exogenous variables on incident duration, fixed and random-parameter, hazard-based models are employed to accommodate the effect of external covariates on hazard at any time t. The proportional hazard form and the accelerated failure time form are two alternatives. Previous research has revealed no strong theoretical or empirical argument to choose one over the other. Because accelerated failure time assumes that covariates rescale time directly, it is more favored. It can capture the direct effect of exposure on survival time and provide more easily interpretable parameters and a linear relationship between the logarithm of duration and covariates. The accelerated failure time equation is written as follows:

$$\ln(T) = \beta X + \varepsilon \tag{3}$$

where

β = coefficient vector of covariates,
X = covariates, and
ε = error term.

Since the data are truncated, left-truncated hazard-based models are estimated based on work by Zhang et al. (*3*) with 120 as the truncation point. To overcome potential issues that erroneous inferences may occur if incident duration is not homogeneous across observations, two options are available. First, the gamma distribution can be applied to incorporate heterogeneity in the Weibull model with mean 1 and variance θ. Second, a prespecified distribution can be assumed to incorporate unobserved heterogeneity, allowing the parameters to change over observations. Random parameters are estimated in the hazard-based models by adding a randomly distributed term. A normally distributed $\sim N(0, \sigma^2)$ term is added to the original β, and simulation-based maximum likelihood using Halton draws is applied to estimate random-parameter incident duration models (*22*). Finally, nine models are estimated by using the maximum likelihood or simulated maximum likelihood methods. These models are fixed- and random-parameter, hazard-based models with and without truncation based on log normal, log logistic, Weibull, and Weibull with gamma heterogeneity distributions.

ANALYSIS RESULTS

The data were error checked, and some of the observations with unreasonable duration were excluded. Based on the 890 large-scale incident observations, Tennessee DOT Region 1 averages about one large-scale incident every other day.

Descriptive Statistics

Table 1 presents descriptive statistics showing that the mean duration of the large-scale incidents is 275 min, which is 129% larger than the mean duration of all incidents in the database. Almost 10% of the large-scale incidents last more than 497 min. Descriptive statistics of key variables (of all variables in Figure 2) are also shown including multiagency responses and incident types. The resulting 890 large-scale traffic incidents exhibit a dispersed distribution with average duration of 275 min and maximum duration of 1,738 min. Multivehicle crashes, vehicle fires, and unscheduled roadwork incidents account for 32%, 8%, and 13% of the total large-scale incidents sample, respectively (of the 17 incident types, outliers are removed and these three types show their significance in the model). Approximately 23% of the incidents occurred during the afternoon peak (4:00 to 8:00 p.m.), whereas 80% of the large-scale incidents occurred on weekdays.

Importantly, the data on response and on-scene times of different agencies are compiled and used in the analyses. These data for different agencies had a substantial number of missing values and were not available for all coded large-scale incidents. As such, to utilize the available information on key operational variables without losing significant data, indicator variables were created for the missing values of response and on-scene times of the different agencies (*23*). For example, response times for the HSP are available for 102 large-scale incidents. Thus, an indicator variable was created for the HSP that equals 1 if the response time is missing and zero otherwise. In the LOCATE/IM detailed operational reports, agency on-scene times at specific incident scenes may not be available for all cases in which a specific agency responded. To illustrate this factor, the HSP response to 102 incidents for which response times are available was considered. However, the on-scene times are available for only 95 incidents to which the HSP responded. Keeping in view the negligible differences between sample sizes of response and on-scene times of the same agency and to avoid collinearity issues among different variables, single indicator variables were created for both missing response and on-scene times of a specific agency and were used in subsequent analyses. Separate indicator variables for response and on-scene times were considered and used in the modeling process. However, the estimation results were not significantly different from those using single indicator variables for both response and on-scene times and thus they were removed from the final models for ease of discussion and interpretation.

Regarding multiple agency responses to large-scale incidents, HIRUs and the HSP and police, ambulance, and towing companies are the main agencies observed in detailed Tennessee DOT operational reports. HIRUs are Tennessee DOT trucks equipped with recovery tools for response to traffic incidents, and Tennessee HSPs are police units responsible for enforcement and accident investigations, reports, and so forth. For HIRUs, the operational reports provide information about response times (first, second, and third units, and so on). However, average response times of three or more than three HIRUs are reported in Table 1 because of the small sample size.

Likewise, response times (in 30 min) are reported for the HSP, police, ambulance, and towing company. Overall, the descriptive statistics for response and on-scene times of different agencies spot important patterns embedded in the data.

In detail, Table 1 shows the average response times for first, second, and more than two HIRUs are 35.4 (1.18 * 30), 77.5 (2.58 * 30), and 134.9 (4.49 * 30) min, respectively. The longer response times for a greater number of HIRUs may reflect the severity of large-scale incidents. Intuitively, among other response agencies, the ambulance has the shortest average response time (14 min) followed by the police (39 min). The response time for towing companies is highest with an average response time of approximately 112 min and a maximum response time of approximately 217 min. With regard to on-scene times, on average, the HSP and police spend the greatest amount of time (173 and 148 min, respectively) at large-scale incident scenes, whereas for towing company it is 114 min and for HIRUs, 90 min. Notably, only 1.6% of the large-scale incidents involved hazardous materials, and the mean response and on-scene times for the hazardous materials removal agency were 54 and 110 min, respectively. Regarding dissemination of incident information to the public through HAR and DMSs, these media are heavily used during large-scale incidents, as expected. Specifically, HAR and DMSs are used in 84.6% and 92.3% of the large-scale incidents, respectively. On average, 2.27 HARs are used for 148 min, whereas 2.11 DMSs are used for 156 min.

For modeling, because of several explanatory variables, it is suspected that multicollinearity may affect modeling results if not addressed properly. As such, VIFs are reported in Table 1 for key variables. It can be seen that these values for key explanatory variables are less than 10; this finding indicates that multicollinearity is not a concern (*10*).

Model Selection and Performance Comparison

Before incident duration models were estimated, potential explanatory variables were identified by developing simple correlation matrices and ordinary least squares regression models (*24*). This development helped in the identification and conceptualization of explanatory variables. Next, a series of fixed-parameter, accelerated failure time, hazard-based duration models were developed. Following Washington et al., different distributions were tested such as log normal, log logistic, Weibull, and Weibull with gamma heterogeneity distributions (*24*). All the variables shown in Table 2 were included in the models. The fixed-parameter, hazard-based duration models were developed by using standard maximum likelihood estimation techniques. For brevity, only the final summary statistics (goodness-of-fit measures) are presented in Table 2. To compare the fixed-parameter models with different distributional assumptions, likelihood ratio statistics were calculated in order to select a statistically superior model (*25*). For details regarding likelihood ratio statistics, readers are referred to the work of Washington et al. (*24*).

A higher value of likelihood ratio statistics for a specific model indicates an improved statistical fit to the data at hand compared with other fixed-parameter models (*24*). It can be seen that the Weibull model resulted in the best fit among all other fixed-parameter models with the highest likelihood ratio statistic of 449.48. In the Weibull model, the P parameter (2.08) was greater than 1 and statistically significant; this finding indicates that the hazard is monotone increasing in duration (*24*). Truncated hazard-based duration models were also developed with log logistic, log normal, Weibull, and Weibull with gamma heterogeneity distributions. However, the estimation results were approximately similar in terms of parameter estimates and likelihood ratio statistics (results can be requested from the authors). Thus, the models with no truncation (for simplicity) are presented and discussed next.

Given that several observed and unobserved factors can contribute to large-scale incident durations, random parameters were incorporated in fixed-parameter, Weibull hazard-based duration models. Conceptually, random-parameter models provide the flexibility to allow parameter estimates to vary across sample observations with some prespecified distribution (*24*). As such, the random-parameter Weibull model was estimated to allow parameter estimates to vary across observations. The goodness-of-fit measures indicate statistically significant superior performance with the highest likelihood ratio statistic of 831.02.

The results of the fixed- and random-parameter Weibull models are presented in Table 3. The final random-parameter model includes 26 correlates (including indicator variables for missing data), of which seven parameters exhibited statistically significant variability (as indicated by the standard deviation of the parameter estimates for random parameters) across the large-scale incidents. For random parameters, different distributions are tested such as the normal, uniform, Weibull, and tent distributions, with normally distributed random parameters having the best fit. This finding is in agreement with several studies that focused on non-large-scale incident duration modeling (*11, 21*).

TABLE 2 Summary Goodness-of-Fit Measures for Hazard-Based Duration Models

	Fixed Parameters				
Performance Index	Lognormal	Log Logistic	Weibull	Weibull with Gamma Heterogeneity	Random Parameter Weibull
Theta	na	na	na	6.97*	na
Sigma	0.232*	0.243*	0.48*	0.068*	0.12*
P	4.3*	4.1*	2.08*	14.52*	8.33*
logL(0)	−695.16	−691.24	−880.65	−457.79	−880.65
logL(β)	−480.99	−478.12	−655.91	−426.72	−462.14
Number of observations	890	890	890	890	890
Likelihood ratio statistics	428.3	426.24	449.48	62.14	831.02

NOTE: Theta = heterogeneity parameter; na = not applicable; *shows statistically significant estimates at 99% level of confidence; P = hazard distribution parameter; logL(0) = log likelihood of constant only model; and logL(β) = log likelihood at convergence.

TABLE 3 Model Estimation Results for Fixed- and Random-Parameter Models

	Fixed-Parameter Weibull[a]		Random-Parameter Weibull[a]		
Variable	Parameter	*t*-Stat.	Parameter	*t*-Stat.	% Changes[b]
Incident type					
Multivehicle crash	−0.159	−4.52	−0.138	−14.13	−12.90
Vehicle fire	0.092	1.6	0.16	10.28	17.30
Unscheduled roadwork	0.4	11.7	0.28	20.59	32.30
Temporal factors					
Afternoon peak	−0.007	−0.24	−0.021	−2.14	−2.08
SD	na	na	0.173	18.24	na
Weekday	−0.052	−1.41	−0.037	−3.61	−3.64
SD	na	na	0.07	15.36	na
Traffic volume					
AADT (log form)	−0.1	−2.26	−0.062	−6.48	−6.01
SD	na	na	0.021	27.39	na
Operational response					
Response time of first HIRU[c]	0.028	1.28	0.028	13.14	2.83
Response time of second HIRU[c]	0.03	6.23	0.016	12.57	1.61
Average response time: third or more HIRUs[c]	0.061	7.64	0.042	18.94	4.28
Response time of HSP[c]	−0.017	−0.27	0.039	3.62	3.90
Response time for police[c]	−0.021	−2.28	−0.025	−11.86	−2.50
Response time for ambulance[c]	−0.003	−0.05	−0.028	−2.29	−2.77
SD	na	na	0.017	1.98	na
Response time for towing company[c]	0.029	3.53	0.032	15.57	3.25
Average on-scene time for HIRU[c]	0.042	4.23	0.044	23.93	4.40
On-scene time for HSP[c]	0.012	1.22	0.005	2.01	0.50
SD	na	na	0.002	1.73	na
On-scene time for police[c]	0.014	2.9	0.01	8.01	1
On-scene time for ambulance[c]	0.005	0.33	0.013	4.3	3
On-scene time for towing company[c]	0.045	4.3	0.047	26.14	4.80
Dummies for missing values of response and on-scene times of different agencies (1 if response or on-scene time is missing, 0 otherwise)					
Dummy variable for first HIRU	−0.019	−0.21	−0.041	−2.57	na
SD	na	na	0.099	12.66	na
Indicator variable for second HIRU	0.138	1.86	0.081	5.81	na
Indicator variable for third or more HIRUs	0.053	0.45	0.043	2.06	na
Indicator variable for HIRU average on-scene time	0.249	2.49	0.195	10.34	na
Indicator variable for HSP	0.001	0.03	0.054	3.05	na
Indicator variable for police	0.004	0.07	0.006	0.47	na
Indicator variable for ambulance	0.095	1.01	0.064	3.66	na
Indicator variable for towing company	0.311	4.78	0.281	17.98	na
SD	na	na	0.071	7.73	na
Constant	6.03	10.8	5.56	46.81	

[a]Dependent variable is log of incident duration in minutes.
[b]Percentage changes in incident duration with respect to unit changes in each explanatory variable; zero to one for binary variables, one-unit increase or decrease in logarithm for log-transformed variables, and 30 min increase for response and on-scene times.
[c]Response and on-scene times scaled in 30 min for ease of interpretation.

Finally, the distributions of normally distributed random parameters are shown in Figure 3.

Key Findings

Table 3 presents the fixed- and random-parameter Weibull model for large-scale traffic incidents. A positive parameter estimate for an explanatory variable correlates with an increase in incident duration or decrease in hazard function with a unit increase in the value of the explanatory variable and vice versa for negative parameter estimates. To obtain deeper insights, the exponents of the parameter estimates in Table 3 translate to the percentage increase or decrease in large-scale incident durations as a result of a unit change in the explanatory variables. As such, the percentage changes in incident durations associated with a unit increase in explanatory variables are given in Table 3 for the random-parameter Weibull model. For response and on-scene times, the percentage changes show the percentage increase or decrease in large-scale incident duration for each 30-min increase in response or on-scene times. For indicator variables, the model translates the percentage change in large-scale incident durations when the indicator variable changes from zero to 1 (footnotes to Table 3).

Regarding the estimation results shown in Table 3, the response and on-scene times of different agencies are observed to play an important role in the determination of large-scale incident durations, whereas hazardous materials, HAR, and DMSs were not found to be statistically significant. The associations between the response and on-scene

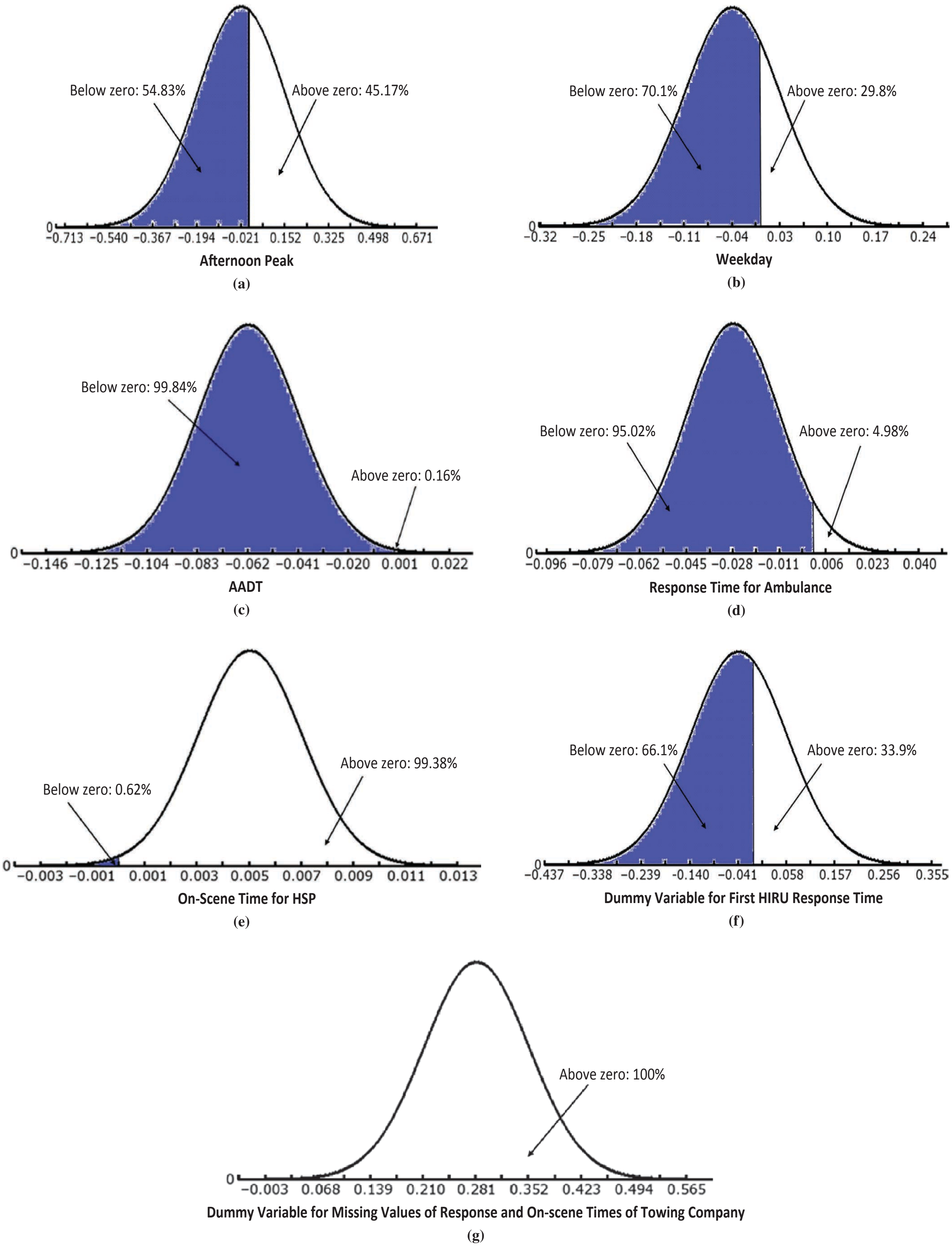

FIGURE 3 Distribution of normally distributed random parameters.

times of different agencies (except the response time for ambulances and on-scene time for the HSP) and large-scale incident durations are fixed across incident observations; that is, the parameter estimates did not vary across incidents. However, incorporation of random parameters significantly enhanced the statistical significance of the parameter estimates. For instance, a 30-min increase in response time for the first, second, and third HIRUs (or more) (averaging the third, fourth, fifth, or sixth units, if they responded and data are available) translates to 2.83%, 1.61%, and 4.28% increases in incident durations, respectively. The mean incident duration is 338 min for the response of the third or more HIRUs, and the mean response time is 135 min. This finding is important since it suggests that the association of the response times for the third or more HIRUs is more pronounced compared with the response times for the first or second HIRUs on incident duration. This finding seems intuitive in the sense that three or more HIRUs may respond to large-scale incidents that are excessively severe, and an increase in response times at this point is likely to result in even longer incident durations.

Likewise, an increase of 30 min in response times of the HSP and towing company is associated with 3.9% and 3.25% increases in large-scale incident duration. This finding is understandable since the HSP and towing company may be required to undertake specific operations at the incident scene, and an increase in response times of these agencies (specifically the towing company) may delay the operations of other agencies. This finding is in agreement with findings by Hojati et al., who found a positive correlation between the indicator variable for towing and the non-large-scale incident duration (*11*).

An increase in response times for the police department and ambulance is associated with 2.5% and 2.7% shorter incident durations, respectively, contrary to expectations. However, it is possible that responses by police and ambulance to larger incidents in the database are quicker, whereas responses to shorter-duration incidents may be relatively slower. This finding may result in the unexpected direction of the correlation observed. Even if an incident is large in scale, the ambulance department may respond more slowly if no severe injuries are reported. Notably, a longer response time by police or ambulance itself does not indicate a reduction in incident duration. It is also possible that efficient responses and operations of other agencies may have resulted in the reduction of incident durations. In Figure 3, the response times for ambulances are found to be a normally distributed random parameter, implying significant heterogeneity (on average 95.02% of the distribution is less than zero and about 4.98% is greater than zero) in associations between ambulance response time and incident duration.

The analysis explicates the associations between large-scale incident durations and on-scene times of different agencies. For instance, a 30-min increase in average on-scene time for a HIRU translates to 4.4% increase in incident duration. Likewise, a 30-min increase in on-scene time for the HSP, police, ambulance, and towing company is associated with 0.5%, 1%, 3%, and 4.8% longer incident duration, respectively. However, the on-scene time for the HSP is a normally distributed random parameter implying heterogeneity in the magnitude of associations, although the direction of the association is positive for 99.3% of observations (Table 3, Figure 3). These findings do not imply causation in the sense that agencies may have to stay longer at large-scale incident sites to respond to injuries, remove damaged vehicles, clear debris, manage traffic at the scene, and more. Large-scale incidents may last even longer if the agencies do not respond or stay.

Finally, the vehicle fire and unscheduled roadwork incident types are associated with 17.3% and 32.3% increases in large-scale incident durations, respectively. Incidents in the afternoon peak are associated with relatively shorter durations. However, the associations vary substantially across observations: they are positive for 45.1% and negative for 54.9% of the data (Figure 3). Likewise, large-scale incidents during weekdays are on average associated with shorter durations; again this finding is a normally distributed random parameter with significant heterogeneity (mean of −0.037 and standard deviation of 0.07) (Table 3, Figure 3). Regarding traffic characteristics, the results suggest that incidents on roadways with higher AADT are relatively shorter; a unit increase in the log of AADT is associated with an approximately 6% reduction in incident duration. Roadways with higher volumes may receive higher priority, more resources, and quicker response times. These findings are generally in agreement with those from the study by Zhang et al., focusing on large-scale incidents on urban freeways in Virginia (*3*). The indicator variables for missing data are statistically insignificant; this finding implies that missing values are randomly distributed, which is the case for most indicated variables.

CONCLUSIONS

This study contributed by creating a unique incident database to investigate and analyze large-scale incidents and focus on the role of multiagency operational responses. The study identified large-scale traffic incidents and their correlates while accounting for unobserved heterogeneity. Before large-scale incidents were investigated empirically, significant effort went into assembling the database from different sources including Tennessee DOT SmartWay, LOCATE/IM, and Google Earth. Then the in-depth investigation of large-scale incidents and the association of incident duration with the operational response and on-scene times of different agencies was able to be conducted.

To conceptualize and quantify the associations between large-scale incident duration and associated factors, hazard-based duration models with different distributional assumptions were developed. Methodologically, this study contributed by addressing unobserved heterogeneity in large-scale duration modeling through estimation of random-parameter, hazard-based duration models. Among all competing models, the random-parameter Weibull model was observed to be the most suitable from a statistical perspective. The final model quantified associations between large-scale incident durations and several explanatory factors, of which seven variables exhibited statistically significant heterogeneity across observations. The key findings are as follows:

- Of 129,088 traffic incidents in Tennessee DOT Region 1 that occurred during 2010–2015, large-scale incidents constitute 0.69%, which requires significant response resources.
- A 30-min increase in response time for Tennessee DOT's first, second, and third or more highway HIRUs translates to a 2.83%, 1.61%, and 4.28% increase in large-scale incident duration. This is an important finding since it suggests that the association of response times for the third (or more) unit is more pronounced as compared with those who respond earlier to large-scale incidents. An increase of 30 min in response time of the HSP and towing company is associated with a 3.9% and 3.25% increase in large-scale incident duration, respectively.
- Of large-scale incidents, those involving a vehicle fire or unscheduled roadwork are likely to last longer on average. Large-scale incidents on weekends—not during the afternoon peak hours—and on lower-AADT roads last relatively longer; however, the magnitude (in some cases direction) of associations is heterogeneous.

The results obtained from this study have several implications for large-scale incident management. The findings suggest that a reduction in response times for HIRUs and the HSP could significantly reduce large-scale incident duration. Specifically, the reduction in response time for the third (or more) HIRU unit (when needed) could potentially reduce the duration of a large-scale incident. However, it may be difficult to find additional units. Segments such as I-40 and I-75 near urban areas are identified as high-risk segments. Incident managers could also potentially reduce incident duration by working with towing companies to perhaps respond more quickly in large-scale incidents. As such, facilitating close coordination between different response agencies and companies could enhance response resource deployment, if required. Researchers could extend the methodology proposed to other locations to further explore practical solutions for mitigating negative consequences of large-scale incidents. Future research on incident duration management could use a case-based approach in which individual large-scale incidents are analyzed to obtain insights on how operations could be improved through better coordination. Also, hazardous material incidents, route diversion and detour management, and spatial analysis need to be investigated further on the basis of additional information obtained from other databases maintained by various response agencies.

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