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MARYLAND DEPARTMENT OF TRANPORTATION
STATE HIGHWAY ADMINISTRATION

RESEARCH REPORT

DEVELOPMENT OF A TRAFFIC MANAGEMENT DECISION SUPPORT TOOL FOR FREEWAY INCIDENT TRAFFIC MANAGEMENT (FITM) PLAN DEPLOYMENT

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16. Abstract

Traffic incidents have long been recognized as the main contributor to congestion in highway networks. Thus, contending with non-recurrent congestion has been a priority task for most highway agencies over the past decades. Under most incident scenarios, if proper diversion plans can be implemented in time, motorists can circumvent the congested segments and best use the available corridor capacity. To tackle this vital operational issue, transportation professionals have proposed a variety of advanced diversion control and route guidance strategies to optimally balance the volumes between the freeway and the arterial. In such a system, reliably estimated incident duration plays a key role in selection of strategies for mitigating incident-related delays and impacts. This research developed a methodology for estimating the duration of a detected incident with association rules (SCAR) and two supplemental models using the CHART-II incident database. To minimize the incident impacts, this study further developed two supplemental models: a deployment strategy for incident response units, and a decision support tool for assessing the need of implementing detouring operations. With these three models, responsible highway agencies can have reliable information to tackle critical issues, such as: "what is the estimated duration to clear the detected incident? How far will the maximum queue reach? Can the projected delay and congestion during incident management warrant the detour operations?"

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Chapter 1: Introduction

1.1 Research Background

Traffic incidents, including disabled vehicles blocking lanes, fire, road debris, construction, police activities, and vehicle crashes, have long been recognized as the main contributors to congestion on highway networks and the related adverse environmental impacts. For example, Skabardonis et al. (2003) discovered that incident-related delay makes up 13 to 30 percent of the total delay during peak periods, based on analysis of two freeway corridors in California. A more comprehensive study by the Federal Highway Administration (FHWA) (2005) revealed that about 25 percent of congestion in the U.S. is incident-related. Furthermore, Lindley (1987) found that non-recurrent traffic congestion due to incidents is responsible for up to 60 percent of the total freeway delays in the United States.

Unlike recurrent congestion that is predictable and follows well-defined temporal and spatial patterns, non-recurrent congestion is random both in occurrence and duration due to the nature of the incidents (i.e., unpredictability of time, space and severity). Thus, an efficient and effective incident management system, including detection, response, clearance, and network-wide traffic management is urgently needed to contend with this common issue.

A large number of studies have proven that a well-designed incident management program can substantially reduce non-recurrent congestion by decreasing incident duration and efficiently diverting traffic. The service patrol program in Hampton Roads, Virginia, one such example of incident management, has reduced the average duration of these occurrences by 70.7 percent (Ryan, 2007). Northern Virginia has reported a decrease of 15.6 percent in average incident duration for crashes, 25 percent for roadway debris, and 17.2 percent for breakdowns (Dougald and Demetsky, 2008). Also, CHART (Coordinated Highways Action Response Team) in Maryland has been able to reduce the average incident duration by approximately 25 percent over the last seven years (Chang and Rochon, 2009). In an attempt to reduce traffic flow and decrease the risk of spillback, TIMS (Traffic and Incident Management System), a detour operation system in Philadelphia, reroutes vehicles immediately following any detected major incident. Since its implementation in 1993, there has been a 40 percent reduction in freeway incidents, a 55 percent decrease in freeway closure time, and an eight percent reduction in incident-severity rate (Taylor, 1997).

An ideal incident management system generally consists of several technical components. For example, it may require input data, such as incident and traffic related information, so that the estimated maximum impact area may be precisely determined. Others may include the evolution of the traffic queue, the predicted travel time, and the projected resulting delays for motorists. However, due to the complex interactions of factors involved and the difficulty of obtaining reliable data, it is quite a challenge to develop such a system. Therefore, in this study, we first investigated the characteristics of the critical factors and their connection to the incident impacts. The results from this investigation served as the basis for the development of the principal system components, including strategies for optimally allocating available resources and models for predicting incident clearance durations, incident-induced impacts, and optimal detour plans.

1.2 Research Objectives

It is widely recognized that the effectiveness of an incident management system is heavily dependent on a reliable estimate of incident duration, the time between its onset of an incident, and its complete removal. In fact, this element is one of the key input variables of most models used in state-of-the-art incident management systems. However, for the reasons stated above, development of a reliable model for estimating such information remains in its infancy. Therefore, the first objective of this research was to develop a system for predicting the duration of a detected incident and for identifying critical associated factors, as well as how they are interrelated.

The second research objective was to develop operational tools for minimizing the incident impact, depending upon its estimated duration. Such a tool would fulfill two essential functions: (1) producing an effective deployment strategy for available incident response units, and (2) offering a decision-making mechanism to help control center staff determine the necessity for detouring/diverting traffic. With a reliable model for predicting incident duration, coupled with an effective tool for response operations as well as managing incident-induced impacts, traffic operators would be able to contend with non-recurrent congestion on highway networks more efficiently and more effectively.

1.3 Report Organization

Based on the proposed research objectives, the primary research tasks were organized into five chapters. Figure 1.1 illustrates the organization of this study and the logical connections among its principal tasks. A brief description of each chapter is presented below:

- ***Chapter 2*** illustrates the overall structure of the proposed system. It discusses in detail how the key technical components are integrated to ensure the smooth functioning of all essential systems. The inputs and outputs for each component and the interrelations between key models in the operational process are examined.
- ***Chapter 3*** presents the results of an effective incident response program. A detailed description of an integer programming model, which was developed to determine the optimal set of locations for available emergency response units, constitutes the core of this chapter. Also included, is an analysis of extensive tests of the model's performance and a comparison of other existing models.
- ***Chapter 4*** summarizes the research findings on critical factors and their interrelationships related to incident clearance duration using the association rules technique. It also includes an illustration of the development procedure for an integrated system designed to estimate the clearance duration of a detected incident. The proposed integrated system is composed of a Sequential Classifier with Association Rules (SCAR) and two supplemental models. Also, the proposed system is evaluated and compared to several other state-of-the-art approaches.
- ***Chapter 5*** discusses critical key factors in the implementation of detour/divert operations. These factors are integrated into an Analytical Hierarchy Process (AHP) to constitute the hybrid multi-criteria decision support system. The team also analyzed a case study which has been put through the developed system.

- ***Chapter 6*** provides a discussion of the contributions of this project to our field and indicates directions for future research, including both theoretical refinement of the proposed models and development of operational tools to ensure that the system functions more efficiently in practice.
- ***Appendix*** summarizes the results of a comprehensive literature review regarding each key component of an incident management system, including incident response management strategies, incident clearance duration estimation/prediction models, and detour decision support models.

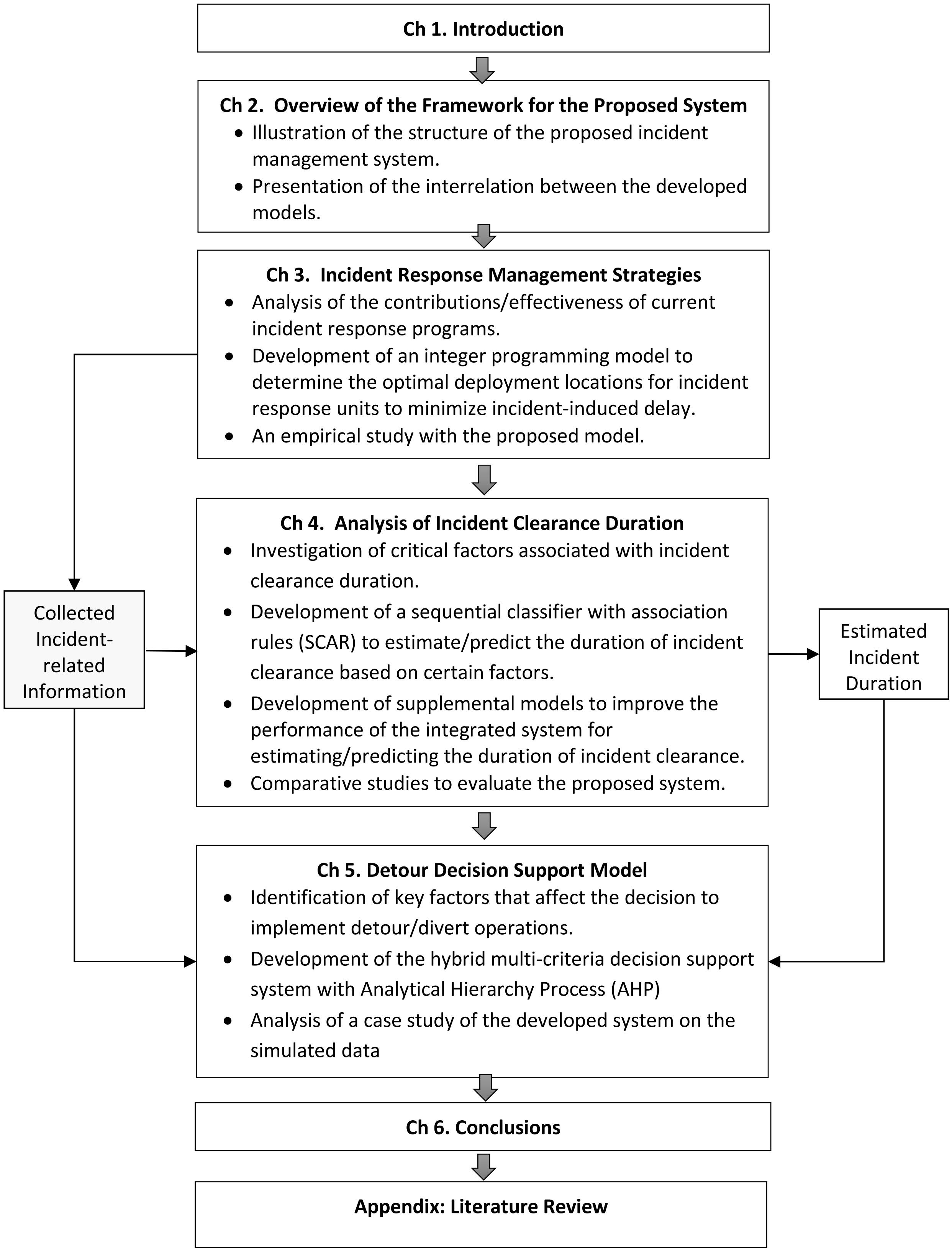


FIGURE 1.1 Research Report Organization

Chapter 2: The Structure of the Proposed Incident Management System

2.1 Introduction

As discussed in Chapter 1, a well-designed incident management system can substantially decrease non-recurrent congestion by reducing the impact of incidents. Over the past several decades, many states in the U.S. have adopted a traffic incident management system (MDOT, 2002; WSDOT, 2007; TTI, 2009; WisDOT, 2010). Although a series of national guidelines and initiatives have been developed in the U.S., the discrepancy in available resources often necessitates that such a system be re-structured and tailored to local needs to ensure greater efficiency in practice (Jin et al., 2014).

In this chapter, the inner workings of the incident management system proposed for the state of Maryland are introduced. The proposed system was developed to enhance the existing system, based on the available resources, infrastructure, and traffic conditions. It consists of several individual modules and embedded technical models to help responsible agents maximize their decision-making ability. In addition, the system's structure and how it will work to mitigate the impact of a detected incident with the assistance of all embedded support models will be explained. Since such a system includes many models and algorithms, the last section will highlight the key functions of the developed models.

2.2 Incident Response and Operational Process

With the proposed incident management system illustrated in Figure 2.1, the traffic control center personnel can take the following steps to effectively respond to traffic incidents and the resulting impacts on freeways:

Step 1: An incident is detected through various detection sources (e.g., patrol units, police, CCTV, alarm systems, etc.) and reported to the operation center.
Step 2: An incident response unit is immediately dispatched to the incident site to direct traffic and clear the incident.
Step 3: Operations center will concurrently collect traffic and incident related data through the arrived response unit and traffic monitoring system.
Step 4: The clearance duration for the detected incident will be estimated/predicted based on the data documented in the previous steps. Such information is one of the key input parameters for executing other primary modules designed to control traffic and to mitigate the impact of non-recurrent congestion.
Step 5: Based on assessment of the data documented and the results estimated in the previous process, the decision on whether a detour/diverting operation is necessary will be made. A well-designed traffic diverting operation, grounded in rigorous assessment, can significantly reduce the impact of a network-wide incident.
Step 6: Once a decision has been reached regarding the detour/diverting operation, this optimal detour/diversion plan is implemented utilizing the embedded models to generate proper control strategies.
Step 7: Up-to-date traffic information will concurrently be provided to drivers affected by the incident to help them adjust their travel plans.

Step 8: The system will be maintained and enhanced through constant evaluation of its performance.

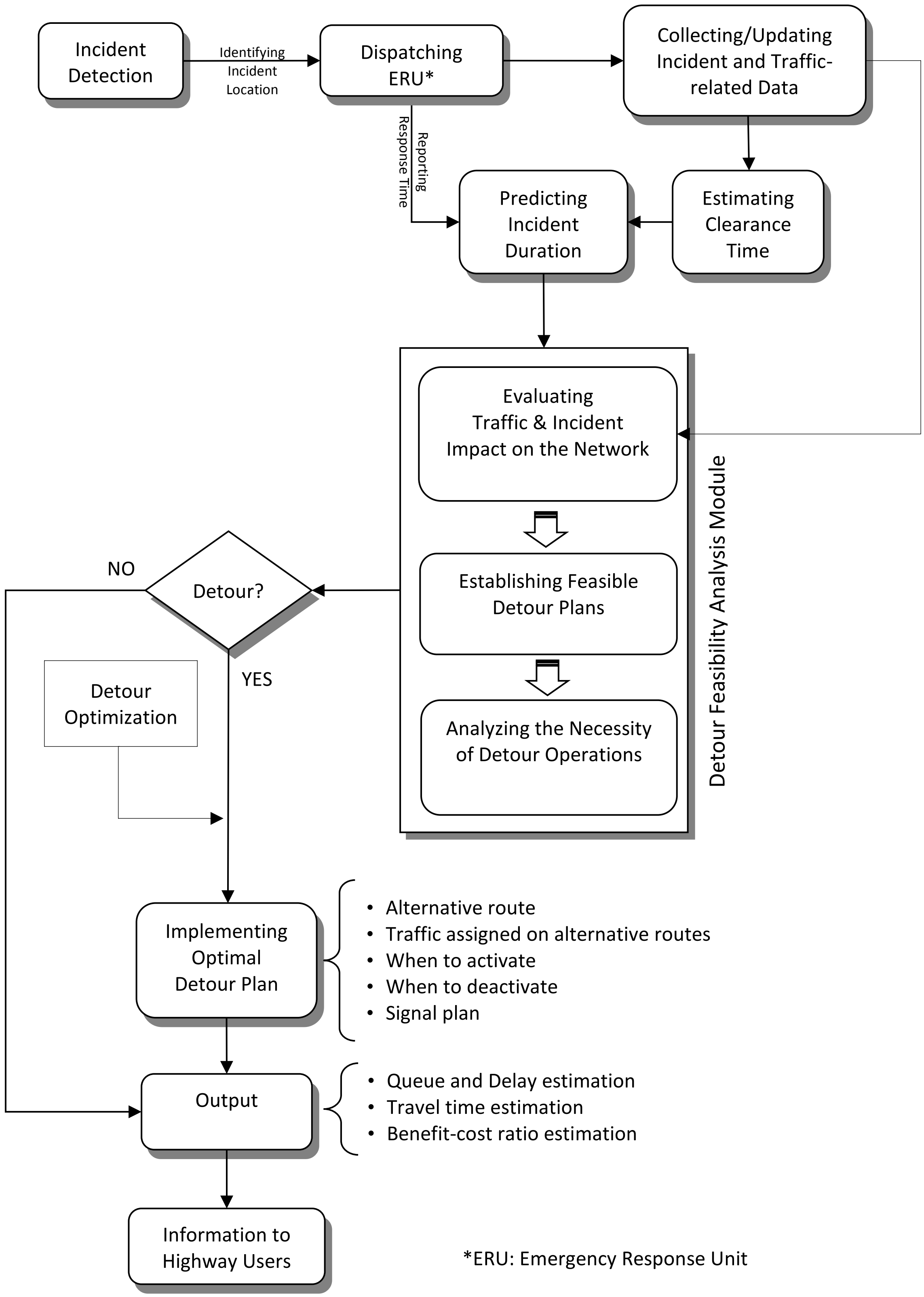


FIGURE 2.1 System Flowchart for the Incident Management Program

Overall, a complete incident management system can support highway agencies to more efficiently contend with non-recurrent traffic congestion and to assist traffic in answering some critical questions, such as: "How long will it take to clear the detected incident?", "How far will the maximum queue reach?", "Does projected delay and congestion during incident management warrant detour operations?", and "What would be the resulting operational costs and total socio-economic benefit of an effective detour operation?"

2.3 Models Needed for the Proposed Incident Management System

Conceivably, to ensure successful operations, such a system would utilize various technical models and algorithms to generate appropriate management strategies. A brief description of all models needed to execute each critical incident management task is summarized below:

1. *Models for Incident Detection*
   Since it is very difficult to predict when and where an incident will occur, the first step for mitigating non-recurrent congestion is to employ a rapid incident detection system, which can use existing traffic sensors and various information sources such as GPS and cell phones, to minimize false alarms and maximize the detection rate. This type of system would certainly decrease response time.

2. *Strategies for Emergency Response*
   Most incidents require emergency services from first-aid staff, wreckers/tow vehicles, police officers, etc. Since most responsible agencies have only limited resources, an efficient strategy to best utilize them is needed to maximize their effectiveness. Hence, efficient operational models or algorithms must be developed to optimally allocate the available resources and to maximize the resulting benefits.

3. *Establishing a Large Scale, Long-Term Database*
   The traffic control center can use the incident management and traffic monitoring systems to collect various incident and traffic related data. In the long run, these documented data will be a valuable asset for relevant agencies to conduct essential operational strategy studies to enhance smoothness of operations. Instituting an effective system for analyzing the performance of incident response operations and the resulting benefits is also critical for sustaining support from both policy makers and the general public.

4. *Models to Estimate/Predict Clearance Times of Detected Incidents*
   An accurate timeframe for clearance duration is one of the primary input parameters for estimating the impacts of incidents and assessing the operational efficiency of the incident management system. This will assist traffic operators in designing successful traffic management strategies in the network within the impacted area and disseminating relevant information to both pre- and en route travelers. The benefits of having an efficient incident response and management system can also be estimated with such information.

5. *Models to Aid in the Decision of Whether a Detour/Diversion Operation is Necessary*
   In many severe lane-blockage incidents, traffic detour/diversion can be one of the most effective ways to lessen network-wide non-recurrent congestion. However, before a rigorous and comprehensive assessment of a wide range of associated variables can be performed, one must estimate the resulting costs and benefits. To support and expedite the decision-making process in real time, control operators must have a reliable tool to assess variables, from various perspectives, to determine whether or not a traffic detour/diversion should be conducted.

6. *Models to Support the Optimal Detour/divert Plan*
   An ideal incident management system would include an efficient operational model to generate an optimal yet feasible detour plan under the given traffic and network conditions. The outputs from such a model would include an optimal diversion rate, adjusted signal plans, and best times to activate and deactivate the detour operations.

7. *Models to Produce Various Traveler Information to Motorists*
   Some models or algorithms introduced in the previous steps are also used to disseminate additional traffic information for motorists in the network. For example, the incident impacts, including the maximum queue length and total delay, can be estimated from the models described in Steps 5 and 6. Also, those models can be used to predict travel time based on up-to-date traffic conditions. Such information can be circulated to motorists through an online traveler information system which suggests best routing strategies to avoid congestion caused by the incident.

8. *A Model to Evaluate the Performance and Resulting Benefits of the Incident Management System*
   To constantly improve the system's performance and provide sustainable support, it is imperative that the responsible agencies establish a convenient and reliable tool for conducting performance evaluations and benefit assessments, which will help them identify the need for any additional resources and plan for better coordinate with other agencies.

2.4 Principal Models Selected for This Study

In view of various functional requirements for an efficient incident response and management system, the team focused on the following critical models for this study:

(1) An operational model for optimizing incident response strategies.
(2) A predictive model for estimating the incident clearance duration of a detected incident.
(3) A decision support module to help operating agencies to evaluate the need for implementing detour/diversion operations.

Figure 2.2 illustrates these models and how they are connected. Key input data for developing and implementing these models are listed below:

- Incident-related information: the incident site, date/time, involved vehicles, incident type, road closure status, pavement condition, etc.
- Traffic-related information: current traffic volume, roadway configuration, signal plan, capacity, speed limits on the relevant routes.

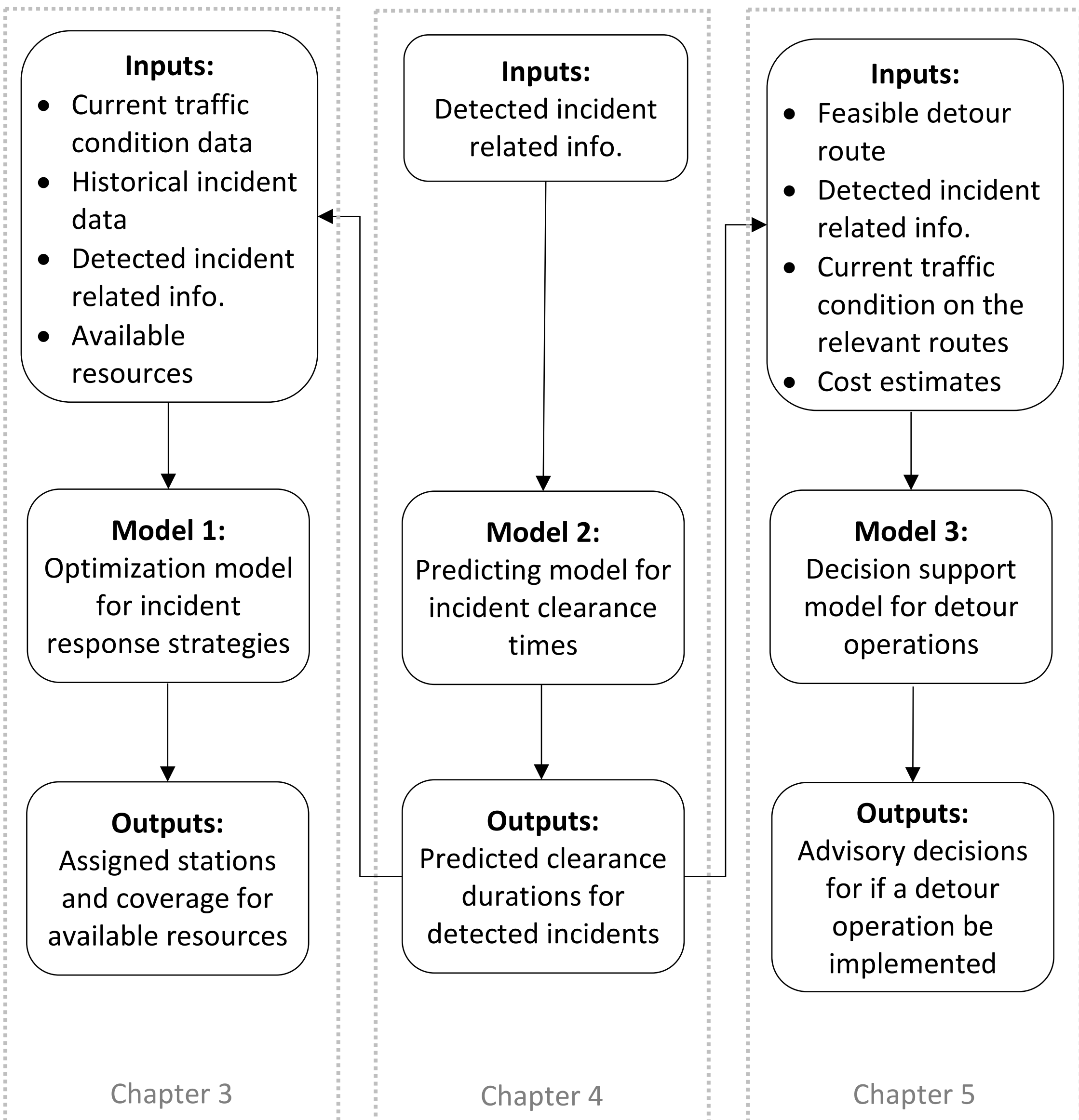


FIGURE 2.2 Principal Model Frameworks

The first model, an optimization model for generating incident response strategies, requires information regarding available resources, historical frequency and duration of these incidents. This developed model seeks to identify the optimal stations and service coverage by each available response unit in order to minimize the total delay by incidents and increase prompt response and clearance operations. A detailed description of the model's structure, formulation, and evaluation is presented in Chapter 3.

The second model is to predict the clearance duration for a detected incident based mainly on the incident information, which then served as the key input of the third model, a decision support model for detour/diversion operations. Also, the predicted durations of incidents will be documented in the incident database and will be used to update the response strategies from the first model. The model development process and its structure are presented in Chapter 4.

The team then devised a decision support model for detour operations, which is aimed to determine, from various perspectives, whether or not a detour/diversion operation is beneficial. The developed model is expected to provide advisories and detour information for travelers within the boundaries of the incident impact area. Chapter 5 will present the developed model's structure, key features, case studies, and the results of validation.

If the models developed in this study are properly integrated with other systems such as incident detection systems, detour optimization system, and travel time information system, then such an integrated system will be able to substantially improve travel on congested highways.

Chapter 3: Design of Incident Response Management Strategies

3.1 Introduction

As discussed in Chapter 1, a well-designed incident management program can substantially ease non-recurrent congestion by reducing the duration of the incident or diverting traffic. Various studies have shown that reduction in delays can yield considerable benefits not only for motorists but also for the environment (Roper, 1989; Maccubbin et al., 2008; Chang and Rochon, 2009). This encouraging news has inspired many state transportation agencies to implement freeway incident management programs (Lindley, 1989), to efficiently clean up traffic congestion resulting from an incident blockage, and subsequently to decrease its impacts.

For successful operation, such a system must be capable of locating and allocating available resources to minimize the effects of incidents. There are two types of strategies for dealing with such occurrences, patrolling and dispatching. In recent years, many transportation agencies have instituted patrol-based response programs to effectively detect and respond to these traffic incidents (Skabardonis et al., 1998; Latoski et al., 1998; Khattack and Rouphail, 2004; Haghani et al., 2006; Chou and Miller-Hooks, 2009). For example, Lou et al. (2010) developed a strategy for the Freeway Service Patrol (FSP) program by considering the likelihood of having more prompt responses by commercial towing services. However, some other researchers (Larson and Odoni, 1981; Hakimi, 1964) claimed that it is more efficient to strategically deploy response units and dispatch them to incident sites, based on the detection information by the traffic surveillance or incident detection system. Hence, the team focused on developing an incident response model with the dispatching rather than patrolling strategies.

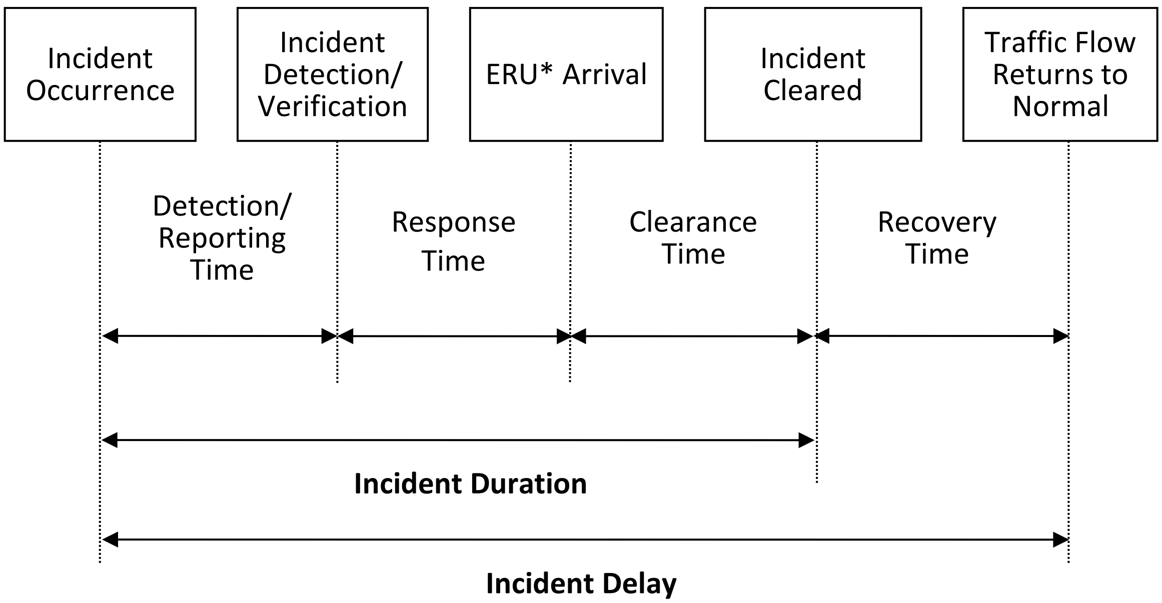
As summarized in the literature review (see the appendix), many dispatching strategies have been introduced, mainly to minimize the number of service stations and the total operational cost as well as to expand the number of incidents covered by a pre-determined group of facilities. The objectives of those studies are to minimize response time or total costs.

However, research with extensive empirical data (Chang and Rochon, 2012; Olmstead, 1999) suggests that prompt reactions would not only lessen response times but also clearance times and total incident-induced delay. Based on the currently available body of knowledge, no researchers of deployment strategies have considered this finding in their model development; therefore, the team first evaluated the effects of a well-run incident management system by reviewing the incident data collected in Maryland. Based on these findings, in this chapter, the report will present a detailed new optimal location/allocation model for deploying available response units to minimize total delay time of detected incidents, instead of focusing on minimizing response time. The performance of the proposed model has been compared with both the traditional *p*-median model designed to minimize response times and the experienced-based patrol strategy, which is currently being employed in Maryland.

3.2 Investigation of the Impact of the Incident Management Program on Incident Duration

3.2.1 Incident Duration

Incident duration can be defined as the time between the onset of an incident and its complete recovery (Garib et al., 1997; Nam and Mannering, 2000; Smith and Smith, 2001). According to the Highway Capacity Manual (TRB, 1994), an incident consists of four components, as shown in Figure 3.1. The first is the detection time that represents the time elapsed from the onset of an incident to its detection. The response time corresponds to the duration between the incident detection/verification and the arrival of the first emergency or incident response unit. The clearance time is defined as the time elapsed from the first arrival of response units (e.g., police or emergency vehicles) to the time that the incident is completely cleared. The last component is the recovery time that measures the time required for the traffic to recover to its normal condition. The incident duration investigated in this study included only the first three components: detection/reporting time, response time, and clearance time.



*ERU: Emergency Response Unit

FIGURE 3.1 Components of Traffic Incidents

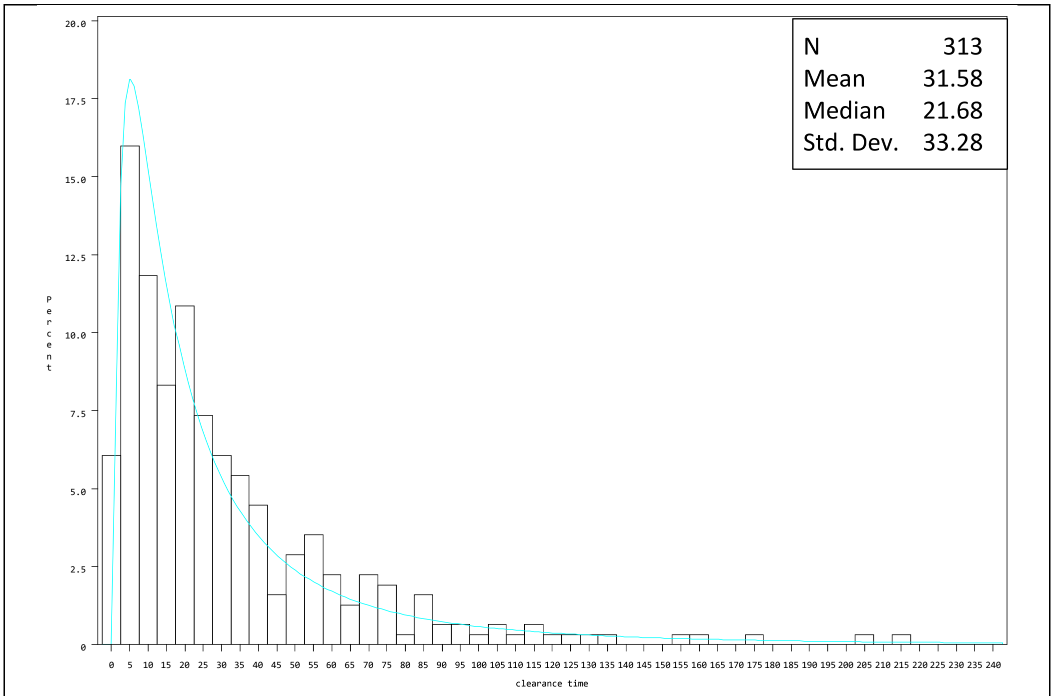
3.2.2 How Well Does the Incident Management Program Lessen Incident Duration?

To answer this question, the team analyzed Maryland incident data collected by the Coordinated Highway Action Response Team (CHART) over the past several years. CHART is a highway incident management program operated by the Maryland Department of Transportation State Highway Administration (MDOT SHA) to decrease the impacts of incidents on freeways through rapid response, clearance, and appropriate traffic management. Their major tasks at incident sites include setting up traffic control devices, managing and controlling traffic flow passing through the site, and assisting the fire department, police, or other agencies to expedite clearance.

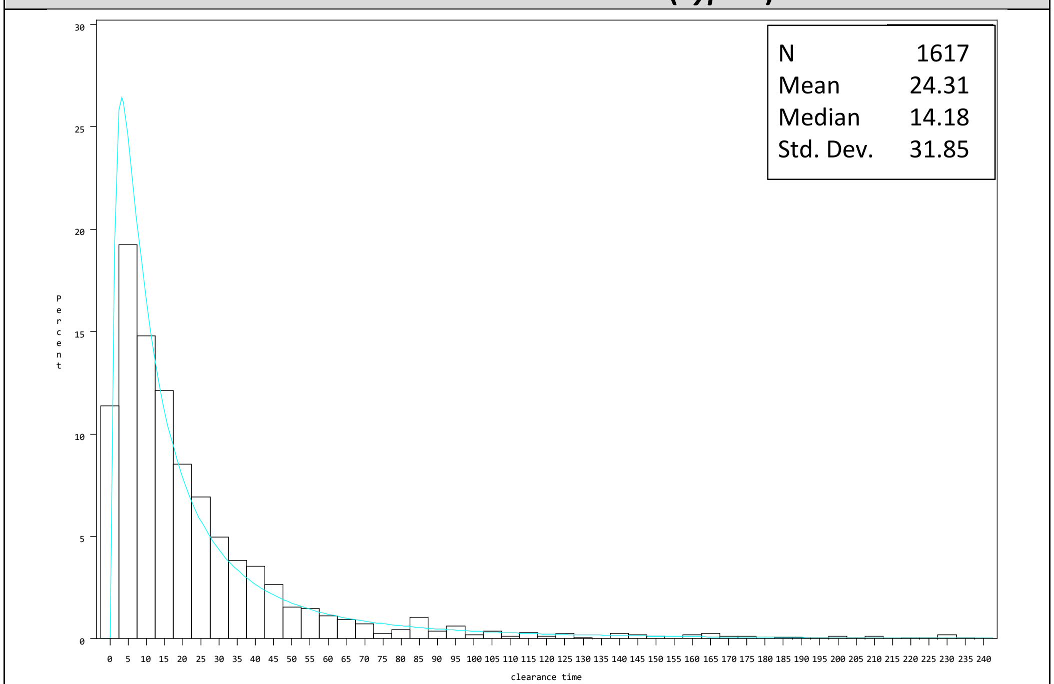
Over the past two decades, CHART has documented incident related information, such as time, location, incident nature, information on involved vehicles, lane closure status, etc., in its database (CHART II Database), and provided analysis for enhancing field operations. The entire dataset can be categorized into two types of incidents:

- ***Type 1***: Incidents to which CHART did not respond.
- ***Type 2***: Incidents in which CHART was involved in clearance.

Figure 3.2 shows the clearance time distributions based on information from the 2012 CHART II Database. Notably, both *Type 1* and *Type 2* distributions were highly skewed to the right in each illustration; however, the clearance times in *Type 2* were much shorter than those in *Type 1*. The average clearance times for *Type 1* and *Type 2* were 31.58 minutes and 24.31 minutes, respectively. The *t*-test results reject the null hypothesis that those average clearance times are equal at the 95 percent significance level. Since the target distributions were highly skewed, the team tested if their central tendencies are equivalent using median (laerd.com). The median clearance times for *Type 1* and *Type 2* were 21.68 minutes and 14.18 minutes, respectively. The *t*-test results also reject the null hypothesis that those values are equal at the 95 percent significance level. Such statistical results confirmed that clearance times of incidents in which CHART was involved were shorter than those in which it was not.



Without CHART involvement (*Type 1*)



With CHART involvement (*Type 2*)

1. Data include incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in Maryland in 2012
2. The analysis only includes clearance times between 1 minute and 4 hours.

FIGURE 3.2 Distributions of Clearance Times (minutes) by CHART Involvement

To further confirm the findings, the team divided the incidents in which CHART was involved in the clearance operations into two groups:

- ***Type 2-1***: Incidents during which CHART responded faster than other agencies.
- ***Type 2-2***: Incidents during which other agencies responded faster than CHART.

Figure 3.3 presents the distribution of clearance times for each group, in which both were also highly skewed to the right. However, the clearance times of incidents in *Type 2-1* indicated a range shorter than those in *Type 2-2*. The average clearance times for *Type 2-1* and *Type 2-2* were 20.54 minutes and 33.02 minutes, respectively, while the medians were 11.33 and 21.03 minutes, respectively. The *t*-test rejects the null hypothesis that those average (or median) clearance times are equal at the 95 percent significance level. The results further confirmed that a prompt response from an incident response team with sufficient traffic management expertise can indeed contribute to a reduction in the incident clearance duration time and resulting impacts.

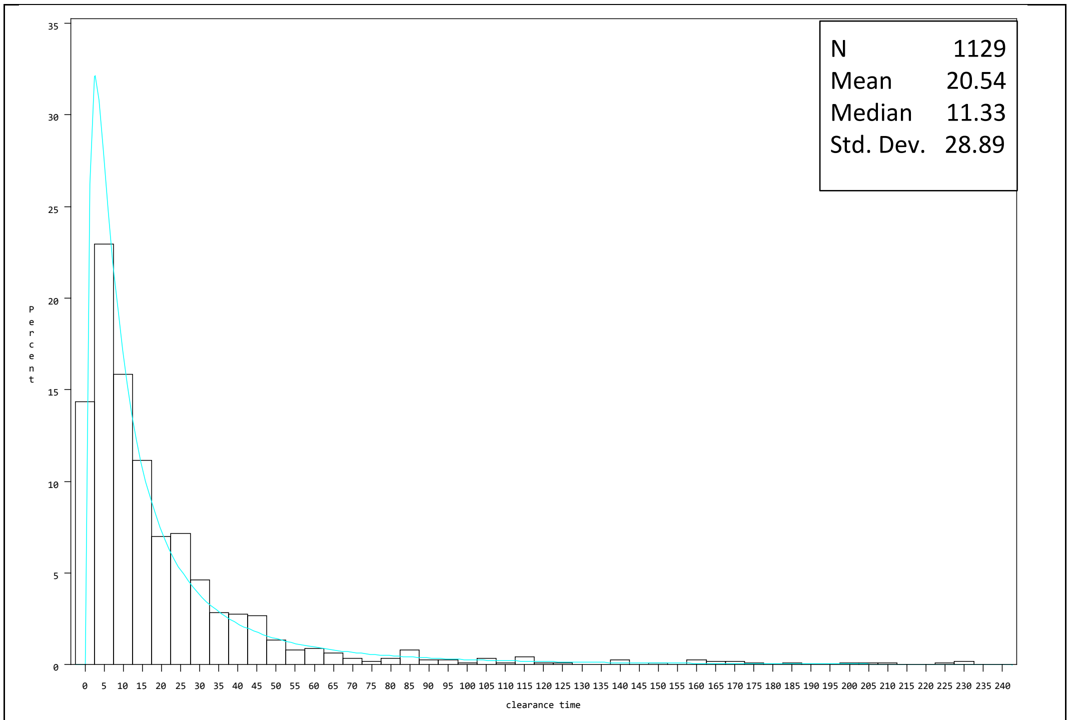
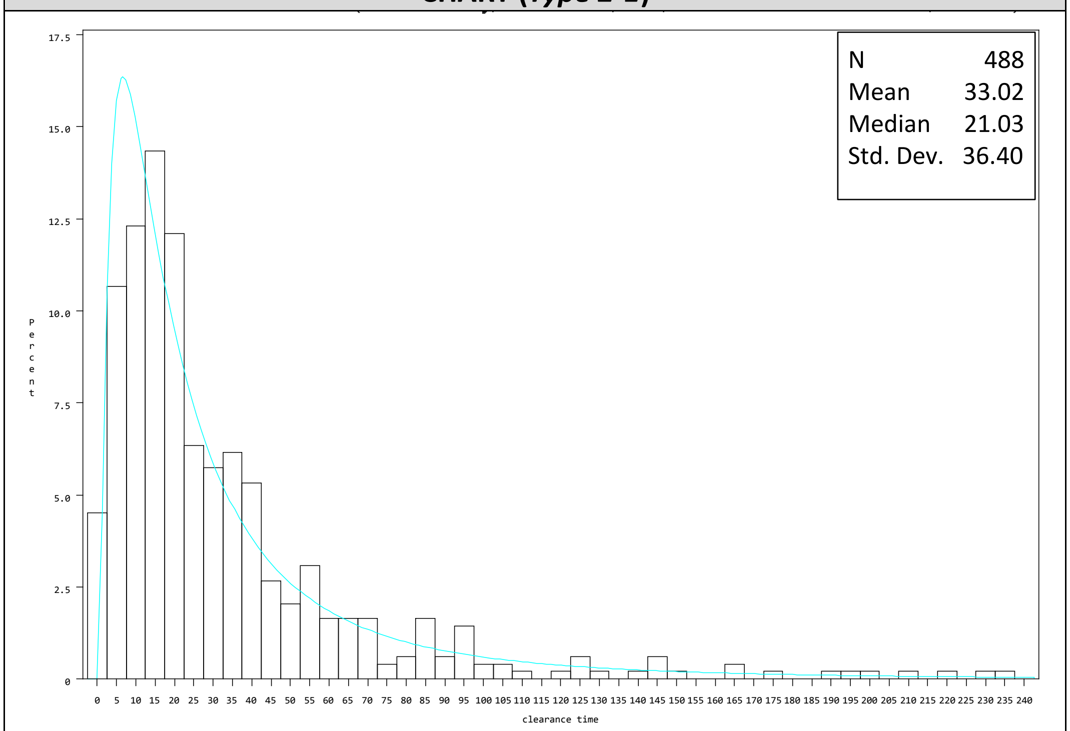


CHART (*Type 2-1*)



Other Agencies (*Type 2-2*)

1. Data include incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in Maryland in 2012.
2. The analysis only includes clearance times between 1 minute and 4 hours.

FIGURE 3.3 Distributions of Clearance Times (minutes) by the First Response Agency

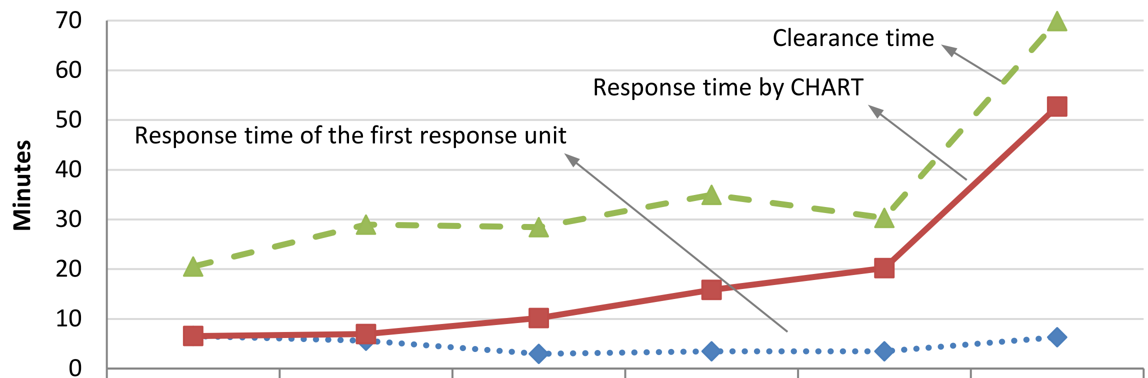
Interestingly, all Traffic Operations Centers (TOCs) in Maryland have observed similar data patterns, as shown in Table 3.1. Note that medians of clearance times in TOC-4 show a slightly different pattern from others due to the relatively small sample size (only nine data were used to estimate the median clearance time for *Type 1* incidents for TOC-4).

TABLE 3.1 Average and Median Clearance Time (minutes) by Response Agency throughout Operations Centers

		TOC-3	**TOC-4**	**TOC-7**	**AOC**	**SOC**
CHART not Involved (Type 1)		24.40 (18.87)	29.06 (6.60)	39.92 (30.88)	26.42 (18.71)	60.04 (52.10)
CHART Involved (Type 2)		22.47 (13.79)	22.53 (13.68)	26.12 (16.38)	17.55 (12.10)	44.23 (22.43)
			⇓			
First Responder	**CHART (Type 2-1)**	20.04 (11.61)	19.80 (10.97)	21.06 (11.60)	12.89 (8.75)	35.99 (18.17)
	Others (Type 2-2)	29.18 (20.60)	32.09 (23.43)	41.43 (27.22)	22.47 (15.92)	54.95 (33.40)

1. Numbers in parentheses represent medians.
2. This analysis included only Maryland incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in 2012.
3. The analysis only included clearance times between 1 minute and 4 hours.
4. MDOT SHA is in charge of seven traffic operations centers throughout Maryland: TOC-3, TOC-4, TOC-5, TOC-6, TOC-7, AOC (Authority Operations Center), and SOC (Statewide Operations Center). TOC-5 and TOC-6 are open on a seasonal basis during summer and winter, respectively.

Figure 3.4 illustrates the relationship between incident clearance durations and response times by the first responding agencies. This figure shows that the average clearance duration is likely to increase if CHART is delayed in arriving at the incident scene, regardless of other agencies' arrival times. This further indicates that the clearance duration is highly correlated with the response time of incident management units.



	0	0 - 5	5 - 10	10 - 15	15 - 20	20 +
	6.53	5.62	2.96	3.50	3.47	6.29
	6.53	6.95	10.16	15.80	20.19	52.69
	20.54	28.99	28.48	34.96	30.34	69.92

1. The horizontal axis represents differences in arrived times between CHART and the first arriving agency, where *0* indicates that CHART arrives at the scene faster than others, and *0 - 5* indicates that CHART arrives within 5 minutes after the arrival of the first agency to respond.
2. Data included incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in Maryland in 2012.
3. The analysis only included clearance times between 1 minute and 4 hours.

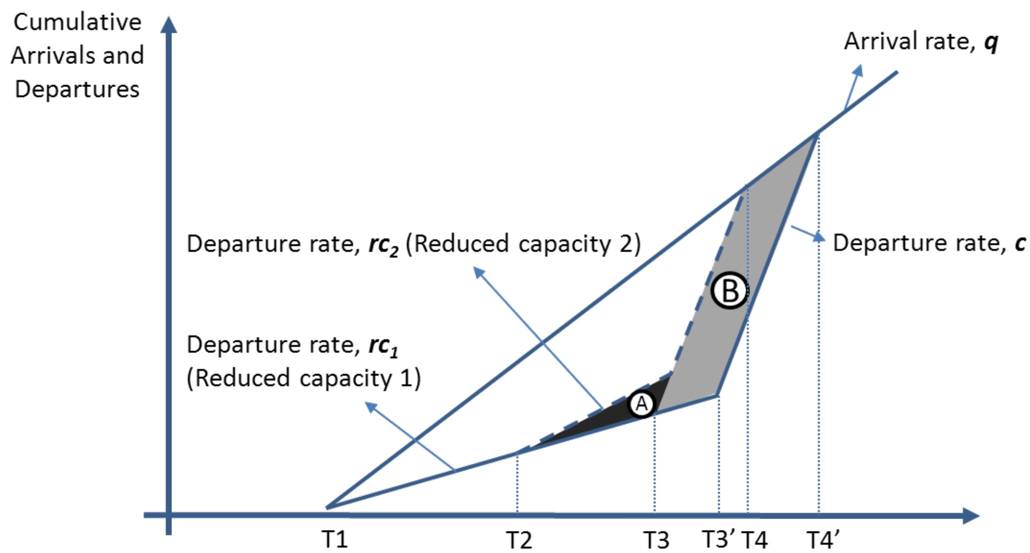
FIGURE 3.4 Relationships between Clearance Times and Delayed Response by CHART

Based on these findings, one could conclude that the rapid response of incident management teams contributes to the reduction not only in response time but also in clearance time. Moreover, reduction in clearance time would increase if CHART were to arrive at the scene faster than other agencies. Due to the limited number of response units, not all incidents can be promptly responded. Thus, it is necessary to develop a strategy in which units under various constraints can be optimally deployed.

3.3 Development of an Optimal Deployment Strategy

3.3.1 Incident Duration and Its Effect on Total Delay

To estimate the impact of an incident in this study, the total delay induced by incidents was used as a measure of effectiveness (MOE). As reported in the literature (Olmstead, 1999; Li et al., 2006), the incident-induced delay varies with several key factors, including traffic demand, freeway capacity, reduced freeway capacity, and especially incident duration. As illustrated in Figure 3.5, prompt response and efficient clearance can reduce incident clearance time from *T3'* to *T3*, and can improve the reduced freeway capacity from rc_1 to rc_2. As a result, the recovery time would be reduced from *T4'* to *T4*, with the resulting total delay as shown in the shaded area (*A* and *B*). Since the data to support delay reduction due to an increased departure rate (rc_2), i.e., area *A*, were not available, the team focused mainly on the reduction of delay associated with a reduced incident clearance time (i.e., the area *B*).



T1: incident onset time.
T2: arrival time of response units.
T3: Time incident was cleared with the assistance of CHART.
T3': Time incident was cleared without the assistance of CHART.
T4: Recovery time with the assistance of CHART.
T4': Recovery time without the assistance of CHART.
q: Traffic arrival rate.
c: Traffic departure rate (roadway capacity).
rc_1: Reduced departure rate due to lane blockages.
rc_2: Increased departure rate with the assistance of CHART.

FIGURE 3.5 Reduced Incident Delay Due to Effective Incident Response and Management

3.3.2 Model Formulation

In this study, the team formulated a model to optimize the allocation of incident response units under the following assumptions:

- Response units will be posted at their designated stations and be dispatched after an incident is detected.
- They will return to their stations when the incident has been cleared.
- Each response unit will manage incidents within its designated coverage area.
- Every freeway is divided into several segments and each segment is covered by only one unit.
- The demand (incidents) within a freeway segment is assumed to be evenly distributed over the area.
- Response units can travel on shoulders during periods of intense traffic congestion.

The network for the model consists of nodes and links that represent exits and freeway segments. The travel times from the assigned locations to an incident site were measured from the node of the assigned location to the middle point of the segment where the incident occurred, since incidents are assumed to occur uniformly along the segment. The proposed model was designed to assign the optimal stationary location and service coverage for each response unit under the given constraints and incident patterns. Notations used in the model formulation are summarized below:

- $G(N, A)$: Network of freeways, where *N* and *A* represent the sets of nodes and links, respectively.
- i and j: Index for nodes. $i, j \in N$
- x_{ij}: Binary decision variable, indicating if a node *j* is covered by a unit at node *i*
- y_i: Binary decision variable, indicating if a unit stays at node *i*
- f_j: Incident frequency at node *j*
- t_{ij}: Travel time from *i* to *j*
- d_j: Predicted delay from incidents occurring at node *j*
- T_{ij}: Incident duration, the sum of response time and clearance time
- α: Proportion of incidents in which freeway incident management teams are involved in clearance (*Type 2*) at a given time
- β: Proportion of incidents in which freeway incident management teams respond faster than other agencies (*Type 2-1*) at a given time
- RT_1: Average minimum response time by other agencies in *Type 1*
- RT_2: Average minimum response time by other agencies in *Type 2-2*
- CT_1: Clearance times of incidents when freeway incident management teams are not involved in response and clearance (*Type 1*)
- CT_{2-1}: Clearance times of incidents when freeway incident management teams respond faster than any other agencies (*Type 2-1*)
- CT_{2-2}: Clearance times of incidents when other agencies respond faster than freeway incident management teams (*Type 2-2*)
- $\overline{CT}_1$: Average clearance time of incidents when freeway incident management teams are not involved in response and clearance (*Type 1*)
- $\overline{CT}_{2-1}$: Average clearance time of incidents when freeway incident management teams respond faster than any other agencies (*Type 2-1*)
- $\overline{CT}_{2-2}$: Average clearance time of incidents when other agencies responded more rapidly than any other freeway incident management teams (*Type 2-2*)
- q_j: Traffic volume at node j
- c_j: Capacity at node j
- rc_j: Reduced capacity due to an incident at node j
- R: Available resources

As previously stated, the team categorized incidents into the following three types:

(1) *Type 1:* Incidents with no assistance from the freeway incident management teams
(2) *Type 2-1:* Incidents in which incident management teams responded faster than other agencies: and
(3) *Type 2-2:* Incidents during which other agencies responded more rapidly than the incident management teams

The proposed model was formulated as follows:

object to $$\min_{x,y} \sum_i \sum_j x_{ij} \cdot f_j \cdot d_j(t_{ij}) \quad \text{(Eq. 3-1)}$$

subject to

$$d_j(t_{ij}) = \frac{1}{2} {T_{ij}}^2 (q_j - rc_j) \left(\frac{c_j - rc_j}{c_j - q_j} \right) \qquad \forall (i,j) \in N \qquad \text{(Eq. 3-2)}$$

$${T_{ij}}^2 = \begin{cases} Type\ 1: \ (RT_1 + \overline{CT_1})^2 + Var(CT_1)\ , & 1-\alpha \\ Type\ 2-1: \ (t_{ij} + \overline{CT}_{2-1})^2 + Var(CT_{2-1}), & \alpha, \beta \\ Type\ 2-2: \ (RT_2 + \overline{CT}_{2-2})^2 + Var(CT_{2-2})\ , & \alpha, 1-\beta \end{cases} \qquad \forall (i,j) \in N \qquad \text{(Eq. 3-3)}$$

$$\sum_i x_{ij} = 1 \qquad \forall\ i \in N \qquad \text{(Eq. 3-4)}$$

$$x_{ij} \le y_i \qquad \forall\ j \in N \qquad \text{(Eq. 3-5)}$$

$$\sum_i y_i \le R \qquad \text{(Eq. 3-6)}$$

$$x_{ij} = [0,1] \qquad \forall (i,j) \in N \qquad \text{(Eq. 3-7)}$$

$$y_i = [0,1] \qquad \forall\ i \in N \qquad \text{(Eq. 3-8)}$$

The purpose of the model is to optimally allocate available resources by minimizing total delay of incidents occurring in the target network.

Constraint (Eq. 3-2) formulates the potential total delay caused by incidents occurring at node *j* based on the widely-used methods (Skabardonis, 1995; Olmstead, 1996; Li et al., 2006), showing that the total delay is a convex function of incident duration. Taking the stochastic nature of incident duration into account, ${T_{ij}}^2$ can be expressed as $(\overline{T_{ij}})^2 + Var(T_{ij})$ (Olmstead, 1996; Li et al., 2006). Constraint (Eq. 3-3) further describes the components of the incident duration time for each type. As shown in the formulation, the response time can be represented by travel times, if this information is available.

Constraint (Eq. 3-4) requires that every freeway segment *i* must be attended. Constraint (Eq. 3-5) ensures that a response unit can only be dispatched from location *i* if it is stationed there. Constraint (Eq. 3-6) ensures that the total number of available response units is limited by available resources, R. In Constraint (Eq. 3-7), x_{ij} equals 1 if node *j* is covered by a unit at node *i*, and 0 otherwise. In the last Constraint (Eq. 3-8), y_i equals 1 if the station of a unit is on node *i*, and 0 otherwise.

3.4 Empirical Study

3.4.1 Study Site and Input Data

The proposed model was applied to segments of I-270, I-70, and US15 in Maryland (see Figure 3.6) to validate its performance. These roadways are 63 miles long with 30 distinct exits, which are managed by TOC-7 (Traffic Operation Center-7), which currently handles three field units for overseeing any incidents that take place in those segments in Frederick, Carroll, and Howard Counties. The field unit staff work 16 hours/day (5 a.m. – 9 p.m.) on weekdays. The proposed model was designed to determine the optimal station and coverage for each response unit within the TOC-7's coverage area to minimize potential total delay depending on the nature of the incidents, during a.m. peak hours (7:00 – 9:30) on weekdays.

FIGURE 3.6 Study Segments of I-70, I-270 and US 50 in Maryland

In this study, the team assumed that the incidents occurred along the highway segments and that response units were deployed at nodes (i.e., highway exits) ready to be dispatched. The input parameters in the model varied depending on the location of incidents and could be re-estimated for different target areas based on the information available. The team used the following two major sources to estimate key model parameters:

- CHART II Database
  - Incident frequency on the freeway segment i (f_i) (Figure 4.7).
  - Average response times to incidents Type 1 and Type 2-2 (RT_1 and RT_2).
  - Average and variance of clearance times for each type ($\overline{CT}_k$ and Var (CT_k), where k indicates one of Type 1, Type 2-1, and Type 2-2).
  - α = 0.87 and β = 0.75.

- Average number of lane closures for determining the extent of reduced capacity (rc_j)

- RITIS (Regional Integrated Transportation Information System)
  - Traffic volume (q_j).

Note that occurrence and frequency of incidents are often fluctuate over the study site, as illustrated in Figure 3.7, which posed a challenge for the traffic operators in optimizing proper deployment strategies. Historical data were used for computing the average response times of *Type 1* (RT_1) and *Type 2-2* (RT_2) (i.e., non-CHART response) incidents, whereas the travel times by CHART from its station *i* to an incident site *j* (t_{ij}) were used as the response times of incidents for *Type 2-1*. The parameters α and β were estimated to be 0.87 and 0.75, respectively, based on the same data sources (Table 3.2). According to these estimates, not only did CHART respond to approximately 87 percent of incidents during a.m. peak periods in the study area they also responded faster than any other agency in 75 percent of cases.

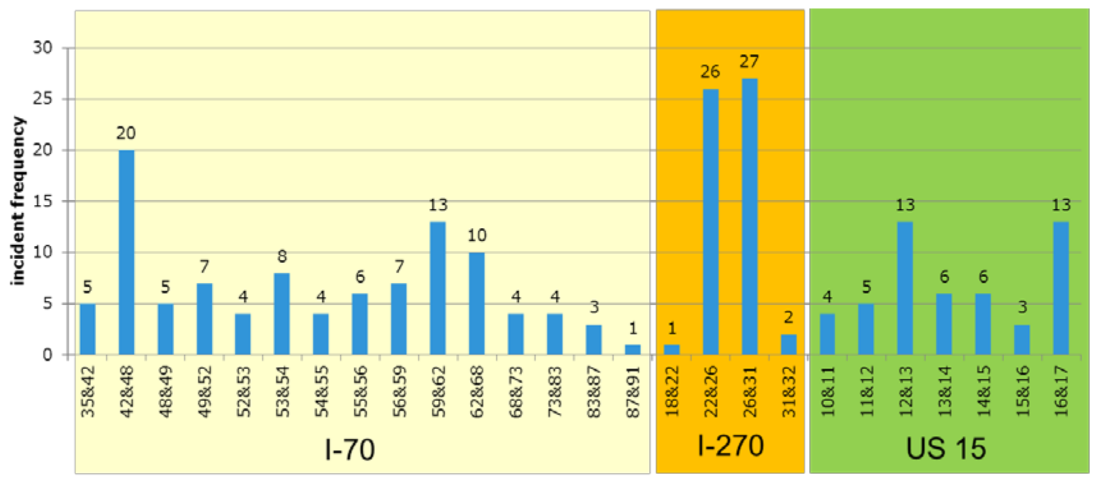


FIGURE 3.7 Average Annual Incident Frequency during AM Peak Hours by Location

TABLE 3.2 Estimations of Input Parameters α and β based on the Empirical Data

CHART Involvement & Promptness		Frequency
CHART Not Involved (*Type 1*)		27
CHART Involved (*Type 2*)	CHART was the first agency to respond (*Type 2-1*)	130
	CHART was NOT the first agency to respond (*Type 2-2*)	43
Total		200

- α **(**percentage of incidents to which CHART responded at a given time**)** **= (130+43)/200 = 0.87;**
- **β (**percentage of incidents to which CHART responded first at a given time**)** **= 130/(130+43) = 0.75**

1. Data include incidents occurring during a.m. peak hours (7 a.m. – 9:30 a.m. on weekdays) in the case study area in 2012.
2. The analysis only includes clearance times between 1 minute and 4 hours.

In addition, reduced capacity due to incidents was estimated according to the average number of blocked lanes (from CHART II Database) and the guidelines from Highway Capacity Manual (TRB, 2000). The average speed of CHART response teams traveling between the station and the incident site was set at 5 mph lower than the speed limit, since they can travel on shoulders even in cases of congestion. The proposed models were solved using CPLEX, a state-of-the-art optimization software package.

3.4.2 Model Results and Analyses for Model Robustness

In this subsection, the model outputs and a detailed evaluation of the results are presented, particularly with respect to the accuracy of the model, via a comparative study and sensitivity analysis. The team compared the model's performance to two existing strategies: (1) the dispatch method for minimizing average response times and (2) the experience-based patrolling method employed by CHART. The key features of each strategy are summarized below:

- *Dispatching Strategy for Minimizing Average Response Time*
  The traditional p-median model was used (Hakimi, 1964; ReVelle and Swain, 1970; Carson and Batta, 1990) as one of the comparative models that assigns optimal positions for available incident response units. The p-median model is aimed to minimize their average response time, which has the following objective function $\min \sum_i \sum_j x_{ij} \cdot f_j \cdot t_{ij}$, where f_j denotes the incident frequency at node j, and t_{ij} represents the travel cost (time)

from station i to the affected freeway segment j. We applied the above constraints (Eq. 3.4) – (Eq. 3.8) in subsection 3.3.2 to this model under the same conditions.

- *Experience-based Patrolling Strategy*
  Currently, CHART utilizes the experience-based patrolling strategy, in which traffic operators place more focus on highway segments with a higher incident frequency or higher traffic volume. A brief description of this practice is explained below:
  - The entire coverage network area is divided into several sub-networks. The organizational plan is to divide the target network varying over time, based on the spatial distribution of total incidents in the historical data and the real-time traffic volumes.
  - The supervisor assigns each available unit to patrol the segments within each sub-network.
  - Patrol officers will respond to incidents they encounter or ones they learn about from announcements by the operation center.
  - The response strategy is on a first-come-first-served basis, unless major incidents such as personal injuries or fatalities occur.

We conducted a sensitivity analysis to evaluate the accuracy and efficiency of the model under various network conditions, including incident frequency and traffic volume on the target network, and the results of which are presented below.

Model Outputs

The proposed model produced two outputs: 1.) optimal stationary positions and 2.) coverage for a given number of response units. Tables 3.3 and 3.4 compare these outputs based on three strategies, minimizing the total delay (the proposed model), minimizing the average response time, and the CHART current practice. As shown, the assigned stations and service coverage based on the proposed model are somewhat different from the traditional p-median model. Note that *others* in Table 3.4 include the junction area of the three corridors (I-70, I-270, and US-15).

TABLE 3.3 Stations Assigned for Available Response Units by Strategy

<table>
<tr><th rowspan="2">No. of Units Available</th><th colspan="3">Assigned Stations (Exits) by</th></tr>
<tr><th>Dispatch minimizing total delay</th><th>Dispatch minimizing avg. response time</th><th>CHART practice</th></tr>
<tr><td>2</td><td>I-70: 42 and 53</td><td>I-70: 52 and 68</td><td>N/A</td></tr>
<tr><td>3</td><td>I-70: 42, 53 / I-270: 26</td><td>I-70: 52, 68 / I-270: 22</td><td>Patrolling all segments</td></tr>
<tr><td>4</td><td>I-70: 42, 52, 68 / I-270: 26</td><td>I-70: 42, 52, 68 / I-270: 26</td><td rowspan="4">N/A</td></tr>
<tr><td>5</td><td>I-70: 42, 53, 68 / I-270: 26 / US-15: 16</td><td>I-70: 42, 52, 62, 80 / I-270: 26</td></tr>
<tr><td>6</td><td>I-70: 42, 48, 53, 68 / I-270: 26/ US-15: 16</td><td>I-70: 42, 52, 62, 80 / I-270: 26 / US-15: 17</td></tr>
<tr><td>7</td><td>I-70: 42, 48, 53, 62, 82 / I-270: 26 / US-15: 16</td><td>I-70: 42, 52, 62, 68, 80 / I-270: 26 / US-15: 17</td></tr>
</table>

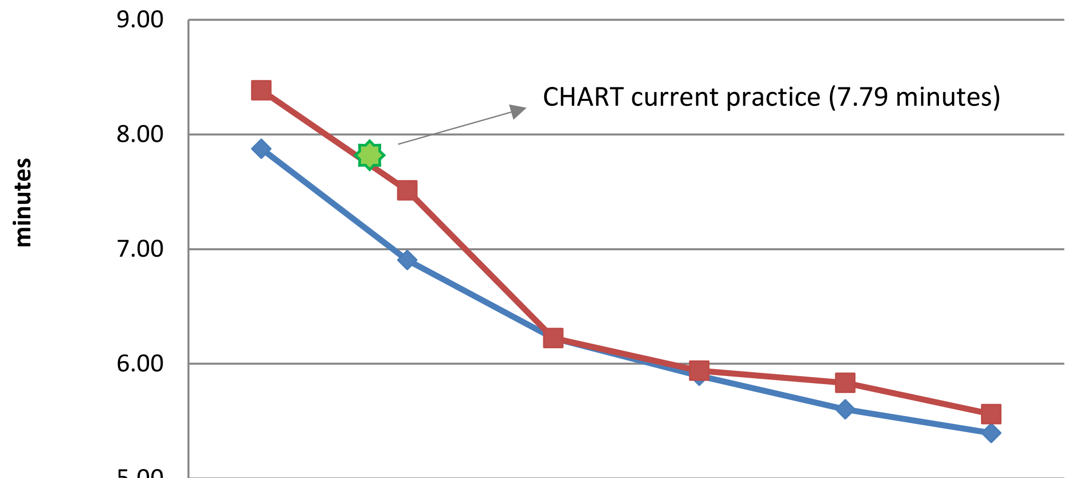
TABLE 3.4 Service Coverage Assigned for Each Response Unit by Strategy

<table>
<tr><th rowspan="2">No. of Units Available</th><th colspan="3">Assigned Service Coverage by</th></tr>
<tr><th>Dispatch minimizing total delay</th><th>Dispatch minimizing avg. response time</th><th>CHART practice</th></tr>
<tr><td>2</td><td>(35 - 42 on I-70), (others)</td><td>(62 - 87 on I-70), (others)</td><td>N/A</td></tr>
<tr><td>3</td><td>(35 - 42 on I-70),
(22 - 26 on I-270), (others)</td><td>(62 - 87 on I-70),
(22 - 26 on I-270), (others)</td><td>Patrolling all segments</td></tr>
<tr><td>4</td><td>(35 - 42 on I-70),
(62 - 87 on I-70),
(22 - 26 on I-270), (others)</td><td>(35 - 42 on I-70),
(62 - 87 on I-70),
(22 - 26 on I-270), (others)</td><td rowspan="4">N/A</td></tr>
<tr><td>5</td><td>(35 - 42 on I-70),
(62 - 87 on I-70),
(22 - 26 on I-270),
(13-17 on US-15), (others)</td><td>(35 - 42 on I-70),
(59 - 68 on I-70),
(73 - 87 on I-70),
(22 - 26 on I-270), (others)</td></tr>
<tr><td>6</td><td>(35 - 42 on I-70), (48 - 59 on I-70),
(62 - 87 on I-70), (22 - 26 on I-270),
(13-17 on US-15), (others)</td><td>(35 - 42 on I-70),
(59 - 68 on I-70), (73 - 87 on I-70),
(22 - 26 on I-270),
(14 - 17 on US-15), (others)</td></tr>
<tr><td>7</td><td>(35 - 42 on I-70), (48 - 59 on I-70),
(62 - 73 on I-70),
(76 - 87 on I-70),
(22 - 26 on I-270),
(13-17 on US-15), (others)</td><td>(35 - 42 on I-70),
(59 - 62 on I-70),
(68 - 73 on I-70),
(76 - 87 on I-70),
(22 - 26 on I-270),
(14 - 17 on US-15), (others)</td></tr>
</table>

Comparative Study for the Model Performance

Since the model outputs do not reflect the advantages of the proposed model over the traditional and current strategies, we further compared the performance of these strategies utilizing two measures of effectiveness (MOEs), the average travel time of the response units and the estimated total delay induced by incidents. To compare the impact of the fleet sizes on the effectiveness of each strategy, the MOEs were estimated with the fleet sizes from two to seven for the proposed and traditional models.

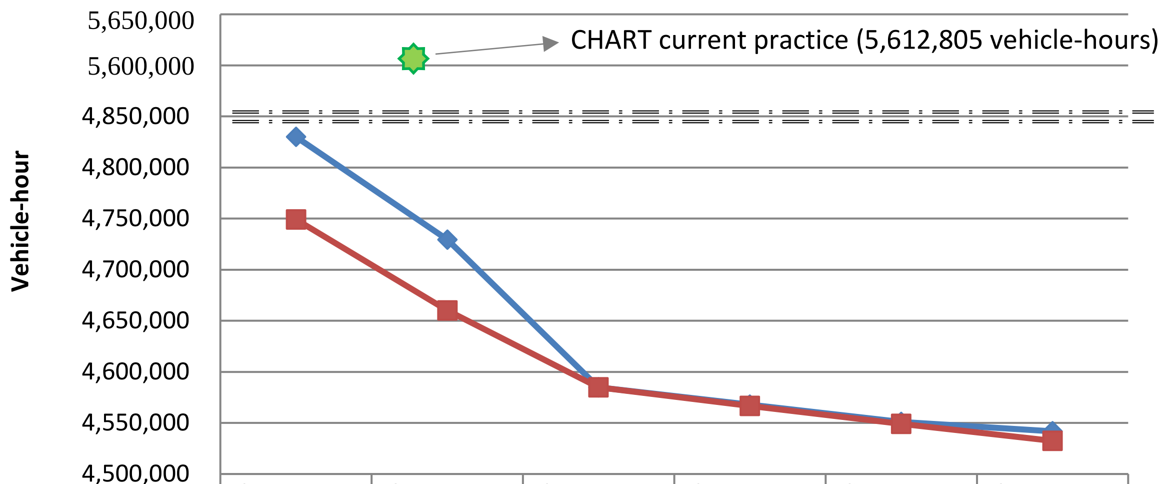
As displayed in Figure 3.8, the estimated average response time was drastically decreased when a unit was added. However, in a fleet of more than four units, the rate of decrease becomes less significant. As expected, the average response time using the model was longer than that under the traditional *p*-median model over most fleet sizes explored in this study. However, the difference progressively decreases, and the models exhibit identical results at a fleet size of four, and it increases again as the fleet size increases but not as much as under the size of small fleets. For a fleet size of three, the size currently used by CHART, the average response time was 7.79 minutes, which is 3.6 percent and 11.4 percent longer than that of the proposed model (7.51 minutes) and the traditional *p*-median model (6.90 minutes), respectively.



	fleet size 2	fleet size 3	fleet size 4	fleet size 5	fleet size 6	fleet size 7
Traditional Model	7.88	6.90	6.22	5.89	5.60	5.40
Proposed Model	8.38	7.51	6.22	5.94	5.83	5.56

FIGURE 3.8 Average Travel Times (in minutes) by Incident Response Strategies

The team found similar patterns in total incident delay, shown in in Figure 3.9. As expected, total delay with the proposed model was less than that of the traditional model, which uses a fleet of two to seven units. The fleet sizes of two or three units showed a significant reduction in total delay of 80,857 and 69,390 vehicle-hours per year, respectively, compared to the traditional *p*-median model. The differences in the total delay between these two strategies would be insignificant with a fleet size of four. For a fleet size of three, as currently used by CHART, the total delay was 5,612,805 vehicle-hours, which was 17 percent and 15.7 percent larger than that of the proposed model (4,659,967 vehicle-hours) and the traditional *p*-median model (4,729,356 vehicle-hours), respectively.



	fleet size 2	fleet size 3	fleet size 4	fleet size 5	fleet size 6	fleet size 7
Traditional Model	4,829,998	4,729,356	4,584,707	4,567,920	4,551,095	4,541,785
Proposed Model	4,749,141	4,659,967	4,584,707	4,566,630	4,549,114	4,532,457

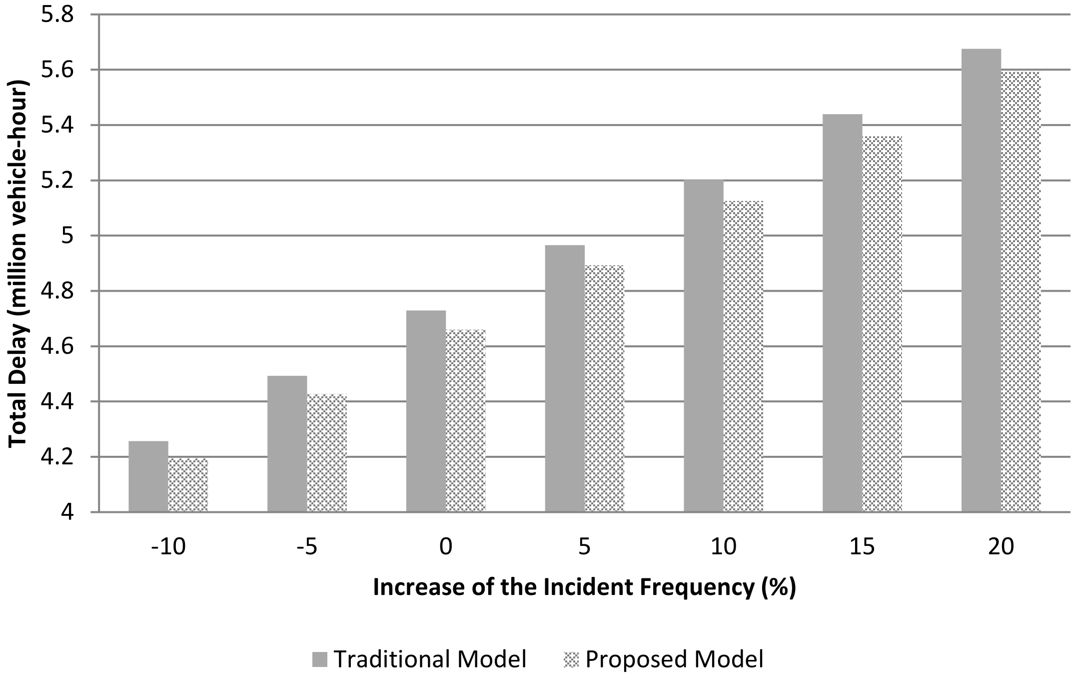
FIGURE 3.9 Total Delays (in vehicle-hours) by Incident Response Strategies

Based on these results, it is evident that the proposed model, if implemented in the TOC-7 region, could outperform the traditional deployment model, which minimizes the response time to clear an incident, in terms of reducing the total incident-induced delay. It also outperformed the CHART's current practice on both reducing average response time and the total delay. Although the results are based only on the incident data and traffic conditions in one region of Maryland, the proposed model seems to be an effective tool for improving freeway incident management programs, especially if the primary concern is to minimize total delay, fuel consumption, and emissions.

Sensitivity Analysis for Key Parameters to Estimate Incident Delay

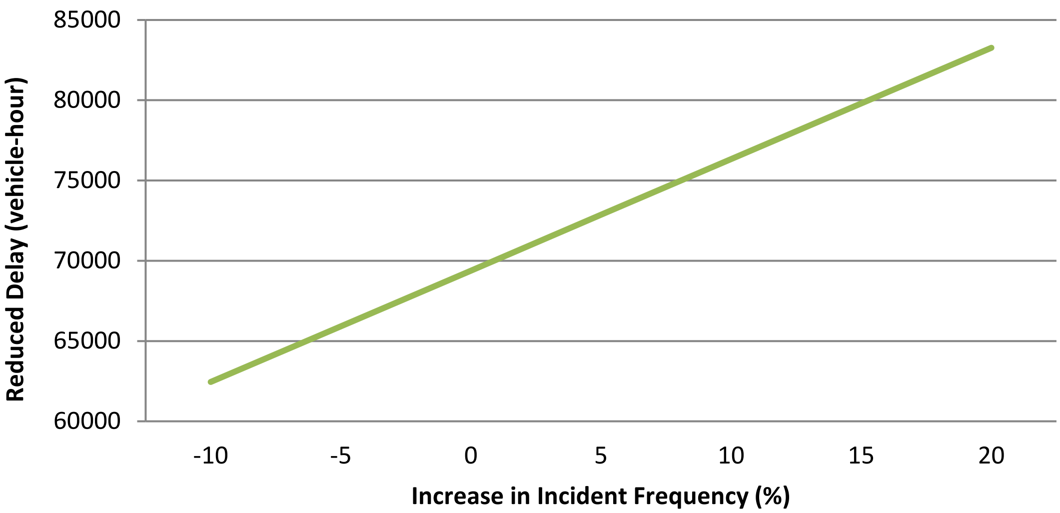
To investigate the performance of the proposed model in various network environments, the team conducted a sensitivity analysis in regard to incident frequency and traffic volume in the target network.

As shown in Figure 3.10, the estimated incident delay from both the traditional and the proposed strategies exhibited an increasing trend as the total incident frequency in the target network increases, given that all other factors remain unchanged. Overall, the delays associated with the proposed model are lower than those from the traditional *p*-median model through all examined incident frequency conditions. The magnitude of the reduction increased linearly, as shown in Figure 3.11, indicating the superior performance of the proposed model regardless of the incident frequency.



* Note: the horizontal axis represents the increase/decrease of the incident frequency in percentage from the value used for the empirical study. ***0*** and ***5*** indicates the incident frequency used in the case study and 5 percent increase from it, respectively, and so on.

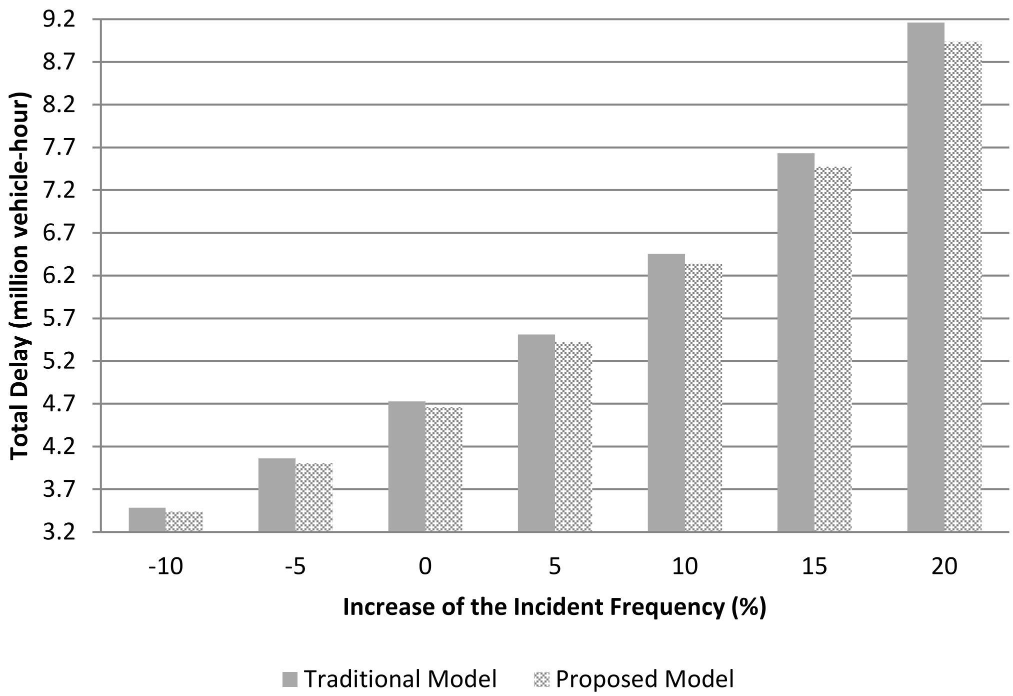
FIGURE 3.10 Model Performance (Incident Delay) by Various Incident Frequencies



* Note: the horizontal axis represents the increase/decrease of the incident frequency in percentage from the value used for the empirical study. ***0*** and ***5*** indicates the incident frequency used in the case study and 5 percent increase from it, respectively, and so on.

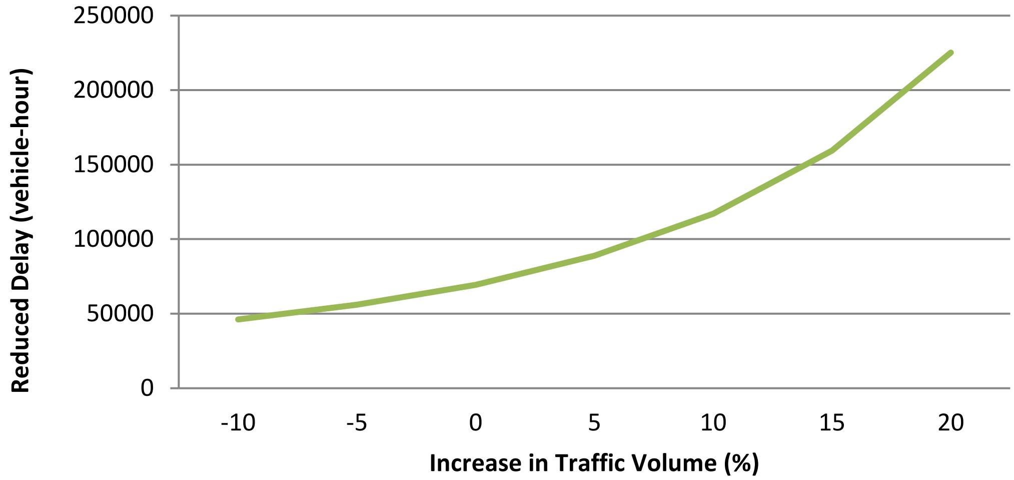
FIGURE 3.11 Reduced Incident Delay by the Proposed Model for Various Incident Frequencies

In addition, the team examined a range of traffic volumes to assess their impacts on the resulting incident delay. As shown in Figure 3.12, the estimated incident delays in both the traditional and the proposed strategies increased with the increase in traffic volume in the target network if all other factors remained the same. The delays based the proposed model show lower than the traditional model over all listed traffic volumes, and the magnitude of the reduction exponentially increased, as displayed in Figure 3.13.



* Note: the horizontal axis represents the increase/decrease percentage of the traffic volume from the value used for the empirical study. ***0*** indicates the traffic volume used in the case study and 5 indicates 5 percent increase from the traffic volume used in the case study.

FIGURE 3.12 Model Results (Incident Delays) for Various Traffic Volumes



* Note: the horizontal axis represents the increase/decrease of the traffic volume in percentage from the value used for the empirical study. ***0*** and ***5*** indicates the traffic volume used in the case study and 5 percent increase from it, respectively.

FIGURE 3.13 Reduced Incident Delay by the Proposed Model for Various Traffic Volumes

The results from the above sensitivity analysis further confirm that the developed model can outperform the traditional deployment models with respect to reducing the total incident delay in most scenarios. Thus, the proposed deployment strategy could be effectively utilized in different highway networks. To sum up, it is obvious that the proposed model outperformed the traditional deployment model, minimizing response time, in terms of reducing the total incident-induced delay. It also outperformed the CHART's current practice with respect to reducing both average response time and total delay. Thus, the proposed model could assist traffic control centers in not only improving freeway incident management programs but also helping the environment with a subsequent decrease in fuel consumption and emissions.

Chapter 4: Analysis of Incident Clearance Duration

4.1 Introduction

As described in Chapter 3, incident duration consists of three phases: detection/reporting time, response time, and clearance time. In general, it is difficult to know the exact timestamp of incident occurrence, and the CHART DB II includes records only for response and clearance times. Thus, in this study, incident duration is defined as the time elapsed from the incident being reported to its clearance, which is the sum of the response and clearance times.

The nature of the response time is somewhat different from that of the clearance time. The critical factors associated with the response time are relatively straightforward, including incident severity, lane blockage status, pavement conditions, incident sites, and responsible operation centers, as reviewed in Chapter 3. The variance of response times is rather small, depending mainly on the incident response strategies operated by the responsible agencies and their available resources. On the other hand, the clearance duration depends on various factors and their complex interactions.

Prior to conducting an in-depth study of the clearance time, this study conducted a preliminary analysis with incident data from CHART DB II, and concluded the following findings:

- *More severe incidents tend to require more time to be cleared.*
- *Adverse environmental conditions can cause a longer clearance time.*
- *Resource availability of an incident management team may affect the duration of the resulting incident clearance.*

According to the first finding, the durations to clear incidents of multiple-lane closures and/or fatalities are generally longer than other incidents. This pattern is more pronounced for fatality-involved incidents, as their resulting clearance times are approximately three times longer than those without a fatality. Similarly, incidents involving heavy vehicles are likely to need more clearance times than passenger car-only incidents.

The second finding reveals that incidents occurring at night and/or on snowy/icy road conditions, on average, are likely to need longer clearance times than those in daytime and/or with non-snowy/icy pavement conditions. This finding is somewhat related to the first finding, since incidents occurring at night (8 p.m. to 6 a.m.) and/or in inclement weather tend to be more severe, especially for collision types of incidents owing to the short sight distance and the difficulty of vehicle maneuverability.

Unlike the first two findings, the last finding is associated with the resource management for response units rather than the incident nature. The analysis results show that the average clearance times for the same type of incidents could vary significantly with their responsible operation center. This discrepancy in clearance efficiency is mostly due to the resource availability or operational strategies. In addition, Chapter 3 shows that the involvement of incident response units is likely to shorten the incident clearance time.

As indicated in the preliminary analysis, clearance times are correlated not only with incident characteristics and environmental factors, but also influenced by other factors such as incident management strategies and resource allocation. The complex interrelationships between all key factors cause the estimation of clearance time to be a more complex task.

The rest of this chapter first presents the proposed model to predict incident clearance duration and then evaluates it by comparing with the performance of other widely used methodologies. The chapter closes with a summary and discussion of the findings.

4.2 Data

This study used the data from 6000 incidents in CHART-II database to develop the model. The dataset was divided into two sets using a random sampling technique - one with 4000 incident records for model development and the other with 2000 incident records for model validation. The independent variables included for model development are listed below:

- Incident duration: responded and cleared timestamps;
- Lane blockage information: number of shoulder lane blockages, total number of lanes at the incident location, and number of lanes blocked (in the same and opposite direction);
- Incident type: property damage, personal injury or fatality by collision, debris, disabled vehicle, vehicle fire, police activities, off-road activities, and emergency roadwork;
- Response team: participation of MDOT SHA patrol (CHART);
- Operation Center: TOC 3, TOC 4, TOC 7, AOC, SOC, and others;
- Detection source: CCTV, system alarm, MDOT SHA, MDOT MDTA, state police, local police, CHART unit, citizen, MCTMC, and media
- Involved vehicles: number of vehicles involved, and types of vehicles involved (truck-trailer, single unit truck, or pickup/van);
- Time: Peak hour (AM or PM peak) indicators, weekend indicator, night indicator, and holiday indicator;
- Location: region, county, road name, and exit numbers for I-495, I-95, I-695, and I-270 only; and
- Pavement condition: dry, wet, snow/ice, chemical wet, and unspecified.

Note that the incident clearance duration in this study is defined as a series of time intervals in view of the following issues:

- The data elements associated with timestamps for each incident are frequently not recorded in a precise manner by the control center operator; and
- An estimated interval, such as 20 to 40 minutes, rather than a precise number, is preferred by incident response operators from the perspectives of both application and the system reliability.

4.3 An Integrated Model to Predict Incident Clearance Duration

The proposed model was developed through three main phases as illustrated in Figure 4.1: 1) filtering out outliers, 2) identifying explicit associations between factors, and 3) developing models to predict unexplainable datasets. The final product from this development was the integrated system of SCAR (Sequential Classifiers with Association Rules) with supplemental models to predict incident clearance times. This algorithm was motivated from the following findings (Kim and Chang, 2012), using a similar source of data:

- Not all clearance times can be clearly attributed to some observable factors.
- Most short (less than 30 minutes) and long (longer than 2 hours) clearance durations show fairly observable relationships with key associated factors.
- It was, however, very challenging to explicitly quantify the interactions between the intermediate (0.5 – 2 hours) clearance times and related variables.

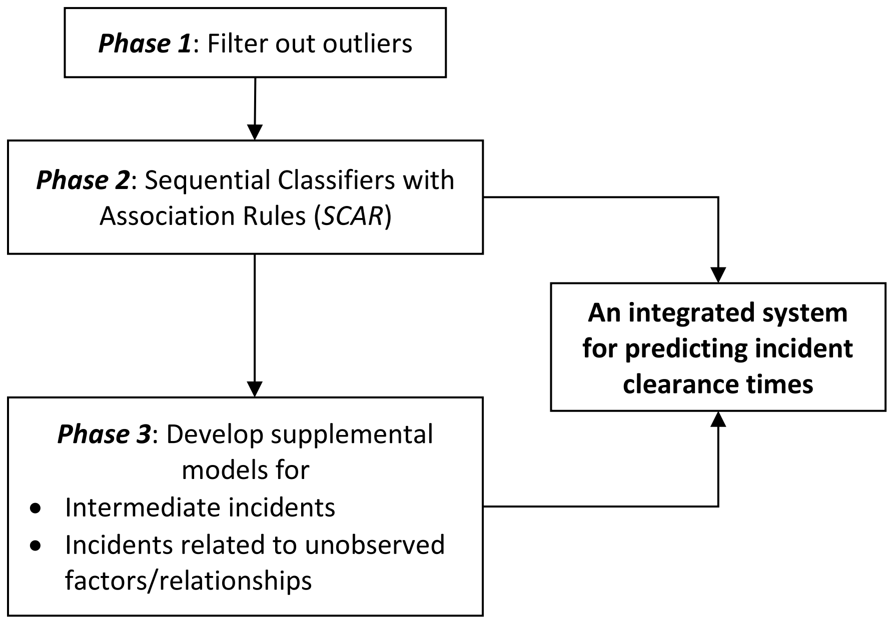


FIGURE 4.1 Flowchart to Develop the Proposed Model

The first phase of model development was focused on identifying potential outliers using a well-known algorithm, *PAM (Partitioning Around Medoids)*. The second phase mainly investigated explicit relationships between the clearance duration and its associated factors and then developed a sequential classifier. The third phase developed a set of supplemental models for 1) intermediate incidents to estimate more precise clearance times; and 2) incidents that cannot be categorized through *Phase 2* (*SCAR*). The details for each phase are discussed below.

4.3.1 Phase 1: Filter out outliers

The dataset for this study was examined to identify potential outliers with two approaches. First, incidents with unreliable or unreasonable information were excluded. For example, some incidents were recoded as being involved with more than 20 vehicles and some incidents have only limited information. Through this process, a total of 39 cases were excluded from the datasets. Furthermore, *Partitioning Around Medoids (PAM)*, was applied to identify any other outliers that cannot be detected by the simple and intuitive criteria.

PAM uses *k representatives*, so-called "*medoids,*" (Kaufman and Rousseeuw, 1987), to construct *k* clusters by assigning each element of the dataset to the nearest medoid. The algorithm is composed of two steps, called BUILD and SWAP (Kaufman and Rousseeuw, 1990), as described below:

- BUILD: Successively select *k* elements to obtain *k* initial clusters, aiming to decrease the object function, which is the sum of the dissimilarities from all other elements to their closest medoids, as small as possible.
- SWAP: Attempt to improve the clustering by switching a selected medoid with an unselected element to minimize the objective function. The step is continued until the value of the objective function is no longer reduced.

In performing the clustering analysis, the major issue was how to determine an appropriate number of clusters based on good clustering (Kaufman and Rousseeuw, 1990). In *PAM*, one uses "*silhouettes*" (Kaufman and Rousseeuw, 1990) to evaluate the quality of clusters and select the best number of clusters, based on the values *s(i)* for each element *i* defined as below:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \qquad \text{(Eq. 4-1)}$$

Where *a(i)* = average dissimilarity of *i* to all other elements in the cluster *A*
d(i, C) = average dissimilarity of *i* to all other elements in the cluster *C* (all clusters that are not *A*)
b(i) = $\min_{C \neq A} d(i, C)$,

From (Eq. 4-1) one can easily see that *s(i)* lies between the interval of – 1 and 1. Absolute values of negative *s(i)* indicate how badly the element *i* is classified, while positive values of *s(i)* indicate how well the element *i* is classified. A zero value of *s(i)* implies that it is not clear whether *i* should belong to *A* or *C*. After computing *s(i)* for every element in the study dataset, one can have the average value of *s(i)* for elements assigned to a cluster, called the *average silhouette width* of the cluster (Kaufman and Rousseeuw, 1990) and used to distinguish strong clusters from weak ones. Furthermore, after running the *PAM* algorithm for different values of *k* (the number of clusters), one can compare the resulting average *silhouettes'* width for the entire dataset from each *k* and choose the "best" *k*, yielding the highest average *silhouettes'* width. Note that *PAM* is more robust than most existing methods using an error sum of squares such as "*k*-means" (MacQueen, 1967; Steinhaus, 1957; Lloyd, 1982) or "*k*-median" (Jain and Dubes, 1998; Bradley et al., 1997) algorithms, since it uses medoids, which are the most centrally located elements, to minimize a sum of dissimilarities (Kaufman and Rousseeuw, 1990). In addition, *PAM* can yield good clusters that are not too stretched and isolate outliers in most cases (Kaufman and Rousseeuw, 1990).

Since *PAM* is mainly applied to identify potential outliers, this study focused on detecting a group of clusters including a small number of elements with the following steps:

1. *Determine the best k:* the most appropriate *k* was found to be 8 with the average *silhouettes* 0.13. According to Kaufman and Rousseeuw (1990), this value indicated that

no significant structure has been found in the given dataset. However, since *PAM* is merely used to discover outliers, further analysis was conducted based on the selected structure.

2. *Select the weakest cluster from the selected structure:* a cluster with 293 elements was selected for further investigation, which showed a relatively large diameter and the largest average dissimilarity within a cluster.
3. *Determine the best k for the selected cluster to sub-cluster:* the best *k* was found to be 3 with the average *silhouettes* of 0.23, and the weakest cluster with 36 incidents was chosen to be a set of outliers in this dataset.

Through *Phase 1*, 45 and 30 incidents were excluded from the datasets for model development and validation, respectively.

4.3.2 Phase 2: Development of Sequential Classifiers with Association Rules (SCAR)

Figure 4.2 displays the distribution of the clearance times of the study dataset (5925 incidents), after excluding potential outliers identified in *Phase 1*. The figure shows that the distribution is highly skewed toward the right, and the clearance durations of most incidents (85 percent) lie within one hour.

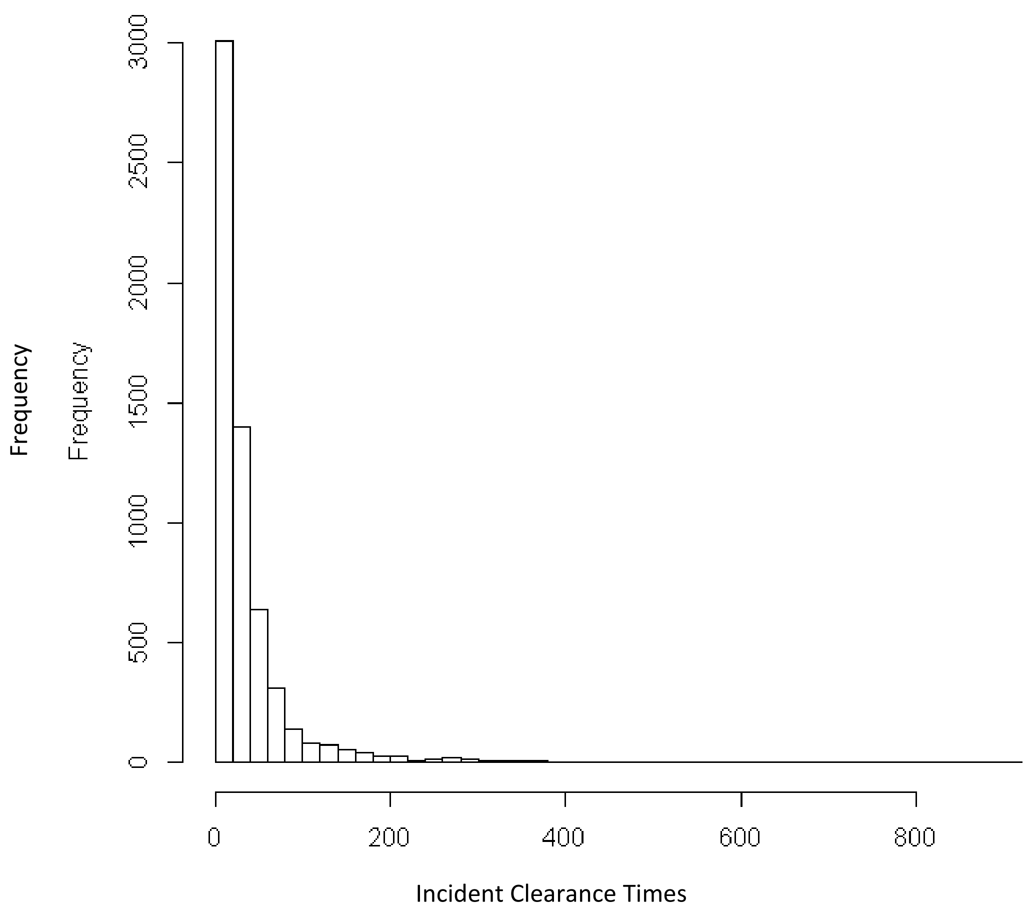


FIGURE 4.2 Distribution of Incident Clearance Times

According to the *Manual on Uniform Traffic Control Devices* (FHWA, 2009) the traffic incidents can be divided into three categories based on their durations: 1) minor: an estimated duration of less than 30 minutes, 2) intermediate: an estimated duration between 30 minutes and 2 hours, and 3) major: an estimated duration longer than 2 hours. Since many response times in the study dataset (90 percent) lie within 10 minutes, this study considered that the incident duration could be replaced with the clearance time to categorize the incident classes.

Table 4.1 presents the distribution of incident clearance times when they were divided into three classes using the standards stated in MUTCD. As observed from Figure 4.2, the time interval class representing clearance times less than 30 minutes (minor incidents) covers 65 – 66 percent of all incidents in both model development and validation datasets. Based on the previous (Kim and Chang, 2012) and preliminary studies, it was found that conventional statistical models may not perform well on such highly skewed data due to their propensity to focus on the major classes.

TABLE 4.1 Distribution of Incident Clearance Times by Time Interval

Time Interval Class (minutes)		**<=30**	**30-120**	**>120**	**Total**
Model Development Set	Frequency	2570	1145	240	3955
	Ratio	65.0%	29.0%	6.0%	100%
Model Validation Set	Frequency	1300	566	104	1970
	Ratio	66.0%	28.7%	5.3%	100%

The selected technique, *Association Rules (AR)*, is a non-statistical theory-based approach that purely concentrates on mining the potential associations between variables. Such characteristics were very effective for analyzing the incident duration, since one of primary objectives for such a study was discovering and understanding the relationships between incident duration and their contributing factors. Such research findings would provide valuable information for traffic-related agencies to plan and enhance traffic incident management programs.

Therefore, this phase first discovered any obvious associations of incident clearance durations with related variables using the *AR* technique. Furthermore, this study proposed a model that consists of rules defined by the mined associations and had the capability to sequentially classify incident clearance durations, namely *Sequential Classifiers with Association Rules (SCAR).*

This section starts with an introduction of *Association Rules*, followed by description of the *SCAR* development procedure and its performance.

Association Rules

Association rules mining is an effective technique to discover interesting relations between variables from large databases. Agrawal et al. (1993) first introduced it to detect and extract useful information regarding products from a large-scale supermarket transaction data in a format of rules such as {onions, meats} → {burger buns}. Such information has long been applied for decisions on marketing activities, e.g., promotion prices, products display or replacement, but recently the applications of the technique have been expanded in various areas, including web-usage mining, intrusion detection, and bioinformatics.

To define the association rules, Agrawal et al. (1993) let $I = \{i_1, i_2, \ldots, i_n\}$ be a set of n binary attributes called *items* and $D = \{t_1, t_2, \ldots, t_m\}$ be a set of transactions called the *database*. Each transaction in D has a unique ID and includes a subset of the items in I. A *rule* is defined as an inference of the form $X \rightarrow Y$, where X and Y are a subset of I and $X \cap Y = \emptyset$. They named X as *antecedent* or LHS (left-hand-side) and Y as *consequent* or RHS (right-hand-side). In the above example {onions, meats} is *antecedent* or LHS, and {burger buns} is *consequent* or RHS.

Association rules are rules that exceed a user-specified minimum support and minimum confidence threshold. The *support* of an itemset X, $supp(X)$, is defined as the proportion of transactions in the database D that include the itemset X. The *confidence* of a rule, $conf(X \rightarrow Y)$, is defined as the proportion of transactions, including itemsets X and Y in the subset of database D that contains the itemset X. It can be mathematically expressed as

$$conf(X \rightarrow Y) = supp(X \cup Y)/supp(X)$$

Thus, an association rule $X \rightarrow Y$ satisfies $supp(X) \geq \alpha$ and $conf(X \rightarrow Y) \geq \beta$, where α and β are minimum support and confidence, respectively.

Another widely-used measure to evaluate association rules is *lift* (Brin et al., 1997), which is defined as:

$$Lift(X \rightarrow Y) = supp(X \cup Y)/(supp(X) \cdot supp(Y))$$

The denominator $supp(X) \cdot supp(Y)$ is defined as the expected confidence, assuming that the occurrence of the rule antecedent is independent of the occurrence of the rule consequent and vice versa. Therefore, a lift is used to measure how many times more often X and Y occur together than expected if they are statistically independent. A lift value between 0 and infinity and greater lift values (>> 1) indicate stronger associations between the rule antecedent and the rule confidence, whereas the value near 1 implies that the occurrence of the rule antecedent has almost no effect on the occurrence of the rule consequent.

Association rules are usually mined through a two-step process (Hahsler and Chelluboina, 2011). First, all itemsets satisfying the minimum support constraint, the so-called "*frequent itemsets*," from the data set are detected. In the next step, all possible rules are generated from each *frequent itemset*, and the algorithm will discard any rules that do not fulfill the minimum confidence constraint. This process provides us with the idea that for a database with n distinct items (variables), there are at most $2^n - n - 1$ *frequent itemsets* generated with more than two items (Hahsler and Chelluboina, 2011). Since each frequent item can generate at least two rules in the worst case, the total number of rules mined is in the order of $O(2^n)$. Typically, the number of mined association rules can be reduced at the manageable size by increasing minimum support, but it has a risk to remove potentially interesting rules with less support (Hahsler and

Chelluboina, 2011). Therefore, one cannot avoid dealing with a massive number of rules in order to find interesting associations between variables, which could be a major drawback of a mining technique with association rules.

The Procedure of Model Development

Figure 4.3 presents the overview of procedures to develop the sequential classifiers with association rules. Details of each step are discussed below:

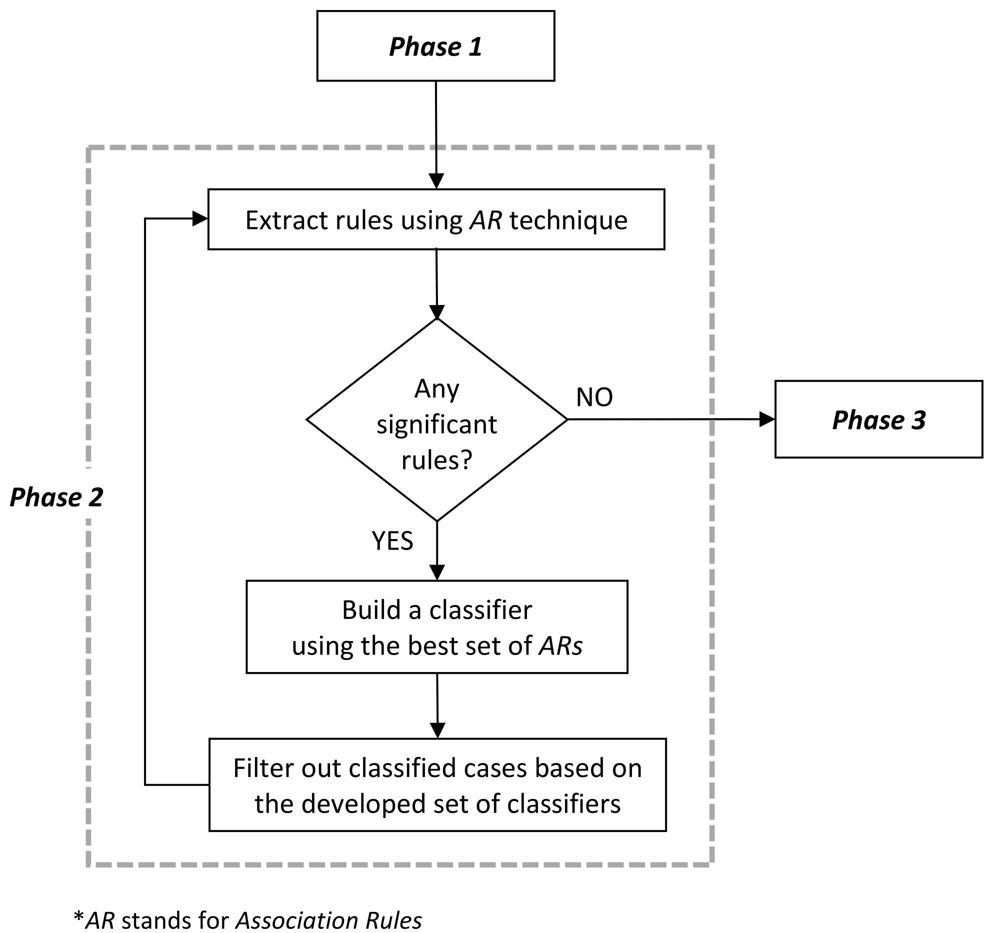


FIGURE 4.3 Flowchart to Develop the Sequential Classifiers with Association Rules (SCAR)

Step 1: Extract association rules from the study dataset.

Using the *AR* algorithm (Hahsler, Grun, and Hornik, 2005) potential association rules are mined from the input dataset. As discussed before, it is very challenging to identify the relationships between the intermediate clearance times (30 minutes – 2 hours) and their factors. Thus, this study set a relatively low value (0.005) for *support* to maximize the discovery of possible association rules related to intermediate clearance times even though they seldom occur in reality (implying a small number of supporting cases). On the other hand, the value for *confidence* was set from an intermediate to a high level (0.60 – 0.90) to discover reliable association rules.

Step 2: Investigate if there is any significant rule.

If *Step1* generates many association rules, one may only need significant or interesting rules, based on the user-defined criteria. This study compared values for *confidence* and *support* among mined rules and chose them with a higher *confidence* and *support*. This step was a preceding assessment to narrow the feasible set to select the most critical *ARs* in the following step.

Step 3: Build sequential classifiers by adding the best set of discovered rule(s).

This step selected the best set of *ARs* from the subset of rules constructed in *Step 2* and used it as a classifier in *SCAR*. Suppose that a set of *m ARs* is generated from *Step 2* and denoted it by Ω. Then, *n ARs* were arbitrarily selected from Ω, and they were denoted by AR_1^1, AR_2^1, …., AR_n^k, where $AR_n^k \in \Omega$, *n* is the number of *ARs* selected from Ω, and *k* indicates the number of trials for the arbitrary sampling of *n*. Note that *n ARs* are combined as a single union set that is expressed by $U_{ARs}^k = \cup AR_n^k$, and *confidence* and *support* values for U_{ARs}^k can be examined. After examining all possible U_{ARs}^k this study selected the one that best satisfies the following objectives:

- Maximize *support*: to reduce the system size (the number of classifiers composing *SCAR*); and
- Maximize the classification accuracy: to decrease the generalized error rate

Based on the process this step can be iterated at most $\binom{m}{n}$ times (= *k*) to examine all possible U_{ARs}^k, and this number will exponentially increase as *n* and *m* increase. Thus, instead of investigating all feasible sets, an alternative way to use the optimization approach, e.g., a generic algorithm, can be considered, and this case becomes the multi-objective optimization problem, since the above objectives conflict with each other. In this study *n* was set to be 2 or 3 for the manageable size of feasible sets, *k*.

Step 4: Build a set of sequential classifiers by adding discovered rule(s).

The selected best set of *ARs* (U_{ARs}^k) from *Step 3* was added to the sequential classifiers to complete *SCAR*.

Step 5: Filter out classified incidents based on the developed SCAR.

The incidents that were classified as supporting cases for the developed classifier through *Steps 3* and *4* were excluded from the input dataset, since their clearance times can be categorized by the developed *SCAR* system. The remaining incidents in the input dataset were used to develop the next classifier though the next iteration of the process; this is where the name of "Sequential Classifiers" with Association Rules system originates.

Step 6: Go back to Step 1 and repeat the above steps until any stopping criterion is satisfied.

This process repeats until either of the following conditions is fulfilled:

- An insufficient number of incidents for further search for association rules remain in the input dataset.
- No substantial association rules are found.

The first condition is the user-defined parameter similar to the concept of having a minimum number of observations included in a node for the attempt to split in *Classification And Regression Trees* (Breiman et al., 1984). In this study the iteration will stop if no interesting association rules satisfying the minimum requirements in *Step 2* have been discovered.

System Illustration and Performance

The complete *SCAR* system includes 44 classifiers, and each is a union set of 2 or 3 association rules mined from the model development dataset as illustrated in Figure 4.4. This formation is inspired by the concept of "*M-of-N rules,*" and it is satisfied if only *M* of *N* conditions are met, where $M < N$ (Craven, 1996). For example, in the *2-of-{a>b, c=d, e≠b, c<f} rules* it is satisfied when any two of four conditions, such as {*a>b,* c<f}, are met. Applying it to the *SCAR* system *M* is set as 1, while *N* is set as 2 or 3 as indicated in *Step 3*. The example used in Figure 5.4 shows that the first classifier is composed of three association rules, namely *AR1*, *AR2*, and *AR3*, and if any of them is satisfied with the detected incident, then it would be likely to be cleared within 30 minutes. If the incident satisfies none of three association rules, then further investigation would be conducted in the next stage (depth) with *Classifier2*. This process continues until any classifier is met or it reaches the terminal node of this system.

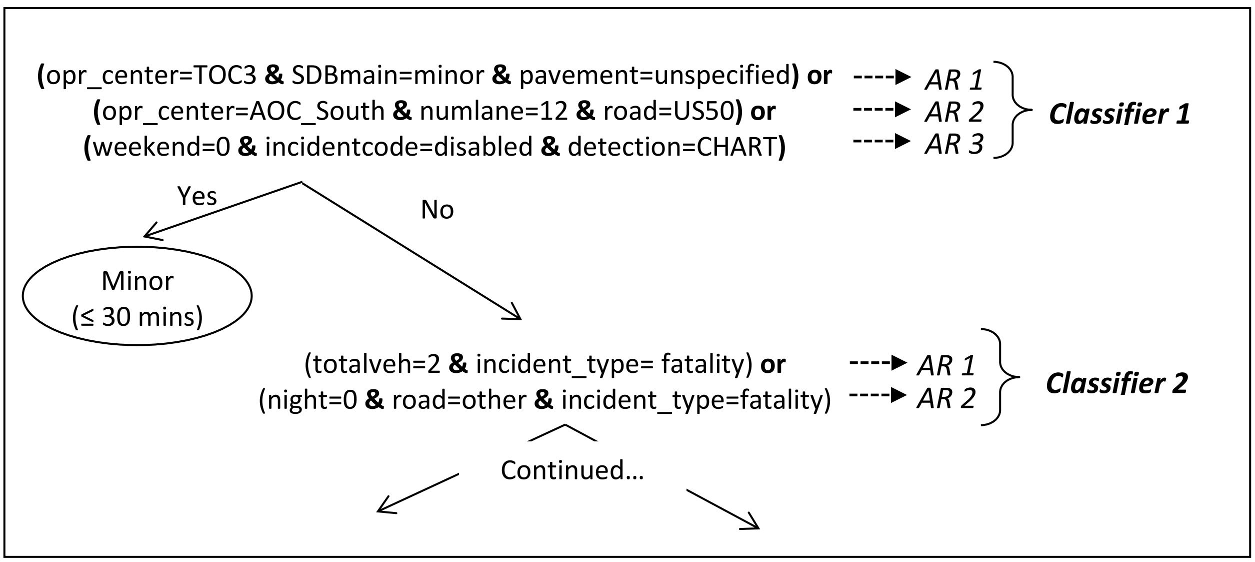


FIGURE 4.4 Illustration of a Single Classifier Composing *SCAR*

The system can classify the clearance durations of 73.1 percent and 72.0 percent of incidents in model development and validation datasets, respectively. Table 5.2 summarizes the performance results of the proposed system.

TABLE 4.2 Results and Performance of the *SCAR* system

Clearance Duration Class (minutes)	Class ratio	Ratio Classified by *SCAR*		# of Classifiers	Intra-accuracy	
		Train	Test		Train	Test
Minor (≤30)	64.98%	81.1%	82.4%	27	87.70%	90.37%
Intermediate (30-120)	28.95%	59.0%	50.5%	13	90.50%	92.51%
Major (>120)	6.07%	55.8%	59.6%	4	75.86%	79.66%
Total	***100.00%***	***73.1%***	***72.0%***	***44***	***87.45%***	***90.20%***

TABLE 4.3 Contingency Table of Observation versus Estimation from the *SCAR* system

Clearance Duration (minutes)		Observation			Intra-accuracy
		Minor (≤30)	Intermediate (30-120)	Major (>120)	
Estimation	***Unclassified***	*487*	*470*	*106*	*NA*
	Minor (≤30)	2040	269	17	87.70%
	Intermediate (30-120)	35	379	7	90.50%
	Major (>120)	8	27	110	75.86%
External-accuracy		97.94%	56.15%	82.09%	***87.45%***

TABLE 4.4 Contingency Table of Observation versus Prediction from the *SCAR* system

Clearance Duration (minutes)		Observation			Intra-accuracy
		Minor (≤30)	Intermediate (30-120)	Major (>120)	
Prediction	***Unclassified***	*229*	*280*	*42*	*NA*
	Minor (≤30)	1060	104	9	90.37%
	Intermediate (30-120)	8	173	6	92.51%
	Major (>120)	3	9	47	79.66%
External-accuracy		98.97%	60.49%	75.81%	***90.20%***

Tables 4.3 and 4.4 present contingency tables for more details of the system results. Both tables have two different types of accuracies – *intra-accuracy* (accuracy by row) and *external-accuracy* (accuracy by column). The intra-accuracy is measured within classifiers, thus indicating the classification confidence (accuracy) of the developed classifiers. On the other hand, the external-accuracy indicates the rate of correct classification (1− misclassification rate) across the observations for the target class. According to the results, the *SCAR* system showed a good capability to correctly classify *Minor* and *Major* incidents. Classifiers embedded in the system had high confidence to classify *Intermediate* incidents, but their accuracy, based on observations

for the target class, was relatively low, owing to misclassifications of classifiers that were targeting for *Minor* incidents.

As shown in the performance result (*Unclassified* in Tables 4.3 and 4.4), not all incidents can be explained by *SCAR*, because some may be related to complex relations between factors and the other may be related to unmeasurable factors. Also, ratios classified by the proposed system vary among different clearance-time classes. As presented in the column named "Ratio Classified by *SCAR*" in Table 4.2, most incidents in *Minor* can be explained with association rules in *SCAR*, but only about half of the incidents in *Intermediate* and *Major* can by classified by the developed classifiers (including misclassified cases). Furthermore, the class of *intermediate* clearance times has a rather wide range from 30 minutes to 2 hours so the classification/prediction results from *SCAR* may need further refinement for practical use. For this reason, further analysis was conducted to supplement *SCAR* with additional models to classify/predict 1) the clearance times of incidents that were not processed by *SCAR*, and 2) the intermediate clearance times into more narrow ranges. *Phase 3* illustrating these analyses is presented in the next subsection.

The established *SCAR* can be presented in two different formats – sequential IF-THEN-ELSE rules or the pruned tree. Table 4.5 exemplifies *SCAR* in the arrangement of sequential IF-THEN-ELSE rules, while Figure 4.5 illustrates it in the form of the pruned tree. Since the developed *SCAR* includes many classifiers, the full description of *SCAR* is presented in the format of sequential IF-THEN-ELSE rules in Appendix.

TABLE 4.5 Presentation of *SCAR* I – Sequential IF-THEN-ELSE Rules

No.	**Description of Classifier**			**Clearance Time**
1	IF	(road=I895 & incident_type=disabled) or (noTT=0 & noSDsh=0 & incident_type=disabled) or (noTT=0 & road=US50 & incident_type=disabled)	THEN	Minor (≤30)
2	ELSE-IF	(OC=TOC3 & noLane=13 & county=MO & incident_type=cpd) or (noTT=0 & road=I495 & incident_type=disabled & pavement=dry) or (chart=1 & noLane=12 & road=I95 & incident_type=disabled)	THEN	Minor (≤30)
3	ELSE-IF	(OC=TOC3 & SDBmain=minor & pavement=unspecified) or (OC=AOC_South & noLane=12 & road=US50) or (Weekday & incident_type=disabled & detection=CHART)	THEN	Minor (≤30)
4	ELSE-IF	(totalveh=2 & incident_type=fatality) or (night=0 & road=other & incident_type=fatality)	THEN	Major (>120)
6	**Continued in Appendix**			

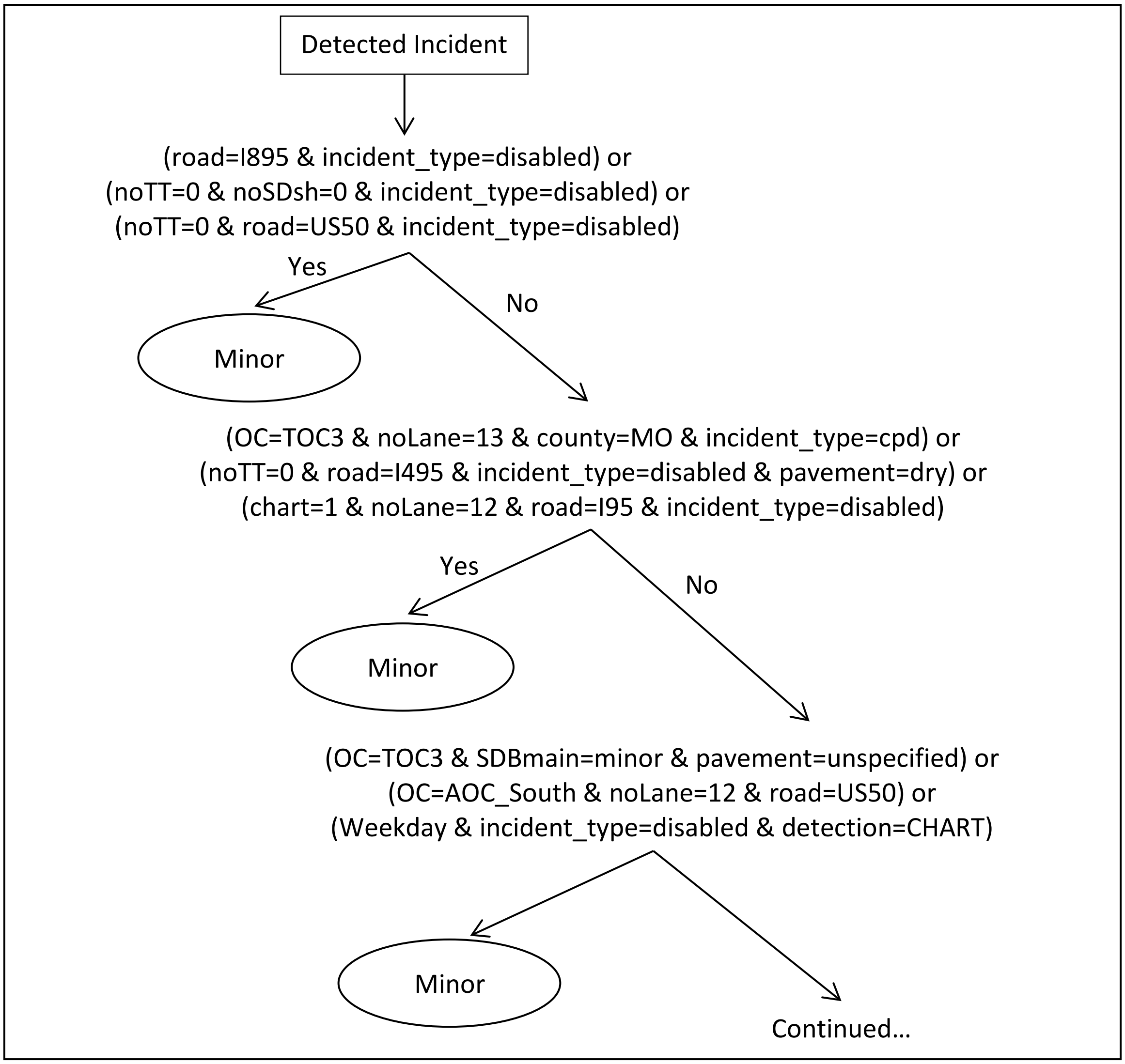


FIGURE 4.5 Presentation of *SCAR* II – Pruned Tree

SCAR first assesses whether the incident entered in the system fulfills the conditions in the first classifier or not. If so, then the clearance time of the incident is classified as *Minor* and is predicted to be less than 30 minutes. Otherwise, it will be sent to the next classifier and reexamined. Through the process of *SCAR* development and reviewing the mined association rules, key findings on the relations between incident clearance times and their associated factors were discovered and summarized below:

<Incident type>

- If an incident type is identified as <u>disabled vehicle(s)</u>, the clearance duration is highly likely to end in 30 minutes (*Minor* class).
- If an incident is related to any <u>fatality</u>, the clearance duration is highly likely to be longer than two hours (*Major* class).

- If an incident occurs during peak hours on major corridors in the Washington and Baltimore Metropolitan regions and is involved with property damage but no heavy vehicles, its clearance duration is likely to end in 30 minutes (*Minor* class).
- If an incident is involved with property damage and tractor-trailer, its clearance duration is likely to be longer than 30 minutes (*Intermediate* or *Major* class).
- If an incident occurs during off-peak hours or on minor roadways in suburban areas in Maryland and is involved with property damage, its clearance duration is likely to be longer than 30 minutes (*Intermediate* or *Major* class).
- If an incident is involved with personal injuries and heavy vehicles and is detected by CHART, the clearance duration is likely to end in 30 minutes (*Minor* class).
- If an incident is involved with personal injuries and heavy vehicles but is detected by other sources than CHART, the clearance duration is likely to be between 30 minutes and 2 hours (*Intermediate* class).

<Detection Source>

- If an incident is detected by CHART, the clearance duration is likely to end in 30 minutes (*Minor* class).
- If an incident is detected by other sources than CHART (SHA, polices, MDTA, CCTV, etc.), during daytime in urban areas, the clearance duration is likely to end in 30 minutes (*Minor* class).
- If an incident is detected by other sources than CHART (SHA, polices, MDTA, CCTV, etc.) and occurs at night or in suburban areas, the clearance duration is likely to be longer than 30 minutes (*Intermediate* or *major* class).

<Night>

- If more than half of the total number of lanes is closed due to an incident occurring during daytime, the clearance duration is likely to end in 30 minutes (*Minor* class).
- If more than half of the total number of lanes is closed due to an incident occurring at night, the clearance duration is likely to be longer than 30 minutes (*Intermediate* or *major* classes).
- If an incident is involved with tractor-trailer(s) and occurs during daytime, then the clearance duration is likely to be between 30 minutes and 2 hours (*Intermediate* class).
- If an incident is involved with tractor-trailer(s) and occurs at night, the clearance duration is likely to be longer than two hours (*Major* class).

<Pavement>

- If an incident occurs on wet pavement (proxy factor for rainy days) at night, the clearance duration is likely to be between 30 minutes and 2 hours (*Intermediate* class).
- If an incident occurs on wet pavement (proxy factor for rainy days) during the daytime, the clearance duration is likely to end in 30 minutes (*Minor* class).

<Region>

- If an incident occurs in Southern or Western Maryland, the clearance duration is likely to be longer than two hours (*Major* class).
- If an incident occurs in Eastern Maryland, the clearance duration is likely to be between 30 minutes and 2 hours (*Intermediate* class).
- If an incident occurs in the Washington and Baltimore Metropolitan Regions, the clearance duration is likely to end in 2 hours (*Minor* or *Intermediate* class).

These findings were consistent with observations that severe incidents causing multi-lane closure and/or fatalities were highly likely to last a long duration, while minor collisions were likely to be cleared in a relatively short time. Moreover, the clearance duration of similar incidents may vary significantly with their onset times in a day. For example, an incident occurring during peak-hours or daytime is likely to be cleared in a shorter duration than a similar one occurring at night. Region was also a significant factor so that incidents in urban areas were likely to be cleared faster than those in suburban or rural areas. An interesting finding associated with detection sources was that incidents detected by CHART are likely to be cleared faster than those detected by other sources. It confirmed the importance and contribution of incident management programs in addition to their prompt responses, as discussed in Chapter 3.

Advantages of SCAR

The proposed *SCAR* system is a recursive partitioning algorithm similar to a Decision Tree model, but with the following additional strengths:

- *Reducing the presentation scale and complexity:*
  The association rule used in *SCAR* implies the interaction of factors so that additional splitting to represent the interaction is not necessary, as illustrated in Figure 4.6. This feature in *SCAR* would be more critical as more factors are related to the interaction. Thus, it would significantly reduce the entire scale of the complete model to improve the interpretability of the model.

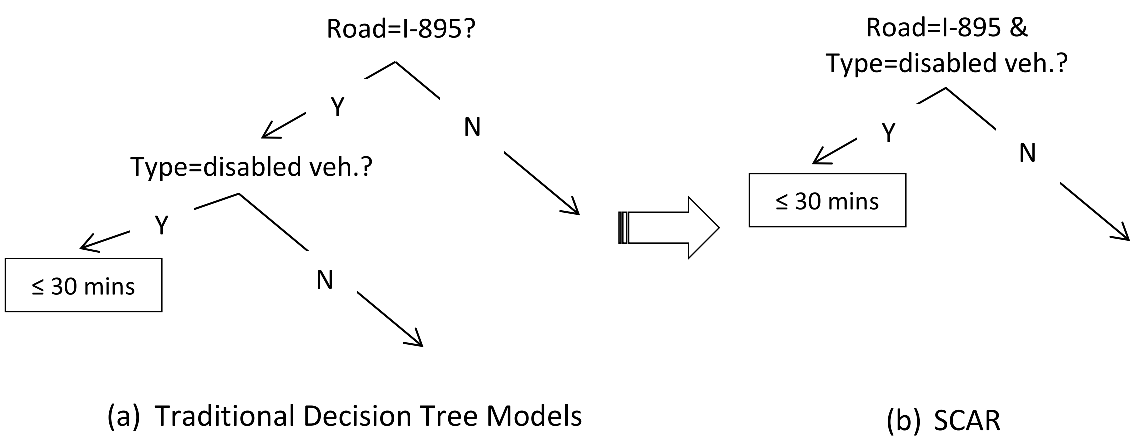


FIGURE 4.6 Reduction of the Presentation Scale and Complexity of *SCAR*

- *Less sensitive to the lack of samples due to the recursive partitioning:*
  In general, after sufficient iterations to expand the tree deeper, the decision tree model loses the capability to split further because of insufficient samples (Craven, 1996). *SCAR* can avoid this limitation due to the recursive partitioning feature (see Figure 4.7). Consequently, *SCAR* provides more opportunities to discover rules regarding the clearance time and its related factors.

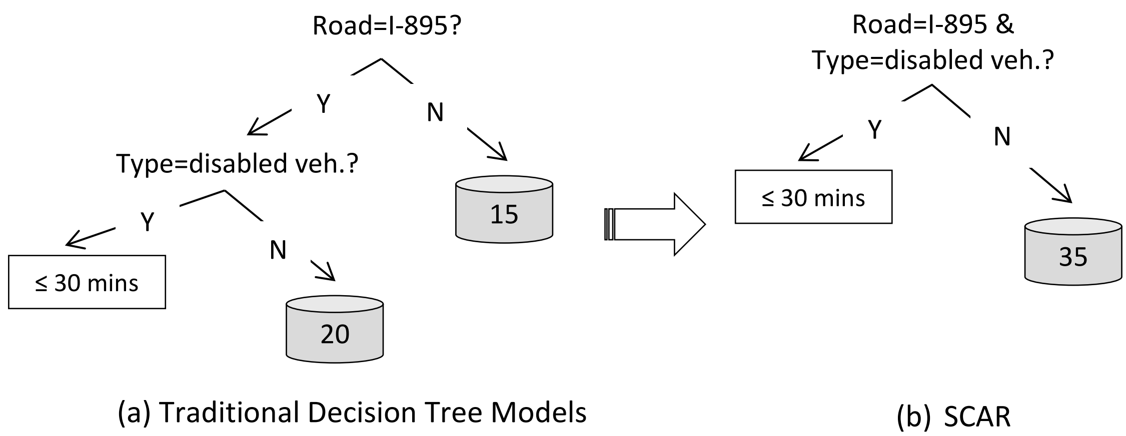


FIGURE 4.7 Prevention from the Lack of Samples in *SCAR*

- *Less sensitive to information loss:*
  Decision tree algorithms can construct multiple different models using the same data set, as exhibited in Figure 4.8, and one must select one out of them. However, *SCAR* combines these in a single model that prevents it from losing information in either decision tree model that is not selected as a final model.

In summary, *SCAR* has several unique features that reduce the model size, complexity, and information loss, and they make *SCAR* more favorable than the traditional decision tree models.

4.3.3 Phase 3: Supplemental Models

The developed *SCAR* in *Phase 2* categorizes incidents into three classes based on the estimated/predicted clearance times – minor, intermediate, and major – as discussed before. Each class defined below is based on the classification in MUTCD (2009):

- Minor: the expected clearance time is less than 30 minutes.
- Intermediate: the expected clearance time is between 30 minutes and 2 hours; and
- Major: the expected clearance time is longer than 2 hours.

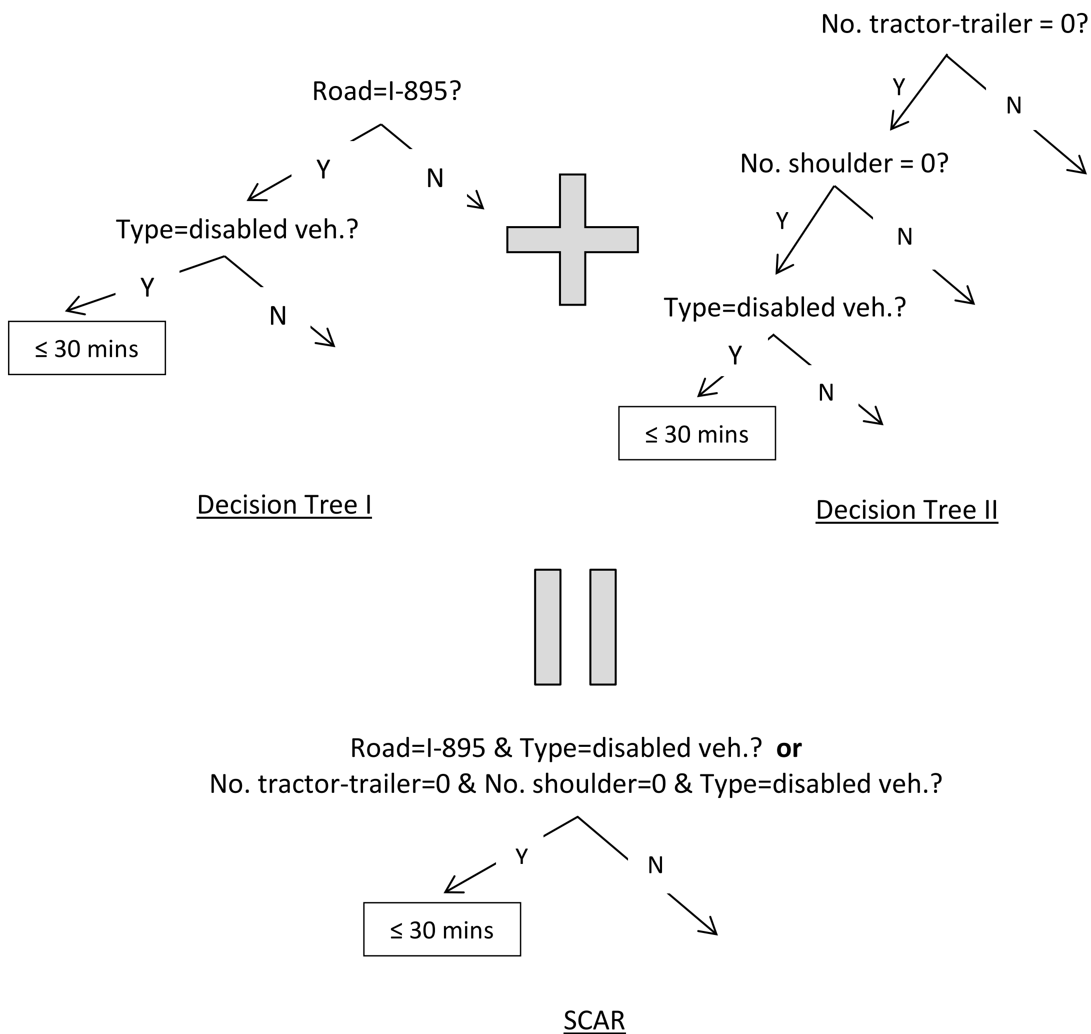


FIGURE 4.8 Prevention from the Information Loss in *SCAR*

Note that the data set used in this study included 344 major incidents (5.8 percent of the total), with clearance times ranging from 2 hours to 15 hours. This wide range of distribution posed a challenge to further refine the model to estimate/predict the clearance times for major incidents.

On the other hand, intermediate incidents can be further divided into the following classes based on the available samples:

- Intermediate-sub1: the expected clearance time is between 0.5 and 1 hour
- Intermediate-sub2: the expected clearance time is between 1 and 1.5 hour; and
- Intermediate-sub3: the expected clearance time is between 1.5 and 2 hours

Additional analysis for incidents that cannot be categorized through *SCAR* was also conducted. Since incidents not categorized by *SCAR* also cannot be explained with interrelationships between factors, the "black-box"-type machine learning algorithms were applied to develop models with those data sets.

This section discusses two potential approaches for these analyses – a support vector machine and a random forest – because they have been gaining popularity among various black-box-type machine learning algorithms.

Support Vector Machine

A support vector machine (SVM) is recognized as one of the most popular and efficient classification methods in the literature of learning algorithms, but has received less attention by the transportation community (Karatzoglou et al., 2006; Bhavsar et al., 2008). The method was developed based on the statistical learning theory and the structural risk minimization principle with solid theoretical properties (Berwick and Idiot, 2009). Thus, SVM demonstrates a unique advantage in solving small sample, time-varying, nonlinear and high dimensional pattern recognition problems (Guoguang et al., 2000; Wu et al., 2011).

The key features of SVM developed by Vapnik and coworkers (Vapnik, 1998; Cortes and Vapnik, 1995) for binary classification can be summarized as follows (Meyer, 2011):

- **Class separation:** As shown in Figure 4.9 (a), the goal is to find the optimal separating hyper-plane between two classes to maximize the "margin" between the closest points of two classes.
- **Overlapping classes:** In cases that the separating hyper-plane cannot perfectly split into "yes" and "no" examples, a "soft margin" method (Cortes and Vapnik, 1995) is applied to allow some points inside or on the wrong side of the margin (i.e., mislabeled examples) as illustrated in Figure 4.9 (b).
- **Nonlinearity:** For cases of a non-linear nature, a kernel method (Boser et al., 1992) is applied to project data points into a higher-dimensional space using kernel functions so that the dataset effectively becomes linearly separable, as demonstrated in Figure 4.10.
- **Problem Solution:** The entire procedure can be formulated as a quadratic optimization problem and can be solved with known techniques. The program to perform all such tasks is called a "Support Vector Machine."

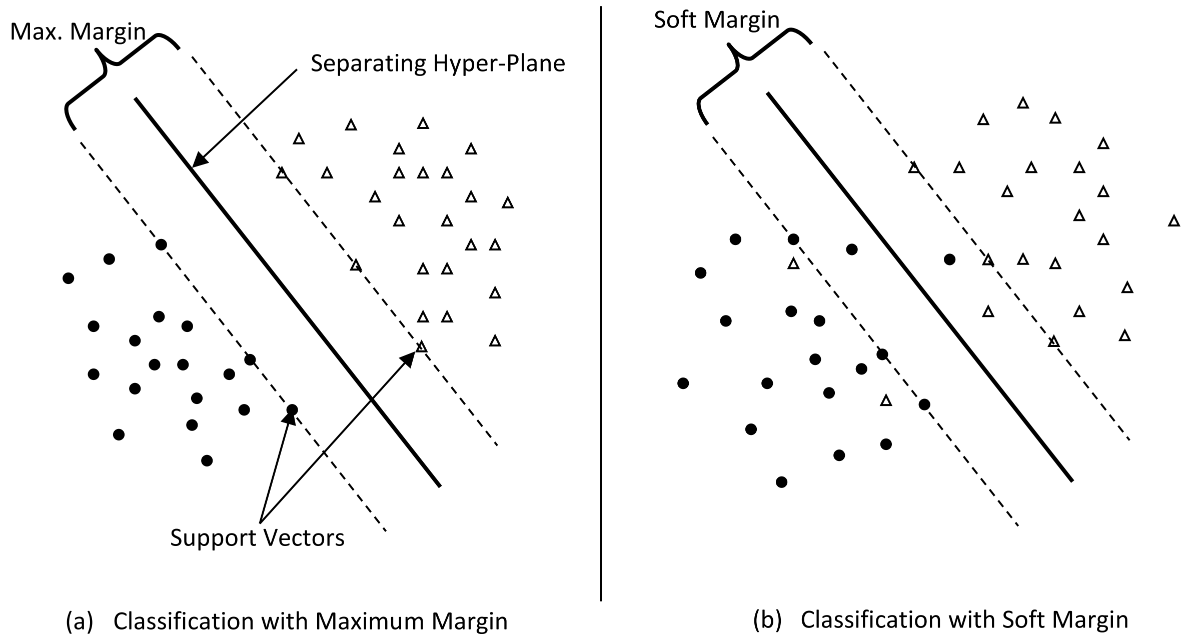


FIGURE 4.9 Illustrations of Support Vector Machines (Meyer, 2011)

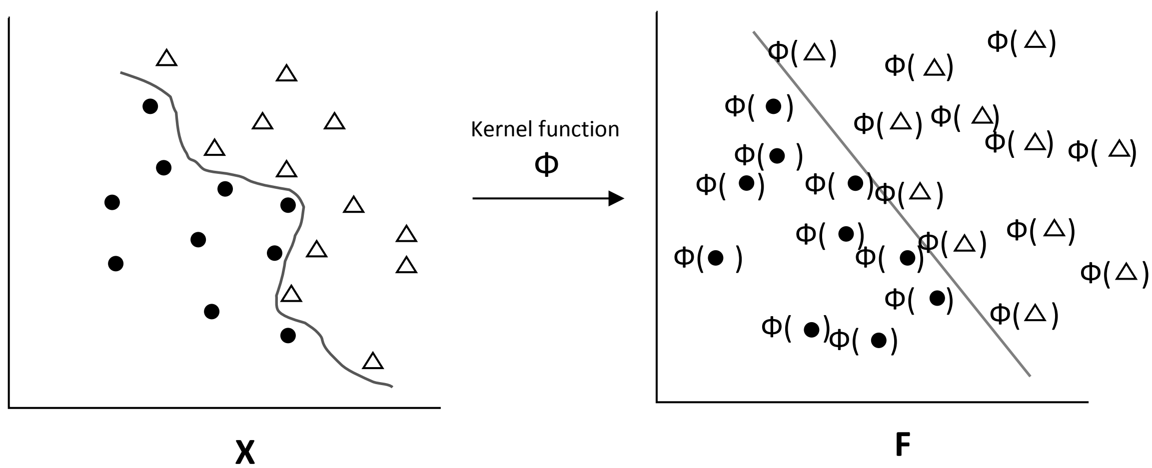


FIGURE 4.10 Illustration of Projection of Non-Linearly Separable Cases to the Higher Dimensional Feature Space (Meyer, 2011)

Despite its strengths, the potential deficiency of SVMs lie in the difficulty of interpreting the estimation results. Similar to the neural network method, SVM is viewed by many researchers as a “black-box” model, because the understanding and interpretation of both the training data and the estimated results are quite challenging for a high-dimensional data set.

Random Forests

Breiman (2001) proposed a method of random forests, an ensemble of un-pruned classification and regression trees, which constructs each tree (a selected classifier) using a different bootstrap sample (sampling with replacement) of a training data set, but the tree induction process is somewhat different from the traditional decision tree. Instead of using a best split among all variables, the random forest method first randomly chooses a subset of predictors at each node and uses the best among them to split the node. The algorithm for random forests is summarized below:

1. Draw ***n*** bootstrap samples from the original data set.
2. At each bootstrap sample, grow *un-pruned* classification or regression trees (CART (Breiman et al., 1984)) with the following process: At each node randomly selects ***m*** predictors and splits the node with the best among those variables.
3. To predict new data, aggregate predictions of ***n*** trees by majority votes for classifications, or average for regression.

Compared with many other classifiers, the random forests showed quite good results that were more robust with respect to noise and over-fitting (Breiman, 2001). They also handled thousands of input variables without deleting any outliers. However, since a random forest consists of many un-pruned fully-grown trees, its outputs are difficult to interpret to be considered as a "black-box"-type model.

Analysis Results for Supplemental Model 1: Estimate More Specified Intermediate Clearance Times

After going through the *SCAR* system in Phase 2, a total of 421 incidents were categorized as intermediate incidents having clearance times between 30 and 120 minutes in the development data set. Among those, 42 incidents (about 10 percent) were identified as misclassifications. Thus, the estimation/prediction model development for sub-classes of intermediate clearance times was conducted with the correctly categorized 379 intermediate incidents.

The sample sizes of sub-classes in intermediate incidents were also unbalanced, as shown in Table 4.6. The sub-class 1 (clearance times between 30 and 60 minutes) dominated the intermediate clearance times, while the sub-class 3 is only 10 percent of the total. Therefore, SVM and RF were highly likely to focus on the dominated class, sub-class 1, to increase their overall model accuracy. To balance sub-classes, weights were applied to observations, and SVM and RF models were developed based on the weighted observations. In addition, regression-type models were developed by using continuous values of clearance times, and the estimated/predicted clearance times were discretized with the same scheme as the one used for the proposed system.

Tables 4.6 and 4.7 summarized the performance results based on the model development data set and validation data set, respectively. SVM-1 was developed without weights (used the original class ratios), while SVM-2 and SVM-3 were developed based on a set of weights that assigns higher values to intermediate-sub 2 and intermediate-sub 3 than intermediate-sub 1. SVM-reg and RF-reg were developed based on the continuous value form of clearance times.

Comparing the performance of the developed SVMs, all showed good estimation results, but only SVM-1 showed fairly good prediction results. Although SVM-3 was somewhat over-fitted and demonstrated the worst overall accuracy, it showed better performance on the sub-class 3 (clearance times between 90 and 120 minutes) than any other SVM models. Similarly, both developed RF models exhibited better overall results than SVM-3, they mainly focused on estimating/predicting the intermediate-sub1. Since this phase focused on developing a model that has a better capability to estimate/predict the minor class (intermediate-sub3), SVM-3 was selected as the final model.

TABLE 4.6 Estimation Results from SVM and RF for Intermediate Clearance Times Analysis

Clearance Duration Class (minutes)	Class ratio	Accuracy					
		SVM-1	SVM-2	SVM-3	SVM-reg	RF-1	RF-reg
Intermediate-sub1 (30 – 60)	64.38%	100.0% (244/244)	76.6% (187/244)	55.7% (136/244)	97.1% (237/244)	61.9% (151/244)	96.3% (235/244)
Intermediate-sub2 (60 – 90)	24.27%	32.6% (30/92)	89.1% (82/92)	67.4% (62/92)	89.1% (82/92)	33.7% (31/92)	53.3% (49/92)
Intermediate-sub3 (90 – 120)	11.35%	18.6% (8/43)	97.7% (42/43)	100.0% (43/43)	48.8% (21/43)	7.0% (3/43)	0.0% (0/43)
Total	NA	74.4% (282/379)	82.1% (311/379)	63.6% (241/379)	89.7% (340/379)	48.8% (185/379)	74.9% (284/379)

TABLE 4.7 Prediction Results from SVM and RF for Intermediate Clearance Times Analysis

Clearance Duration Class (minutes)	Class ratio	Accuracy					
		SVM-1	SVM-2	SVM-3	SVM-reg	RF-1	RF-reg
Intermediate-sub1 (30 – 60)	61.27%	94.3% (100/106)	54.7% (58/106)	40.6% (43/106)	64.2% (68/106)	81.1% (86/106)	85.8% (91/106)
Intermediate-sub2 (60 – 90)	29.48%	7.8% (4/51)	19.6% (10/51)	17.6% (9/51)	35.3% (18/51)	23.5% (12/51)	23.5% (12/51)
Intermediate-sub3 (90 – 120)	9.25%	0.0% (0/16)	18.8% (3/16)	37.5% (6/16)	0.0% (0/16)	25.0% (4/16)	0.0% (0/16)
Total	NA	60.1% (104/173)	41.0% (71/173)	33.5% (58/173)	49.7% (86/173)	59.0% (102/173)	59.5% (103/173)

Analysis Results for Supplemental Model 2: Estimate Clearance Times of Incidents Uncategorized by SCAR

As discussed previously, *SCAR* was not able to categorize all incidents, since some incidents were associated with factors or their relationships that cannot be measured, observed, or identified. As presented in Table 4.2, *SCAR* could classify the clearance durations for 73.1 percent and 72.0 percent of incidents in model development and validation data sets, respectively. Thus, an additional study for incidents that cannot be categorized by *SCAR* was conducted in this phase.

Like supplemental model 1, SVM-1 was developed based on the original class ratios (no weights are applied), and SVM-2 used a set of weights to balance the class ratio. SVM-reg and RF-reg were developed based on clearance times with the continuous value format. Tables 4.8 and 4.9 summarize the model performance results based on the development data set and validation data set, respectively. SVM-1 demonstrated its good performance only for minor and major incidents, while the overall result of SVM-2 was not acceptable. SVM-reg was over-fitted, and RF-reg only focused on the intermediate-sub 2 class. Since RF-1 showed fairly good performance on intermediate and major incidents, it was selected to improve the estimation/prediction performance.

TABLE 4.8 Estimation Results from SVM and RF for Incidents Uncategorized by *SCAR*

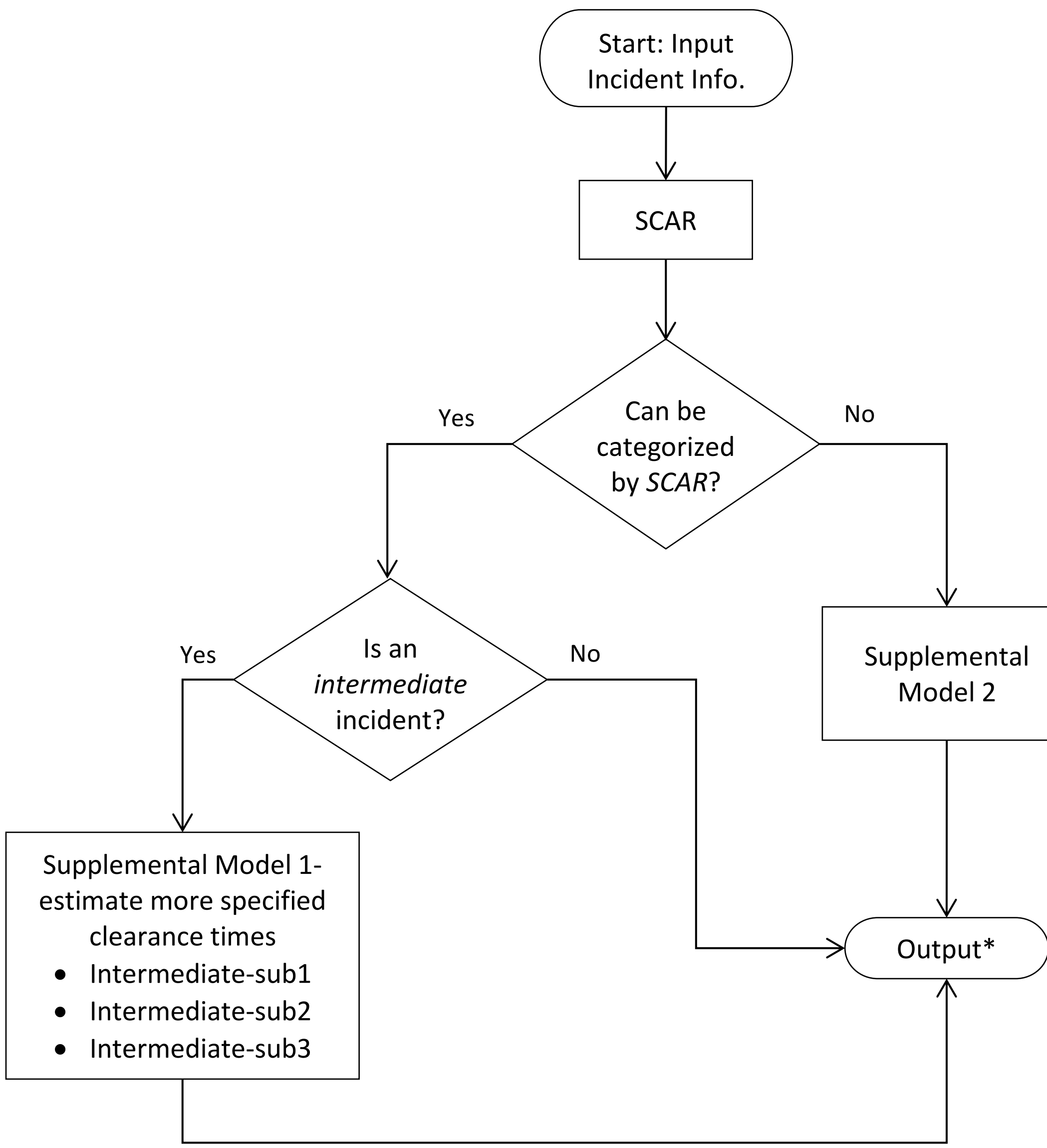
Clearance Duration Class (minutes)	**Class ratio**	**Accuracy**				
		SVM-1	SVM-2	SVM-reg	RF-1	RF-reg
Minor (≤ 30)	44.36%	96.% (468/487)	13.3% (65/487)	99.8% (486/487)	4.7% (23/487)	59.3% (289/487)
Intermediate-sub1 (30 – 60)	32.22%	26.2% (85/325)	46.8% (152/325)	9.8% (32/325)	50.8% (165/325)	82.5% (268/325)
Intermediate-sub2 (60 – 90)	10.59%	2.7% (3/112)	36.6% (41/112)	98.2% (110/112)	28.6% (32/112)	37.5% (42/112)
Intermediate-sub3 (90 – 120)	3.66%	6.1% (2/33)	75.8% (25/33)	97.0% (32/33)	0.0% (0/33)	18.2% (6/33)
Major (> 120)	9.17%	63.2% (67/106)	59.4% (63/106)	100.0% (106/106)	26.4% (28/106)	50.9% (54/106)
Total	NA	58.8% (625/1063)	32.5% (346/1063)	72.1% (766/1063)	23.3% (248/1063)	62.0% (659/1063)

TABLE 4.9 Prediction Results from SVM and RF for Incidents Uncategorized by *SCAR*

Clearance Duration Class (minutes)	**Class ratio**	**Accuracy**				
		SVM-1	SVM-2	SVM-reg	RF-1	RF-reg
Minor (≤ 30)	44.36%	86.0% (197/229)	11.4% (26/229)	33.6% (77/229)	3.5% (8/229)	25.3% (58/229)
Intermediate-sub1 (30 – 60)	32.22%	9.2% (18/195)	36.9% (72/195)	39.0% (76/195)	52.8% (103/195)	55.9% (109/195)
Intermediate-sub2 (60 – 90)	10.59%	0.0% (0/59)	18.6% (11/59)	22.0% (13/59)	40.7% (24/59)	13.6% (8/59)
Intermediate-sub3 (90 – 120)	3.66%	0.0% (0/26)	34.6% (9/26)	23.1% (6/26)	11.5% (3/26)	11.5% (3/26)
Major (> 120)	9.17%	28.6% (12/42)	45.2% (19/42)	19.0% (8/42)	31.0% (13/42)	9.5% (4/42)
Total	NA	41.2% (227/551)	24.9% (137/551)	32.7% (180/551)	27.4% (151/551)	33.0% (182/551)

4.3.4 The Integrated System to Predict Incident Clearance Times

Figure 4.11 illustrates the proposed system flow to estimate/predict the clearance time of the detected incident with collected information. Once an incident is reported to the traffic operation center with related information, such as location, type of incident, lane closure status, involved vehicles, and so on, the traffic operation center staff enters the information into *SCAR*. In summary, if the incident can be categorized by *SCAR* and the result is an *intermediate* incident, then it will be entered the supplemental model 1 for further estimation. If the incident cannot be categorized by *SCAR*, then it will go through the supplemental model 2 to be further categorized into one of five classes.



*output (mins): minor (≤ 30), intermediate-sub 1 (30-60), 2 (60-90), and 3 (90-120), and major (>120)

FIGURE 4.11 System Flowchart to Estimate/predict Incident Clearance Times Using the Proposed System

Table 4.10 shows that the overall performance of the proposed integrated system was promising. The system could well estimate/predict the *Minor* incident clearance, while its performance on the clearance times for the other classes was relatively poor. Considering the ratio of the original sample size in the data set, the probability that one could correctly classify an incident in *intermediate–sub3* by random guess was only 0.24. This value would not increase significantly even if the related agents have much experience. On the other hand, the proposed system increased the probability nearly 10 times larger than the results with random guessing.

TABLE 4.10 Performance Result from the Proposed Integrated System

Incident Class	**Clearance Duration (minutes)**	**Class ratio**	**Accuracy**	
			Train	Test
Minor	≤ 30	65.0%	80.3% (2063/2570)	82.2% (1068/1300)
Intermediate-sub1	30 – 60	20.0%	38.1% (301/790)	37.8% (146/386)
Intermediate-sub2	60 – 90	6.6%	35.9% (94/262)	24.4% (33/135)
Intermediate-sub3	90 – 120	2.4%	46.2% (43/93)	20.0% (9/45)
Major	> 120	6.0%	57.5% (138/240)	57.7% (60/104)
Total		**100.0%**	**66.7% (2639/3955)**	**66.8% (1316/1970)**

Measures of Performance to Evaluate the Proposed System

Further analysis of the contingency tables with respect to the system outputs and the observations is presented in Tables 4.11 and 4.12 for the model development and validation data set, respectively. The numbers on the main diagonal in both tables indicate the correct estimations/predictions that are used to determine the accuracy in Table 4.10.

TABLE 4.11 Contingency Table of Observations versus Model Estimations

Clearance Duration (minutes)		**Observation**				
		≤ 30	30 – 60	60 – 90	90 – 120	> 120
Estimation	≤ 30	2063	236	53	11	24
	30 – 60	284	301	76	20	44
	60 – 90	163	148	94	8	25
	90 – 120	31	79	19	43	9
	> 120	29	26	20	11	138

TABLE 4.12 Contingency Table of Observations versus Model Predictions

Clearance Duration (minutes)		Observation				
		≤ 30	30 – 60	60 – 90	90 – 120	> 120
Prediction	≤ 30	1068	95	20	3	11
	30 – 60	130	146	50	16	23
	60 – 90	81	96	33	9	5
	90 – 120	13	37	23	9	5
	> 120	8	12	9	8	60

To compare the performance of the proposed system correctly estimating/predicting with the random guess, Cohen's kappa (Cohen, 1960) and weighted kappa (Cohen, 1968) were adopted. Cohen's kappa, denoted as K, is defined as follows:

$$K = \frac{P_o - P_e}{1 - P_e} \qquad \text{(Eq. 4-2)}$$

where P_o and P_e represent the proportions of observed and expected agreements (chance agreement), respectively. K represents how much two raters agree with each other when excluding the probability that they agree by chance. Thus, K=1 implies that two raters completely agree with each other, while K=0 indicates that they agree only by chance. When Cohen's kappa was applied to evaluate the model's performance in estimating clearance times, K represented the true capability of the model.

When ordinal scaled categories such as this study were used, Cohen's weighted kappa was more appropriate, since the misclassification between *Minor* and *Intermediate* was less severe than the misclassification between *Minor* and *Major*. The weighted kappa (K_w) assigned penalties (weights) to off-diagonal cells and was computed in the following way (Cohen, 1968):

$$K_w = \frac{P_{o(w)} - P_{e(w)}}{1 - P_{e(w)}} = 1 - \frac{\sum_i \sum_j w_{ij} p_{o,ij}}{\sum_i \sum_j w_{ij} p_{e,ij}} \qquad \text{(Eq. 4-3)}$$

where w_{ij}, $p_{o,ij}$, and $p_{e,ij}$ represent the weight for cell (i, j), the observed proportion in cell (i, j), and the expected proportion in cell (i, j), respectively. Cohen originally introduced two types of weights – linear and quadratic (Cohen, 1968). Linear weights are proportional to the number of categories apart (=$|i-j|$), while quadratic weights are proportional to the square of the number of categories apart (=$|i-j|^2$).

In this study, if one randomly selects the clearance time without any knowledge, then the probability that the guess is correct is 0.2. Only with the information of the clearance time distribution, the probability of the correct estimation/prediction would be 0.65, since the first category, *Minor*, would be always selected due to its highest probability. This value was very close to the accuracy of the proposed system. For both cases, however, K and K_w (with linear weights) were zero because their agreements were due to a random nature, whereas K and K_w for the developed system were approximately 0.4 and 0.5, respectively. These values were interpreted as fair or moderate according to the most widely used index (Table 4.13). The best way to evaluate the true capability of the proposed system was compared with those of other comparable models and are discussed in the next subsection.

TABLE 4.13 Strength of Agreement (Landis and Koch, 1977; Altman, 1991)

Kappa value	**Strength of agreement**
<0.2	Poor
0.21-0.40	Fair
0.41-0.60	Moderate
0.61-0.80	Good
0.81-1.00	Very good

Cohen's weighted kappa motivates another measure of performance that was more practical. This was because the implementation of traffic/incident management based on overestimated clearance times would be acceptable in view of the operational needs, even though some resources may not be best used. On the other hand, underestimated clearance times would cause serious delays on the relevant network. Hence, the cases in the cells below the main diagonal in Tables 4.11 and 4.12 were acceptable to traffic operators. To provide only partial credits to these slightly overestimated results, the following weights (w_{ij}) were assigned to cells (i, j):

$$w_{ij} = 1 - \frac{|i-j|}{(n-1)} \qquad \text{(Eq. 4-4)}$$

where n is the number of categories and $1 \leq i, j \leq n$. The assigned weights are presented in Table 5.14. Note that the weights for the cells above the main diagonal were zero, since their misclassification was not acceptable.

TABLE 4.14 Assigned Weights to Compute the New Measure of Performance

Clearance Duration (minutes)		**Observation**				
		≤ 30	**30 - 60**	**60 - 90**	**90 – 120**	**> 120**
Estimation/ Prediction	≤ 30	1	0	0	0	0
	30 – 60	0.75	1	0	0	0
	60 – 90	0.5	0.75	1	0	0
	90 – 120	0.25	0.5	0.75	1	0
	> 120	0	0.25	0.5	0.75	1

The new measure of performance, defined as *acceptability*, is defined below, and the results are summarized in Table 4.15:

$$acceptability = \frac{\sum_i \sum_j w_{ij} * c_{ij}}{\sum_i \sum_j c_{ij}} \qquad \text{(Eq. 4-1)}$$

where c_{ij} represents the number of cases in a cell (i, j). According to this criterion the proposed system demonstrated that approximately 80 percent of the given incidents can be categorized in the acceptable range.

TABLE 4.15 Performance Result (Acceptability) of the Proposed Integrated System

Incident Class	Clearance Duration (minutes)	Class ratio	Acceptability	
			Train	Test
Minor	≤ 30	65.0%	92.0% (2365/2570)	93.0% (1209/1300)
Intermediate-sub1	30 – 60	20.0%	58.0% (458/790)	62.2% (240/386)
Intermediate-sub2	60 – 90	6.6%	45.0% (118/262)	40.7% (55/135)
Intermediate-sub3	90 – 120	2.4%	54.8% (51/93)	33.3% (15/45)
Major	> 120	6.1%	57.5% (138/240)	57.7% (60/104)
Total		**100.0%**	**79.1% (3130/3955)**	**80.2% (1579/1970)**

Comparative Evaluation of the Proposed System

For performance evaluation, this model was compared with the other most widely applied methodologies, which include:

- Support vector machine (SVM) (Vapnik, 1998; Cortes and Vapnik, 1995), random forests (RF) (Breiman, 2001), and multiple linear regression (MLR) (Greene, 2003)

Since the clearance time was a continuous variable, this study calibrated a typical continuous model for comparison. To compare its performance with the proposed system, the clearance time was discretized into five bins, based on the same discretization scheme as used in this study. Tables 4.16 and 4.17 summarize the performance of each model in estimation and prediction, respectively.

TABLE 4.16 Performance Results of the Comparable Models based on the Model Development Data Set (Regression Type Models)

Methodology	Measure of Performance	Clearance Duration (minutes)					
		≤ 30	30 – 60	60 – 90	90 – 120	> 120	Total
SVM-1	# of cases correctly estimated	2262	279	11	0	0	2552
	accuracy	88.0%	35.3%	4.2%	0.0%	0.0%	64.5%
	kappa	NA					0.25
	w-kappa	NA					0.29
	acceptability	96.9%	37.2%	4.2%	0.0%	0.0%	70.7%
SVM-2	# of cases correctly estimated	2350	485	89	23	100	3047
	accuracy	91.4%	61.4%	34.0%	24.7%	41.7%	77.0%
	kappa	NA					0.55
	w-kappa	NA					0.65
	acceptability	97.6%	64.1%	35.9%	26.9%	41.7%	81.7%
SVM-3	# of cases correctly estimated	2565	774	258	91	240	3928
	accuracy	99.8%	98.0%	98.5%	97.8%	100.0%	99.3%
	kappa	NA					0.99
	w-kappa	NA					0.99
	acceptability	100.0%	98.1%	98.5%	97.8%	100.0%	99.4%
RF	# of cases correctly estimated	2091	476	49	17	144	2777
	accuracy	81.4%	60.3%	18.7%	18.3%	60.0%	70.2%
	kappa	NA					0.46
	w-kappa	NA					0.63
	acceptability	94.9%	66.3%	24.0%	26.9%	60.0%	80.8%
MLR	# of cases correctly estimated	2319	219	14	4	56	2612
	accuracy	90.2%	27.7%	5.3%	4.3%	23.3%	66.0%
	kappa	NA					0.27
	w-kappa	NA					0.39
	acceptability	97.2%	31.3%	7.6%	9.7%	23.3%	71.6%
Proposed System	# of cases correctly estimated	2063	301	94	43	138	2639
	accuracy	80.3%	38.1%	35.9%	46.2%	57.5%	66.7%
	kappa	NA					0.41
	w-kappa	NA					0.50
	acceptability	92.0%	58.0%	45.0%	54.8%	57.5%	79.1%

TABLE 4.17 Performance Results of the Comparable Models based on the Model Validation Data Set (Regression Type Models)

Methodology	Measure of Performance	Clearance Duration (minutes)					
		≤ 30	30 – 60	60 – 90	90 – 120	> 120	Total
SVM-1	# of cases correctly predicted	1122	136	11	0	0	1269
	accuracy	86.3%	35.2%	8.1%	0.0%	0.0%	64.4%
	kappa	NA					0.23
	w-kappa	NA					0.28
	acceptability	96.5%	36.5%	8.1%	0.0%	0.0%	71.4%
SVM-2	# of cases correctly predicted	1054	144	19	4	30	1251
	accuracy	81.1%	37.3%	14.1%	8.9%	28.8%	63.5%
	kappa	NA					0.27
	w-kappa	NA					0.41
	acceptability	94.5%	44.3%	18.5%	13.3%	28.8%	74.1%
SVM-3	# of cases correctly predicted	873	149	23	6	37	1088
	accuracy	67.2%	38.6%	17.0%	13.3%	35.6%	55.2%
	kappa	NA					0.21
	w-kappa	NA					0.36
	acceptability	89.0%	50.3%	24.4%	24.4%	35.6%	72.7%
RF	# of cases correctly predicted	934	180	11	5	32	1162
	accuracy	71.8%	46.6%	8.1%	11.1%	30.8%	59.0%
	kappa	NA					0.25
	w-kappa	NA					0.39
	acceptability	91.7%	53.6%	17.0%	15.6%	30.8%	74.2%
MLR	# of cases correctly predicted	1159	107	10	1	27	1304
	accuracy	89.2%	27.7%	7.4%	2.2%	26.0%	66.2%
	kappa	NA					0.25
	w-kappa	NA					0.37
	acceptability	97.0%	30.1%	11.1%	6.7%	26.0%	72.2%
Proposed System	# of cases correctly predicted	1068	146	33	9	60	1316
	accuracy	82.2%	37.8%	24.4%	20.0%	57.7%	66.8%
	kappa	NA					0.40
	w-kappa	NA					0.51
	acceptability	93.0%	62.2%	40.7%	33.3%	57.7%	80.2%

Since support vector machines were defined based on selective values of several parameters in wide ranges, various combinations were tested, and the best three calibrated support vector machines were selected, so-called SVM-1, SVM-2, and SVM-3. SVM-1 was the calibrated result by not applying weights to balance sample sizes for each clearance time class, whereas different combinations of weights were used to calibrate SVM-2 and SVM-3.

SVM-1 showed its overall performance was like the proposed model in accuracy and acceptability. However, the model can well estimate/predict the major class (≤ 30 minutes) as evidenced by the low values for kappa and weighted kappa. SVM-2 had better capability to estimate those in the classes of *Intermediate* and *Major* clearance time than SVM-1, while SVM-3 exhibited the best overall performance in most clearance time classes, even though its overall prediction ability was not as reliable as the proposed system due to the over-fitness.

The random forests were also defined based on several parameters such as the number of trees and the number of predictors randomly selected to determine the best splitter. The best RF was selected after numerous experiments and it demonstrated good performance to estimate/predict those incidents with clearance times less than one hour, although it did not show the desirable performance for the remaining cases.

In addition to SVM and RF, this study has also calibrated a multiple linear regression model based on the following procedure:

1. *Transform the dependent variable (clearance times) to the normal distribution* − According to Figure 4.2, it is obvious that clearance times were not normally distributed. Since the linear regression model assumes that the dependent variable has a normal distribution (determined by the distribution of error term (u_i)) (Koutsoyiannis, 1972; Greene, 2003), the box-cox transformation test was conducted to find the best lambda (λ) to transform to the normal distribution (Box and Cox, 1964). The estimated λ is -0.0393, which is close to zero; thus, the natural logarithm form of the original variable was adopted (Box and Cox, 1964). Figure 4.12 presents the distribution of the transformed clearance times.

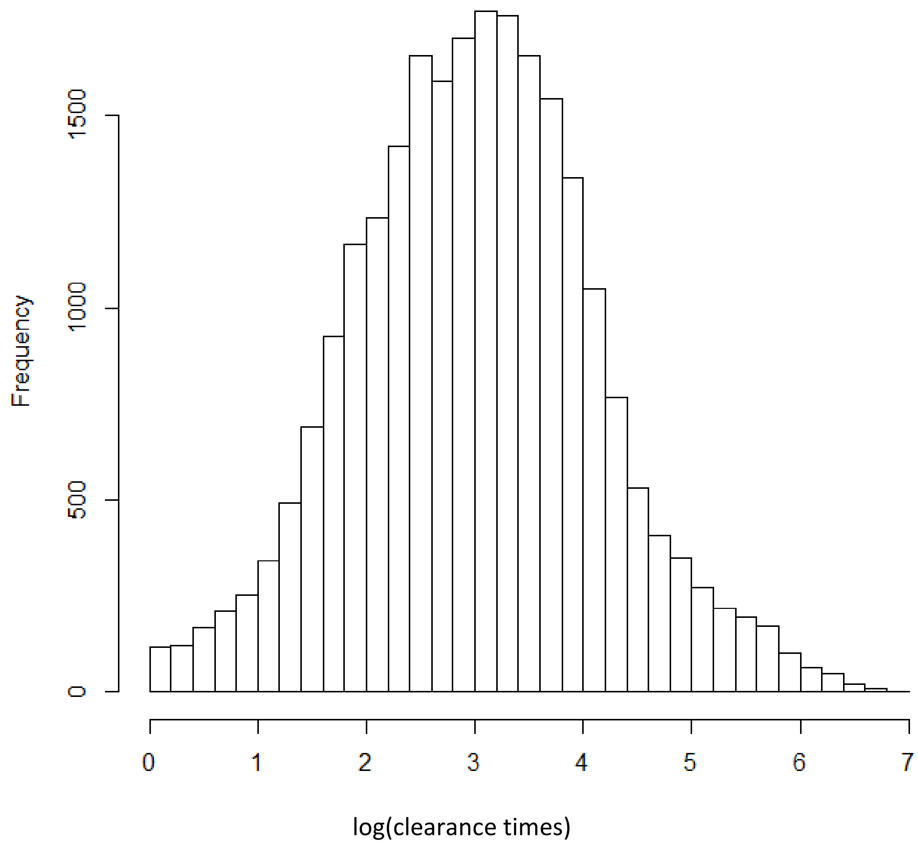


FIGURE 4.12 Distribution of the Transformed Clearance Times

2. *Add a variable at a time and observe if it is statistically significant* − If it is not significant at the 95 percent confidence level, then it is removed from the model. At this level, various functional forms for those independent variables were also considered, but most of those were not significant.
3. *Test multicollinearity between independent variables in the final model using variance inflation factors (VIF) (Fox and Monette, 1992)* − *VIF* values for all predictors showed smaller than 10, indicating that no significant multicollinearity existed in the selected model.
4. *Evaluate the model homoscedasticity using Breusch-Pagan test (Breusch and Pagan, 1979)* − Chi-square value, based on the selected model, was 2.006; thus, it did not reject the null hypothesis that the residuals were homoscedastic. Figure 4.13 also confirmed that no significant heteroscedasticity was presented in the model.

The linear regression model is widely used in the transportation field because of its advantage over other "black-box" type models − the interpretability of the model. The developed MLR summarized in Table 4.18 shows each variable's impact on the clearance time. Notice that the dependent variable is the natural log of clearance times (minutes). The number of tractor-trailer incidents (*noTT*) showed the highest significance, reflecting that the clearance time increased with the involvement of tractor-trailers. Similarly, other types of heavy vehicles (i.e., single unit trucks (*noSUT*), pickup trucks, vans, and SUVs (*noPVS*)) also contributed significantly to increasing the clearance times. Obviously, the incident type was an important factor to determine the clearance times. The indicator for fatality involved (*CF*) was the second most significant variable, according to MLR.

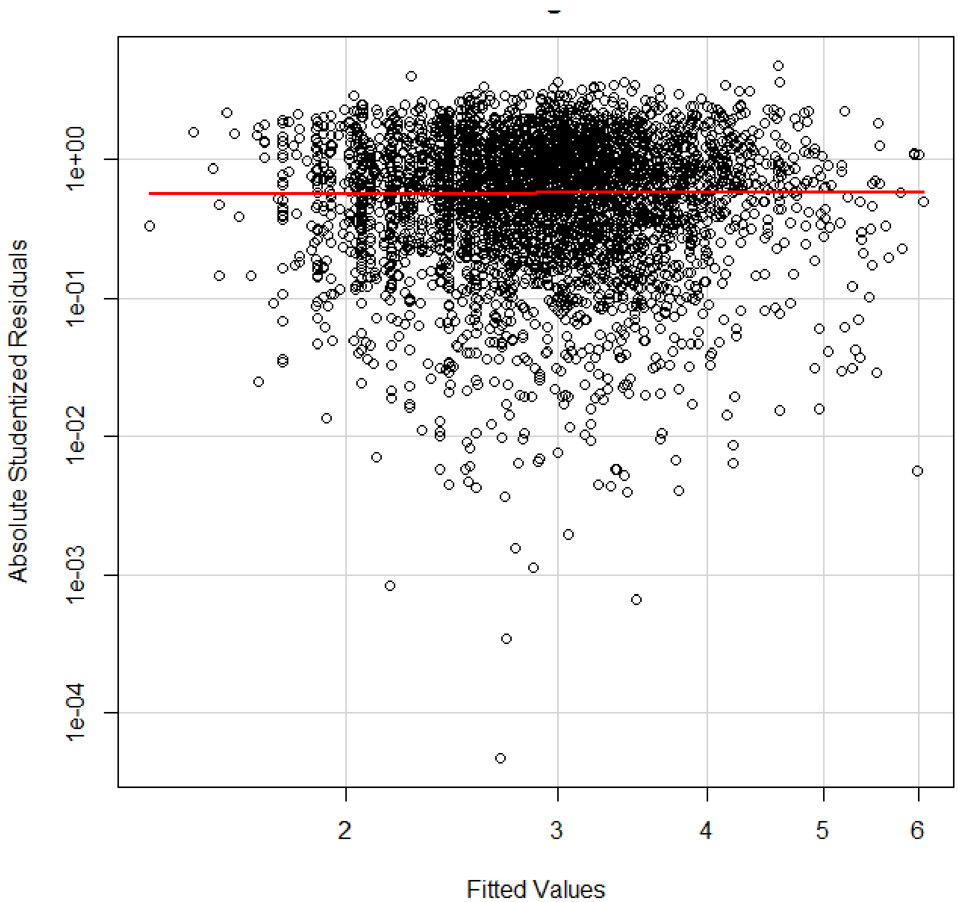


FIGURE 4.13 Distribution of Residuals versus Fitted Response Values

TABLE 4.18 (a) The Developed Multiple Linear Regression Model

Log(ClearanceTime (minutes)) = 2.77 – 0.47*TOC4 – 0.22*TOC3or7 – 0.48*AOC_S
(30.40) (-9.77) (-4.09) (-6.97)

– 0.20*noVeh + 0.12*noPVS + 0.37*noSUT +0.47*noTT + 1.72*CF + 0.82*CPI + 0.47*CPD
(-5.54) (4.04) (8.45) (13.48) (11.74) (9.54) (5.55)

– 0.36*Disabled + 0.38*Fire + 0.69*PolAct + 0.10*SIorWet – 0.28* noSDsh3 + 0.49*SDBmain
(-4.25) (3.23) (3.10) (2.46) (-1.97) (9.31)

+ 0.33*ODBmain + 0.59*Southern – 0.42*Washington + 0.27* LocalPol + 0.14* StatePol
(3.55) (3.41) (-7.23) (2.95) (4.05)

+ 0.37*MCTMC - 0.40*I895 – 0.10*I95 + 0.12*OtherRd
(-4.81) (-2.06) (2.82) (2.49)

F-statistic= 90.52 Adjusted R-squared= 0.36
(Numbers in parentheses are t-statistic values)

TABLE 4.18 (b) Descriptions of Variables Included in MLR

Variable	Description
TOC4	1 if the responsible operation center is TOC 4; otherwise 0
TOC3or7	1 if the responsible operation center is TOC 3 or TOC 7; otherwise 0
AOC_S	1 if the responsible operation center is AOC South; otherwise 0
noVeh	Number of total vehicles involved with the incident
noPVS	Number of pickup trucks, vans, or SUVs involved with the incident
noSUT	Number of single unit trucks involved with the incident
noTT	Number of tractor-trailers involved with the incident
CF	1 if the incident is involved with any fatality; otherwise 0
CPI	1 if the incident is involved with any personal injuries; otherwise 0
CPD	1 if the incident is involved with any property damage; otherwise 0
Disabled	1 if the nature of incident is disabled vehicle; otherwise 0
Fire	1 if the nature of incident is vehicle on fire; otherwise 0
PolAct	1 if the incident is involved with police activity; otherwise 0
SIorWet	1 if the pavement condition is snow/ice or wet; otherwise 0
noSDsh3	1 if at least 3 shoulder lanes exist on the same direction of where the incident occurred; otherwise 0
SDBmain	The ratio of number of closed lanes to the total number of lanes on the same direction of where the incident occurred
ODBmain	The ratio of number of closed lanes to the total number of lanes on the opposite direction of where the incident occurred
Southern	1 if the incident occurred in Southern MD; otherwise 0
Washington	1 if the incident occurred in Washington D.C. area; otherwise 0
LocalPol	1 if the incident is detected by local polices; otherwise 0
StatePol	1 if the incident is detected by state polices; otherwise 0
MCTMC	1 if the incident is detected by Traffic Management Center in Montgomery County; otherwise 0
I895	1 if the incident occurred on I-895; otherwise 0
I95	1 if the incident occurred on I-95; otherwise 0
OtherRd	1 if the incident occurred on minor roads in suburban or rural areas; otherwise 0

Also, other incident types from minor (disabled vehicles and fire) to major (personal injuries, property damage, and police activities) showed statistical significance to the incident clearance time. Note that the sign for the variable *Disabled* is negative, which indicated that the clearance time of the incident primarily due to disabled vehicles would be relatively shorter than those of other types of incidents.

MLR, interestingly, included variables related to regions (*Southern* and *Washington*). This implied that it would take longer time to clear incidents occurring in Southern Maryland, but exhibited a shorter time in the Washington metropolitan area. Similarly, the clearance times of incidents would be shorter if they occurred on I-895 or I-95, but longer on minor roads in suburban or rural areas. Moreover, several detection sources were included in the model. They implied that incidents detected by those sources (local/state polices or MCTMC) are likely to have longer clearance times than those detected by other sources. These statistical observations with other factors included in MLR were consistent with some of the findings from *SCAR*. However, MLR was limited to catch interrelationships between factors since most variables were binary, while association rules used to compose *SCAR* can capture various relationships between factors.

Based on the relatively low value of adjusted R^2, MLR did not show a good performance. However, using the same measures of performance, MLR demonstrated results comparable with other models. The overall model accuracy was very close to the one from the proposed system owing to the high accuracy on clearance times less than 30 minutes, but the MLR was not reliable to estimate/predict clearance times between 1 hour and 2 hours. The acceptability of MLR was significantly lower than that of the proposed systems. This indicated that MLR has a strong tendency to concentrate on the dominated domain of the study data set (short clearance times).

To sum up, the proposed system outperforms other models in various aspects. First, its accuracy and acceptability for both the overall level and the individual class level were better than other models. In addition, the proposed model provided some insightful information on the impacts of related factors and their collective impacts on incident clearance times. Research findings listed in subsection 4.3.2 would be useful for traffic agencies to plan and improve their incident management programs.

Chapter 5: An Integrated Multi-criteria Support System for Assessing Detour Decisions during Non-Recurrent Freeway Congestion

5.1 Introduction

As discussed in Chapter 1, traffic incidents have long been recognized as the main contributor to congestion in highway networks. Thus, contending with non-recurrent congestion has been a priority task for most highway agencies over the past decades. Under most incident scenarios, if proper diversion plans can be implemented in time, motorists can circumvent the congested segments and best use the available corridor capacity. To tackle this vital operational issue, transportation professionals have proposed a variety of advanced diversion control and route guidance strategies (Papageorgiou, 1990; Messmer and Papageorgiou, 1995; Morin, 1995; Pavlis and Papageorgiou, 1999; Wu and Chang, 1999; Liu et al., 2011) to optimally balance the volumes between the freeway and the arterial. Certainly, those strategies could improve the efficiency of incident management in freeway corridors, if properly implemented.

Nevertheless, before implementing any detour strategy, traffic operators must justify its necessity based on various factors, since such operations usually demand a substantial amount of resources and personnel efforts. In this regard, very limited information is available in the literature to assist decision makers in assessing the benefits and costs of implementing detour operations, although numerous traffic safety and operations manuals (e.g., Delaware DOT, 2011; State Police NJ, 2010; University of Kentucky, 2009; FHWA, 2009; Wisconsin DOT, 2008) have addressed the need for properly diverting traffic flows during major incidents or emergencies.

One source offering such guidelines is *Alternate Route Handbook* (2006), which provides comprehensive and general guidelines on how to plan and execute the detour operations involving various stakeholder agencies. According to this document, the key factors to consider include the incident duration, the number of lanes blocked, the observed traffic condition, the time of day, and the day of the week. The capacity of the proposed alternative route and its background traffic are also critical factors.

Table 5.1 summarizes the criteria used in several states to decide whether to execute the pre-developed alternate route plan. Notice that the District IV of Florida DOT will typically activate its detour plan when two or more lanes are closed for at least two hours. On the other hand, most states require an incident duration longer than thirty minutes or a complete closure of the roadway to implement detour plans. The *Manual on Uniform Traffic Control Devices* (MUTCD) (2009) states that major and intermediate incidents lasting more than thirty minutes usually require traffic diversion or detouring for road users, due to partial or full roadway closures, while traffic diversion may not be necessary for minor incidents usually cleared within thirty minutes. A comprehensive review of this subject clearly shows that a reliable tool for traffic control operators to decide when and how to implement detour operations has yet to be developed.

TABLE 5.1 Criteria for Deciding the Implementation of Detour Plans in Various States

Agency	Criteria
North Carolina DOT – main office	• Complete closure of the highway in either direction is anticipated for fifteen minutes or longer.
North Carolina DOT – Charlotte regional office	• No action or discussion occurs until fifteen minutes after the incident. After fifteen minutes, an alternate route plan is deployed only if the highway is completely closed (all lanes closed, including the shoulder) and closure is expected to last at least an additional fifteen minutes (thirty minutes' total).
New Jersey DOT	• Level 1: Lane closures on a state highway that are expected to have a prolonged duration and impact on traffic. • Level 2: Complete closure of a highway that is anticipated to last more than ninety minutes.
Oregon DOT	• Incident with two or more lanes blocked, or • Incident with one lane blocked and expected to last more than twenty minutes.
New York State DOT Region 1	• Implemented only when the highway is completely closed. • Will not be implemented if at least one lane (or even the shoulder) is open.
Florida DOT District IV	• Two or more lanes blocked for at least two hours.
ARTIMIS (Ohio/Kentucky)	• This plan has a detailed table with four different levels, based on some present criteria, such as: - During the morning and afternoon peak hours, an advisory alternate route is deployed in the event of a two-lane closure for more than two hours or a closure of more than two lanes for less than thirty minutes. - Mandatory alternate routes are deployed during the peak hours when more than two lanes are closed for at least thirty minutes.
Ada County, Idaho	• This plan specifies different levels of severity, including: - Levels C and D require implementation of a diversion route. - Level C is an incident taking thirty to 120 minutes from detection to full recovery of the traffic flow. - Level D is an incident taking over two hours from its detection to full recovery (including full freeway closure in one or both directions).
Wisconsin DOT (Blue Route)	• Incident causes delays that will exceed thirty minutes.

Source: Alternate Route Handbook (2006)

In view of the strengths and limitations in the existing studies, this study was proposed to assist responsible agencies to mitigate incident impacts on freeways with the following tasks:

1. Provide reliable guidelines and tools to help responsible agencies design, evaluate, and operate traffic management plan under non-recurrent congestion.

2. Deliver an integrated system that can assess the necessity of traffic detour/diversion based on a comprehensive review of associated factors. Such a system can be used as a prototype and/or applied in real-time traffic operations.

The rest of this chapter presents the proposed decision-support system, the key logic and models embedded in each component of the system. Also, the evaluation and application of the developed system are presented with scenario-based analysis and sensitivity evaluation in the last section.

5.2 Development of the Detour Decision Support System

This section presents the proposed system, including the core design concept, principal system components, and key models embedded in each component.

5.2.1 The Proposed System based on Analytical Hierarchy Process (AHP)

During the incident management process, multiple factors may affect the final decision of responsible traffic managers on whether to implement detour operations, such as the expected benefits and costs, impacts on traffic safety, reliability of travel, and the accessibility and acceptability of detour routes. Detour operations that fail to consider those critical factors may result in a waste of traffic management resources and the exacerbation of traffic congestion in the target corridor.

The traditional decision-making model, when it adopts multiple criteria, usually evaluates these factors individually in a specific directional flow. Since each criterion is evaluated independently and one at a time, the importance (weight) of every criterion is identical. However, in many decision-making processes, including the detour decision process, each individual criterion may influence the final decision to a different degree, thus necessitating the prioritization of these criteria.

One well-known decision-making process that considers the relative importance of criteria is the AHP developed by Saaty in the early 1970s (Saaty, 1980). The AHP provides a structured system for organizing and analyzing a complex decision problem by decomposing it into a hierarchy of more easily understandable subproblems (i.e., decision criteria and alternatives). The various elements in the constructed hierarchy are systemically evaluated by comparing them two at a time to observe how they affect an element at a higher level of the structure. In these pairwise comparisons, decision makers can use either tangible data or their judgments to determine the relative importance of those elements. The AHP converts these evaluations into numerical values that serve as the basis for the final stage — computing the numerical priorities of all decision alternatives to reflect their relative abilities to accomplish the decision goal.

The main advantage of the AHP is that it allows the comparison of both qualitative and quantitative criteria using informed judgments to derive their weights and priorities. Also, the AHP can assist decision makers in discovering the decision that best suit their goal and their understanding of the problem. Further discussions of the AHP are available in the references (Saaty, 1980; Saaty, 1982; Haas and Meixner, 2010; Teknomo, 2006).

Considering the nature of the proposed detour decision problem and the capabilities of the AHP, this study developed a hybrid decision support system by integrating the traditional decision-making model with the AHP model, as shown in Figure 5.1. Details for the system structure and supporting technical models are presented in the following subsections.

5.2.2 Architecture of the Proposed System

The developed system executes the decision on whether to activate the detour operations, based on the resulting costs and benefits. To reach any conclusion, one would build a procedure to systematically evaluate potential outcomes, which may either positively or negatively affect drivers, traffic networks, or environments. A level-by-level description of the overall system structure is presented below, along with its graphical illustration in Figure 5.1:

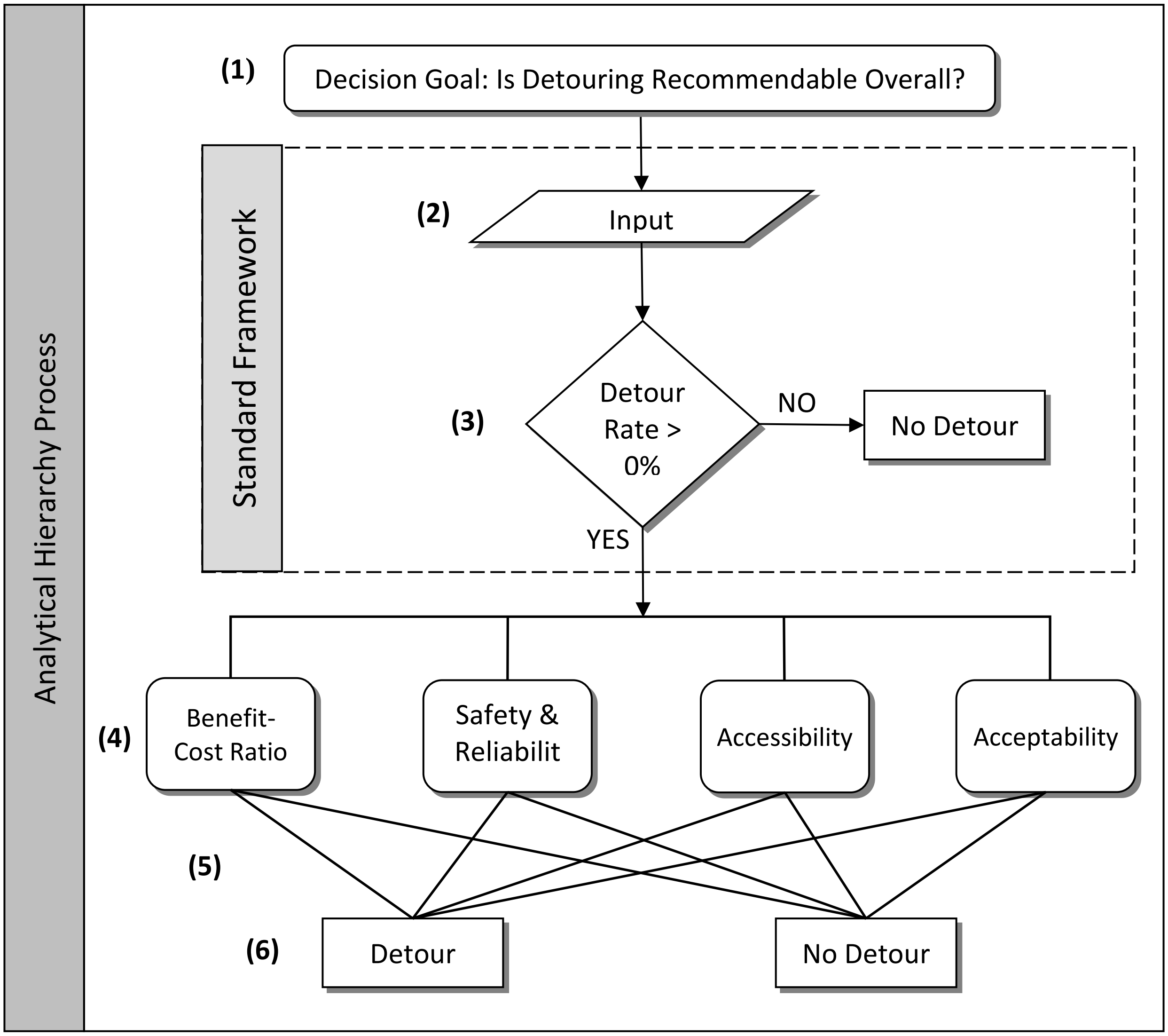


FIGURE 5.1 Overall Structure of the Proposed Detour Decision Support System

Level 1: The decision goal setup

The decision goal, the first level of the hierarchical system for decision makers to establish, is to determine if the proposed detour operation should be implemented with sufficient benefits to justify the operational costs.

Level 2: Model inputs by users

As discussed previously, this level and the following lower level are developed with the standard algorithm flowchart. The model variables entered at this level are used to estimate and evaluate quantitative criteria at the lower levels. At this level, users need to input the key variables listed below:

- Incident information: incident duration, lanes blocked, and incident location.
- Network information: number of lanes on primary (freeway) and detour routes, the number of signals on the detour route, and the distance of the detour path.

- Traffic information: traffic volume on primary and detour routes, heavy vehicle volume, and speed limit for the detour route.
- Operations information: anticipated compliance rate if detour operations are implemented.

Level 3: Initial assessment for deploying the detour operations

The conditional criterion at this level is to judge the need for the detour operation under the available information, given the objective of minimizing the total delay in the entire network. If the estimated optimal detour rate turns out to be near zero, then traffic operators can conclude that the candidate detour plan would not contribute to relieving the incident-induced congestion and they should consider other detour plans or strategies, if available. A positive estimate for the optimal detour rate should cause the responsible operators to consider additional vital factors before reaching the conclusion.

As shown in Figure 5.1, if the answer to the question in *Step 3* is “No,” the traffic operators would terminate the decision process with “no detour”; otherwise, they would continue the process by using additional criteria to reach the definitive conclusion.

Level 4: Development of additional decision criteria and their relative importance for the AHP

If the decision from the initial assessment in *Step 3* is “detour,” the decision system will apply the AHP to evaluate the comprehensive impacts of other criteria before making the final decision. The standard hierarchy of the AHP model consists of three levels, with the goal at the top, alternatives at the bottom, and criteria in between. Additional levels of the hierarchy can be added if developers want to break down the criteria into sub-criteria, sub-sub-criteria, and so forth.

Unlike the simple criteria used in the literature (i.e., the incident duration and the number of lanes blocked), the proposed system employs the following criteria to effectively evaluate the overall benefits of the target decision:

- **Benefits/costs**
  - Benefits: total travel time (minutes/vehicle), fuel consumption, and emissions saved from detour operations;
  - Costs: operational and maintenance costs to implement detour plans (converted into monetary values to facilitate comparison).
- **Safety and reliability**
  Reducing traffic demand on the primary route by the diversion of traffic would alleviate the congestion caused by the primary incident and consequently reduce secondary incidents. Note that, to quantify such results, one can estimate one of the following MOEs (measures of effectiveness): 1) reduction in secondary incidents; 2) reduction in the probability of having secondary incidents; or 3) reduction in the congestion area (queue length) due to the detour operations. This study uses the maximum queue length on the freeway.
- **Accessibility**
  Some factors — such as longer travel times, distances, delays at traffic signals or stop signs, and lower speed limits on the detour route — may degrade the accessibility of the detour route to travelers. To capture this nature, this study

measured the estimated travel times for the primary and alternative routes and used such information as the accessibility criteria.

- **Acceptability**
  The acceptability of a detour plan significantly affects its performance. However, a plan's acceptability depends on the characteristics of drivers (e.g., risk takers, conservative or patient drivers, etc.) and the quality as well as the availability of real-time traffic information. Moreover, drivers might not prefer the selected detour route due to the existence of signalized intersections, stop signs, turning movements and queues. Thus, drivers may downgrade the acceptability of the detour plan. Considering the scenarios, this study used drivers' anticipated compliance rate as the criterion for measuring this factor.

Usually, informed judgments by decision makers are used to derive the relative importance of the criteria. They can come from concrete measurements or experts' judgments. A core idea of the AHP methodology is to involve human judgment in the evaluation process. Informed judgments, such as "Criterion A is two times as important as Criterion B" and "Criterion B is three times as important as Criterion C" are expressed in numerical scales of measurement using a series of pairwise comparisons. The final product from these procedures is a priority ranking of criteria against the goal. Details of the procedures for standard pairwise comparisons, normalization, and determination of final ranking of priorities are available in the literature (Saaty, 1980; Saaty, 1982; Haas and Meixner, 2010; Teknomo, 2006).

Level 5: Determination of the relative ranking of alternatives under each criterion.

The next task of the AHP development is to determine the relative ranking of alternatives with respect to each criterion. Using a similar method to obtain the relative importance of all criteria, one can derive the preference of each alternative over one another with respect to each criterion.

Level 6: Determination of the overall relative ranking of alternatives concerning the decision goal.

Given the weights for criteria and alternatives from *Step 4* and *Step 5*, the decision makers will be able to estimate the priorities of alternatives against the goal.

5.2.3 Supplemental Models to Support the Proposed System

Completing the system requires several supplemental models to estimate the measurements for some quantitative criteria. This subsection presents details for each supplemental model.

Integrated Control Model for Freeway Corridors under Non-Recurrent Congestion

The developed system conducts an initial assessment to determine the necessity of the detour operation with the input data at *Level 3*, as described in the previous subsection 5.2.2. Since the decision is made based on the estimated optimal detour rate, models or tools are needed to produce such measurements. In this case, this study used an integrated control model for freeway corridors under non-recurrent congestion developed by Liu and Chang (2011). This model produced the optimal diversion rates from the freeway mainline to mitigate congestion at the incident segment while concurrently adjusting signal timings along the arterial intersections to best accommodate the detour traffic. The model has two distinct features:

- Explicitly modeling the evolution of detour traffic along the ramps and surface streets with a set of dynamic network flow formulations to prevent local bottlenecks caused by demand surge from diversion operations and to properly set responsive signal timing plans; and
- Providing a multi-objective optimization model to maximize the use of the available corridor capacity via detour operations without causing excessive congestion on the arterials and ramps.

Its multi-objective functions can further be stated as:

- Maximizing the total throughput of the freeway corridor during incident management by using a parallel arterial as the detour route; and
- Minimizing drivers' total times on the detour route to ensure their compliance with the routing guidance.

This integrated control model also simulated an identified incident and traffic scenario on the given network and output the optimized detour rate as well as total travel times over the network. For each decision scenario, this model provided the results for operations with and without the detour. While the third level used the optimal detour rate for the initial decision making, the derived delay reduced by detour operations served as the basis for estimating the user benefits for the benefit-cost ratio criterion at the following level.

Benefit Estimation Procedure

The primary goal of implementing a detour plan is to ease the congestion and reduce the resulting delay due to incident-caused lane closures. However, operating detour plans will incur significant costs. Thus, responsible traffic managers need to assess whether the resulting benefits can compensate for the operational costs. The developed system conducted this benefit-cost analysis at *Level 4* along with other analyses for the more rigorous and comprehensive review. The benefits contributed by the detour operations were estimated in an economic way by following the steps presented below:

Step 1: Compute the difference in travel times between the two scenarios — i.e., operations with and without the detour.

This study used the ***total travel time over the network*** from the output of the integrated corridor control model to compute the reduced delay due to detour operations.

Step 2: Select other impacts which could also be part of the benefit analysis.

Reducing the delay for any reason may also decrease its associated MOEs. This study included reductions in fuel consumption and emissions (i.e., HC, CO, NO, and CO_2) in the benefit estimation.

Step 3: Estimate the reduced MOEs using available references

The amount of fuel consumption reduced directly from a traffic delay was estimated by using the following conversion factors: 0.156 gallons of gasoline/hour for passenger cars (Koerner, 2008) and 0.85 gallons of diesel/hour for trucks (Lutsey et al., 2004).

Similarly, reduced emissions were estimated from either the reduced amount of delay or fuel consumption, using the following conversion factors:

- HC: 13.073 grams/hour of delay (Maryland Department of Transportation, 2000)
- CO: 146.831 grams/hour of delay (Maryland Department of Transportation, 2000)
- NO: 6.261 grams/hour of delay (Maryland Department of Transportation, 2000)
- CO_2: 19.56 lbs CO2/gallon of gasoline (Energy Information Administration, 2009)
  22.38 lbs CO_2/gallon of diesel (Energy Information Administration, 2009)

Step 4: Convert the related delay, fuel, and emissions to monetary values

This step used the monetary conversion factors listed below to estimate the reduced delay and associated MOEs:

- Delay: $28.57/hour for passenger cars (U.S. Census Bureau, 2009)
  $20.68/hour for truck drivers (U.S. Census Bureau, 2009)
  $45.40/hour for cargo drivers (De Jong, 2000; Levinson and Smalkoski, 2003)
- Fuel: $2.83/gallon for gasoline (Energy Information Administration, 2010)
  $2.99/gallon for diesel (Energy Information Administration, 2010)
- HC: $6,700/ton (DeCorla-Souza et al., 1998)
- CO: $6,360/ton (DeCorla-Souza et al., 1998)
- NO: $12,875/ton (DeCorla-Souza et al., 1998)
- CO_2: $23/metric ton (CBO, 2007)

Given the estimated operational costs, one can approximate the benefit-cost ratio with the above steps to use as the criterion at the fourth level of the system.

Maximum Queue Length Estimation

Another key factor that traffic managers should consider when making their decision is the extent to which the congestion mitigation strategy would improve safety and reliability for motorists. To estimate this benefit, the best MOE would be the reduction in secondary incidents. Unfortunately, a rigorous methodology and data availability remains a research issue (Chou and Miller-Hooks, 2010; Zhan et al., 2009). Meanwhile, this study used the maximum queue length as a proxy variable, because the frequency of secondary incidents correlates highly to the queue length caused by the primary incident (Chou and Miller-Hooks, 2010; Zhan et al., 2009).

The maximum queue estimate model, the tool used here to evaluate the safety and reliability of a candidate detour plan, was developed based on simulation experiments with CORSIM (Kim et al., 2009). The entire network used for these experiments was a four-lane loop format highway similar to I-495 (Capital Beltway) in the Washington D.C. metropolitan area. The simulation did not consider lane drops, grades, and any other local bottlenecks to generate a queue solely due to incidents. The queue, defined as the length of the maximum spillback consisting of vehicles moving under 20 mph, was measured from the congestion caused by one isolated incident. In addition, this model development did not consider the queue in the opposite direction caused by the rubbernecking factor. To identify factors contributing to the queue induced by incidents, the simulation experiments explored several related variables, such as incident duration, the number of blocked lanes, traffic volume, on- and off-ramp volumes, the number of heavy vehicles, rubbernecking, and incident location.

Table 5.2 and Figure 5.2 summarize a regression model for estimating the maximum queue length, developed by using 285 samples acquired from the CORSIM output. All 14 variables included in the proposed queue model show reasonable parameter signs, and they are all significant at the 10 percent confidence level. Note that the dependent variable is in a natural logarithm form of the maximum queue, implying that the simulated maximum queues approximately follow a log-normal distribution.

The estimation results showed that, as expected, the queue length grows with increases in traffic volume and incident duration. Lane closures for Lanes 2, 3, and 4 have statistically significant impacts on the maximum queue, while rubbernecking effects do not play an important role.

Interestingly, the queue model is proved to be highly sensitive to the locations of incidents. Most variables defined to capture the nature of the incident location (see Table 5.2) show significant contributions to the model, except for the variable *Away_On_1*, defined as 1 if an incident occurred about one mile away after passing an on-ramp and 0 otherwise. It is also noticeable that the variable *Away_On_2/3* (defined in Table 5.2) is much less significant than other incident-location variables. Moreover, variables indicating incident locations before reaching the next on-ramp (e.g., *Away_Off_1/3*, *Near_Off_Bf*, *Near_Off_Af*, and *Btw_On_Off* in Table 5.2) show greater significances, with higher estimated coefficients. This implies that incidents occurring before reaching the next on-ramp are more likely to increase the queue.

TABLE 5.2 The Maximum Queue Estimation Model and Descriptions of Variables

$$
\begin{aligned}
\text{Log(queue(ft))} = {} & \underset{(51.07)}{6.6736} + \underset{(3.92)}{0.0191}\text{*HeavyVeh} + \underset{(15.79)}{0.0002}\text{*Main\_Vol} + \underset{(13.53)}{0.0149}\text{*Inc\_Dur} \\
& + \underset{(3.32)}{0.1930}\text{*LnB2} + \underset{(1.97)}{0.1147}\text{*LnB3} + \underset{(2.71)}{0.1528}\text{*LnB4} + \underset{(7.63)}{1.0079}\text{*Away\_Off\_1/3} \\
& + \underset{(6.82)}{0.8094}\text{*Near\_Off\_Bf} + \underset{(9.23)}{1.0020}\text{*Near\_Off\_Af} + \underset{(6.18)}{0.8100}\text{*Btw\_On\_Off} \\
& + \underset{(5.51)}{0.6371}\text{*Near\_On\_Bf} + \underset{(5.66)}{0.6284}\text{*Near\_On\_Af} + \underset{(5.31)}{0.5501}\text{*Away\_On\_1/3} \\
& + \underset{(1.68)}{0.1604}\text{*Away\_On\_2/3}
\end{aligned}
$$

Number of observations used : 285

$R^2 = 0.7360$, F-value for Model = 53.76, P-value for Model = < 0.0001

Note : Numbers in parentheses are *t*-statistic values

Descriptions of Variables

Variable	Description
HeavyVeh	Heavy vehicle percentage (%)
Main_Vol	Volume on main lanes (vph)
Inc_Dur	Incident duration in minutes
LnB2	1 if Lane 2 is blocked due to the incident; 0 otherwise (Note: Lane 1 is defined as the right-most lane, i.e., adjacent to the right shoulder)
LnB3	1 if Lane 3 is blocked due to the incident; 0 otherwise
LnB4	1 if Lane 4 is blocked due to the incident; 0 otherwise
Away_Off_1/3	1 if an incident occurred about 1/3 miles before the nearest off-ramp; 0 otherwise (Area 1 in Figure 6.2)
Near_Off_Bf	1 if an incident occurred near (within 500 ft), but before passing, an off-ramp; 0 otherwise (Area 2 in Figure 6.2)
Near_Off_Af	1 if an incident occurred near (within 500 ft), but after passing, an off-ramp; 0 otherwise (Area 2 in Figure 6.2)
Btw_On_Off	1 if an incident occurred somewhere between an on-ramp and off-ramp; 0 otherwise (Area 3 in Figure 6.2)
Near_On_Bf	1 if an incident occurred near (within 500 ft), but before passing, an on-ramp; 0 otherwise (Area 4 in Figure 6.2)
Near_On_Af	1 if an incident occurred near (within 500 ft), but after passing, an on-ramp; 0 otherwise (Area 4 in Figure 6.2)
Away_On_1/3	1 if an incident occurred about 1/3 miles after passing an on-ramp; 0 otherwise (Area 5 in Figure 6.2)
Away_On_2/3	1 if an incident occurred about 2/3 miles after passing an on-ramp; 0 otherwise (Area 5 in Figure 6.2)

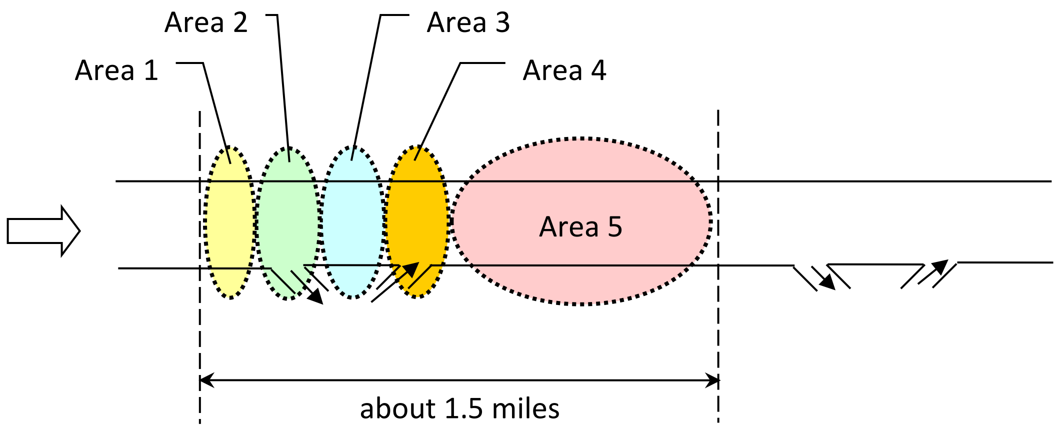


FIGURE 5.2 Illustrations of Incident Locations for the Queue Model

The estimated maximum queue length is used as one of the criteria for the comprehensive assessment at *Level 4* of the developed system.

5.3 The System Evaluation and Applications

This section illustrates the system performance to various experimental scenarios and some key system parameters. The experimental analysis includes five scenarios for comparing the performance of the developed system with state-of-the-practice methods. The sensitivity analysis provides a comparison of the system outputs, based on different emphases for criteria.

5.3.1 Illustration of the System Performance and Evaluation by Comparative Analysis

To illustrate the system's performance this study selected five experimental scenarios, as shown in Table 5.3 (Scenario No. 1 to 5). Simulation results showed that proper detour operations decreased the total travel time for all selected scenarios (see the row named "saved travel time" in Table 5.3). This analysis further investigated whether the detour operations were still beneficial from other perspectives and with different MOEs. Table 5.4 presents the system's outputs for those scenarios, and further compared with those by other state DOTs to evaluate the merit of the proposed system (see Table 5.5). For these experimental analyses the weights for benefit-cost ratio, safety and reliability, accessibility, and acceptability were set at 0.31, 0.31, 0.18, and 0.20, respectively.

TABLE 5.3 Descriptions of Scenarios

Scenario No.		1	2	3	4	5	6
Scenarios for Incident And Traffic Conditions	# of freeway lanes	4	3	2	3	3	3
	# of lanes in the detour route	1	1	1	1	2	1
	freeway volume (vplph)	250	250	250	750	750	250
	local volume 1 (vplph)*	400	200	200	800	800	800
	local volume 2 (vplph)*	600	300	300	200	200	200
	local volume 3 (vplph)*	600	600	300	300	200	300
	# of signals on detour	2	7	5	2	5	3
	compliance rate	0.9	0.6	0.5	0.5	0.6	0.5
	incident location	near off-ramp	middle of segment	near off-ramp	near on-ramp	near on-ramp	near on-ramp
	incident duration (mins)	15	15	75	60	90	15
	# of lane blockage	1	3	1	3	3	3
	speed limit on detour route (mph)	40	30	30	50	40	40
MOEs for Criteria	optimal detour flow	0.76	0.80	0.25	0.85	0.54	0.77
	total travel time (hr) w/ detour	734	746	1,517	3,232	10,163	703
	total travel time (hr) w/o detour	855	801	1,527	3,617	10,182	787
	saved travel time (hr)	121	55	10	386	19	84
	B/C w/ detour	6.6	2.98	0.33	14.74	0.60	4.58
	B/C w/o detour	0.15	0.34	3.00	0.07	1.68	0.22
	max queue w/ detour (mile)	0.5	0.36	1.26	1.37	2.24	0.59
	max queue w/o detour (mile)	0.58	0.39	1.28	1.66	2.59	0.63
	travel time (min) via freeway	2.52	2.52	2.52	2.52	2.52	2.52
	travel time (min) via detour	7.52	9.15	11.44	6.55	7.52	7.52

* Local volume 1 represents the volume for the road connecting from freeway to detour route.
Local volume 2 represents the volume for the parallel detour route.
Local volume 3 represents the volume for the road connecting from detour route to freeway.
Operational and maintenance costs for the B/C estimates are provided by Maryland State Highway Administration (Maryland State Highway Administration, 2009).

TABLE 5.4 Final System Outputs for Criteria and Alternatives

Scenario No.		1	2	3	4	5	6
B/C	Detour	0.98	0.9	0.1	0.99	0.26	0.95
	No Detour	0.02	0.1	0.9	0.01	0.74	0.05
Safety and reliability	Detour	0.53	0.52	0.5	0.55	0.54	0.51
	No Detour	0.47	0.48	0.5	0.45	0.46	0.49
Accessibility	Detour	0.25	0.22	0.18	0.28	0.25	0.25
	No Detour	0.75	0.78	0.82	0.72	0.75	0.75
Acceptability	Detour	0.53	0.43	0.38	0.38	0.43	0.38
	No Detour	0.47	0.57	0.62	0.62	0.57	0.62
Final synthesized confidences for alternatives	Detour	**0.62**	**0.56**	0.30	**0.60**	0.38	**0.58**
	No Detour	0.38	0.44	**0.70**	0.40	**0.62**	0.42

TABLE 5.5 Comparisons of the Decisions, Using the Criteria by Different Highway Agencies and by the Proposed System

Scenario No.		1	2	3	4	5
Decision Criteria (used by agencies in the literature)	Lane Blockage (# of closed lane(s)/total # of lanes)	1/4	3/3	1/2	3/3	3/3
	Incident Duration (minutes)	15	15	75	60	90
Decisions by Agency	NC DOT-main office	N	Y	N	Y	Y
	NC DOT-Charlotte	N	N	N	Y	Y
	NJ DOT	Not clear	Not clear	Y	Y	Y
	Oregon DOT	N	Y	Y	Y	Y
	NY DOT	N	Y	N	Y	Y
	FL DOT	N	N	N	N	N
	ARTIMIS (Ohio/Kentucky)	N	N	N	Y	Y
	Idaho (Ada County)	Not clear	Y	Not clear	Y	Y
	Wisconsin DOT	Not clear	Not clear	Not clear	Not clear	Not clear
Decision by Proposed System		Y	Y	N	Y	N

Y and *N* represent "Detour" and "No Detour", respectively, for the decision.
Not clear represents insufficient clarity in the available decision criteria to make a concrete answer.

The key incident characteristics associated with each scenario and the resulting recommendations by the proposed decision system are summarized below; the focus of which was mainly on the lane blockage status and incident duration, since they were the primary decision criteria used in the literature:

- Scenario 1: The incident causes a partial road closure (one out of four lanes is closed), and its duration is relatively short (15 minutes).

  System recommendation: Detour operations were recommended (beneficial), with 62 percent confidence.
- Scenario 2: The incident causes a complete road closure on a three-lane highway segment for 15 minutes.

  System recommendation: Detour plans were recommended (beneficial), with 56 percent confidence.
- Scenario 3: The estimated incident duration is 75 minutes, and it blocks one lane on a two-lane highway segment.

  System recommendation: Detour operations were not recommended (not beneficial), with 70 percent confidence.
- Scenario 4: The incident causes a complete road blockage on a three-lane segment, and its duration is rather long (60 minutes).

  System recommendation: Detour plans were recommended (beneficial), with 60 percent confidence.
- Scenario 5: The incident causes a complete road blockage on a three-lane segment, and its duration is rather long (90 minutes).

  System recommendation: Detour plans are not recommended (not beneficial) with 62 percent confidence.

Note that the proposed system recommended that properly detouring traffic in Scenario 1, with only partial lane blockage over short incident duration, still yielded a sufficient total benefit if considered from the economic, environmental, and societal perspectives. The conclusion, however, would be quite different if one employed any of the state-of-the-practice methods shown in Table 5.1. The third column in Table 5.5 represents the discrepancy of decisions between different traffic agencies in the literature and the proposed system.

Similarly, based on the rules reported in Table 5.1, one may conclude that the incident condition in Scenario 3 justified a detour operation (see decisions from New Jersey and Oregon DOTs in Table 5.5). However, the proposed decision support system, by applying multiple criteria from various perspectives, did not recommend the detour implementation with fairly high confidence (70 percent). The system considered that the partial lane blockage and the light traffic demand on the freeway (500 vph) would not cause an excessive delay. Moreover, the long alternative route, with its several signalized intersections and low speed limit, would result in a longer detour travel time. Consequently, such an operation may result in a low compliance rate and a less favorable benefit-cost ratio.

Scenarios 2 and 5 demonstrated how the decision would change if different decision criteria were used. For example, the main offices of the North Carolina DOT and New York State DOT used a single factor to decide for detour implementation. Based on their decision criterion, these agencies implemented detour operations for both Scenarios 2 and 5, because of the complete closure of the primary route. However, the proposed system produced different recommendations for those two scenarios, since their incident durations and the traffic conditions on the freeway and the alternative route were quite different, which lead to significantly different benefit-cost ratios (see Table 5.3).

By the same token, the New Jersey DOT would make identical decisions for Scenarios 4 and 5 using their criteria, i.e., complete road closure and long incident duration. However, the proposed decision support system, by considering additional criteria, made the opposite recommendations for those two scenarios. The major contributor to this discrepancy was the number of signalized intersections on the alternative route. In Scenario 4, only two signalized intersections lay on the main detour route, whereas Scenario 5 had five of them. Signalized intersections on the alternative route increased its travel times and delays. Thus, the optimization model was less likely to divert traffic to the detour route. Although the estimated optimal detour rate for Scenario 5 was about 54 percent, the total benefits from the saved total travel time were not sufficient to offset the operational expenses. Therefore, the multi-criteria decision-support system recommended no detour operations for Scenario 5, in contrast with the decision by the New Jersey DOT as well as most traffic agencies listed in Table 5.5.

5.3.2 The Analysis for the Effect of Weights for the Evaluation Criteria on the Final Results

This analysis demonstrated how the confidence associated with the recommendation by the proposed decision support system varies with the relative weights placed on the set of employed evaluation criteria. This study further used Scenario 6 in Table 5.3 as a base case and divided it into three sub-scenarios for further analyses. Table 5.6 summarizes all data associated with each sub-scenario and the results of sensitivity analysis. Key findings from the analysis are presented below:

1) **Scenario 6-A:** Viewing economic gain and safety as the two most important criteria implied that the decision maker should place higher weights on the **benefit-cost ratio** and on **safety and reliability**. Consequently, the decision support system yielded the following recommendation, even though vehicles taking the detour route may experience much longer travel times than via the freeway: "***Detour operations are recommended, with 58 percent confidence.***"
2) **Scenario 6-B**: If the decision makers place higher weights on **accessibility** and **acceptability** factors that may affect compliance rates, the proposed decision support system yielded the following recommendation to not implement detour operations, unlike the conclusion for Scenario 5-A: ***"Detour operations are not recommended, with 53 percent confidence."***
3) **Scenario 6-C**: If all factors were equally important, the system then yielded the following decision: ***"Detour operations are recommended, with 53 percent confidence."***

TABLE 5.6 Summary of Sensitivity Analysis for Relative Importance of Criteria

Scenario No.		**6-A**	**6-B**	**6-C**
Weights for evaluation criteria	B/C	0.31	0.18	0.25
	Safety & Reliability	0.31	0.20	0.25
	Accessibility	0.18	0.31	0.24
	Acceptability	0.20	0.31	0.26
Final synthesized confidences for alternatives	Detour	**0.58**	0.47	**0.53**
	No Detour	0.42	**0.53**	0.47

*The base scenario for this analysis is Scenario 6 in Table 6.3.

In summary, this analysis sought to highlight the fact that choosing whether to implement a detour operation, when detecting an incident, is a complex decision-making process that should consider various associated factors, ranging from conventional traffic delay to socioeconomic impacts, such as creating a low-emission environment. The simple rules used in most state-of-practices along with the widely-used MOE (delay reduction) used by practitioners and researchers may not be sufficient to yield the decision that best fits the traffic operational needs and the socio-environmental concerns.

For this sake, this study presented a comprehensive decision system to rigorously incorporate all critical factors in making timely detour decisions to contend with non-recurrent congestion. The performance analysis results showed that the proposed system made more reliable decisions, based on comprehensive and rigorous review of various factors associated with advantages and disadvantages of detour operations, than those practices by state DOTs. Responsible traffic agencies, however, ought to place proper priorities on those key decision criteria, based on their local constraints such as available resources, mission for a real-time incident response system, and/or priority concerns of the general public.

Chapter 6: Conclusions and Future Research

6.1 Conclusions and Contributions

Traffic incidents have long been recognized as the main contributor to congestion in highway networks and the related adverse environmental impacts. The fact that the congestion induced by incidents is random in nature necessitates an efficient and effective incident management system, including detection, response, clearance, and network-wide traffic management. Extensive field evaluations have also confirmed that an efficient incident management indeed can yield significant benefits and will be an essential program for any state highway administration.

For this sake, this project proposed a freeway traffic incident management system that can enhance the efficiency of existing operations and minimize the impacts to commuters by efficiently allocating available response units, reliably estimating incident duration, rigorously assessing traffic detour need, and properly implementing control measures. However, to develop an effective incident response system, most highway agencies encounter the following critical issues:

- *Perform Emergency Responses with Limited Resources*: Most incidents require emergency response services from EMT staff, wreckers/tow vehicles, police, and so on. Since most responsible agencies have only limited resources (e.g., staff and tow trucks), especially during the peak periods, an efficient strategy to optimize the response allocation is needed to maximize their effectiveness. Hence, this study proposed an operational model to optimally allocate the available response units to minimize the total incident-induced delay.
- *Need of Models or Algorithms for Reliably Estimating Clearance Times of Detected Incidents*: Predicting the duration needed for incident clearance is one of the essential tasks for estimating the resulting traffic impacts and assessing the operational efficiency. In view of the need for such tools, this study developed an integrated system to provide a reliable estimate of the clearance duration for a detected incident. With the estimated duration for incident clearance, responsible agencies can then implement traffic managing strategies in the network within the impacted area and disseminate related traffic information to en route and pre-route travelers.
- *Need of Models or Algorithms to Support the Evaluation on the Benefits to Activate Detour/diversion Operations*: During the clearance time for severe lane-blockage incidents, traffic detour/diversion could be one of the most effective ways to reduce the network-wide impacts. To ensure the efficiency of detour operations, it is vital to have a rigorous process that allows the responsible agencies to consider costs and benefits from various perspectives: However, the state of practices on this regard merely rely on mainly experience or engineering judgments. Hence, this study developed a decision support tool to assist control operators in tackling this essential issue.
- *Need of Models to Produce Reliable Traveler Information*: Providing traffic conditions in real time to roadway users is also one of the primary tasks for incident traffic management. Some models or algorithms introduced in this study produced additional traffic information for the network motorists, such as the maximum queue length and total delay. Such information can be disseminated to motorists through an online traveler

information system and can be used to assist them in best selecting their routing strategies during the incident operational period.

Taking the critical issues into account, this research made contributions on the following aspects:

- Empirically investigated the effectiveness of a well-operated incident response program and found that an efficient response operation can also reduce the incident clearance duration and produce significant benefits.
- Developed an efficient model for optimally allocating the available response units from a new perspective of minimizing the total incident-induced delay, rather than minimizing the total response time, as reported in most existing studies. The developed model's performance and robustness have been confirmed from the extensive numerical results and the comparative study with the existing models and several states of the practice.
- Developed a reliable model to predict the clearance duration of a detected incident, which features its strengths on the following aspects – 1) reducing the presentation scale and complexity, 2) being less sensitive to the available sample data due to the recursive partitioning, and 3) being more robust to the scenarios of having incomplete information. The performance of the developed prediction system has been demonstrated with the extensive incident data from CHART-MSHA.
- Provided some insightful information on the interrelationships between key factors contributing to incident duration and their collective impacts on clearance times, which would be useful for traffic agencies to plan and improve their incident management programs.
- Provided operational guidelines and tools for responsible agencies to conduct their assessment of traffic diversion plans as well as to design control strategies during the incident management period.
- Integrated all essential models for incident response and traffic management into an efficient operational system that enables responsible agencies to maximize the benefits and minimize operating costs when contending with daily non-recurrent congestion.

In summary, extensive field analyses conducted in this study have confirmed the need to contend daily non-recurrent congestion with an efficient and effective incident management program for optimal use of available resources and best coordination between all responsible agencies. For such needs, this study proposed an enhanced freeway traffic incident management system and developed several efficient, reliable, and robust technical models for its operations. If properly integrated with other systems for incident detection, diversion optimization, and travel time information, the integrated system developed in this study will substantially improve the quality and efficiency of motorists' travel over congested highways.

6.2 Future Research

Although this study made significant progress on several critical issues associated with enhancing the efficiency and reliability of the freeway traffic incident management system, much remains to be further investigated. Some priority research areas to be pursued in the future are listed below:

1. **Enhancing reliability of the incident response management strategy:** The proposed strategy for allocating incident response units is developed under the assumption that only one incident may occur at a given time window and the distribution of incident frequencies over the target network is known and consistent over time. However, in very congested networks during peak periods, multiple incidents may happen concurrently and the response unit at the nearest depot location may not be available. Moreover, since incidents are random in nature, historical data of incident frequency usually exhibit significant variances. To contend with this issue, one will enhance the proposed incident management system with the following additional features:
    - Considering the likelihood of having multiple incidents over a short time period: the optimal allocating strategy can be redesigned to dynamically take care of multiple incidents occurring over the same time period.
    - Considering probability so that the optimal allocating strategy can be reformulated, based on both the mean and the variance of the incident distribution, to reflect its stochastic nature.
    - Investigating the pros and cons between the dispatching and patrolling strategies for different times of a day and further identify the strategy that would be more beneficial under various traffic conditions and incident patterns.
    - Studying the optimal fleet size based on the benefit-cost analysis for a given incident distribution, and then further determining the optimal fleet size, considering both the resource constraints and operational costs.
2. **Enhancing computational efficiency for real-time operations of the detour decision support system:** In view of the critical role of computing efficiency in real-time operations, it is expected that some more efficient models should be developed to supplement or replace simulation- or optimization-based models to generate key traffic control parameters, such as optimal diversion rate and reduced total travel time by detour operations.
3. **Developing real-time models to evaluate the integrated incident response and management system:** To assess the effectiveness and maintain the efficiency of an established system, it is essential that a rigorous evaluation process be developed and activated. The results of a real-time evaluation can help responsible agencies to better identify the appropriate MOEs (measures of effectiveness), effectively detect any area for further improvement, and distribute available information in a timely manner to other coordinated agencies as well as target roadway users.

APPENDIX

Literature Review

Introduction

This chapter summarizes some major studies concerning freeway traffic incident management over the past decades, focusing on critical issues, modeling approaches, and potential research directions. This chapter divides the review results into the following categories:

- Incident response strategies: focused on how best to use the available resources in response to detected potential incidents over the service area during a target time period; and
- Incident duration estimation: highlighting the data issues and the major stream of methodologies to reliably estimate/predict the duration of a detected incident.

The remaining sections present a summary of existing studies related to each category in sequence.

Incident Response Strategies

Many traffic studies have pointed out the critical role of efficient response to the total delay incurred by incidents and concluded that an increase in incident response time may contribute to the likelihood of having secondary incidents (Bentham, 1986; Brodsky and Hakkert, 1983; Mueller et al., 1988). The study results by Sanchez-Mangas et al. (2009) showed that a reduction of ten minutes in emergency response time could reduce vehicle collision and fatalities by 33 percent. Most studies also conclude that dispatching emergency services units and clearing the incident scenes in a timely manner are the key tasks for minimizing incident impact (Kepaptsoglou et al., 2011; Huang and Fan, 2011).

In improving the efficiency of emergency incident responses, both the availability and the accessibility of service units play essential roles. The availability of response units can differ, depending on the relationship between the emergency response resources and the likely distribution of incidents. Accessibility is usually measured in terms of transportation costs (e.g., travel time, travel distance, etc.) between dispatching sites and incident locations. Hence, two vital decisions often arise in planning and managing emergency services: how many response units are needed and where they should be allocated in response to the temporal and spatial distribution of incidents. The core methodology for dealing with this issue belongs to the category of facility location assignment.

The core issue of the facility location problem is to locate a single warehouse from all candidate sites (Weber, 1929). Similar models have also been developed and applied in a variety of fields, including healthcare facilities, plants and warehouses, post offices, and landfills (Eiselt, 2007; Owen and Daskin, 1998).

The two main issues in associating facility location studies with the emergency incident response are: (1) allocating emergency service units for recurrent emergency events, and (2) planning the locations; such as: the response centers to house the resources for emergency services and incident management. Typically, key factors to be considered while designing and distributing emergency service resources include the total assets, operational costs, incident demand coverage, and incident response timeliness. The next three sections summarize three categories of studies, respectively, for optimizing incident response efficiency: covering models, *P*-median models, and *P*-center models.

Covering Models

Covering models, the most widely used approach for allocating emergency service units, attempt to provide "coverage" to all demand points that are considered covered only if a response unit is available to provide services to the demand points within a pre-specified distance limit. Two major schools of such methods are reported in the literature: the location set covering problem (LSCP) and the maximal covering location problem (MCLP).

The LSCP is an earlier version of the emergency facility location model by Toregas et al. (1971); it seeks to minimize the required number of facility locations to cover all demand points. To overcome the deficiencies of the LSCP, several researchers (Church and ReVelle, 1974; White and Case, 1974; Schilling et al., 1979) developed various forms of the MCLP model. Their models aim to maximize the coverage of demands subjected to resource constraints and the minimal service standards. The MCLP and its variants have been broadly applied to various emergency service problems. One such study by Eaton et al. (1985) that involved planning the location of emergency response vehicles in Texas was reported to actually decrease the average emergency response time.

The covering methodology for locating emergency services has also been extended to considering the stochastic or randomly determined nature of emergency events. One approach that reflected the complexity and uncertainty of the response allocation issue used chance-constrained models (Chapman and White, 1974) to guarantee a certain level of service reliability. For instance, Daskin (1983) estimated the probability that at least one server is available to serve the request from any demand and formulated the maximum expected covering location problem (MEXCLP) to position *P* facilities to maximize the average of demand coverage. MEXCLP was enhanced later by ReVelle and Hogan (1986). With their proposed model, the probabilistic location set covering problem (PLSCP), uses an average server busy faction (q_i) and a service reliability factor (a) for demand points and then places the facilities to maximize the probability of service units being free to serve within a particular distance. MEXCLP and PLSCP have been further modified and improved for other EMS (emergency medical service) location problems by many researchers. The modeling details of their studies are available in the literature (ReVelle and Hogan, 1989a; Bianchi and Church, 1988; Batta *et al.*, 1989; Goldberg *et al.,* 1990; and Repede and Bernardo, 1994).

Another approach to tackle the stochastic properties of the emergency service location issue uses a scenario planning methodology to handle the multiple possibilities that a random event may vary over different emergency scenarios. In practice, responsible agencies may evaluate each scenario individually and then aggregate all strategies to develop scenario-specific solutions. For example, MCLP was extended by Schilling (1982) to incorporate scenarios, aiming to maximize the demand coverage over all considered scenarios. Schilling used individual scenarios to discover a range of good location decisions and then to determine the final locations designed to all scenarios based on a compromise decision. Although such an approach is conceptually and computationally simple, it may not yield reliable results. Thus, Serra and Marianov (1999) developed a stochastic approach to represent the uncertainty of target parameters. Some other stochastic methods reported in the literature include stochastic programming (SP) and robust optimization (RO). In general, SP focuses on the expectation of performance measures so that it relies on the complete probability distribution of random parameters and thus has less consideration for the risk (Birge and Louveaux, 1997). In contrast, RO places more emphasis on the worst-case scenario, which tends to yield more conservative results.

Similarly, Nair and Miller-Hooks (2009) solved a multi-objective, probabilistic, and integer programing model to relocate EMS units between calls in expectancy of future demand, and assessed its benefits over traditional static location strategies. Their results showed that a relocation strategy can be beneficial when resources are scarce.

P-median models

Another key method for evaluating the effectiveness of deployment strategies for emergency service involves measuring the average (or total) distance between the facilities and their demand sites. In general, as the average/total distance decreases, the accessibility and effectiveness of facilities increase. Hakimi (1964) used this property in developing his model, introducing the *P*-median method to locate *P* facilities to minimize the average (or total) distance between facilities and demands. The original *P*-median model assumed that the demands at each node and the travel distances between the nodes of the network are deterministic. ReVelle and Swain (1970) later modeled the *P*-median problem as a linear integer program and solved it with a branch-and-bound algorithm.

In similar research, Carson and Batta (1990) developed a *P*-median model to produce the dynamic strategy that could best position ambulances to minimize the average response time for campus emergency service. Berlin et al. (1976) studied two *P*-median models to locate hospitals and ambulances. Their first model mainly focused on patient needs and aimed to minimize the average distance between the hospitals and demand points, as well as the average response time by ambulances from their bases to the demand points. Their second model was designed to enhance the performance of a system by adding a new objective function to minimize the average distance from the ambulance bases to the hospitals. Mandell (1998) adopted priority dispatching in a *P*-median problem to optimize the locations of emergency units for an EMS system that consisted of advanced life support (ALS) units and basic life support (BLS) units.

The *P*-median model has also been extended to account for uncertainty in travel times and demand patterns. For instance, Mirchandani (1980) considered situations where service was unavailable for a demand and solved the problem by using a Markov process to create a system whose states were characterized by demand distribution, service and travel time, and service unit availability. Serra and Marianov (1999) introduced the concept of regret and min-max objectives in locating a fire station in Barcelona. Their model explicitly tackled the uncertainty in demand, travel time, and distance, using scenarios to integrate the variation of uncertain factors. Their model searched for a compromise solution by minimizing the maximum regret over the identified scenarios.

Haghani et al. (2003) proposed a model for the same subject by integrating a dynamic shortest path algorithm. They categorized incidents into five priorities based on severity. These priorities were applied to the objective function to minimize the total weighted travel time by giving higher weights to incidents with higher priorities, so that severe incidents would be responded to faster. Integrating a dynamic shortest path algorithm based on the real-time traffic information, their proposed dynamic dispatch model allows an en route diversion to avoid congested routes and reallocating units for more prompt responses to severe incidents under a set of constraints. This approach had been extended by integrating the generic algorithm (GA) to determine the optimal depot locations and the fleet size at each depot (Yang et al., 2004) to minimize the average travel time and the capital/operating costs (total fleet size). Yang et al. (2005) had further improved their model by enabling reallocation of depots for remaining vehicles (when several units are on duty) to maximize the service area coverage.

P-center models

While the *P*-median model pays attention to optimizing the overall system performance, the *P*-center model concentrates on minimizing the worst system performance, emphasizing the importance of service inequity rather than the average system performance. The *P*-center model assumes that a demand is to be served by the nearest facility, thus making full coverage for all demand points always possible by minimizing the maximum distance between any demand and its nearest facility. However, unlike the full coverage offered by covering models, which requires excessive resources, the *P*-center model achieves its aims with limited resources.

The first *P*-center model, posed by Sylvester (1857) more than a century ago, sought to identify the center of a circle with the smallest radius that could cover all target destinations. Since then, this model has been extended to a wide range of facility location applications, including medical (e.g., EMS centers and hospitals) and public facilities. For example, Garfinkel et al. (1977) modeled their problem with integer programming and successfully solved it with a binary search technique and a combination of exact tests as well as heuristics. The formulations by ReVelle and Hogan (1989b) for their *P*-center problem sought to minimize the maximum distance for available EMS units with a specified reliability (α). They considered system congestion and derived the probability of a service unit being busy to constrain the service reliability for all demands.

The *P*-center models have also been extended to consider their stochastic aspect. For instance, Hochbaum and Pathria (1998) tried to minimize the maximum distances on the network over all time periods. Since the costs and the distances between locations differ in each time period, they used k fundamental networks to represent different time periods and then developed a polynomial-time approximation algorithm to solve for each problem. Another instance is the application for locating and dispatching three emergency rescue helicopters for EMS demands due to accidents related to skiing, hiking and climbing the north and south Alpine mountains during holiday seasons (Talwar, 2002). The problem was solved by using effective heuristics to minimize the worst response time.

In addition to the mentioned studies, a wide range of applications with different formulations can be found in the literature (Handler, 1990; Brandeau et al., 1995; Daskin, 2000; and Current et al., 2001).

<u>Incident Duration Estimation</u>

Reliable estimation of incident duration has been studied by researchers for several decades with various methodologies. At the early stage, researchers mostly used descriptive statistics of the data from closed-circuit television (CCTV) logs (1964), police logs (1971), and time lapse cameras (1974) to estimate the incident duration distribution. As more advanced technologies for data collection emerged over the past decades, traffic researchers have developed more analytical methodologies. Most existing approaches found in the literature can be sorted into the following categories: (1) probabilistic distributions, (2) conditional probabilities, (3) regression models, (4) discrete choice or classification models, (5) decision, classification or regression trees, (6) time sequential models, and (7) unconventional methodologies. The rest of this section discusses each approach in detail.

Probabilistic Distributions

Probabilistic models, the first category of approaches for estimating incident duration, are relatively straightforward. These models center on the idea of viewing an incident's duration as a random variable and attempting to find a probability density function (PDF) that can fit the data set. Golob et al. (1987) conducted their research using approximately 530 incidents involving trucks and found that they could model incident duration with a log-normal distribution. Their findings were later supported by Giuliano (1989), Garib et al. (1997), and Sullivan (1997) in their studies of freeway incident duration. Ozbay and Kachroo (1999) also found that the distribution of incident durations from their data set showed a shape very similar to a log-normal distribution, although a few statistical significance tests rejected their hypothesis. However, they realized that when the study data set was subdivided by incident type and severity, these subsets followed a normal distribution. This finding has important implications, since it supports the theory that incident duration is a random variable (Smith and Smith, 2002). Similarly, Jones et al. (1991) discovered that a log-logistic distribution could be used to describe their study data set from Seattle. Nam and Mannering (2000) found that their data set could be illustrated with the Weibull distribution. However, Smith and Smith (2002) could not find an appropriate probability distribution, including log-normal and Weibull distributions, to fit the incident clearance times for their study data.

Conditional Probabilities

Probability models for incident duration can be extended to integrate with a conditional probability methodology. The key idea of such models is to find the probability distribution of incident durations under certain given conditions — for example, the probability that an incident duration will run over thirty minutes, given that the incident has already lasted for ten minutes. It seems intuitively clear that the probability of an incident being removed within a given period of time would vary with how long the incident has already lasted — described as "duration dependence" by Nam and Mannering (2000) — and the incident's characteristics. One interesting approach using this concept is the hazard-based duration model. This model allows researchers to calculate incident duration with conditional probability models. Such approaches expand the focus from simply estimating and predicting an incident's duration to computing the likelihood that the incident will be cleared in the next short time period, given its sustained duration.

One study with this methodology was by Nam and Mannering (2000) who used a two-year data set from Washington State. Their study showed that each incident duration component (i.e., detection/reporting, response, and clearance times) was significantly affected by numerous factors in a different magnitude and direction so that different distribution assumptions were recommended for each component. Exploring various distributions (i.e., exponential, log-logistic, log-normal, Weibull, and Gompertz) for hazard functions, this study showed that the Weibull model produced the best results for estimating incident detection/report durations and response times, whereas clearance times were performed the best on the log-logistic model. According to their research, it is a critical finding that the clearance times more likely end soon until an inflection point (89.20 minutes on their data) but less and less likely end soon afterward, while the probabilities that detection/reporting and response times end soon monotonously increase as time goes by. They also found that the estimated coefficients were unstable through the two-year data used in model development. Although Nam and Mannering concluded that this approach is useful for determining how each explanatory variable influences each component of the incident duration, they did not address the direct potential of this methodology to estimate or predict the incident duration for given explanatory variables.

Chung (2010) recently used a very similar approach, the log-logistic accelerated failure time (AFT) metric model, but focused on estimating/predicting accident durations by using a two-year (2006 and 2007) accident data set from the Korean Highway Corporation (KHC). The estimated duration model, based on year 2006 data, was evaluated in two ways: the mean absolute percentage error (MAPE) and the percentage of predictions that are within a certain tolerance of their actual duration times. The model showed results in 47 percent of MAPE on year 2006 data, 45 percent estimation accuracy within ten-minute errors, and 61 percent estimation accuracy within fifteen-minute errors. The author concluded that the prediction accuracy of the developed model was reasonably acceptable according to the scale of evaluation developed by Lewis (1982). However, the author did not validate his model on the new data. Instead, he tested the temporal transferability of the model by using year 2007 data and noted that the estimated model parameters can be stable over time, which was different from the results reported by Nam and Mannering.

Regression Models

Another simple methodology for predicting incident duration uses regression. Regression models usually include several binary indicators of independent variables to reflect incident characteristics and a continuous or categorical variable as a dependent variable (i.e., incident duration). One of the best-known linear regression models for incident duration prediction was developed by Garib et al. (1997) using 277 samples of data from California. They used various independent variables to represent incident characteristics (e.g., incident type, number of lanes affected by the incident, number of vehicles involved, and truck involvement) and weather conditions (rainy or dry). Their proposed final incident duration model has the following structure:

$$Log(Duration) = 0.87 + 0.027X_1X_2 + 0.2X_5 - 0.17X_6 + 0.68X_7 - 0.24X_8$$

where Duration = incident duration (minutes)

X_1 = number of lanes affected by the incident

X_2 = number of vehicles involved in the incident

X_5 = truck involvement (dummy variable)

X_6 = morning or afternoon peak hour indicator (0: morning peak hour; 1: afternoon peak hour)

X_7 = natural logarithm of the police response time (minutes)

X_8 = weather condition indicator (0: no rain; 1: rain)

The logarithm form of incident duration indicates that the incident durations in this data set follow a log-normal distribution based on the Kolmogorov-Smirnov test. This result is similar to those of Golob et al. (1987) and Giuliano (1988). According to the authors, the police response time was the most significant factor affecting the resulting incident duration, followed by weather conditions, peak hour, truck involvement, and the combined effect of the number of lanes and the number of vehicles involved in the incident.

Discrete Choice or Classification Models

While most studies in the literature have viewed incident duration as a continuous variable, several researchers recategorized the continuous variable of incident duration into discrete time intervals (e.g., 10 to 25 minutes) to apply discrete choice or classification approaches. For instance, Lin et al. (2004) developed a system that integrates a discrete choice model and a rule-based model to predict incident duration. They adopted the ordered probit models to first predict incident durations in a time interval format, followed by applying a rule-based supplemental model to enhance the accuracy of prediction results. Boyles et al. (2007) also redefined their original incident duration data into an interval format in developing their naïve Bayesian classifier (NBC), based on incident data from the Georgia Department of Transportation. They argued that the NBC has the following distinct advantages: (1) flexibility in accommodating changeable amounts of information (incomplete information or information received at different points in time), (2) increased robustness to outliers over standard techniques like linear regression, (3) computational simplicity, (4) easy adaptability as the number of samples for calibration grows, and (5) relative ease in interpreting the research results.

Decision, Classification or Regression Trees

Another approach frequently appearing in the incident duration literature is the decision, classification or regression tree method that has proven quite useful for discovering patterns in each data set without considering the fundamental probabilistic distribution (Smith and Smith, 2001). This property is very helpful, since most incident data sets do not fit well to any commonly used distribution. Smith and Smith (2001) also pointed out that the pattern-recognition model has been used recently to develop incident duration models. One representative model, developed by Ozbay and Kachroo (1999) for the Northern Virginia region, began with a model to predict the clearance time using linear regression based on a large sample size. Unfortunately, the completed analysis produced an unsatisfactory result ($R^2 \approx 0.35$), showing that their incident clearance time data followed neither a log-normal nor a log-logistic distribution. As an alternative method, they explored a decision tree model and finally generated relation patterns (see Figure A.1) for use in predicting clearance time.

Note that the decision tree comprises a series of decision variables. This is another advantage of the tree-type methodologies — their self-explanatory nature, which is rooted in the tree-structure. Users can easily understand the output by following the branches related to the conditions of variables. For instance, the tree uses an incident type as the first variable to decide if the detected incident type is known or not. Once it is classified as an unknown type, then the tree immediately provides an estimate of 45 minutes for the average clearance time. Otherwise, it moves to the next level to determine the type of an incident.

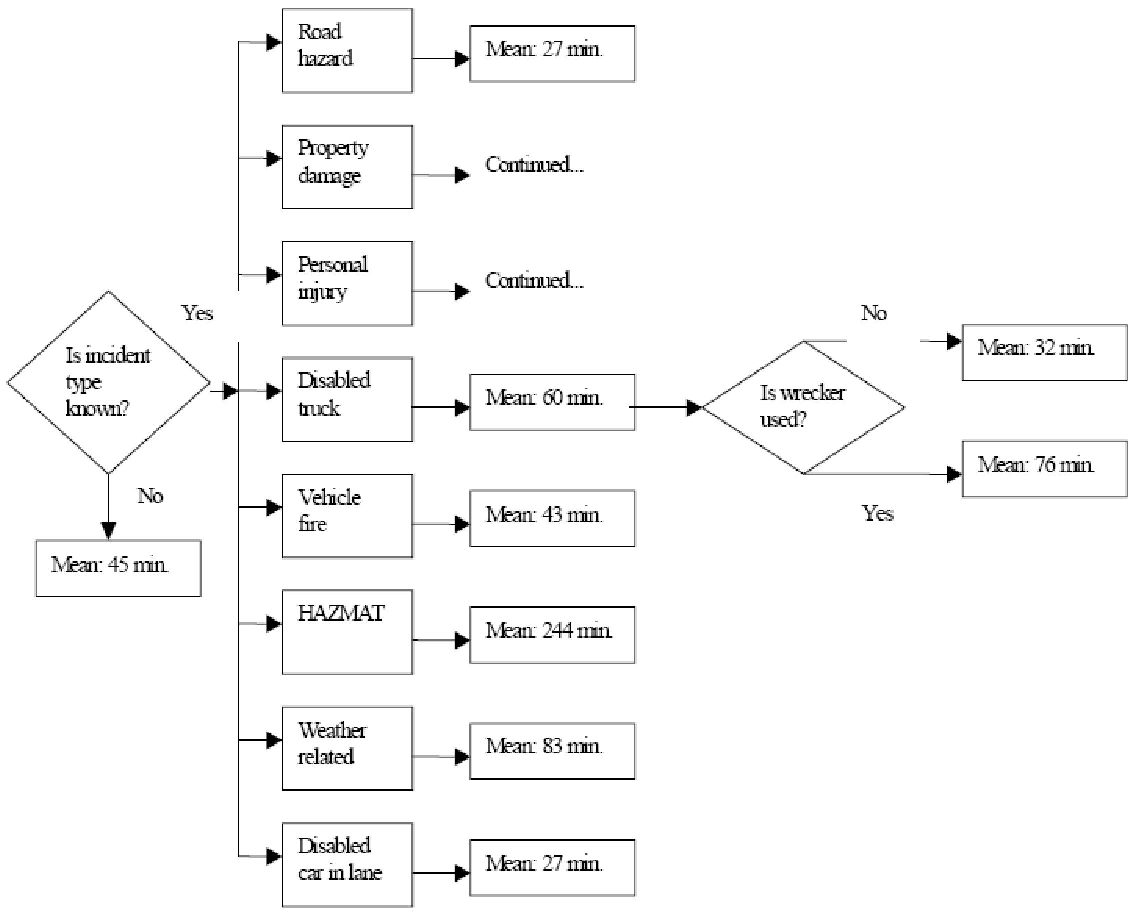


FIGURE A.1 A Part of the Complete Decision Tree to Predict Clearance Time by Ozbay and Kachroo (1999)

Smith and Smith (2001), inspired by the study of Ozbay and Kachroo, tried to develop a classification and regression tree (CART) using 6,828 accident clearance times collected from the Smart Travel Lab in Charlottesville, Virginia. Smith and Smith separated clearance times into three classes – 1-15 minutes as short, 16-30 minutes as medium, and over 30 minutes as long clearance times. Their optimal classification tree includes only five distinct binary decision variables among several available independent variables—tow-truck response, emergency medical service (EMS) response, day of the week, police response, and three or more vehicles involved. They also found out that the tree does not follow a chronological progress of an event; therefore, complete accident information is required before making the best prediction. The prediction accuracies on 1,707 test sets were about 77 percent, 19 percent, and 64 percent for short, medium, and long clearance times, respectively. They noted that the model results imply that the relationship between accident characteristics and clearance times might be weak or independent from each other. However, they concluded that such a tree, developed based on a reliable and sufficient database, performs well, even though theirs yielded unsatisfactory results due to poor data quality.

Xiaoqiang et al. (2009) also used CART to develop an incident duration model using a data set from the Beijing Transportation Management Bureau. The presented independent variables included time of day, incident type, incident severity, location, and disposal type. After removing statistically irrelevant variables by using multiple linear regressions, they developed a regression tree based on 65,000 data that consisted of 40 nodes. The model was validated with an 8,000-test data set by road in Beijing for 10-minute, 15-minute, and 20-minute error tolerance. The results showed about 30 percent average error. Despite relatively good model results, their tree model did not indicate decision criteria for each branching.

The recent notable research of Ozbay and Noyan (2006) used Bayesian Networks (BN) to create dynamic incident duration estimation trees that enhance their adaptability to incomplete information in real-time prediction. Unlike a conventional classification tree, the variables consisting of nodes in BN are stochastic so that the state of the variable is determined by the probability distribution rather than by a fixed value. Moreover, BN can describe the overall dependency structure of many variables that allow bi-directional induction, while CART is limited to examine one-directional pair-wise associations. Using probabilistic inference, the model becomes a scenario-based decision tree that not only answers the predicted clearance time given immediately available incident related information but also diagnoses missing variables based on specific scenarios. For instance, the decision maker can estimate the clearance time for the incident on a two-lane roadway with three vehicles and three ambulances involved. Yet, he/she can also estimate how many injuries would occur due to this incident when its clearance time is between 0 and 30 minutes. The model was developed with 600 incident cases to estimate 30-minute interval clearance times (i.e., 0-30 minutes, 30-60 minutes, etc.). Two validation methods, batch-prediction and cross-validation, were used with 100 samples, and the results were 78.4 percent and 79.56 percent, respectively.

Like Ozbay and Noyan, Yang et al. (2008) includes a Bayesian theorem to develop a decision tree to predict incident durations with missing or inconsistent information. They inserted Bayesian nodes, following every decision node, to ask whether the required information is available or not. If the information is available, no further calculation will occur for that node. Otherwise, the model uses Bayesian theory to compute the value of the node. Then, the computed Bayesian node value is used to estimate the time interval class to which the detected incident belongs. They generated a validation data set that includes 20 percent missing or incomplete data to test the adaptability and robustness of their model. Their model reportedly outperformed the traditional classification tree model developed on the same data set; the Bayesian decision tree and classification tree yielded 74 and 46 percent prediction accuracies, respectively.

Time Sequential Models

Khattak et al. (1995) realized that the full set of variables for incident forecasts would be available at the moment the incident was cleared. Although prediction models based on this total set of variables would be more accurate and reliable, they are less practical for use in real-time incident management operations, precisely because a full set of variables would only become available after clearing the incident. Thus, they introduced a time sequential model that focuses on predicting real-time incident duration under partial information. Their model considers ten distinct stages of incident duration, based on the availability of information. Each stage estimates different ranges of incident duration with a separate truncated regression model. As the model moves to the next stage, it includes progressively more variables to explain the stage's duration. Despite its originality and reasonability, this model was not tested or validated due to the lack of field data. The authors also mentioned that the purpose of their study was to introduce and demonstrate the time sequential model rather than to prove its performance in traffic operations.

Since then, their approach has been extended and enhanced by several researchers. For instance, Wei and Lee (2007) proposed an adaptive procedure that includes two artificial-neural-network-based models for sequentially forecasting an incident's duration. The first model, the so-called *Model A*, was designed to predict the duration of the detected incident at its notification, at which point *Model B* takes over and updates the duration at multiple periods until clearance of the incident. The performances of these models were evaluated with three criteria: mean absolute error (MAE), mean absolute percentage error (MAPE), and root mean square error (RMSE), for six experiments of predicted incident durations at every forecast time period. The results showed that most MAEs were less than 800 seconds, and most MAPEs were less than 40 percent. Moreover, most RMSEs were less than 1100 seconds, and these results were highly likely to decrease as the time point of forecast passes. Based on the results, the authors concluded that the proposed models can yield reasonable forecasts as time goes by. However, their model was trained with only 18 quite homogeneous incidents as they are all from the same roadway over a 6-month period, and they did not specify the sample size for testing their model. In addition to the incident characteristics, the proposed model required traffic data from the loop video detector (VD), the time-space relationship between a detected incident and the VD data, and the geometry characteristics as inputs, which are usually unavailable in a common incident database.

Later, they tried to improve their model by adding a procedure to select a best-performing subset of features using k-mean clustering method (Lee and Wei, 2008), but the results were not satisfactory. Then, they used a generic algorithm (GA) (Lee and Wei, 2010) and found that reducing the dimensionality of input features can decrease the cost of acquiring data and increase the interpretability and comprehensibility of model outputs. Furthermore, they claimed that data simplification can eliminate irrelevant data that can mislead the learning process and impair the development of the final model. In fact, they reported that the MAPE for forecasted incident duration at each time period dropped, mostly falling below 29 percent after they applied their proposed feature selection method. However, similar to their previous research, their model was developed and tested based on only 24 and 15 accidents, respectively, which are, again, collected from one roadway over a 6-month period. Although the proposed feature selection method significantly reduced the number of required input variables and achieved better prediction accuracy, the model still required traffic data as an input.

Qi and Teng (2008) also developed a time sequential procedure that divides the incident management process into multiple stages (three stages in their example), depending on the availability of information. They developed a log-logistic hazard-based duration regression model for each stage, with different variables representing different available data. These developed regression models provide the estimates for coefficients of explanatory variables and the parameters of a probability distribution describing incident duration. The truncated median of incident duration, based on these estimates, could predict the remaining incident duration online. They evaluated the prediction performance of their proposed model with respect to the percentage of correctly predicted duration at a specific percentage of error tolerance. As the percentage of error tolerance increased, the percentage of correctly predicted incident duration also increased as expected. Also, the prediction accuracy for the third stage model was higher than the one for the second stage model, and the prediction accuracy of the second stage model was higher than that of the first stage model at any error tolerance level. They concluded that the prediction accuracy increased as more information was integrated into the developed models. However, they did not validate their models on the new dataset.

Unconventional Methodologies

While statistical analysis had been the main approach in the early history of the incident duration study, recent research focuses on the applications of unconventional methodologies, including machine learning algorithms. One of the most popular approaches is artificial neural networks (ANN). Wang et al. (2005) pointed out that many problems and parameters in the transportation field are ambiguous, characterized by linguistic variables, and non-linearly related. Such characteristics are difficult to model by traditional methodologies. Thus, they used ANN to analyze the duration of incidents, particularly vehicle breakdown duration, and compared its results with the fuzzy logic (FL) ones. Two ANNs with 10 neurons and17 neurons in the hidden layer, respectively, and a fuzzy logic model were trained using 113 vehicle breakdown incidents occurring on M4 in UK. There were four input variables available: vehicle type, location, time of day, and report mechanism. Through the comparison of model results, they found that the ANN with 17 neurons performed the best with respect to the adjusted R^2 and the root mean square error (RMSE), followed by the fuzzy logic model and ANN with 10 neurons in the hidden layer. Their sensitivity tests on the input variables showed that all input variables have a significant influence on estimated vehicle breakdown durations. They also reported that their best model (ANN with 17 neurons) showed 0.411 for R^2 and 19.5 minutes for RMSE, better than the estimates with the operator's judgment, which is 42 minutes for RMSE. However, they admitted that the proposed model failed to predict the larger values and outliers due to insufficient explanatory variables.

Guan et al. (2010) also used ANN with 25 nodes in a hidden layer to develop a model for 660 incidents data collected from Guangzhou in China. Unlike other reported incident data in the literature, their average incident duration was longer (60.5 minutes) and only a few cases lasted less than 10 minutes. The model developed with 8 input factors was validated based on 170 incidents and showed 33 percent prediction accuracy within 10 minutes' error tolerance and 63 percent accuracy within 20 minutes' error tolerance. The correlation coefficient of predicted and observed values was 0.85. They concluded that the model results are acceptable by the incident management process but not very accurate for predicting itself. According to them, the unsatisfactory prediction accuracy may be due to the randomness in the incident data itself rather than the model, since they experienced no significant improvement on the prediction accuracy through various approaches.

In the incident duration study by Wu et al. (2011), support vector regression (SVR) was applied on 1636 incidents from the Netherlands, since this approach demonstrates advantages in solving small sample, non-linear and high-dimensional pattern recognition problems. Their database included three incident types: vehicle break down, lost load, and accident. Since they show different natures in terms of the processing mechanism and associated factors, a separate duration model was developed for each type of incident. The model was validated on 327 samples with three criteria. The incident duration model for breakdown showed the highest correlation coefficient (0.54), followed by the models for accident (0.22), and lost load (0.17). The mean absolute errors were 12.9, 13.2, and 12.3 minutes for models for breakdown, lost load, and accident, respectively. The prediction accuracies with 10 minutes' error tolerance were 44.09 percent, 53.97 percent, and 55.03 percent, whereas the prediction accuracies with 15 minutes' error tolerance were 68.82 percent, 76.92 percent, and 71.01 percent for breakdown, lost load, and accident, respectively. These results were comparable to other studies' results, but one should note that their data were preprocessed to exclude too short (less than 10 minutes) and too long (over 90 minutes) incident durations in the analysis. They also pointed out that the common large errors in the long incident durations possibly may be due to the lack of detailed or unobservable explanatory variables to capture the randomness of incident durations and the inconsistency of responsible agencies' operational efficiency.

Finally, a few comparative studies are reported in the recent literature. One interesting study was conducted by Valenti et al. (2010) to compare various statistical modeling and machine learning algorithms, including multiple linear regression (MLR), prediction/decision tree (DT), artificial neural network (ANN), support/relevance vector machine (RVM), and k-nearest neighbor (KNN). Based on 237 incident data occurred during a three-month period in Italy, they reported that the RVM showed the best performance with 13.65 minutes and 17.29 minutes for MAE and RMSE, respectively, whereas the DT was the least reliable, showing 16.66 minutes and 23.07 minutes for MAE and RMSE, respectively. However, they also found that each approach has its own strengths and weaknesses. For instance, the MLR best performed for short durations (< 30 minutes) with 9 minutes of MAE, while DT and RVM showed good results for medium durations (31-60 minutes). On the other hand, the ANN was the only model predicting well for the long duration (> 90 minutes). Based on these findings, they concluded that to enhance the prediction reliability a preliminary incident classification scheme could be conducted before, and then an appropriate approach could be applied for each category of incident durations.

In summary, although a variety of models has been proposed in the literature and reported to achieve acceptable results, most of such studies were developed on a limited-scale data set that collected either during a short period or on a specific roadway segment. Furthermore, many of those models were not validated with real-world data, and some real-world operational constraints were not included in the formulations. Besides, most research findings are location-specific, unlikely to be transferable to other locations. Therefore, any target application in practice needs to either recalibrate existing models in the literature with new data sources, or to develop new formulations to reflect the constraints and unique operational nature of the target application.

Grounded on the accomplishments of existing studies on various aspects of incident management, this research aims to further develop a reliable operational system that can effectively address the following critical issues:

- Tackling heterogeneity in most incident data sets;
- Enhancing the prediction performance;
- Investigating the interactions between incident clearance durations and associated factors; and
- Assessing the prediction model’s transferability and robustness for different data sets

Descriptions of Classifiers Constituting *SCAR*
(continued from TABLE 4.5)

TABLE A.1 Descriptions of Classifiers Constituting *SCAR*

No.	Description of Classifier			Clearance Time (minutes)
1	IF	(road=I895 & incident_type=disabled) or (noTT=0 & noSDsh=0 & incident_type=disabled) or (noTT=0 & road=US50 & incident_type=disabled)	THEN	Minor (≤30)
2	ELSE-IF	(OC=TOC3 & noLane=13 & county=MO & incident_type=cpd) or (noTT=0 & road=I495 & incident_type=disabled & pavement=dry) or (chart=1 & noLane=12 & road=I95 & incident_type=disabled)	THEN	Minor (≤30)
3	ELSE-IF	(OC=TOC3 & SDBmain=minor & pavement=unspecified) or (OC=AOC_South & noLane=12 & road=US50) or (Weekday & incident_type=disabled & detection=CHART)	THEN	Minor (≤30)
4	ELSE-IF	(totalveh=2 & incident_type=fatality) or (night=0 & road=other & incident_type=fatality)	THEN	Major (>120)
5	ELSE-IF	(noTT=0 & county=3 & incident_type=disabled) or (OC=TOC3 & noSDBmain=0 & incident_type=cpd)	THEN	Minor (≤30)
6	ELSE-IF	(noSUT=0 & non-holiday & exit=22 on I495, I270, I695, and US50) or (SDBmain=minor & county=MO & detection=CHART) or (noSDsh=2 & noSDBmain=0 & noODBsh=0 & incident_type=disabled)	THEN	Minor (≤30)
7	ELSE-IF	(night=0 & noODBsh=0 & exit=31 on I495, I270, I695, and I83) or (noODmain=3 & SDBmain=minor & county=Anne Arundel) or (chart=1 & noLane=13 & noSDBmain=0 & peakhr=PMpk)	THEN	Minor (≤30)
8	ELSE-IF	(noLane=12 & SDBmain=minor & road=I495 & incident_type=cpd) or (totalveh=2 & noSDBmain=0 & county=Frederick & incident_type=cpd) or (noLane=12 & noSDBsh=1 & incident_type=cpd & peakhr=PMpk)	THEN	Minor (≤30)
9	ELSE-IF	(region=Baltimore & incident_type=cpi & detection=CCTV) or (county=BC & incident_type=cpi & pavement=unspecified & detection =MDTA) or (OC=AOC_Central & totalveh=3 & incident_type=cpi & non-holiday)	THEN	Intermediate (30 – 120)

10	ELSE-IF	(noSUT=0 & noSDsh=2 & noSDBsh=1 & exit=29 on I95, I495, and I695) or (noSDBsh=0 & ODBmain=minor & road=I895 & county=BC) or (OC=TOC4 & noPVS=0 & noSDBsh=1 & incident_type=fire)	THEN	Minor (≤30)
11	ELSE-IF	(night=0 & SDBmain=minor & road=I495 & pavement=unspecified) or (OC=TOC7 & noPVS=1 & noSUT=0 & incident_type=cpd) or (noSDBmain=0 & road=I695 & incident_type=cpd & peakhr=AMpk)	THEN	Minor (≤30)
12	ELSE-IF	(night=0 & chart=1 & totalveh=5 & noSDBsh=1) or (Weekend & road=I495 & region=Washington & incident_type=cpi)	THEN	Intermediate (30 – 120)
13	ELSE-IF	(noPVS=0 & noTT=0 & ODBmain=minor & incident_type=unknown) or (night=0 & noLane=12 & county=Baltimore & incident_type=disabled) or (OC=TOC3 & totalveh=2 & noSDsh=2 & pavement=unspecified)	THEN	Minor (≤30)
14	ELSE-IF	(OC=AOC_North & noSDBsh=0 & region=Baltimore & incident_type=cpi) or (noPVS=1 & SDBmain=minor & incident_type=cpi & peakhr=PMpk) or (chart=1 & noSDBsh=0 & incident_type=cpi & detection=MDTA)	THEN	Minor (≤30)
15	ELSE-IF	(night=0 & pavement=dry & non-holiday & exit=27 on I-495/95, I-695, US 50, and I-83) or (OC=TOC4 & noSDsh=2 & SDBmain=minor & pavement=unspecified) or (OC=TOC4 & noSUT=0 & road=I95 & incident_type=cpd)	THEN	Minor (≤30)
16	ELSE-IF	(night=0 & noSUT=0 & noSDmain=4 & noODsh=4) or (night=0 & totalveh=1 & SDBmain=severe & region=Baltimore) or (OC=AOC_Central & chart=0 & noLane=13 & peakhr=non-pk)	THEN	Minor (≤30)
17	ELSE-IF	(totalveh=2 & noTT=2 & peakhr=non-pk) or (chart=1 & incident_type=cpd & detection=local police) or (Weekday & chart=1 & region=Southern & peakhr=non-pk)	THEN	Major (>120)
18	ELSE-IF	(night=0 & SDBmain=minor & road=I495 & pavement=wet) or (OC=TOC4 & noLane=9 & incident_type=cpd & detection=CHART) or (night=0 & noSDBsh=0 & pavement=wet & detection =MDTA)	THEN	Minor (≤30)
19	ELSE-IF	(noSUT=1 & noLane=12 & road=I695 & pavement=dry) or (OC=TOC4 & noSDsh=2 & incident_type=cpi & detection=SHA) or (totalveh=1 & SDBmain=very-severe & ODBmain=minor & road=I95)	THEN	Intermediate (30 – 120)
20	ELSE-IF	(pavement=dry & non-holiday & exit=11 on I-695) or (noTT=0 & noSDBmain=1 & incident_type=disabled) or (OC=TOC4 & totalveh=2 & noLane=12 & noSDBmain=1)	THEN	Minor (≤30)
21	ELSE-IF	(OC=SOC & noSUT=1 & road=other) or (chart=1 & noPVS=0 & region=Western & detection=state police) or (night=1 & totalveh=1 & noTT=1 & incident_type=cpd)	THEN	Minor (≤30)
22	ELSE-IF	(night=0 & noTT=2 & noODBmain=0 & incident_type=cpd) or (noSDBsh=1 & region=Eastern & incident_type=cpd & detection=state police) or (noTT=1 & road=I95 & incident_type=cpd & peakhr=non-pk)	THEN	Intermediate (30 – 120)
23	ELSE-IF	(noPVS=0 & noSDmain=4 & exit=23 on I495, I695, and US50) or (night=0 & noPVS=0 & noSDsh=0 & incident_type=cpd) or (noPVS=0 & noTT=0 & noSDBmain=1 & county=Howard)	THEN	Minor (≤30)

24	ELSE-IF	(road=I695 & exit=7) or (chart=1 & noTT=1 & noSDBmain=0 & incident_type=cpd) or (OC=TOC3 & noSUT=0 & incident_type=cpd & peakhr=AMpk)	THEN	Minor (≤30)
25	ELSE-IF	(Weekday & totalveh=4 & road=I95 & incident_type=cpi) or (night=0 & noSDBsh=1 & noSDBmain=2 & road=US50) or (night=0 & noTT=0 & SDBmain=very-severe & county=MO)	THEN	Intermediate (30 – 120)
26	ELSE-IF	(OC=TOC3 & totalveh=2 & SDBmain=moderate & detection=CHART) or (noSDBmain=0 & incident_type=cpd & peakhr=AMpk & detection=state police) or (OC=SOC & noODBsh=0 & peakhr=PMpk & detection=CHART)	THEN	Minor (≤30)
27	ELSE-IF	(noPVS=3 & noODBmain=0 & incident_type=cpi) or (noTT=0 & noSDBsh=2 & noODBmain=0 & detection=250) or (noSUT=0 & noSDBsh=1 & road=I70 & peakhr=PMpk)	THEN	Intermediate (30 – 120)
28	ELSE-IF	(OC=TOC7 & noSDsh=2 & incident_type=fire & pavement=dry) or (OC=TOC7 & totalveh=1 & noSDmain=2 & incident_type=cpd) or (totalveh=2 & noSDBsh=1 & noSDBmain=0 & road=other)	THEN	Minor (≤30)
29	ELSE-IF	(chart=1 & peakhr=non-pk & exit=19 on I-495 and I-695) or (OC=TOC4 & totalveh=2 & noSDmain=3 & incident_type=cpd) or (noSDBmain=1 & incident_type=cpi & peakhr=PMpk & detection=CHART)	THEN	Minor (≤30)
30	ELSE-IF	(totalveh=3 & noTT=0 & noSDmain=4 & county=MO) or (night=1 & chart=0 & pavement=wet & non-holiday)	THEN	Intermediate (30 – 120)
31	ELSE-IF	(night=0 & noPVS=0 & detection=MDTA & exit=64 on I95) or (OC=TOC3 & noLane=12 & county=MO & detection=state police) or (chart=0 & SDBmain=minor & pavement=wet & peakhr=non-pk)	THEN	Minor (≤30)
32	ELSE-IF	(noODBmain=0 & incident_type=cpi & exit=20 on I495, I695, I83) or (noSDBsh=0 & noSDBmain=1 & detection=MDTA & exit=56 on I95) or (noSDsh=2 & road=I95 & county=PG & detection= state police)	THEN	Minor (≤30)
33	ELSE-IF	(noODBsh=1 & SDBmain=minor & region=Baltimore & peakhr=AMpk) or (Weekend & noPVS=1 & noTT=0 & SDBmain=minor) or (noPVS=1 & noTT=0 & SDBmain=very-severe & pavement=dry)	THEN	Intermediate (30 – 120)
34	ELSE-IF	(totalveh=2 & noSDsh=2 & pavement=dry & detection=local police) or (night=1 & totalveh=3 & noTT=0 & noSDmain=4) or (noSDmain=4 & road=other & county=Baltimore & incident_type=cpd)	THEN	Intermediate (30 – 120)
35	ELSE-IF	(night=0 & noTT=0 & detection=MDTA & exit=74 on I-95) or (night=0 & noSUT=0 & noSDBmain=0 & county=Cecil) or (noLane=13 & noSDBmain=1 & county=Baltimore & detection=CHART)	THEN	Minor (≤30)
36	ELSE-IF	(Weekday & noSUT=0 & noLane=7 & region=Washington) or (noPVS=1 & county=Balimore & incident_type=cpd & detection=CHART) or (Weekend & noLane=13 & noSDBsh=0 & road=I95)	THEN	Minor (≤30)
37	ELSE-IF	(noTT=0 & road=I95 & county=Harford & pavement=unspecified) or (Weekday & chart=0 & noSDsh=1 & noSDmain=4) or (OC=TOC4 & noLane=13 & road=I95 & non-holiday)	THEN	Intermediate (30 – 120)

38	ELSE-IF	(OC=TOC3 & totalveh=1 & incident_type=cpi & detection=CHART) or (noLane=12 & SDBmain=minor & peakhr=AMpk & detection=state police) or (OC=TOC7 & totalveh=2 & noSDmain=4 & detection=CHART)	THEN	Minor (≤30)
39	ELSE-IF	(night=1 & detection=local police) or (OC=SOC & totalveh=1 & ODBmain=very-severe) or (night=1 & noODsh=2 & noODBsh=2 & ODBmain=very-severe)	THEN	Major (>120)
40	ELSE-IF	(noSDmain=3 & noSDBmain=2 & region=Washington) or (OC=TOC5 & noODsh=2 & noODBsh=0 & SDBmain=minor) or (noLane=13 & pavement=dry & peakhr=AMpk & detection=CHART)	THEN	Minor (≤30)
41	ELSE-IF	(totalveh=4 & noSDBmain=1 & noODBmain=0 & region=Baltimore) or (chart=1 & noSDBsh=0 & incident_type=cpi & pavement=unspecified) or (night=1 & noSDBmain=1 & incident_type=cpi & non-holiday)	THEN	Intermediate (30 – 120)
42	ELSE-IF	(totalveh=6 & noTT=0 & noSDBsh=1 & noSDBmain=0) or (OC=TOC7 & noSDBmain=0 & road=other & pavement=wet) or (noSDBsh=1 & incident_type=cpi & pavement=unspecified & detection=CHART)	THEN	Minor (≤30)
43	ELSE-IF	(SDBmain=minor & road=other & peakhr=non-pk & detection=SHA) or (night=1 & chart=1 & totalveh=1 & SDBmain=very-severe) or (night=1 & totalveh=2 & county=Baltimore & detection=state police)	THEN	Intermediate (30 – 120)
44	ELSE-IF	(Weekday & incident_type=cpi & pavement=dry & exit=24) or (OC=AOC_Central & totalveh=1 & noSDBmain=2 & non-holiday) or (noLane=12 & noSDBsh=1 & road=I695 & detection=state police)	THEN	Minor (≤30)

* MO = Montgomery, BC = Baltimore City, PG= Prince George, and MDTA = Maryland Transportation Authority

TABLE A.2 Descriptions of Variables Included in *SCAR*

Variables	Descriptions
Incident_type	Types of incidents: • disabled: disabled vehicles • cpi: collision with personal injury • cpd: collision with property damage • fatality: collision with fatality • fire: vehicle on fire • unknown: no specific information available
noTT	Number of tractor-trailers involved with the incident
noPVS	Number of pickup trucks, vans, or SUVs involved with the incident
noSUT	Number of single unit trucks involved with the incident
totalveh	Total number of vehicles involved with the incident
noLane	Number of lanes on both directions (including shoulders and medians)
noSDsh	Number of shoulder lanes on the same direction that an incident occurred

noSDBsh	Number of blocked shoulder lanes on the same direction that an incident occurred
noODsh	Number of shoulder lanes on the opposite direction that an incident occurred
noODBsh	Number of blocked shoulder lanes on the opposite direction that an incident occurred
noSDmain	Number of main lanes on the same direction that an incident occurred
noSDBmain	Number of blocked main lanes on the same direction of where an incident occurred
SDBmain	The ratio of number of blocked lanes to the total number of lanes on the same direction of where an incident occurred: • minor: ≤ 0.25 • moderate: 0.25 – 0.5 • severe: 0.5 – 0.75 • very-severe: > 0.75
noODmain	Number of main lanes on the opposite direction that an incident occurred
noODBmain	Number of blocked main lanes on the opposite direction of where an incident occurred
ODBmain	The ratio of number of blocked lanes to the total number of lanes on the opposite direction of where an incident occurred: • minor: ≤ 0.25 • moderate: 0.25 – 0.5 • severe: 0.5 – 0.75 • very-severe: > 0.75
OC	Responsible operation center
pavement	Pavement conditions: dry, wet, snow/ice, chemical wet, and unspecified
chart	1 if CHART is involved in the clearance; otherwise 0
detection	Incident detection sources
night	1 if an incident occurs during 8 p.m. – 6 a.m.
peakhr	• AMpk: AM peak periods (7 a.m. – 9:30 a.m.) • PMpk: PM peak periods (4:00 p.m. – 6:30 p.m.) • Non-pk: off peak periods
region	• Washington: Fredrick, Montgomery, Prince George, and D.C. • Baltimore: Anne Arundel, Baltimore City, Baltimore, Carroll, Harford, and Howard • Eastern: Caroline, Cecil, Dorchester, Kent, Queen Anne's, Somerset, Talbot, Wicomico, and Worcester • Southern: Calvert, Charles, and Saint Mary's • Western: Allegany, Garrett, and Washington

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