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Research Article

Evaluating the Impact of Freeway Service Patrol on Incident Clearance Times: A Spatial Transferability Test

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Freeway service patrol (FSPs) programs have been considered as an effective tool for traffic incident management in minimizing the adverse effects of traffic incidents. In this study, random parameters hazard-based duration modeling method was used to evaluate the impact of the newly implemented Alabama Service and Assistance Patrol (ASAP) program, using incident clearance time as a performance measure. It was determined that there is a statistically significant difference in the factors that influence incidents clearance times between incidents that occurred inside and outside the ASAP regions. A total of five variables (on-road, nighttime, peak hours, rain, and fire response present) were observed to have random effects along with ten fixed effects variables on incidents occurring inside the ASAP regions. On the other hand, incidents that occurred outside the ASAP regions were found to have three random effects variables (on-road, nighttime, and fire response present) and seven fixed effects variables. The estimation results indicate a significant association of incident clearance times to incident related variables such as involvement of CMVs, fatality, vehicle towing, seat belt indicated as involved, and on-road incidents that occurred both inside and outside the ASAP regions. The results also reveal that incident clearance times are influenced strongly by temporal variables (e.g., nighttime), traffic factors (e.g., AADT), and operational variables (e.g., fire response present) for incidents both inside and outside the ASAP area models. Overall, it was observed that the incident clearance times recorded in the regions where the ASAP program is in effect are significantly different. The findings of this study are expected to be useful for the state traffic incident management (TIM) agencies in developing and executing strategies to minimize incident clearance times. Ultimately, the study provides a data-driven evidence-based assessment of the ASAP program in the state.

1. Introduction

Nonrecurrent traffic incidents cause acute traffic congestion which can lead to secondary crashes, travel delay, excessive fuel consumption, vehicle emissions, air pollution, and social and economic insufficiency [1, 2]. To mitigate the negative effects of nonrecurrent incident related congestion, many major cities have adopted intelligent transportation systems (ITS) in their incident management plans [3–5]. Traffic incident management (TIM) requires the coordination and cooperation among different agencies, including fire and rescue, hazardous material response, towing and recovery, law enforcement, emergency medical services and freeway service patrols (FSPs) for quick and efficient detection, verification, response, and clearance of the incidents [6–8]. As one of the most popular and efficient TIM programs, FSPs can improve traffic conditions, and hence traffic safety by decreasing the incident duration through quicker response [9, 10] as well as reducing the possibilities of consequences of traffic incidents, such as secondary crashes [11].

FSP programs use roving vehicles, usually and specially equipped pick-up or tow trucks, to provide several types of assistance to motorists [1]. Typically, these vehicles are assigned to patrol higher traffic volume areas such as freeways and provide services such as removing obstructions (e.g., abandoned vehicles and debris), extinguishing fires, providing emergency gas and mechanical services to disabled vehicles, and providing emergence medical service [12]. FSP programs are also intended to reduce incident durations by detecting, responding, and clearing traffic incidents quickly and timely in cooperation with other emergency agencies [6, 9]. Additionally, these programs help provide real-time traffic status to motorists through variable massage signs (VMSs) and traffic apps [2, 13].

The Alabama Department of Transportation (ALDOT) operates FSP programs, referred to as the Alabama Service and Assistance Patrol (ASAP), in conjunction with its Traffic Management Centers (TMCs). Currently, the ASAP program is the only FSP program in the state and monitors and covers the regions around four major cities in the State (Montgomery, Mobile, Birmingham, and Tuscaloosa). The goals of the ASAP program are to restore mobility by reducing incident durations and to eliminate the adverse effects of traffic incidents [14].

This paper uses a random parameter hazard-based duration modeling method to investigate the impact of the ASAP program on incident clearance times. Freeway traffic crash incidents that occurred within and outside program coverage areas were obtained and the factors that influenced clearance times of were examined to identify the contribution of the ASAP program. To assess the effectiveness of the ASAP program, incidents that occurred outside the coverage area were also analyzed to serve as baseline condition for comparison. The findings of the study will be useful for the traffic management agencies in developing and executing strategies to minimize incident clearance times.

2. Review of Previous Studies

Over the past several decades, there have been many previous studies to evaluate the effectiveness of FSP programs. For example, Latoski et al. [15] conducted a benefit-cost analysis of the FSP program, known as Hoosier Helper, operated by the Indiana Department of Transportation, and calculated the benefit-cost ratio based on the savings on delay caused by nonrecurrent congestion and vehicle operating cost, as well as reduction in secondary crashes. Hagen et al. [16] estimated the benefit-cost ratio for the Florida Road Ranger FSP program based on savings on vehicle delay and fuel consumption. Also, several other studies evaluated the benefit-cost ratio of FSP programs using simulation techniques. For example, Ma et al. [1] used a microscopic simulation software PARAMICS to estimate the benefits of FSP program by focusing on the reduction of roadway blockage and delays caused by crashes. Similarly, Chou et al. [17] used a different microscopic simulation tool, CORSIM, to evaluate the benefits of the Highway Emergency Local Patrol (HELP) operated by New York State, and estimated the benefit-cost ratio based on vehicle emission, fuel consumption, secondary incidents, and travel delay reduction. Li and Walton [18] used event-driven simulation model in estimating the benefit-cost ratio of Kentucky FSP program, known as Safety Assistance for Freeway Emergencies (SAFE) Patrol in low-traffic areas, and shown that event-driven simulation model is better than analytical model in terms of faster simulating speed, larger road network, and longer period of simulation. Zhang et al. [19] assessed the relationship between incident data sample sizes and the reliability of incident duration analysis models. They observed that the variation of estimated coefficients decreases as the sample size increases and becomes stabilized when the sample size reaches a critical threshold value. They recommended a sample size of 6,500 to be enough for a reliable incident duration model. Huang et al. [20] proposed a knowledge transferability analysis method, featuring an automated process to assess, select, and transfer existing prediction rules to perform incident duration estimate for new target highways in Maryland, USA. Zou et al. [21] proposed a Bayesian Model Averaging (BMA) to account for uncertainty by averaging all plausible models using posterior probability as the weight. They observed that the BMA approach provides a better prediction performance than the Cox proportional hazards model and the accelerated failure time models. Zhao et al. [22] explored an ensemble learning method based on multiple clustered individual models to provide good and diverse prediction performance for traffic incident models and they found that the ensemble model performs better than the traditional model with fixed clusters and the classical model without clustering.

FSP programs are generally considered to be an efficient low-cost approach of incident management and some past studies have assessed the effectiveness of FSP programs based on incident duration [18, 23, 24]. In an early study, Sullivan [25] developed a model called IMPACT in predicting nonrecurrent freeway incidents along with the associated vehicle delay based on traffic volume, freeway characteristics, and incident management with or without FSP in six different urban areas for both weekday peak and off-peak periods. Dougald and Demetsky [6] developed a deterministic queuing methodology to determine incident durations with or without FSP for Northern Virginia region and applied the results to quantify the benefits of FSP in association with reductions in motorist delay, fuel consumption, and emissions. Chou and Nichols [26] proposed a queuing technique in evaluating the safety impact of FSP program focusing on reduced incident duration. Karlaftis et al. [11] developed logistic regression models to evaluate the efficiency of Indiana's Hoosier Helper FSP program based on savings from reducing the probability of secondary crash occurrence and the findings showed that improvements can be made on road safety and cost-effectiveness of FSP program using the presented methodology. Salum et al. [2] developed a quantile regression model and showed that Florida Road Rangers response resulted in shorter incident clearance duration. Fries et al. [27] used PARAMICS as a traffic simulation tool to ultimately estimate the financial impact of quick-clearance legislation and compared it with other incident management strategies, such as FSP program, traffic cameras, and sensors.

Simulation modeling is used not only for evaluating the benefit-cost ratio of FSP program, but also for assessing the performance and overall operational impact of FSP programs. For instance, Pal and Sinha [23] developed a simulation model for evaluating FSP, Hoosier Helper program, and the results of this study showed that the existing FSP program can be improved by changing some specific parameters, including fleet size, area coverage, service hours, beat design, and dispatching policies. Wu et al. [24] used a discrete event-based simulation model for examining the performance of the existing FPS program and for planning new FPS program. Hadi at al. [9] developed a simulation tool to evaluate the performance of FSP program by changing incident durations in terms of delay, road safety, vehicular emission, fuel consumption, and dollar value, and the benefit-cost assessment proved that the developed model could help in planning FSP program by adjusting FSP operation parameters, such as number of beats and vehicles, area of operation, and hours of operation.

Although many previous studies have evaluated the performance of FSP program, very few studies have evaluated the impact of FSP program using incident clearance time as a key performance metric. Incident clearance time is an important measure of highway performance as it indicates how quickly the highway returns to normal performance after an incident. Programs such as freeway service patrol schemes have therefore been instituted to aid in incident identification and clearance efforts. While incident identification is the key to incident management, the time that it takes to clear the incident is perhaps a more appropriate measure of the performance of highway patrol programs. This study therefore makes a unique contribution to the body of work, by using a random parameter hazard-based duration model to evaluate the effects of the ASAP program by assessing the statistical significance in the differences of the factors that influence the clearance times for crash incidents that occurred in and outside of the ASAP coverage areas.

3. Data Description

In this study, a total of 2,206 crash incidents that occurred on Alabama freeways in 2018 were examined. The final data for the study was obtained by matching and merging four different datasets: freeway incident duration data from the Alabama Department of Transportation (ALDOT) Traffic Management Centers (TMCs), freeway crash data from the Center for Advanced Public Safety (CAPS) at the University of Alabama, traffic volume data from the Highway Performance Management System (HPMS), ALDOT, and ASAP data from ALDOT. The data was divided into two groups: incident occurring inside (76.16% of the total crash incidents) and incidents occurring outside (23.84% of the total crash incidents) of ASAP existing coverage in order to investigate whether there are any differences in the explanatory variables that influence incident clearance times. Figure 1 represents the current coverage of the ASAP program in the state of Alabama. In this study, incident clearance time was considered as dependent variable and

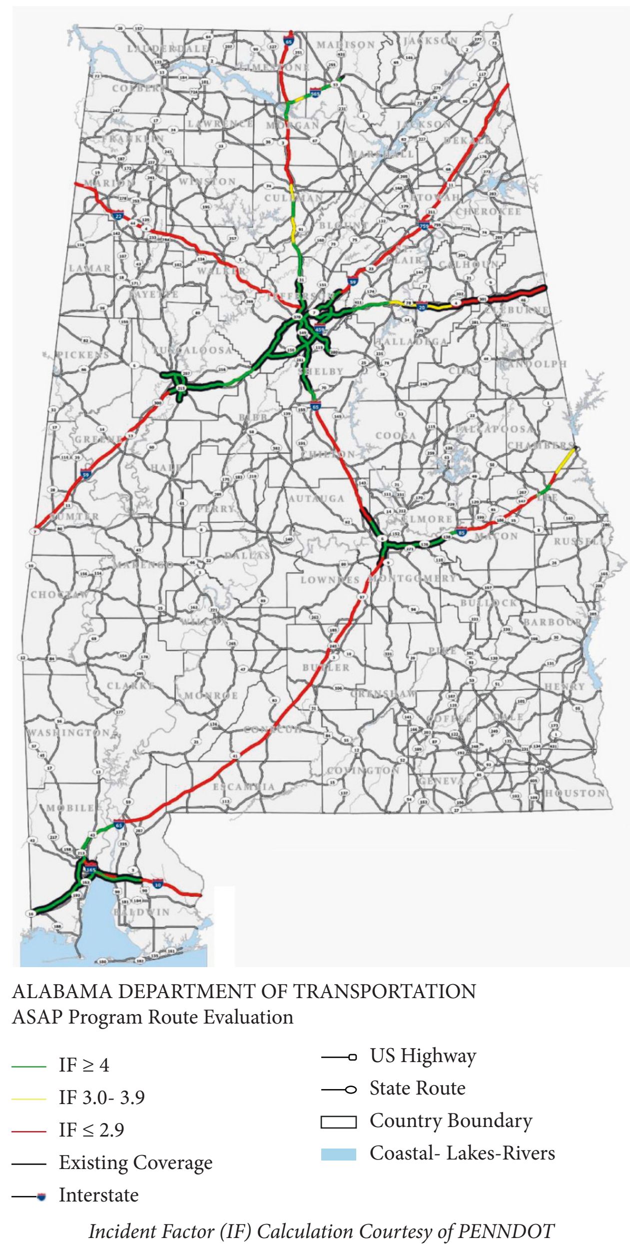

Figure 1: ASAP coverage area.

was defined as the time between the arrival of the first responder on the incident scene and the moment when the incident has been cleared from the freeway [28].

The descriptive statistics of the variables included in the random parameters hazard-based duration models are represented in Table 1. As shown in Table 1, average annual daily traffic (AADT), detection time (in minutes), and response time (in minutes) variables were considered as continuous variables, and the other remaining 18 variables were categorical. The average incident clearance time was 48 minutes and 74 minutes for inside and outside the ASAP existing coverage areas, respectively. Preliminary data analysis showed that the proportion of multivehicle crash incidents was higher inside the ASAP coverage area (75%) than the outside the ASAP area (55%). About 7% of incidents inside the ASAP area involved commercial motor

Table 1: Descriptive statistics of the variables included in the random parameters duration models.

Variables	Inside ASAP area (76.2%)		Outside ASAP area (23.8%)	
	Mean	Standard deviation	Mean	Standard deviation
Dependent variable				
Incident clearance time	47.823	38.447	74.131	55.197
Explanatory variables				
Incident characteristics				
Multiple vehicles involved in crash incident (1 if yes, 0 otherwise)	0.748	0.434	0.550	0.498
Commercial motor vehicle (CMV) involved (1 if yes, 0 otherwise)	0.066	0.248	0.097	0.296
Fatality involved (1 if yes, 0 otherwise)	0.005	0.069	0.032	0.177
Vehicle towed (1 if yes, 0 otherwise)	0.543	0.498	0.688	0.463
Seat belt indicated as involved (1 if yes, 0 otherwise)	0.815	0.388	0.848	0.359
On-road (1 if yes, 0 otherwise)	0.820	0.383	0.646	0.478
Overturn (1 if yes, 0 otherwise)	0.032	0.176	0.061	0.239
Collision type: rear end collision (1 if yes, 0 otherwise)	0.485	0.500	0.344	0.475
Temporal characteristics				
Nighttime (lighting condition at time of crash incident: 1 if yes, 0 otherwise)	0.274	0.446	0.280	0.449
Winter (incident occurred in month of December, January, or February: 1 if yes, 0 otherwise)	0.261	0.439	0.183	0.386
Peak hours (1 if incident occurred between 7 AM–9 AM and 4 PM–6 PM, 0 otherwise)	0.488	0.500	0.373	0.484
Environmental characteristics				
Rain (1 if yes, 0 otherwise)	0.156	0.363	0.173	0.378
Traffic characteristics				
Average annual daily traffic (AADT/1000)	87.634	27.309	46.658	18.776
One lane in the traffic way	0.013	0.113	0.008	0.087
More than two lanes in the traffic way	0.911	0.285	0.920	0.271
Less than four lanes in the traffic way	0.208	0.406	0.095	0.293
Operational characteristics				
Detection time (in minutes)	1.460	4.019	1.328	5.983
Response time (in minutes)	0.831	6.070	0.831	6.069
Police response present (1 if yes, 0 otherwise)	0.955	0.208	0.973	0.161
Fire response present (1 if yes, 0 otherwise)	0.326	0.469	0.283	0.451
Hazardous materials response present (1 if yes, 0 otherwise)	0.003	0.054	0.002	0.044

vehicles (CMVs), whereas 10% of incidents that occurred outside the ASAP region involved CMVs. Only 0.5% of incidents that happened inside the ASAP area recorded fatality, while fatality was recorded in 3.2% of incidents that occurred outside the ASAP area. Also, about 82% of incidents that recorded in the ASAP region occurred on-road, compared to 65% outside the ASAP area. The proportion of nighttime crash incidents was almost the same for inside (27.4%) and outside (28%) of the ASAP area. About 49% of incidents that occurred inside the ASAP area were recorded during peak hours (AM and PM), compared to 37% for outside the ASAP area. Crash incidents with police and fire response present were about 95.5% and 32.6%, respectively, for incidents that occurred inside the ASAP area, and these values were 97.3% and 28.3% of incidents that happened outside the ASAP area, respectively. The presence of hazardous material response was found in 0.3% of incidents that occurred inside the ASAP area and 0.2% of incidents outside the ASAP area.

4. Methodology

Previous studies have found various statistical modeling methods to be appropriate for examining incident clearance times. These models include simple regression models [29], switching regression models [30], quantile regression models [2, 31], hazard-based duration models [32–38], accelerated failure time (AFT) models [33, 39, 40], finite mixture models [41], generalized F distribution models [42], artificial neural network models [43], and Bayesian network models [44]. Hazard-based duration models have been found to be more appropriate in examining duration data [32, 45, 46]; therefore, in this paper, random parameters hazard-based duration models were employed to identify contributing factors of incident clearance time.

In studying incident duration data, the hazard-based duration models are employed to study the conditional probability of a time duration ending at some time t, given that the duration has continued until time t [46]. Since, in many instances, the probability of a duration ending is related to the length of the time in which the duration has lasted, the concept of probability of a duration ending is important [32]. In this study, the incident clearance time is a continuous random variable T, with a cumulative distribution function $F(t)$, which is also known as the failure function. Alternatively, the survival function, $S(t)$, is the probability of the duration being greater than or equal to some specific time t. Mathematically,

$$F(t) = P(T < t) = 1 - P(T > t) = 1 - S(t). \quad (1)$$

The hazard function $h(t)$ is the conditional probability that an incident will occur between time t and $t = dt$, given that the incident has not occurred up to time t [46] and is given by

$$h(t) = \frac{f(t)}{1 - F(t)}. \quad (2)$$

The slope of hazard function defines the dependence of the probability of a duration ending on the length of the duration. The hazard function can be decreasing with the incident clearance duration increasing $(dh(dt)/dt < 0)$, which indicates that the probability that an incident clearance duration will end soon decreases as the incident lasts longer. Conversely, the hazard function can be increasing as the incident clearance duration decreases $(dh(dt)/dt > 0)$, indicating the probability that an incident clearance duration will end soon increases as the incident lasts longer. If the hazard function has a slope of zero $(dh(dt)/dt = 0)$, it means that the probability in which an incident clearance duration will end soon is independent of the length of time in which the incident has lasted.

Proportional-hazard approach has been proven appropriate while examining the effects of the explanatory variables (i.e., covariates) on the incident clearance times, which act multiplicatively on some baseline hazard functions $h_0(t)$ [46, 47] and is expressed as

$$h(t|X) = h_0(t)e^{\beta X}, \quad (3)$$

where $e^{\beta X}$ represents the effect of explanatory factors on the hazard, X is the vector of external contributing factors, and β is the vector of estimable parameters.

Proportional-hazard functions can be applied using a variety of fully parametric models, including gamma, exponential, Weibull, and log-logistic [46]. Among all these distributions, the Weibull distribution is the most used parametric model in examining duration data, as this model form allows the hazard function to be monotonically increasing (the probability of an incident clearance duration ending decreases over time) or decreasing (the probability of an incident clearance duration ending increases over time) [32]. The Weibull distribution has the hazard function with parameters $\lambda > 0$ and $P > 0$ and is given by

$$h(t) = (\lambda P)(\lambda t)^{P-1}. \quad (4)$$

In hazard-based duration models, the typical proportional-hazard method is based on the assumption that the effect of any explanatory variable is homogeneous across observations. However, there is a possibility that the incident duration is not homogeneous across observations and this can lead to inaccurate model results. In order to examine the homogeneity assumption, a randomly distributed term is introduced in the duration models in a way that allows some (or all) of the model parameters to vary across observations [46, 48] and is expressed as

$$\beta_n = \beta + \omega_n, \quad (5)$$

where β_n is a vector of parameters that varies across n observations and ω_n is a randomly distributed term (e.g., normally distributed term with mean zero and variance σ^2). The random parameters incident clearance duration models are estimated by simulating the maximum likelihood using Halton draws, an efficient substitute to random draws [46].

In this study, likelihood ratio test was performed to determine if there is a difference in the model estimation based on whether incidents happened inside or outside of the ASAP existing coverage area as

$$\chi^2 = -2\left[LL(\beta_{\text{Total}}) - LL(\beta_{\text{in}}) - LL(\beta_{\text{out}})\right], \quad (6)$$

where χ^2 is a chi-squared distributed parameter with degrees of freedom equal to the total number of estimated parameters in both the inside and outside ASAP coverage area models minus the number of estimated parameters in the combined model. $LL(\beta_{\text{Total}})$ is the log-likelihood at convergence of the model estimated with all the data, $LL(\beta_{\text{in}})$ is the log-likelihood at convergence of the model estimated with the incidents that occurred inside ASAP coverage area, and $LL(\beta_{\text{out}})$ is the log-likelihood at convergence of the model estimated with the incidents that occurred outside the ASAP coverage area.

5. Estimation Results

A likelihood ratio test was conducted to justify the estimation of separate random parameters hazard-based duration models between inside and outside of ASAP regions. Using (6), the likelihood ratio was found to be 59.6 with 17 degrees of freedom and P-value <0.001. Therefore, the null hypothesis indicating that the models are statistically indistinguishable is rejected with 95% level of confidence. In other words, it is determined that two separate random parameters hazard-based duration models should be developed for incidents that occurred inside and outside of ASAP regions.

Before developing these two separate models, a combined model analysis was employed to identify statistically significant influential variables of incident clearance times on incident duration data in general. Table 2 represents the model estimation results of the three models along with the parameter estimate, t-statistics for significant variables, and the model parameters and the log-likelihood at convergence. The random parameters models were evaluated based on simulated maximum likelihood using 200 Halton draws for all three models [33, 49]. In order to capture unobserved heterogeneity, the random parameters duration models used continuous mixing distribution where the random parameters were normally distributed. All the explanatory variables were found to significantly affect the incident clearance time at 95% level of confidence. In interpreting the signs of the parameter estimate, a positive sign indicates decrease in the hazard function (since NLOGIT estimates the parameter vector as $-\beta$ instead of just β) and hence indicates increase in the incident clearance time, and a negative sign indicates an increase in the hazard function which means decrease in the

Table 2: Random parameters hazard-based duration model results.

Variables	Combined		Inside ASAP area		Outside ASAP area	
	Estimated parameter	t-statistic	Estimated parameter	t-statistic	Estimated parameter	t-statistic
Constant	4.167	64.07	3.843	51.42	4.302	29.11
Incident characteristics						
Multiple vehicles involved in crash incident (1 if yes, 0 otherwise)	0.154	4.28	0.211	4.90		
Commercial motor vehicle (CMV) involved (1 if yes, 0 otherwise)	0.397	8.70	0.437	8.20	0.413	4.43
Fatality involved (1 if yes, 0 otherwise)	0.818	7.52	1.106	5.06	0.617	4.41
Vehicle towed (1 if yes, 0 otherwise)	0.364	13.59	0.408	13.39	0.219	3.74
Seat belt indicated as involved (1 if yes, 0 otherwise)	−0.155	−5.00	−0.070	−1.96	−0.319	−4.54
On-road (1 if yes, 0 otherwise)	−0.190	−5.01	−0.247	−5.26	−0.090	−1.35
Standard deviation of normal distribution parameter	0.320	26.45	0.363	27.93	0.144	4.94
Overturn (1 if yes, 0 otherwise)			0.225	2.63		
Collision type: rear end collision (1 if yes, 0 otherwise)					0.161	2.59
Temporal characteristics						
Nighttime (lighting condition at time of crash incident: 1 if yes, 0 otherwise)	0.096	3.67	0.092	3.03	0.124	2.22
Standard deviation of normal distribution parameter	0.169	7.86	0.197	8.06	0.163	3.44
Winter (incident occurred in month of December, January, or February: 1 if yes, 0 otherwise)					0.194	3.05
Peak hours (1 if incident occurred between 7 AM–9 AM and 4 PM–6 PM, 0 otherwise)	−0.111	−4.65	−0.099	−3.68		
Standard deviation of normal distribution parameter	0.127	7.72	0.124	6.78		
Environmental characteristics						
Rain (1 if yes, 0 otherwise)	0.070	2.23	0.077	2.09		
Standard deviation of normal distribution parameter			0.270	8.27		
Traffic characteristics						
Average annual daily traffic (AADT)	−0.006	−14.33	−0.004	−8.44	−0.004	−2.27
Standard deviation of normal distribution parameter	0.002	14.26				
One lane in the traffic way			−0.265	−2.07		
More than two lanes in the traffic way					0.185	1.98
Less than four lanes in the traffic way	−0.110	−3.79				
Operational characteristics						
Detection time (in minutes)	0.007	2.60			0.016	4.34
Response time (in minutes)	0.009	3.80	0.011	3.99		
Police response present (1 if yes, 0 otherwise)	0.139	3.16	0.153	3.27		
Fire response present (1 if yes, 0 otherwise)	0.197	7.46	0.224	7.53	0.178	3.23
Standard deviation of normal distribution parameter			0.085	3.80	0.185	4.33
Hazardous materials response present (1 if yes, 0 otherwise)	1.043	4.58				
Sigma (scale parameter)	0.531	63.71	0.529	55.60	0.532	31.37
Log-likelihood at convergence	−2426.087		−1866.010		−530.256	
Number of observations	2206		1680		526	

incident clearance times. Similar variables were used in all three models to identify their effects on incident clearance times. A total of sixteen variables were found to be statistically significant with four random effects variables (on-road, nighttime, AADT, and peak hours) and twelve fixed effects variables for the combined model. For the incidents in the ASAP area model, fifteen variables were found significant with five random effect variables (on-road, nighttime, rain, peak, and fire response present) and ten fixed effects variables, whereas a total of twelve variables were observed to have significant effects on incident clearance time with three random effects variables (on-road, nighttime, and fire response present) and seven fixed effects variables in the model for incidents that occurred outside the ASAP area.

The random parameters hazard-based duration models revealed that incidents that involve CMVs, fatality, and those in which the vehicle(s) had to be towed were found to be associated with longer incident clearance times in all three models. This finding is consistent with observations of previous studies [32, 33, 37, 39, 40]. The variable for incident location being on-road was found to be random and normally distributed for inside the ASAP area model (with mean of −0.247 and standard deviation of 0.363) and for outside the ASAP area model (with mean of −0.090 and standard deviation of 0.144). This indicates decreased incident clearance times associated with 24.8% and 26.6% of incidents that, respectively, occurred in and outside the ASAP coverage area. Incidents occurring on-road are more

Table 3: Percent changes in the random parameters hazard-based duration models.

Variables	Changes (%) Combined ASAP	Inside ASAP area	Outside ASAP area
Incident characteristics			
Multiple vehicles involved in crash incident (1 if yes, 0 otherwise)	16.6	23.5	
Commercial motor vehicle (CMV) involved (1 if yes, 0 otherwise)	48.7	54.8	51.1
Fatality involved (1 if yes, 0 otherwise)	126.6	202.2	85.3
Vehicle towed (1 if yes, 0 otherwise)	43.9	50.4	24.5
Seat belt indicated as involved (1 if yes, 0 otherwise)	−14.4	−6.8	−27.3
On-road (1 if yes, 0 otherwise)	−17.3	−21.9	−8.6
Overturn (1 if yes, 0 otherwise)		25.2	
Collision type: rear end collision (1 if yes, 0 otherwise)			17.5
Temporal characteristics			
Nighttime (lighting condition at time of crash incident: 1 if yes, 0 otherwise)	10.1	9.6	13.2
Winter (incident occurred in month of December, January, or February: 1 if yes, 0 otherwise)			21.4
Peak hours (1 if incident occurred between 7 AM–9 AM and 4 PM–6 PM, 0 otherwise)	−10.5	−9.4	
Environmental characteristics			
Rain (1 if yes, 0 otherwise)	7.3	8.0	
Traffic characteristics			
Average annual daily traffic (AADT/1000)	−0.6	−0.4	−0.4
One lane in the traffic way		−23.3	
More than two lanes in the traffic way			20.3
Less than four lanes in the traffic way	−10.4		
Operational characteristics			
Detection time (in minutes)	0.7		1.6
Response time (in minutes)	0.9	1.1	
Police response present (1 if yes, 0 otherwise)	14.9	16.5	
Fire response present (1 if yes, 0 otherwise)	21.8	25.1	19.5
Hazardous materials response present (1 if yes, 0 otherwise)	183.8		

likely to block one or more lanes. Lane blocking of traffic can be detected more rapidly, which increases the probability of quicker incident notification and clearance. This finding is supported by a recent study conducted by Islam et al. [37] and Islam et al. [38]. In terms of the environmental characteristics, incidents that occurred during rain events were found to be associated with longer incident clearance times in the combined model and were observed to be random in the ASAP area model (with mean of 0.077 and standard deviation of 0.270). This means that, for 61.2% of crash incidents that occurred during rain events in the ASAP coverage area, incident clearance times were higher. In terms of temporal characteristics, nighttime variable was found random and normally distributed (with means of 0.092, 0.124, and 0.096 and standard deviation of 0.197, 0.163, and 0.169) for inside ASAP area model, for outside ASAP area model, and for the combined model, respectively, and was observed to be associated with increased incident clearance times in all three models. This finding is consistent with many previous studies [30, 32, 37, 38]. On the other hand, peak hour was found significant and random (with means of −0.099 and −0.111 and standard deviations of 0.124 and 0.127) for the ASAP coverage area and combined models, respectively. The peak hour incident variable was found to be associated with decreased clearance time for only a proportion of the observations.

With respect to the traffic characteristics, the variable for AADT (with mean of −0.006 and standard deviation of 0.002) was found random and normally distributed only in combined model with shorter clearance times for a fraction of the crash observations. Also, AADT was found to be associated with shorter incident clearance times for crashes that occurred both inside and outside the ASAP areas. This indicates that incident clearance times decrease on freeways as AADT increases. This may be due to the early detection and notification of crash incidents on freeways. Also, higher AADT means that delay in clearing crash incidents may lead to traffic build-up and this can lead to significant economic loss and even the occurrence of secondary crashes. This finding is also consistent with observations in many previous studies [30, 37, 38, 40, 50, 51]. The effects of some of the operational variables were found be consistent across the all three models. For example, crash incidents that require fire response are more likely to be associated with longer clearance times in all the three models and were found random and normally distributed (with means of 0.224 and 0.178 and standard deviations of 0.085 and 0.185) for the ASAP coverage area and outside ASAP area models, respectively.

6. Discussion

Table 3 shows the percent change in incident clearance times for each variable found to be significant in the combined model, ASAP coverage area model, and model for incidents that occurred outside the ASAP area. While considering all other variables at their means, the exponent of the estimated parameter coefficient of a variable is converted to a percentage change in incident clearance times, resulting from a unit increase in continuous explanatory variables and a change from zero to one for binary explanatory variables [52]. For example, the exponent of the estimated parameter coefficient of overturn in the ASAP coverage area model was 1.25, which indicates that crashes involving overturn will require 25% longer clearance time compared to crashes with the average clearance time. For incidents involving CMVs, the incident clearance time increased by 48.7%, 54.8%, and 51.1% for the combined model, ASAP coverage area model, and outside the ASAP area model, respectively. Also, for crashes that resulted in fatality, the incident clearance time increased by 126.6%, 202.2%, and 85.3% in the combined model, ASAP area model, and outside ASAP area model, respectively. These findings indicate that crashes involving CMV and those that resulted in fatality inside ASAP areas required longer incident clearance times than outside ASAP areas. Since the ASAP coverage areas fall within the mostly populated and urban areas in the state (Figure 1), perhaps, the higher traffic volumes in these areas contribute to the longer incident clearance times.

The estimation results further reveal that crashes that occurred on the roadway (not off the road) inside the ASAP area were found to have 21.9% lower incident clearance time than those that occurred outside the ASAP area. This indicates that crashes that occurred inside the ASAP coverage area required less time to clear on-road crashes compared to those that occurred outside the ASAP area. This finding underscores the effectiveness of the ASAP program in lowering incident clearance times. Similarly, crashes that occurred during nighttime resulted in 13.2% increased clearance times outside the ASAP area. However, crashes that occurred during nighttime inside the ASAP area had only 9.6% increase in incident clearance time. This suggests that crashes that occurred outside the ASAP regions during nighttime required more time to clear. Also, crashes that occurred during peak hours were found to be associated with 9.4% decrease in incident clearance times in the ASAP coverage area.

Crash incidents that occurred during rain events were observed to have 8% longer clearance times inside the ASAP area. An interesting finding is that, for each 1% increase in AADT, the incident clearance time decreased by same percentage both inside and outside the ASAP areas. The results further show that the incident clearance times in the ASAP coverage area increased by 25.1% and 16.5% for crashes that required fire response and police response, respectively. However, the percent change for crashes with fire response present was lower (19.5%) outside the ASAP area. Crashes that result in fire or involve hazardous materials are often severe [2]. As such, crashes that require the presence of fire response team inside the ASAP areas needed more time to clear.

7. Conclusion

FSP programs have been considered as an effective tool for traffic incident management in minimizing the adverse effects of traffic incidents. Many previous studies have evaluated the benefits of FSP program using simulation models as well as various statistical models based on different performance measures. This paper used the random parameters hazard-based duration modeling method to investigate the impact of the ASAP program on freeway incident clearance times. The hazard-based duration model specification with random parameters enables correlation across random parameters to capture heterogeneity, revealing underlying information in the incident duration data. A total of 2,206 freeway crash incidents that occurred in Alabama in 2018 were investigated by combining and matching four different datasets: freeway incident response data from TMCs, ALDOT, freeway crash data from CAPS at the University of Alabama, ASAP data from ALDOT, and traffic volume data from HPMS, ALDOT. Based on a likelihood ratio test, two incident clearance time models were justified for crash incidents that occurred within the ASAP coverage area and those that occurred outside the coverage area.

The estimation results indicate that a total of five variables (on-road, nighttime, peak hours, rain, and fire response present) were observed to have random effects on incidents occurring inside the ASAP regions, whereas three variables (on-road, nighttime, and fire response present) were found to have random effects on incidents occurred outside the ASAP regions. A total of five incident related variables, including involvement of CMVs, fatality, vehicle towing, seat belt indicated as involved, and incidents that occurred on-road were found to have significant influence on incident clearance times. Incidents that occurred during nighttime were found to have higher likelihood to be associated with longer incident clearance times in the outside ASAP coverage area model. Also, incidents that required fire response presence were identified to have longer incident clearance times in the ASAP regions, compared to the incidents that occurred outside the ASAP regions. An interesting observation of this study is that AADT had similar influence on incident clearance times for incidents that occurred both inside and outside the ASAP regions.

Given the significant cost savings associated with faster incident clearing times, the findings of this study validate the expected benefits of the ASAP program in the state. In view of these findings, it is recommended to expand the ASAP program to cover most freeways in the state. In addition, either the ASAP members should be trained in postcrash care or the program should include trained professionals to help stabilize crash victims at the scene of the incident before being transported to the hospital. Further studies are however recommended to evaluate the impact of the ASAP program using incident datasets for other states and for multiple years. Additionally, other phases of incident duration times may also be used as an alternative to incident clearance times to reassess the ASAP program in the state [53–55].

Data Availability

Some or all data, models, or codes that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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